TECHNISCHE UNIVERSITÄT DRESDEN

Faculty of Environmental Sciences

Integrative Assessment and Modelling of the Non Timber Forest Products Potential in Nuba Mountains of Sudan by Field Methods, Remote Sensing and GIS

Dissertation for awarding the academic degree

Doctor of Natural Science (Dr. rer. Nat.)

Submitted by

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Dresden, February 2019

Explanation of the doctoral candidate

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Dresden, February 2019

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Acronyms and Abbreviations

AAS	African Academy of Sciences
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AOD	Aerosolmoptical Depth
BI	Brightness Index
CBS	Central Bureau of Statistics
CRISP	Centre of Remote Sensing and Image Processing
CAF	Charities Aid Foundation
CIPD	Chartered Institute of Personnel and Development
CI	Coloration Index
CAM	Complementary or Alternative Medicine
CBD	Convention on Biological Diversity
DEM	Digital Elevation Model
DNs	Digital Numbers
EO	Earth Observation
EC	Environmental Change
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agriculture Organization of the United Nations
FCS	Food Consumption Score
FEWS NET	Famine Early Warning Systems Network
FNC	Forests National Corporation
FRA	Forest Resources Assessment
FSMU	Food Security Monitoring Unit
GEOBIA	Geographic Object-Based Image Analysis
GIS	Geographic Information System
GOBCD	Geographic Object-Based Change Detection
GPS	Global Positioning System
GWR	Geographically Weighted Regression analyses
HAC	Government of Sudan’s Humanitarian Aid Commission
HS	Harmonized commodity description and coding System
ID	Image Differencing
IDPs	Internally Displaced People
IGSSS	Indo-Global Social Service Society
IFAD	International Fund for Agricultural Development
IFRC	International Federation of Red Cross and Red Crescent Societies
INSPIRE Directive	INSPIRE Thematic Working Group Land Cover
IOM	International Organization for Migration
ISIC	International Standard Industrial Classification
IVI	Importance value index
KBIC	Knowledge Based Image Classification
KNNC	K-Nearest Neighbor Classification
KSLA	Royal Swedish Academy of Agriculture and Forestry
LC	Land Cover
LU	Land Use
ME	The dichloromethane and methanol
MEAs	Multilateral Environmental Agreements

MFPs	Minor Forest Products
MNDWI	Modified/Normalized Difference Water Index
MSF	Médecins Sans Frontières
MSS	Multi-spectral Scanner
NAS	National Academy of Sciences
NDVI	Normalized Difference Vegetation Index
NDRE	Normalized Difference Red edge index
NGS	National Geographic Society
NIR	The near infrared band value for the segment
NOAA	National Center for Environmental Information
NTFPs	Non-Timber Forest Products
NWFPs	Non-Wood Forest Products
OLI & TIR scenes	The Operational Land Imager and Thermal Infrared Sensor
OLS	Ordinary Least Squares regression
PBIA	Pixel-Based Image Analysis
PCD	Post Change Detection technique
PCC	Pearson Correlation Coefficient
PPS	Principle of Population proportional to Size
QUAC	QUick Atmospheric Correction
RI	Redness Index
RMSE	Root Mean Square Error
RRA	Rapid rural appraisal
RS	Remote Sensing
SAF	Sudanese Armed Forces
SAR	Spatial Autoregression
SAVI	Soil Adjusted Vegetation Index
SDGs	Sustainable Development Goals
SITC	Standard International Trade Classification
SPLA	Sudan People's Liberation Army
SPLM-N	Sudan People's Liberation Movement-North
SRO	Spearman Rank-Order
SPSS	Statistical Package for Social Sciences
RED	The red band value for the segment
SDGs	UN Sustainable Development Goals
TM	Thematic Mapper
TTA	Training and Test Area
UN	United Nations
UNEP	United Nations Environment Program
UNDESA	United Nations Department of Economic and Social Affairs
UNDP	United Nations Development Programme
UNHCR	Office of the UN High Commissioner for Refugees
UNOCHA	UN Office for the Coordination of Humanitarian Affairs
UNSD	United Nations Statistical Division
USGS	United States Geological Survey
VRRC	Voluntary Return and Reintegration Commission
WBGU	German Advisory Council on Global Change
WCO	The World Customs Organization

WHO	World Health Organization
WFP	World Food Programm
WWF	World Wildlife Fund for Nature
6S	The Second Simulation of Satellite Signal in the Solar Spectrum

ACKNOWLEDGEMENT

To almighty GOD: for manifold blessings and guidance up to now and in future.

This dissertation would not have been come into this shape without hearty contribution of many scholars, and people from Nuba Mountains of Sudan.

First of all, I would like to express my sincere gratitude to my supervisor Prof. Dr. habil. Elmar Csaplovics who has patiently advised, support and guided me in both personally and scientifically levels, as well as provide me continuous encouragement, meticulous inputs and constructive criticism. His insight has always enlightened me. From him I learned how to think critically, how to select problems, how to solve them, and how to present their solutions. I am extremely grateful for his contributions to improved my research skills and lifting me up to this level.

I would also like to extend my deepest appreciation to the members of my graduate committee, Prof. Dr. Judith Miggelbrink (Head of the exam commission) for her kind support. I’m also deeply grateful to Prof. Dr. Mohamedelnour Taha (Director of Kordofan University), and Dr. habil. Hannelore Kusserow (Free University of Berlin) for their generous support, fruitful suggestions and comments as well as for spending their valuable time on the evaluation of this study. I do appreciate their exerted efforts to facilitate this study.

I also wish to extend my thanks for help and encouragement from Dr. Mustafa Mahmoud El-Abbas (University of Khartoum) who taught me the science in very different and fascinating ways; I am very appreciative for him. Also I would like to extend my gratitude to Prof. Dr. John Healey (Bangor University) for his support and provide the needed scientific materials. I like to express further greatest thanks to Prof. Dr. Osman Elkhair (University of Khartoum), who gave me many valuable ideas and suggestions. I am very grateful for his time to editing and correction the thesis. My sincere thanks go to Mr. Christopher Marrs (TU Dresden) as well for his valuable time to proofreading the dissertation.

I’m particularly indebted to Rosa Luxemburg Stiftung (RLS) for availing financial support, and made this study a success by assisting me in several respects. Special appreciation also goes to German Federal Foreign Office (Auswärtiges Amt), Graduiertenakademie of TU Dresden and German Academic Exchange Service (DAAD) for their financial support during the finalization stage of my work. Thanks extended to the Gesellschaft von Freunden und Förderern der TU Dresden (GFF) for their valuable financial support to attend some international scientific events. Data for the study described in the thesis have been obtained from several organizations, including DLR (Deutschland für Luft- und Raumfahrt) under the RESA (RapidEye Science Archive) project, NASA's Earth Observing System (EOS) and USGS (United States Geological Survey). I extend my thanks to all these organizations for their generous support.

I also acknowledge and appreciate hearty supports given by Forest National Cooperation (FNC) offices in Khartoum and South Kordofan States for their unlimited logistic support during the study period. Sincere gratitude goes to Dr. Mohamad Ali Elhadie (General manager of FNC) and Dr. Abdel-Al Azeem Margnie to provide me the needed data and logistic support, without their assistance it would not have been possible for me to carry out the field work.

I am extremely grateful to Dr. Patrick Meier (Executive Director of WeRobotics Foundation), Prof. Dr. Bernhard Schipp (Head of institute of Quantitative methods SEP econometrics, TU Dresden), Dr. Sandra Thieme (Speaker funding program of RLS) and Dr. Katrin Schäfgen (Director of Studies in RLS), for their support when it was most need. My sincere thanks go to my friends and colleagues at TU Dresden, RLS, United Nations Volunteers and United Nations Office for the Coordination of Human Affairs for scientific discussions, advices and continuous support.

I would like to express my deepest thanks to people from Rashad, Elabbassia and Dar Elsalam Localities, who shared information about their daily livelihood in a friendly manner. They accepted me as a family member. I will always remember the warm hospitality and support given by Miss. Muna Elsanosi and her family and Mrs. Rabiea Mohamad and her family.

My especial thank with my sincere gratitude goes to my dear family for their generous supports and encouragement throughout my study which was invaluable for the successful completion of this research work.

My advance thanks as well for everyone helped me or gave invaluable comments and suggestions that helped to shape the present form of dissertation.

Abstract

Pressure imposed at any one place or point in time results in a complexity of spatial and temporal interactions within topographical ecosystems. It can be propagated through the system and may have implications for future ecosystem functions over a wide array of various spatial and temporal scales. Under conditions of wars and other socio-economic conflicts, these processes are most forceful in developing countries amidst declining economic growth, lack of awareness, deterioration of ecosystem services, loss of existing traditional knowledge bases and weak governance structures. Forests are an essential part of ecosystem services, not only as a resource but as a contributor to biological systems as well. They represent one of the most important sectors in the context of Environmental Change (EC), both from the point of mitigation as well as adaptation. While forests are projected to be adversely impacted under EC, they are also providing opportunities to mitigate these changes. Yet this is one of the least understood sectors, especially at the regional level - many of its fundamental metrics such as mitigation potential, vulnerability and the likely impacts of EC are still not well understood until now. Thus, there is a need for research and field investigations into the synergy of mitigation and adaptation so that the cost of addressing EC impacts can be reduced and the co-benefits can be increased.

The aim of this study is to focus particularly on forest-based ecosystem services and to use forests as a strategy for inducing environmental change within the Nuba Mountains in Sudan, specifically for systems in poor condition under EC, and furthermore to explore forests as an entry point for investigating the relationship between urban and rural development and ecosystem services. In addition, the aim is also to raise understanding of the relations between patterns of local-level economic and demographic changes, the nature and value of local ecosystem services, and the role of such services in increasingly interlinked urban and rural livelihood systems. The methodology applied in the current research is three-pronged: a formal literature review, a socio–economic survey (based on semi-structured interviews of household heads via Rapid Rural Appraisal (RRA), with a focus on group discussions, informal meetings, free listening and key informant techniques), and multi-temporal optical satellite data analysis (i.e. Landsat and RapidEye). Landsat imagery was utilized to gather the spatial characteristics of the region and to study the Land Use/Land Cover (LU/LC) changes during the period from 1984 to 2014. Meanwhile, RapidEye imagery was used to generate the tree species distribution map. Qualitative and quantitative techniques were applied to analyze socio-economic data. Moreover, Food Consumption Score (FCS) was used to gauge both diversity and frequency of food consumption in surveyed areas. Geographic object-based image analysis (i.e. K-Nearest Neighbour classifier and knowledge-based classifiers) based on a developed model of integrated features (such as vegetation indices, DEM, thematic layers and meteorological information) was applied. Post Classification Analysis (PCA) as well as Post Change Detection (PCD) techniques were used. Hotspot analysis was conducted to detect the areas affected by deforestation. Furthermore, Ordinary Least Squares regression (OLS), Autocorrelation (Moran's) analysis, and Geographically Weighted Regression analyses (GWR) were applied to address the interaction of the different socio-economic/ecological factors on Non Timber Forest Products (NTFPs) collection and to simulate the dependency scenarios of NTFPs along with their impact on poverty alleviation. Additionally, simulation was performed to estimate the future forest density and predict the dependency on forest services. An increasing impact of intensive interactions between the rural and urban areas has long been acknowledged. However, recent changes in the global political economy and environmental systems, as well as local dynamics of the study area driven by war, drought and deforestation, have led to an increasing rapidity and depth in rural transformation, as well as to a significant impact on

urban areas. Like most environmental problems, the effects of these drivers are complex and are stressed diversely across different geographic regions by the socio-political processes that underlie recent economic and cultural globalization. These interactions and processes have increasingly brought rapid changes in land cover, social, institutional and livelihood transformation across broad areas of South Kordofan. Moreover, the study unveils new dynamics such as high rates of migration and mobility by the indigenous population and the increasing domination of market-centric livelihoods in many villages that were once dominated by rural agricultural and natural resources-based socio-economic systems. Furthermore, the research highlights the significant roles of NTFPs and trees in contributing to Nuba Mountains' economic development, food security and environmental health, indicating which requirements need to be addressed in order to improve these potentials. The study proves that drawing on a wide range of these products for livelihood strengthens rural people's ability to deal with and adapt to both EC and extreme events. Moreover, the results underline the importance of participatory approaches of rural women and their impact on NTFPs management with recommendations of more emphasis on potential roles and the ability of women to participate in public fora. Furthermore, the study shows that the use of high-resolution satellite imagery, integrated with model-based terrestrial information, provides a precise knowledge about the magnitude and distribution of LU/LC patterns. These methods can make an important contribution towards a better understanding of EC dynamics over time. The study reveals that more information exchange is needed to inform actors and decision makers regarding specific experiences, capacity gaps and knowledge to address EC. Subsequently, new policies and strategies are required to much more specifically focus on how to deal with consequences of longer-term EC rather than with the impacts of sudden natural disasters.

Zusammenfassung

Druckausgeübt auf einen bestimmten Ort zu einem bestimmten Zeitpunkt führt zu komplexen räumlichen und zeitlichen Wechselwirkungen innerhalb von Ökosystemen. Diese können sich innerhalb des Systems ausbreiten und Auswirkungen auf zukünftige Ökosystemfunktionen entfalten, verteilt über ein breites Spektrum verschiedener räumlicher und zeitlicher Skalen. Unter den Einflüssen von Krieg und anderen Konflikten sind diese Prozesse in Entwicklungsländern am stärksten, aufgrund von nachlassendem Wirtschaftswachstum, sich verschlechternden Ökosystemsdienstleistungen und dafür fehlendem Bewusstsein, sowie verloren gehendem traditionellen Wissen und schwachen Verwaltungsstrukturen. Wälder sind ein wesentlicher Bestandteil der Ökosystemleistungen, nicht nur als Ressourcen, sondern auch als aktive Bestandteile biologischer Systeme. Sie stellen einen der wichtigsten Sektoren im Zusammenhang mit Umweltveränderungen, (Environmental Change, EC), dar, sowohl im Hinblick auf Milderung als auch auf Anpassung. Während Wälder durch Umweltveränderungen eher nachteilig beeinflusst werden, bieten sie auch Möglichkeiten, diese Veränderungen abzuschwächen. Trotzdem sind sie, vor allem auf regionaler Ebene, einer der am wenigsten verstandenen Sektoren - ein Großteil der grundlegenden Parameter wie Abschwächungspotenzial in Bezug auf negative Einflüsse, Anfälligkeit und wahrscheinliche Auswirkungen von Umweltveränderungen sind bis heute noch nicht bzw. noch nicht gut verstanden worden. Daher besteht Bedarf an Forschung und Feldarbeiten bezüglich der Synergie zwischen Milderung und Anpassung, so dass die Kosten für die Bewältigung der Auswirkungen von Umweltänderungen gesenkt und das Potential an Nutzen erhöht werden kann.

Ziel dieser Studie ist es, sich vor allem auf forstbasierte Ökosystemdienstleistungen zu konzentrieren und Wälder als Strategie für die Stimulation positiver Umweltveränderungen in den Nuba-Bergen im Sudan zu nutzen, insbesondere für Systeme, die sich durch negative Umweltveränderungen in einem schlechten Zustand befinden. Ferner dient die wald-bezogene Forschung als Einstiegspunkt für die Untersuchung der Beziehungen zwischen städtischer und ländlicher Entwicklung sowie Ökosystemdienstleistungen. Außerdem soll das Verständnis für die Zusammenhänge zwischen den Ausformungen des wirtschaftlichen und demographischen Wandels auf lokaler Ebene, der Art und des Wertes lokaler Ökosystemdienstleistungen und der Rolle dieser Dienstleistungen in zunehmend vernetzten städtischen und ländlichen Systemen der Existenzsicherung verbessert werden. Die in dieser Forschung angewandte Methodik ist dreigliedrig: eine formelle Literaturrecherche, eine sozioökonomische Inventur (basierend auf teilstrukturierten Interviews mit Haushaltsvorständen via Rapid Rural Appraisal (RRA), mit Fokus auf Gruppendiskussionen, auf informelle Treffen, freies Zuhören und auf Schlüsselinformanten mittels sogenannter, key informant techniques) und multitemporale optische Satellitenbild-Analyse (Landsat und RapidEye). Landsat-Bilddaten wurden verwendet, um die räumlichen Merkmale der Region zu erfassen und die Änderungen der Landnutzung/ Landbedeckung (Land Use/Land Cover Changes, LU/LC) im Zeitraum von 1984 bis 2014 zu untersuchen. Satellitenbilder von RapidEye wurden genutzt, um die Verteilungskarte der Baumarten zu erstellen. Zur Analyse der sozioökonomischen Daten wurden qualitative und quantitative Techniken angewandt. Darüber hinaus wurde der Food Consumption Score (FCS) verwendet, um sowohl die Vielfalt als auch die Häufigkeit der Konsumation von Lebensmitteln in den untersuchten Gebieten zu bestimmen. Geografische objektbasierte Bildanalyse (z. B. K-Nearest Neighbour Klassifikation und wissensbasierte Klassifikatoren) basierend auf einem entwickelten Modell integraler Merkmale (wie Vegetationsindizes, DGM, thematische Datenlayer und meteorologische Informationen) wurde. ebenso genutzt wiePost Classification Analysis (PCA) und Post Change Detection (PCD). Eine Hotspot-Analyse wurde durchgeführt, um die von Abholzung

betroffenen Gebiete zu extrahieren. Darüber hinaus wurden Methoden der kleinsten Quadrate (Ordinary Least Squares regression, OLS), eine Autokorrelationsanalyse (Moran's) und eine Geographisch gewichtete Regressionsanalyse (GWR) angewendet, um die Wechselwirkung der verschiedenen sozio-ökonomischen / -ökologischen Faktoren bei der Nutzung von Nichtholzprodukten (Non-Timber Forest Products, NTFPs) zu erfassen und die Abhängigkeitsszenarien von NTFPs, sowie deren Auswirkungen auf die Armutsbekämpfung, zu simulieren. Zusätzlich wurde eine Simulation durchgeführt, um die zukünftige Walddichte abzuschätzen und die Abhängigkeit von waldbezogenen Dienstleistungen vorherzusagen.

Die zunehmende Bedeutung intensiver Interaktionen zwischen ländlichen und städtischen Gebieten ist seit langem anerkannt. Die jüngsten Veränderungen in der globalen politischen Ökonomie und in den Umweltsystemen, sowie die lokale Dynamik im Untersuchungsgebiet zufolge Krieg, Dürre und Abholzung haben jedoch zu einer zunehmenden Geschwindigkeit und Tiefe der ländlichen Transformation, sowie zu erheblichen Auswirkungen auf die städtische Entwicklung geführt. Wie die meisten Umweltprobleme sind die Auswirkungen dieser Vorgänge komplex und in unterschiedlichen geografischen Regionen durch die sozialpolitischen Prozesse, die der jüngsten wirtschaftlichen und kulturellen Globalisierung zugrunde liegen, unterschiedlich beeinflusst. Diese Wechselwirkungen und Prozesse haben in weiten Teilen von Süd-Kordofan zu rapiden Veränderungen in der Landbedeckung sowie zu sozialen und institutionellen Veränderungen und Umgestaltungen der Art und Weise der Existenzsicherung geführt. Darüber hinaus belegt die Forschungsarbeit neue Dynamismen hohe Migrations- und Mobilitätsraten der einheimischen Bevölkerung und die zunehmende Dominanz marktorientierter Existenzsicherung in vielen Dörfern, in denen früher landwirtschaftliche und naturressourcen-basierte sozioökonomische Systeme vorherrschten. In der Dissertation wird außerdem die bedeutende Rolle von NTFPs und Bäumen für die wirtschaftliche Entwicklung, die Ernährungssicherheit und die Intaktheit der Umwelt der Nuba-Berge untersucht und hervorgehoben. Des weiteren wird aufgezeigt, welche Anforderungen zu erfüllen sind, um diese Potenziale zu verbessern. Die Forschungsarbeit zeigt, dass die Nutzung eines breiten Spektrums dieser Produkte für den Lebensunterhalt die Fähigkeit der ländlichen Bevölkerung stärkt, sowohl mit Umweltveränderungen als auch mit Extremereignissen umzugehen und sich zu adaptieren. Zusätzlich unterstreichen die Ergebnisse die Bedeutung partizipativer Aktionen von Frauen im ländlichen Raum und ihre Auswirkungen auf das NTFP-Management und geben Empfehlungen, dass die potenzielle Stellung und die Fähigkeit von Frauen, an öffentlichen Foren teilzunehmen, stärker betont werden müssen. Außerdem wird nachgewiesen, dass die Verwendung hochauflösender Satellitenbilder, die in modellbasierte terrestrische Inventuren integriert sind, exakte Informationen über die Größe und Verteilung von LU/LC-Flächenmustern liefert. Diese Methoden können einen wichtigen Beitrag zum besseren Verständnis der Dynamik der Umweltveränderungen im Laufe der Zeit leisten. Die Studie zeigt auf, dass mehr Informationsaustausch erforderlich ist, um Akteure und Entscheidungsträger über bestimmte Erfahrungen, Kapazitätslücken und Wissenspotentiale zur Bewältigung negativer Einflüsse von Umweltveränderungen zu informieren. Folglich sind neue Richtlinien und Strategien erforderlich, um sich wesentlich intensiver auf den Umgang mit den Folgen längerfristiger Umweltveränderungen statt nur auf dieAuswirkungen plötzlicher Naturkatastrophen zu konzentrieren.

CHAPTER ONE

INTRODUCTION

1.1 General Background

In recent years, the importance of natural resources in supporting rural livelihoods over the world was increasingly being recognized in national and international policy (Cottray *et al.*, 2006; Deafalla, 2011; Ratner *et al*., 2017). However, human well-being relies on our ability to exploit these resources diverse and often fragile sustainability, and as well as into the far distant future. Approaches to development are therefore required that enable incomes to be derived from natural resources, while supporting the effective conservation of these resources. Non Timber Forest Products (NTFPs) are broadly defined as any forest-derived tradable products other than commercial timber (Akinyerni *et al.*, 2003; Vantomme and Walter, 2003; FAO, 2009), offer an important example of how such goals may be achieved in practice, many rural livelihoods are based on the collection and sale of products derived from forest resources, including fruits, nuts, fiber and resins (KSLA, AAS and FAO, 2005; Cottray *et al*., 2006; CAF, 2008). As a consequence, trade in NTFPs can act as an incentive for forest conservation by providing a source of income from resources that might otherwise appear to have little financial value (Deafalla, 2012). Fruit, basketry, honey and medicinal plants are just a few examples of economically and socially valuable products that can be produced from a sustainably managed natural resource base (Cottray *et al.*, 2006). In addition, the environmental impact of harvesting NTFPs is generally much lower than typically results from timber harvesting. NTFPs have been a particular focus of development interest recently in developing country. The hope is that forest-dependent communities can gain new income-generating opportunities with minimal environmental costs. To offer a long-term source of income, NTFPs production will still require careful planning, management and monitoring. Researches regarding NTFPs harvesting and commercialization are still relatively recent and numerous of the datasets with more details necessary for a thorough analysis of these questions, are still lacking (Rajchal, 2006; Deafalla, 2011; Deafalla, 2012). Therefore, tools are needed that could be used to direct external support to those areas with the highest potential for success.

This research describes an approach to define NTFPs and their potential in poverty alleviation, ecosystem conservation and sustainable development. As well as to demonstrate how development zones for NTFPs may be delineated through building a demonstration model using socio-economical data, Remote Sensing (RS) and Geographic Information System (GIS), with an explicit focus on environmentally sustainable income-generating opportunities for the poorest sections of society. In addition to exploring the linkages between the environment, security and conflict, especially in vulnerable areas that face multiple stresses at the same time, and identify how important are natural resources, more specifically NTFPs, in limiting conflicts. This is achieved using Nuba Mountains of Sudan as a case study. Nuba Mountains's rich natural heritage, and its position as one of the most rapidly growing economies in the country, serves to highlight the conflict between national development efforts and the need for a globally responsible approach to natural resource conservation. The results offer a strong indication of the most appropriate sites for the sustainable development of NTFPs harvesting and commercialization. Such 'expert systems' can be made accessible to any number of stakeholders, providing a truly participatory and inclusive tool for the sound management of our common natural heritage.

1.2 Aim and scope of the study

1.2.1 Research questions and concepts

Many of the challenges we face nowadays are the unintended consequences of efforts to enhance the sustainable management and biodiversity conservation with welfare of humankind. When one goes deeply within these challenges, one can find that the land use mosaics and sustainable development are the principal concepts guiding natural resources (namely; agricultural, pastoral and forestry lands) sector development. This is true in many Africana countries, where the area hosts a wealth of biodiversity and provides vital regional as well as global ecological services.

In Sudan, environmental planning and resources management sector face hindrance of data collection that requires comprehensive information on Land Use/Land Cover (LU/LC) dynamics. Although, there is an urgent need to improve the estimation methods of NTFPs, while they provide a good basis for rational assessment that contribute to rural livelihood, there is scarcity of studies on socio-ecological and socio-economical factors affecting NTFPs at different steps. Furthermore, there are no advanced techniques, namely RS and GIS, integrated with such studies in semi-arid region to address the interactions between heterogeneous factors affecting NTFPs. In addition to that, no systematic attempt has been made, so far, towards assessment and mapping these resources. Nowadays, worsening socioeconomic, environmental, human and political circumstances in Nuba Mountains of Sudan have underscored the urgency of understanding of the interactions between these factors to prepare successful forest management strategies which can variously be helpful to implement a development paradigm and selecting appropriate pathways which contribute to both environment sustainability and conservation objectives. As well, there is still an urgent need for mapping and monitoring, using RS and GIS data to LC concerning different fields and NTFPs. This is particularly according to an important role in enhancing the general environment, through encouraging conservation of the tree cover, which will, in the long run, lead to more land being converted to tree cover, thereby reversing the current trend of tree cutting for crop cultivation.

Despite decades of massive infusion of advanced technology from the developed world, and proposed solutions to tackle these problems in different ways, there are continuous elicited questions regarding the appropriateness of these technologies in the country. From the above mentioned perspective, pertinent research questions to be tackled by this research are:

1. What consequences do these interactions have for the ecosystem of the study area?
2. How can NTFPs contribute both to rural poverty eradication and forest conservation?
3. How do spatial factors affect these two goals? Based on currently available information, where do specific NTFPs have the highest chances of being successfully developed and commercialized in an economically and environmentally sustainable way?
4. How can the advanced technology (i.e., RS and GIS) be refined in the future to give a more complete picture?

The current study will focus on advancing the following concepts;

1. Currently the Earth's land cover has been transformed, especially in the study site, according to the interaction of multiple stresses such as; endemic poverty, ecosystem degradation and conflicts. There is, therefore, an urgent need for mapping and monitoring the land features and their dynamics;
2. NTFPs have an important contribution to poverty alleviation, ecosystem conservation and sustainable management;

3. Advanced technology provides accurate and precise methods for mapping, monitoring and modeling NTFPs effectively.

1.2.2 Research objectives

The study will investigate the following objectives:

1. To address the environmental changes and their impacts on Nuba Mountains Region.
This objective will be achieved in the following chapter by:

- Analyze the spatio-temporal remotely sensed data in relation to the heterogeneous factors, that affect local ecosystem services, for strategic decisions;
- Raise understanding of the relations between patterns of local- level economic and demographic changes;

The data was collected by different methods to cover a wide range of research topics necessary to achieve the objectives. Firstly; natural, physical and topographical data will be gathered in form of shapefiles (i.e. points, lines and polygons) of the villages, roads and markets reading by Global Positioning System (GPS) in addition to shapefiles for the forests, obtained from the Forests National Corporation (FNC) for security reasons. Remotely sensed data provides an immense amount of LU/LC data, accordingly it is used as a series of temporal satellite data to study the LC changes in the study area for the past decades. Landsat (1984, 1994, 2002 and 2014) imagery, in addition to high resolution Digital Elevation Model (DEM) data from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and meteorological information, was used to gather the spatial characteristics of the region such as; vegetation cover (density and type), terrain features, surface temperature… etc.;

Secondly; Semi-structured interviews of household heads, as well as Rapid rural appraisal (RRA), with focus on group discussion, informal meetings, free listing and key informants techniques, and direct observations were applied, to address and detect the war's impact, demographic and LU/LC changes. Additionally, the study utilized observation questionnaire to identify the LU/LC, forest characteristics, topographic, water and vegetation information.

Third; a formal literature review was utilized to cover the area directly related to difficulties of data collection, due to security reasons.

In order to perform an appropriate temporal analysis, the Geographic object-based classification (i.e. K-Nearest Neighbor classifier model and knowledge-based classifier) based on a developed model of integrated features (such as: vegetation indices, DEM and thematic layers) was applied, which allowed for an overall assessment of change over the past decades. Furthermore, to evaluate the results of conversions, Post Change Detection technique (PCD) was applied to quantify and locate the changes. Subsequently, Hotspot analysis was conducted to detect the affected areas by deforestation. Descriptive statistics methods were applied in three ways; first, to describe the basic features of the community as well as the social characters of respondents. In addition to describing household hunger scale based on the idea that the experience of household food deprivation causes predictable reactions, especially in the new life, and finally to assess the prevalence of household food insecurity (access component) and to detect changes in the food insecurity situation of a population over time. The Food Consumption Score (FCS) was used to gauge both diversity and frequency of food consumption in surveyed areas of study area. Moreover, the correlation analysis was applied to test the war impact on the local community as well as on the LU/LC.

2. To identifying the nature and value of local ecosystem services based on NTFPs;
This objective was achieved in chapter three by:

- Mapping the NTFPs species;
- Detecting the role of such services in an increasingly interlinked urban/rural livelihood system of Nuba Mountains of Sudan;

The data were collected in two ways in this chapter; the first way through semi-structured interviews of household heads as well as RRA based on free listing and key informants techniques which were applied as well, to identify different aspects of the NTFPs activities to attain information on matters such as products uses, seasonal patterns and income generation from these products in relation to other occupations. The second form was by high reolution RapidEye (2012 and 2013) satellite imagery integrated with high resolution DEM image, thematic layers and additionally meteorological information. These data were used to generate the tree species distribution map.

Importance Value Index (IVI) method was utilized to reflect the cultural significance of the species and use category. Descriptive statistical methods were applied to analyze data concerning social characteristics and respondents perspectives about different aspects of the NTFPs production activities. Summary information of the social – economic characteristics of the study sample was obtained in form of frequency, percentages, distribution, mean, minimum, maximum, sum and standard deviation. K-Nearest Neighbor Classifier (KNNC) model based on a developed model of integrated features was applied to generate the species map.

3- Modeling and simulating the heterogeneous factors effect in NTFPs;
This objective was achieved in chapter four by:

- Identifing value chain of these products;
- Modeling different natural, topographical, human, social, physical, and financial factors as well as their interactions which affecting NTFPs commercialization from upstream to downstream of value chains to assess the performance of the value chain and it's efficiency in supplying markets and consumers;
- Simulating the dependency scenarios of NTFPs and their impact on poverty alleviation, to be used for the future prediction of microstructure of rural livelihood.
- Estimate the future forest density and predict the dependency on forest services.

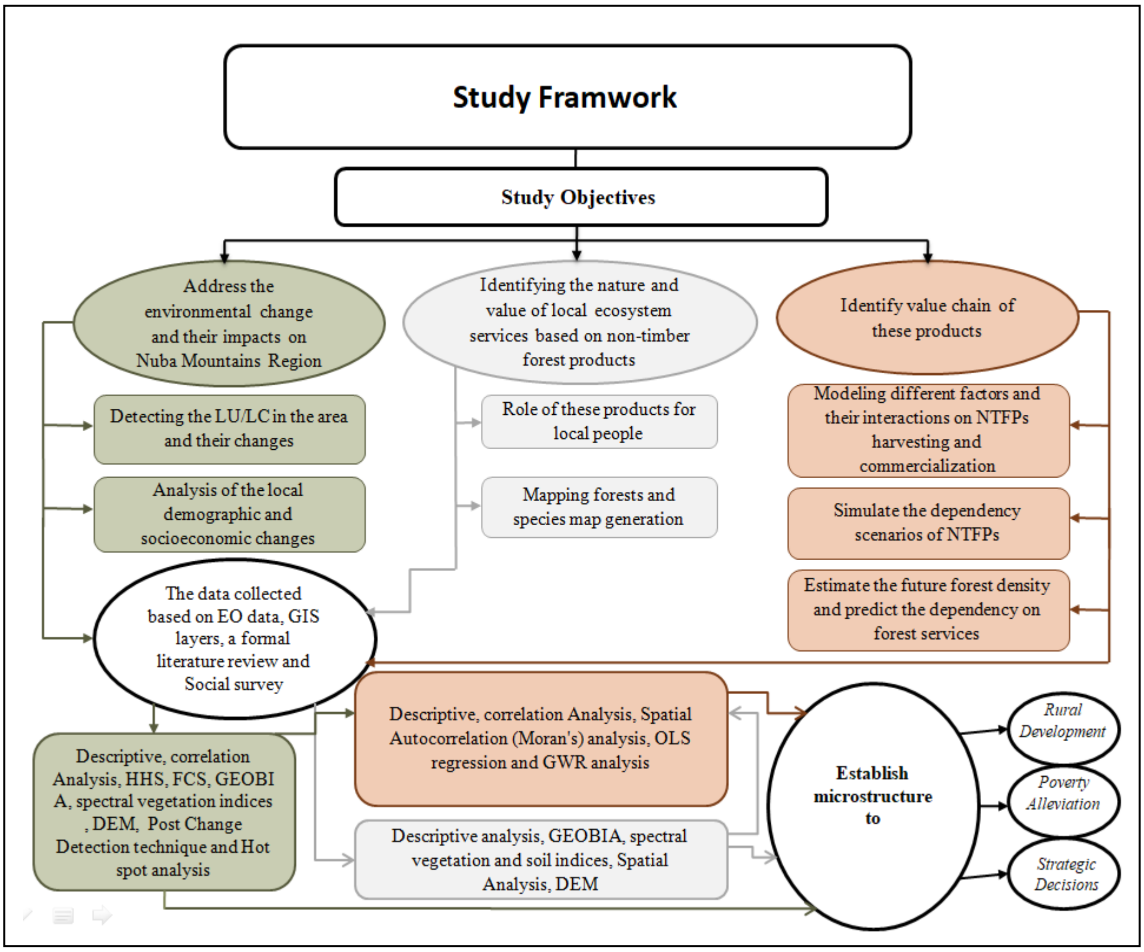
In this chapter, primary data was collected through different forms; i.e. semi-structured interviews, interviews and informal/ formal meetings, to recognize the value chain of NTFPs. The specific trades NTFPs information was gathered from reports and records of FNC, statistics of local and international trade data and through purposive interviews at different levels of trading chain and at different areas. The last form utilized in this study was integrated GIS shapefile data with optical satellite data (i.e. 2014 Landsat imagery) for modeling and predicting the heterogeneous factors effecting NTFPs.

Correlation and regression analyses were utilized to describe and test the relationship between different factors, and to estimate the probability of participation of households in NTFPs collection as well as the relative magnitude of such probabilities based on different socio-economic/ ecological factors (ethnicity, gender, education, age, main occupation, duration of the main occupation, war, migration, markets, vegetation cover (density and type), terrain features, surface temperature ...etc.)

that affect such activities. Geostatistical analysis i.e.; the Ordinary Least Squares regression (OLS), Autocorrelation (Moran's) analysis, and Geographically Weighted Regression analyses (GWR) were applied to address the interaction of the different socio-economic/ ecological factors on NTFPs collection. The output of different parameters modeled was used as a base for the simulation. GWR is a powerful tool for spatial prediction as well as for exploring spatial heterogeneity; accordingly it was applied to simulate the dependency scenarios on NTFPs and the estimation of future forest density as well as for predicting the dependency on forest services.

The research was concluded by chapter five, where a summary of the study's findings was provided, its theoretical contributions, and some recommendations for both future studies and policy for sound, sustainable and scientific management to our common natural heritage. Figure 1.1 below shows the study framework.

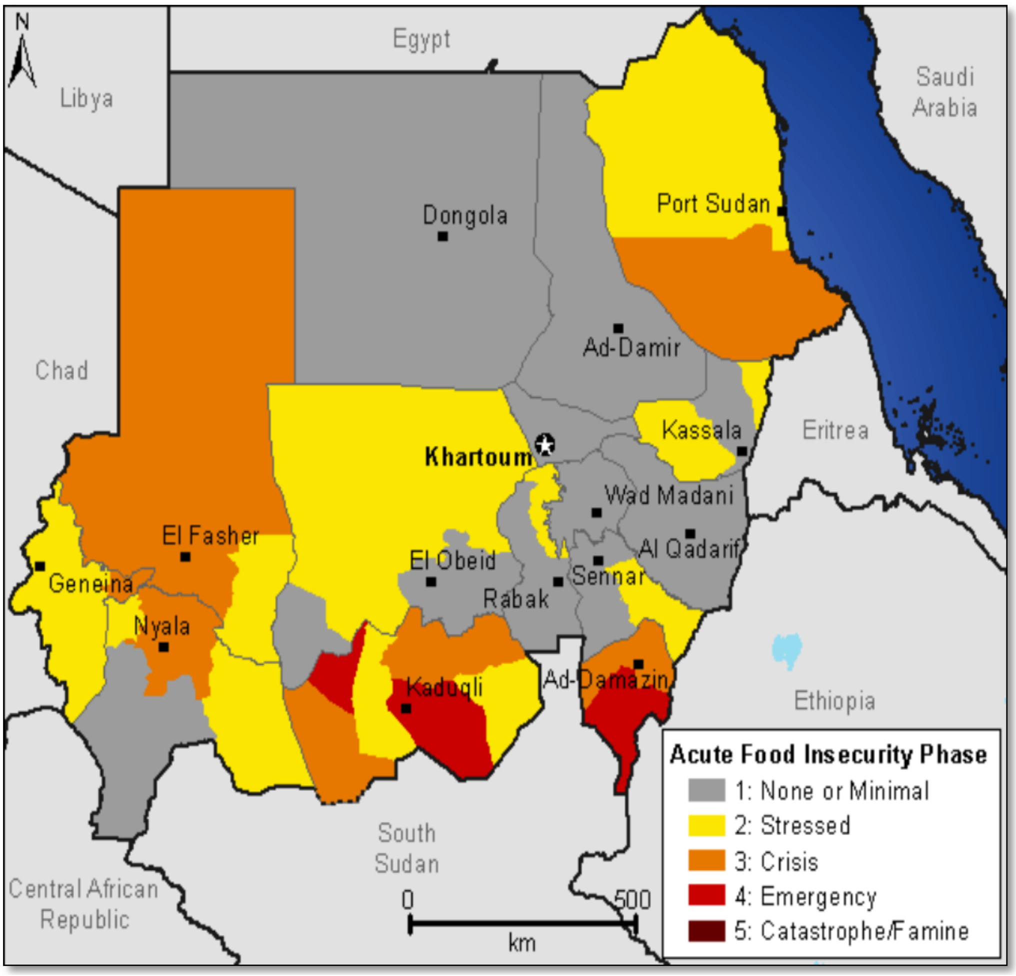
Figure 1.1: The study framework.



1.3 Overview of the Study Site

As a case study, Nuba Mountains of Sudan, is rich with various tree species which grow naturally, however nowadays has existing risks and vulnerabilities associated with many reasons; the environmental and climatic impacts, high rate of poverty, moreover, ethnic and religious fractionalization, ethnic conflicts between nomads and sedentary farmers, as well as the socio-political conflicts destabilizing the critical areas on the western and southern parts of the state. The interaction of these factors put and leads the area to critical situations, compared with other states of the country. Figure 1.2 below clarifies that.

Figure 1.2: Projected food security outcomes, 2012.

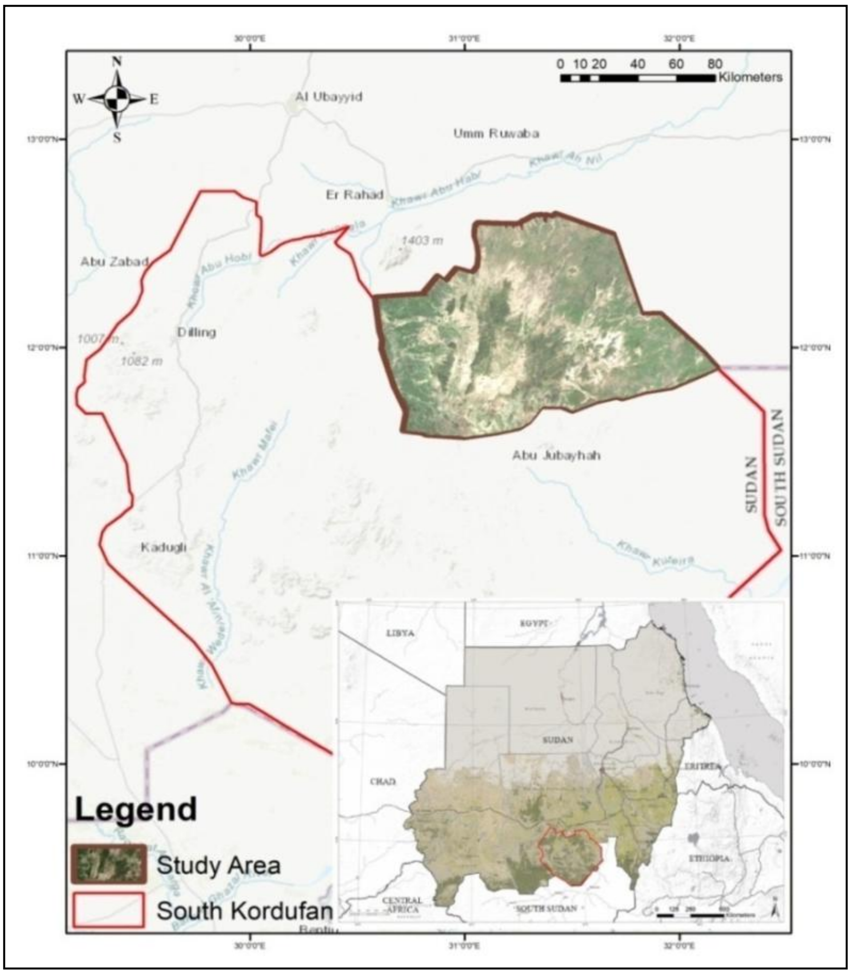


Source: FEWS NET (2011)

1.3.1 The geographical location

The study site is located in Southern Kordofan State (Fig. 1.3). The State is bordered by Darfur in the west, Abyei and Republic of South Sudan in the South, White Nile and North Kordofan state in the North. The state is subdivided into 5 districts, Dilling, Kadugli, Rashad, Talodi and Abujubayha (Deafalla *et al.*, 2017). The present research was carried out in Rashad district as shown in Figure 1.3 below. It lies between latitudes 11° and 12° N, and longitudes 30° and 32° E, with a total area of 135,696 km² (Ahamed, 2009; Deafalla, 2012). The study selected three different locations in the Eastern Nuba Mountains namely; Elabbassia, Rashad and Abu Karshola localities. Each locality is divided further into smaller administrative units. A commissioner is responsible for administering the locality, through legislative and executive bodies. At the village level, the government is represented by the tribal system.

Figure 1.3: Location of the study site



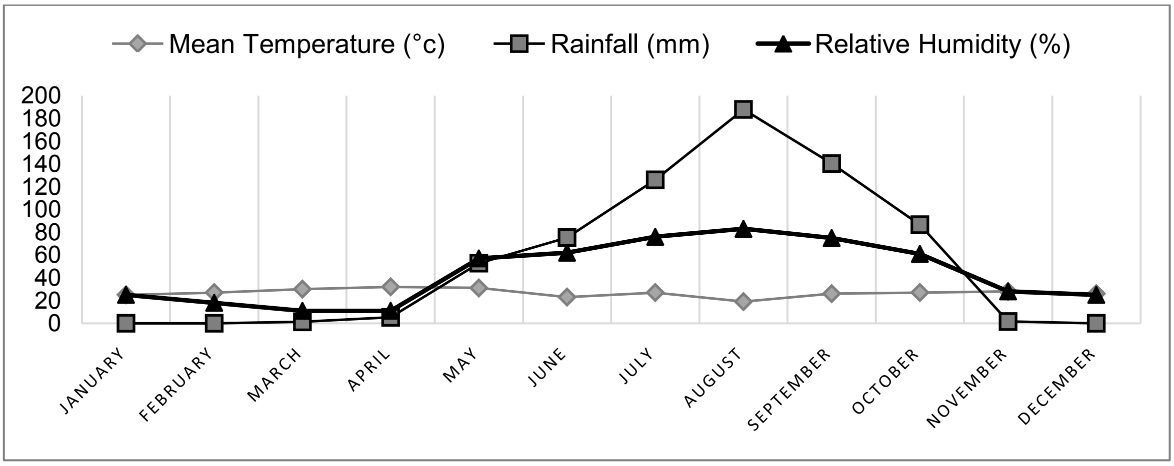
Source: DIVA-GIS, developed by author

1.3.2 Basic Characterization of Nuba Mountains

1.3.2.1 The climate, topography and soil

The region has a varying climate, ranging from low-rainfall woodland savannah in the north to rich savanna in the south. Annual rainfall ranges from less than 350 mm on the northern border to more than 900 mm on the southern border. The rainy season varies from about five months or less, with rains occurring between May and October (Mohammed, 2011). The average daily temperature ranges from 10 to 35°C with an annual variation of 15°C (Fig. 1.4). April to June is the hottest period and December to February is the coldest. Wind direction differs according to seasons: northeast in winter and southwest in summer (El Tahir *et al.*, 2010).

Figure 1.4: Mean annual rainfall, temperature and relative humidity in study area during the period 1981 – 2010 (Rashad station)



Source: National Centers for Environmental Information (2016)

The region is a mountainous area where elevation reaches up to 1,000 meters. Around 50,000 km² is covered by Mountains. The high hills are mostly ridges separated by narrow V-shaped valleys. In these areas, there is extensive erosion and loss of topsoil. The area is classified as a sub-humid region (Babiker *et al.*, 1985; UNDP, 2006).

The soil in the region ranges from sandy with organic matter, nitrogen and phosphorous in the north, to heavy cracking clay, low in nitrogen and phosphorus, in the south. In between, there are the so-called "*Gardud*" soils, which are compacted soils found on the high ridges of undulating plains, developed in-situ from the local igneous and metamorphic rocks. The clay plains comprise about 32 % while the *Gardud* and sandy soils comprise about 27% and 21% of the total state area, respectively (Deafalla, 2012).

1.3.2.2 Water Resource

There are no permanent watercourses in the area, although, the study site has heavy rains, however, this forms only seasonal streams. The most prominent of these streams are Khor Aldelib, Khor Kadada, Khor Tagmala and Khor Umbrumbita, which carry substantial run-off between July and October (IOM, 2009). The other water's sources in the area are Hafirs, shallow wells and deep boreholes. In general, there is scarcity in freshwater sources, due to the unsuitability of the area for drilling boreholes and poor development of other water sources, which is causing tension between local communities. Furthermore, Iodine is not available in water there (UNDP, 2006).

1.3.2.3 Vegetation cover

The region has diverse and rich vegetation, resulting from the variability in soils and rainfall (Harrison and Jackson, 1958). The vegetation of Nuba Mountains ranges from semi-arid in northern part to sub-humid vegetation type in the southern part (Ballal *et al.,* 2014). The landscape in the area is characterized by flat thorn bush savannah, grassland with acacia and baobab trees, and resembles desert in the dry season (IOM, 2009). The area covered by forest trees in Rashad district is estimated to be in the order of 2,717,000 hectares making about 60% of the total area of the district (El Tahir *et al.*, 2010; Deafalla, 2012). The types of forests in the region are reserve forests, natural, community forests or integration of private farms. The central reserved forest is about 20,475.5 hectare and this is about 0.9% of the total size of the local forest. At the same time, as the community forests are estimated to be 8,093.9 ha., while the proposed forest reserves are estimated to be 229,927.2 ha., in the district (Deafalla*,* 2012).

Figure 1.5: Forestland characteristic of the study site

Source: Taken by author (2014)

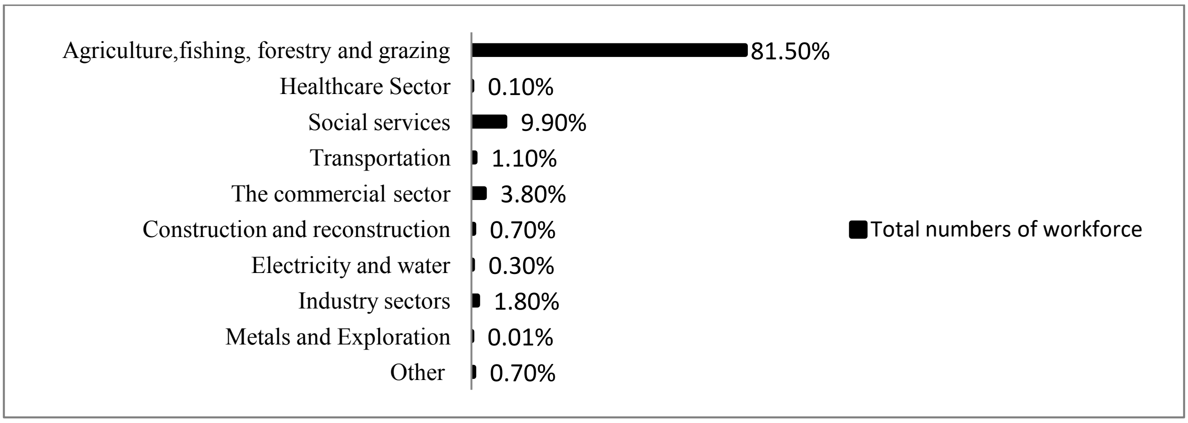
1.3.2.4 Population and socio-economic situations

According to the latest residential census in 2008 by Sudan Central Bureau of Statistics (CBS), the total population of Southern Kordofan State was 1.3 million with population growth (2.4%) distributed into 120,986 households, which is about 15% of the total population of Sudan. The urban population constitutes 21% of the total population of South Kordofan, nomads 1.1% and the sedentary rural population 76.9% (CBS, 2009). The main ethnic groups include: firstly, Nuba which represents the largest tribe (61%). It consists of sub-groups. Each one of these groups has its own local dialect, and traditions, which are slightly different from each other, but the Arabic Language is a lingua franca in the region (Bello, 2014). They are largely sedentary farmers, but some are semi-nomads rearing cattle. They inhabit the Nuba mountains, located in the center of Southern Kordofan. Secondly, Baggara and other minor Arab tribes which represent 26% of the population. These are of Arabic origin and consist of diverse groups, namely; Hawazma, Messiria Humr, Messiria Zurug, Rizeigat, Taisha, Habbaniya, Beni Halba, Awlad Himayd, and Beni Selam. They are mainly transhumant rearing cattle. The Misseriya are pastoralists with nomadic life style. They are dominant in the western part of Southern Kordofan. The Hawazma have abandoned the nomadic life style and mainly settled in the eastern part of Southern Kordofan (IOM, 2009). Thirdly, West Africans who represent 8%, they are predominantly sedentary farmers, but manage some livestock. Then Nilotic and others, who represent 5%, are formerly cattle owners used to practice transhumant life, but recently have settled and engaged in sedentary farming and livestock management (El Tahir and Gebauer, 2004; Department of Statistics, Southern Kordofan State, 2008; El Tahir *et al.*, 2010). Despite the fact that some villages are overwhelmingly Islamic or Christian, and some communities practice traditional religions, the Nuba have a long tradition of religious tolerance.

1.3.2.5 Economic activity of the community

The livelihood activities found in the area are agro-pastoralism, nomadic pastoralism, horticulture and rain-fed agriculture; both traditional farming for subsistence and mechanized farming for commercial operations. In addition to that, a third source of livelihood is related to natural forests in form of woody and non-woody production derived from various tree species (UNDP, 2006; Deafalla *et al.*, 2017). Key economic activities of the inhabitants are dominated by the work in fishing, agriculture and forestry (82%), followed by the services sector (10%), the commercial sector (4%) with the rest of economic activities making about 2% according to Deafalla (2011) as shown in Fig.1.6.

Figure 1.6: Types of economic activities



Source: Deafalla (2011)

1.3.2.6 Transportation

Rashad district in South Kordofan suffers deterioration of the roads. The town is connected by a road to the north of Sudan. But recently it experienced a shortage of public transport due to the deterioration of the security situation. In the study site, road access to other areas is difficult, particularly in the rainy season (IOM, 2009). The road from Elabbassia locality ascends over a rocky area, reaching 900 meters above sea level, before it reaches Rashad town at an altitude of 1,000 meters. Stock routes exist in the area, but are not demarcated because of the high cost of opening the routes, which at present cannot be borne by the district budget. Most of the areas are completely cut-off from the rest of the country during the rainy season as displayed in Figure 1.7 below, due to the muddy soil type inhibiting vehicles (UNDP, 2006). Between April and October, Rashad province is accessible only by road using trucks, animals or on foot.

Figure 1.7: Road to Rashad province during rainy season

Source: Taken by author (2014

CHAPTER TWO

Environmental Changes and Their Impact

General overview

The links between climate change, environmental degradation, and conflict are highly complex and poorly understood as yet. Resources always constitute risks of conflict in developing countries, particularly if poverty is widespread, the resource is scarce, and property rights are insecure and/or unclear. Some of these causal factors are manifested in, and are driving forces behind, armed conflicts in Nuba Mountains of Sudan, often with broader geographical, socioeconomic, and political repercussions, displacement of people, and unsustainable use of natural resources. This chapter is a context chapter, providing detailed background on the Environmental Change (EC) and its impact on Nuba Mountains Region that has systems in poor condition (under EC reconsider). Having described the nature of the driver, and its socio-ecological impact, the chapter sets out the effects of demographic and associated cultural changes on territorial LU, and explains how it may be contributing to transformative changes among traditionally resource-dependent communities. It concludes with a discussion of the possible coping strategies for EC.

2.1 Introduction

Exploring the linkages between the environment, security and conflict is not a novelty. It is theoretically backed up and scientifically evidenced (Miljkovic, 2008; Behnassi, 2017) even if it has not yet reached the satisfaction and acceptable level. The EC is a complex dynamic system; it's defined as a change or disturbance of the environment caused by human influences or natural ecological processes (Andrews, 1971; Porter, 1985, 1990; Khanna and Palepu, 1997; Johnson *et al.*, 1997; Suarez and Oliva, 2005). The characteristics and importance of each driving force may vary from one area to another. However, the long-range interactions of pressures may lead to the EC (Deafalla *et al.*, 2017). In addition to that, the ability to create and transfer environmental pressures or stress onto the environment of other societies varies from one area to another. For example, developed countries are significantly contributing to global and transboundary environmental pressures than the less affluent societies which have minimal interaction with the environment in which they live (UNEP, 2007a). Lein in his study (2012), referred to the transformations characterizing EC as subtle and slow to emerge, or dramatic and quick to materialize. In either case, they reflect the consequence of disturbances that alter material and energy flows within the environmental system. Here, the concept of a ‘‘disturbance’’ becomes a convenient way to connect environmental stress to actions that will display both in temporal and spatial dimensions (White and Picket, 1985).

EC is the most important one, of the security, climatic and developmental challenges facing humanity, particularly in developing countries (Deafalla *et al.*, 2018). EC is, in effect, a ‘threat multiplier’ that makes existing concerns, such as drought, desertification, water scarcity, food insecurity and land degradation, more complex and intractable. However, it is non-climate factors, such as poverty, conflict management, governance, regional diplomacy etc., which will largely determine whether and how EC moves from being a development challenge to presenting a security threat (Brown *et al.*, 2007; Brown and Crawford, 2009).

Indeed, over the past two decades, the concept of human security has been used to frame and analyze problems of social change. Recently, particulary since 1994, the concept of human security has been expanded to comprise threats in seven intertwined areas: economic security, food security, health security, political security, community security, personal security and environmental security (UNDP, 1994; Turner, 2004; O'Brien and Barnett, 2013; Olokeogun *et. al*, 2014). Global EC has the potential to undermine human security in a direct way, i.e. the needs, rights, and values of people and communities, where the real risks that resource depletion, as well as severe forms of environmental degradation, may increase social and political tensions in unpredictable but potentially dangerous ways.'Global', in this sense, does not mean that responsibility for EC is shared equally among all people, or that the impacts of these changes are uniformly distributed among all places. Instead, global refers to the linkages between EC and social consequences across distant places, groups, and time horizons (UNEP, 2007a; Barnett *et al.*, 2008; Barnett *et al.*, 2010).

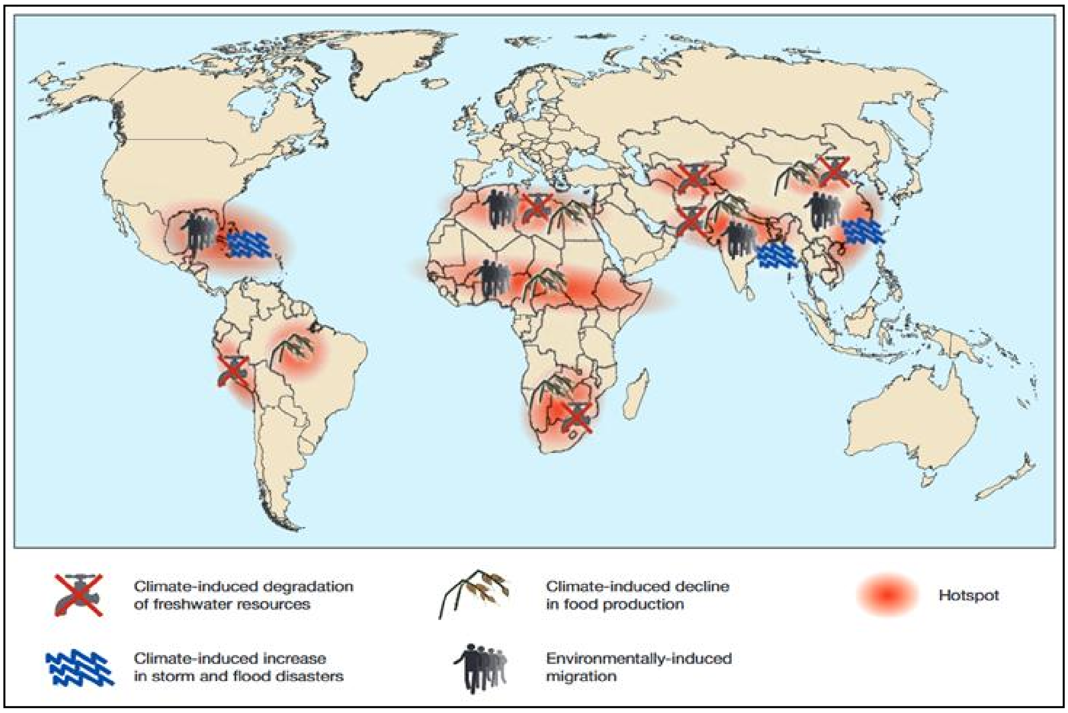
In recent times, many concerns have been raised about the relationship between EC and human activities. Within the concept of this relationship, it is found that they simultaneously reinforced each other and formed avicious circle. Several studies, such as Foley *et al.* (2004); Mahmood *et al.* (2010) and Deafalla *et al*. (2014a), confirmed that there is a strong and complex link between environmental variability and LU/LC. This relationship takes more important dimension when one starts thinking of building resilience against insecurity or problems related to sustainable management of ecosystem services.

The changes caused by human-induced impact on atmospheric composition, climate, land, water, and biodiversity are occurring so rapidly that the natural systems are increasingly losing their adaptive capacity. The resulting degradation of the planet's resources and life-support systems may be irreversible at scales relevant to present human society. Moreover, the inertia in many natural processes means that the damage may take only years or decades later to become fully apparent (Melese, 2016).

Natural resources play a key role in increasing the likelihood of onset, the duration and the return to conflict; particularly in African developing countries, the high profile case of Sudan is often cited when looking at environment and conflict dynamics (Bannon and Collier, 2003; Collier, 2003). The links between environmental resources and conflicts are, however, highly complex, non-linear and influenced by a combination of factors, including political, social, economic, environmental, historical, and the different aspects of vulnerability (Notaras, 2009). Actually, the interaction of these factors plays a role in either preventing or stimulating conflict. Nevertheless, large open access natural resources can undermine the quality of governance, aggravate corruption, weaken economic performance and, thereby, increase the vulnerability of countries to conflicts. Moreover, conflicts can also occur over the control and exploitation of resources (Deafalla, 2012). On the other hand, the forced movement of people in those areas undermines, sometimes for decades, the economic development, sustainable livelihoods as well as the capacities of societies and nations. The shortage or degradation of natural resources contributes directly to lower levels of well-being and higher levels of vulnerability. However, in many developed societies, they clearly recognized the contribution of natural resources to poverty reduction efforts (UNEP, 2007b; Deafalla, 2012).

German Advisory Council on Global Change (WBGU) in 2007, have identified the so called "hot spots"; regions of the world where climate change is interacting with other social, political, economical and historical factors to the extent of being deemed a security threat. As 'societies' adaptive capacities are overstretched, risk can attain the dimension of conflict, Figure 2.1 below indicates that.

Figure 2.1: Security risks associated with climate change



Source: WBGU, (2007)

Environmental factors such as climate change are rarely the main driver of conflict. However, the related environmental stresses have a determining influence on peace and security. Furthermore, resource abundance or possession of specific high-value resources in socio-political contexts of weak institutions and poor governance are not only associated with low economic growth, but can contribute in increasing the likelihood and incidence of civil or armed conflicts, stimulates violence between rival groups as well as the stakeholders of the resource (UNEP, 2007b; Ekbom, 2009; Deafalla *et al.*, 2014a). The changes in and depletion of natural resources linked to climate change have been considered as a causal factor in the current crisis in many regions of Sudan. Even through this brief mention, Sudan's Darfur region is a striking example of a vicious cycle where environmental sources are being fought over and at the same time being destroyed as a result of violence, one that highlights that peace is not possible unless underlying and closely linked environmental and livelihood issues are resolved (Miljkovic, 2008).

As mentioned earlier, the links between EC, seen as a destabilizing interference in the ecosystems equilibrium, on the one hand, and the outbreak of violent conflicts, on the other, remain ambiguous and very complex (Miljkovic, 2008; Deafalla *et al.*, 2017). Unfortunately up to date, there is a gap in the researches that focus on the intersections between global EC and human security based on LU/LC changes (Behnassi, 2017). In reality, LC patterns play an important role on EC detection studies, where they reflect the underlying natural and social processes, thus providing essential information for modeling and understanding many phenomena on the earth, including the complex interactions between global EC and human activities (Bounoua *et al.*, 2002; Jung *et al.*, 2006; Liang, 2008; Running, 2008; Gong *et al.*, 2013; Jia *et al.*, 2014; Miller *et al.*, 2017). Timely and accurate LC data are, therefore, an essential factor for improving the performance of ecosystem (Bounoua *et al*., 2002; Jung *et al*., 2006; Running, 2008; Miller *et al*., 2007; Gong *et al*., 2013) and have a permanent place in the international policy of sustainable development and ecosystem preservation.

Given the history of Nuba Mountains of Sudan, as a case study, the communities there live in fragile and unstable conditions, high poverty, high dependence upon natural resources as well as ethnic and religious fractionalization. The geography of the area, as well as the ethnic and political conflicts, makes them more vulnerable to the risk of violent conflict and environmental change's effects. Unfortunately, the EC in the area based on the interaction of these factors could aggravate territorial and border disputes and complicate conflict resolution as well as mediation processes in the future, in addition to hindering the process of development in the region. Some concerned scientists have warned of this prospect for several decades (e.g. Burr, 1998; Faki *et al.*, 2011; Deafalla, 2012; Totten and Grzyb, 2015), but the debate has been constrained by lack of carefully compiled evidence.

To address this shortfall of data, the study will examine the interplay between environmental factors, human security, and conflict. It will focus to raise understanding of the links between patterns of local-level economic and demographic changes of Nuba Mountains region, specifically of those systems in poor condition under EC. As well as detecting the LU/LC in the area and their changes during the past decades. It also outlines some of the actions being taken to help a country adapting to the changing environment, and makes recommendations for how such actions could become more effective.

2.2 Research Methods

Three approaches were applied to analyze the long term environmental changes and trends during the period from 1984 to 2017 in the Nuba Mountains: RS techniques, multi source social- economical-ecological data and a formal updated literature review.

2.2.1 RS data

The term "remote sensing", was first used in the United States mid of 1950s by Ms. Evelyn Pruitt when she was a geographer/oceanographer with the U.S. Office of Naval Research (Herring, 2005; Al-doski *et al*., 2013). RS is now commonly used to describe the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation (Singh, 1989; Rogan and Chen, 2004; Lillesand *et al*., 2015). Basically, two types of RS instruments are available: active and passive. Active instruments provide their own source of energy (electromagnetic radiation) to illuminate the object or scene they observe whereas passive instruments detect the natural energy that is reflected or emitted from the observed scene (Horning *et al*., 2009; Baumann, 2013). The data of these techniques are acquired in predetermined spectral bands (wave lengths). Visible and near infrared spectral bands are chosen to amplify or separate specific earth features such as vegetation, urban area, snow rocks and water (Csaplovics, 1984). This way one can separate a chosen land feature from other land features by choice of the wavelength (Nirupama and Simonovic, 2002; Alshaikh, 2016).

Indeed, Earth Observation (EO) data from airborne and space-borne platforms including aerial photographs, satellite images, spatial data set and other data provide a huge amount of valuable information about our earth's surface (van Westen, 2000; Paradzayi *et al*., 2008; Gong *et al*., 2013; Gómez *et al*., 2016). Based on earlier work, including Darwish *et al*. (2003); Mostafa *et al*. (2014) and El-Abbas (2015), this up-to-date image data is a promising tool for producing accurate LC maps this is largely due to the ability to more accurately identify small features on the Earth's surface.

Over the last few decades, RS has experienced rapid and dramatic growth. This growth is expected to continue, although it is difficult to predict the rate of these developments (Horning *et al*., 2009). The technological advances due to technical advances in computers and increased sensitivity of instruments as well as increasing availability of mid- to fine-resolution satellite imagery since the early 1990s, offers repetitive data that vary among themselves in terms of spatial, radiometric, spectral, temporal resolution and its synoptic view (Stoney, 2006). Moreover, the digital format makes their data suitable for many computer image processing softwares (Al-doski *et al*., 2013). All these properties have made satellite imagery the main source for various RS applications (Lu *et al*., 2004a; Kennedy *et al*., 2009; Lu *et al*., 2010a; Lu *et al*., 2010b). Furthermore, remotely sensed imagery, in the form of satellite and aerial photography, has become an indispensable tool in resource management and in numerous areas of scientific research.

The environmental policies at the international level are related to such issues as natural resource management, sustainable development and global climate change. More recently, interest has developed in using satellites to the monitoring, evaluation and regulation of existing environmental policies, particularly Multilateral Environmental Agreements (MEAs) such as the Kyoto Protocol. Where it used to ensure compliance with MEAs requirements by both direct enforcement and by more indirect means through high levels of transparency, and that due to many international laws, in fact, lack compulsory inspection regimes or sufficient resources to ensure compliance (Kline and Raustiala, 2000; Mayer, 2011). These laws and policies govern different types of forces leading to earth’s surface changes. As a component of the environmental studies, the land cover change is an important aspect of resource management and environmental mitigation, being a complex indicator of the effects of the local, national and international policies regarding the environment (Deafalla, 2017).

Generally, the earth’s surface changes are divided into two categories: Land Use (LU) and Land Cover (LC) (Barnsley *et al*., 2001). Although the terms LC and LU are often used interchangeably, their actual meanings are quite distinct; therefore it is important to define them clearly. According to the definition of INSPIRE Directive (2013) and Rawat and Kumar (2015), LC represents the physical and biological cover of the Earth’s surface captured in the distribution of vegetation, surface water and groundwater, soil and other physical features of the land and build-up areas. In contrast, LU refers to the way in which human beings exploit the land and its resources, usually with accent on the functional role of land for economic activities. However, LC and LU are often used interchangeably because the two terms are interdependent and closely related (Verburg *et al*., 2003; Verburg *et al*., 2009; Al-doski *et al*., 2013).

LC is the most important element for description and study of the environment (Herold *et al*., 2006). Indeed, LU affects LC, in turn changes in LC affect LU, the relationship between them is very complex due to the mutual relation that involves the interaction between numerous fundamental factors (Kabba and Li, 2011; Wang and Wang, 2013; Yohannes *et al.*, 2018). Rawat and Kumar in (2015) describe the change in LC as a phenomenon resulting from human interactions in the environment has significant implications for sustainable resource use, as it generally reflects the situation or irreversible losses in the natural resources by differing rates and on different scales. It mainly arises from diverse and ever-increasing demands for space and resources for human well being. It is worth mentioning, these changes do not necessarily imply degradation of the land only. However, many shifting LU patterns driven by a variety of social causes, biophysical factors, technological and economic considerations, as well as institutional and political arrangements (Lambin, and Ehrlich, 1997), result in LC changes that affect biodiversity, water and radiation budgets, trace gas emissions and other processes that come together to affect climate and biosphere (Riebsame *et al.,* 1994; Peter *et al*., 2015; Melese, 2016).

Since the beginning of concern over the major consequences of LU/LC changes that were globally recognized such as; global warming (Aggarwal *et al*., 2012), loss of biodiversity and ecosystem functioning (Lawler *et al*., 2014) and increase vulnerability of regional biomes and human well-being (Salazar *et al*., 2015), it has been widely recognized that changes have very significant impact across many sectors of the society, economy and the environment (Aggarwal *et al*., 2012; Deafalla *et al*., 2018). To understand how these changes affect and interact with LU/LC dynamics, information is needed on what changes happen, where and when they occur, the rates at which they happen, as well as the driving forces behind these changes (Lambin, 1997; Prakasam, 2012). This information on LU/LC, and their possibilities optimal use, is critical for more understanding the dynamics and predicting the patterns and trend of changes in a natural landscape and associated ecosystems at different scales (Lu *et al*., 2004b; Cotter *et al*., 2014; Yohannes *et al.*, 2018). Furthermore, it is essential for the selection, planning and implementation of LU schemes as well as for improving land management policies to meet the increasing demands for basic human needs and welfare (Olokeoguna *et al*., 2014; Amamo and Amenu, 2017). To achieve that, it is very important to have continual, historical and precise information on LU/LC changes of the earth's surface (Iqbal and Khanb, 2014).

Although the visible alterations evidences in the environmental system induced by human activities have been well documented for decades (Stern *et al*., 1992; Roberts, 1994; Mannion, 1997; Lein, 2012) the causes promoting these alterations are more complex and less obvious. Therefore, EO-based techniques are well suited to monitoring and assessment earth system in a consistent and robust manner over large areas (Gómez *et al*., 2016). The role of RS data in this context is to define and detect the transformations in the landscape, and to provide the needed information concerning the how-and-why behind what is seen (Lein, 2012; Pause *et al*., 2016). With the rapid development of technology, interpretation, analyses and integration of that information has certainly started a new era in land mapping (Di Gregorio, 2016).

Remotely sensed EO data has revolutionized our understanding of our dynamic environment (Leeuw *et al*., 2010). Now, more than ever, RS is being an indispensable tool in resource management and in numerous areas of scientific research. Where it has given the scientists an excellent opportunity to understanding the drivers, state, trends and impacts of LU/LC on social and natural processes as well as helps to reveal how changes happen, and the resultant consequences (Cardille and Foley, 2003; Verburg *et al*., 2015).

Satellite images have an important role in regional planning at different spatial and temporal scales and give a valuable database. As well, this technology offers a cost-effective, reduced timeframes and an accurate alternative for the understanding of landscape dynamics and human-environment interaction (Dale *et al*., 1993; Nirupama and Simonovic, 2002; van Westen, 2000; Matinfar *et al*., 2007; Lein, 2012; El-Abbas, 2015). Among the advantages of satellite imagery for geographical research, is the ability to capture in an instant a synoptic view of a large part of the Earth's surface and to acquire repeated measurements of the same area on a regular basis. Additionally, this technology has also made it possible for these observations to be continued for a long time in the future. Furthermore, RS allows us to collect data from dangerous or inaccessible areas (Pumayalli, 2012). Moreover, the properties measured by RS techniques can be classified, inferred and estimates of its corresponding area, particularly in combination with ancillary data or a priori knowledge (Amdie, 2007; Kim, 2016). Thematic maps are the common form of extracted information to the end users in a format that is understandable and accessible based on continuously developed classification approaches (El-Abbas, 2015). It is precisely these properties that make satellite remote sensing such an important source of data for studies of the dynamics of the Earth's surface and atmosphere (Donoghue, 2002). The Earth is a highly complex system formed by mutually interlinked components, therefore, accurate, timely, and reliable data are very important to analyze and study these variations (Ramachandran *et al*., 2011).

The latest RS and spatial analysis technology has become available to researchers (Al-doski *et al*., 2013), and anymore it is not elitist and expensive or a black box for the governmental stakeholders from national to regional level as in former decades. Scientists have availed recent advances in these techniques for studying the land system, especially to name EC, where it remains a constant theme that resonates worldwide. RS plays a key role in monitoring the various manifestations of global EC (Purkis and Klemas, 2011; Deafalla *et al*, 2018), where, it provides a database from which the evidence left behind, by EC that have occurred before, can be interpreted, as well as the potential relations between interacting elements, both in the temporal and spatial dimension and combined with other information to arrive at the maps. Moreover, this technique assesses threats to various components of natural systems, and in the identification of priority areas for conservation (Purkis and Klemas, 2013; Bello and Aina, 2014). Their mapping and monitoring can be recorded only by using satellite remote image platforms (Poursanidis and Chrysoulakis, 2017).

RS technology has catalyzed several aspects of LU/LC studies, and a myriad of approaches have been developed for many purposes such as; the social and environmental effects of war (Gbanie *et al*., 2018), crop rotation of agriculture (Waldhoff *et al*., 2017), forest cover change (Inzamul and Basak, 2017), deforestation assessment (El-Abbas *et al*., 2014), yield assessment and estimation (Lobell, 2013), land degradation detection (Higginbottom and Symeonakis, 2014), vegetation mapping (Meera *et al*., 2015), in wetland landscape changes (Ballanti *et al*., 2017), urban change detection (Hegazy and Kaloopb, 2015), in coastal zone changes (Devi *et al*., 2015) and other applications, by providing panoptic views and time-series measurements of earth's surface in ways nearly impossible to replicate by traditional ground-based methods.

In developing countries as general, and Sudan in particular, environmental planning and resources management sector face hampering of data collection that requires comprehensive information on LU/LC dynamics. Enormous efforts have been made to delineate LU/LC on a local scale by applying different traditional methods such as field surveys, collateral and ancillary data analysis, but they proved not effective, to acquire the required data, because they are time-consuming, date-lagged and too expensive. Based on that, the current study used RS approach to assists in maintaining update LU/LC dynamics information between 1984 and 2014 for a sound decision and a cost-effective planning.

2.2.1.1 Data

1- Image type used

Selection of the most appropriate RS image considers different factors such as complexity of the area, coverage, time, and level of spatial detail required for the specific objective (Ayele *et al*., 2018). Medium spatial resolution optical data such as Landsat satellite data dating back to 1972 are the most widely used data types for mapping and assessing the earth's surface and to update existing geospatial features (Lu *et al*., 2010b; Al-doski *et al*., 2013). It is characterized by free-availability and systematic global acquisition as well as it has contributed significantly to the development of RS applications such as LC classification (Haack, 1982; Masek *et al*., 2001; Phiri and Morgenroth, 2017).

Landsat (name indicating Land + Satellite) imagery is available from six satellites in the Landsat series. These satellites have been a major component of NASA's Earth observation program, with four primary sensors evolving over forty years, according to Centre of Remote sensing and Image

Processing (CRISP) in (2001) and United States Geological Survey (USGS) in (2015) can be described as follows:

a) MSS (Multi-spectral Scanner): On LANDSAT-1 to 5. Being one of the older generation sensors, routine data acquisition for MSS was terminated in late 1992. The resolution of the MSS sensor was approximately 80 m with radiometric coverage in four spectral bands from the visible green to the near-infrared (IR) wavelengths. Only the MSS sensor on Landsat 3 had a fifth band in the thermal-IR.
b) TM (Thematic Mapper): First operational on LANDSAT-4. TM sensors primarily detect reflected radiation from the Earth surface in the visible and IR wavelengths, but the TM sensor provides more radiometric information than the MSS sensor. The wavelength range for the TM sensor is from the visible (blue), through the mid-IR, into the thermal-IR portion of the electromagnetic spectrum. Sixteen detectors for the visible and mid-IR wavelength bands in the TM sensor provide 16 scan lines on each active scan. Four detectors for the thermal-IR band provide four scan lines on each active scan. The TM sensor has a spatial resolution of 30 m for the visible, near-IR, and mid-IR wavelengths and a spatial resolution of 120 m for the thermal-IR band.
c) ETM+ (Enhanced Thematic Mapper Plus): Is carried on board Landsat 7. The ETM+ instrument is an eight-band multispectral scanning radiometer capable of providing high-resolution image information of the Earth's surface. Its spectral bands are similar to thoss of TM, except that the thermal band (band 6) has an improved resolution of 60 m (versus 120 m in TM). There is also an additional panchromatic band at 15 m resolution. Landsat supplies high resolution visible and infrared imagery, with thermal imagery and a panchromatic image also available from the ETM+ sensor.
d) OLI & TIR scenes (The Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS): Are instruments onboard the Landsat 8 satellite, which was launched in February of 2013. (The spectral bands of the OLI sensor, similar to Landsat 7's ETM+ sensor, which provide enhancement from prior Landsat instruments, with the addition of two new spectral bands: a deep blue visible channel (band 1) specifically designed for water resources and coastal zone investigation, and a new infrared channel (band 9) for the detection of cirrus clouds. Two thermal bands (TIRS) capture data with a minimum of 100 meter resolution, but are registered to and delivered with the 30-meter OLI data product.

The increased availability of this satellite imagery since the early 1990s, offers repetitive and comparative data that vary among themselves in terms of spatial, radiometric, spectral, temporal resolution and its synoptic view (Stoney, 2006; Al-doski *et al*., 2013; Haque and Basak, 2017). They have been successfully utilized for monitoring LU/LC changes especially in lands that have been affected by human activity to various degrees. For instance, Deafalla *et al*. (2014b) used MSS, Landsat TM and ETM+ RS data for Earth and its resources mapping in South Kordofan of Sudan. Meanwhile, Zaki and Abotalib (2011) applied Landsat images (TM) for detecting LC changes in Northeast Cairo, Egypt. While, Fan *et al*. (2007) used TM and ETM+ images for detecting and predicting Earth's surface change in the Core corridor of Pearl River Delta, China.

RS time series research and applications have a rich history for large area monitoring of land dynamics (Gerylo *et al*., 2002; Ayele *et al*., 2018). Many studies have shown that classification results have improved with the use of multitemporal images rather than single time-shots (Pulver, 2006). Time series of Landsat imagery have demonstrated high capacity for characterization of environmental phenomena, describing trends as well as discrete change events (Williams *et al*., 2006; Al-doski *et al*., 2013; Gómez *et al*., 2016). Multiple-year data from Landsat data have been used in several fields of study such as: crop identification (Schmedtmann and Campagnolo, 2015), urban areas (Shao *et al*., 2016) and surface water bodies (Sarp and Ozcelikb, 2017), to characterize LC change (Zhu and Woodcock, 2014) and to recognize the nature of LC changes (Deafalla *et al*., 2018). Time series enable modeling and estimation of ecosystem structural variables and have been used to estimate aboveground biomass (Gómez *et al*., 2014), Zhu *et al*. (2012) used it for forest monitoring, while Gómez *et al*. (2012) mapped forest carbon sinks and forest degradation assessment by (Schneibel *et al*., 2017). Beside that, intra-annual time series have proven to be of great value when it is needed to acquire phenological insights for LC mapping (Ayele *et al*., 2018), as well as in strategies of near-anniversary annual series data (Gómez *et al*., 2016).

Sixteen Landsat imagery data time series (path/row: ranging from 174/051 to 173/052) over the study area were used. Four images for each selected year, these images include; four MSS data acquired on 9, 18 and 25 November 1984, followed by four Landsat TM images acquired on 21 and 30 November 1994. Then four ETM+ remote sensing data acquired on 28 November, 21 and 30 December 2002 were used as 2004 images not available. Finally, four Landsat 8 OLI & TIR images acquired on 5, 12 and 28 November 2014. The selection of the satellite images dates was influenced by the quality of the image especially the issue of cloud coverage. The RS data were downloaded from the USGS official website (http://glovis.usgs.gov/). The study used time series Landsat imagery (Table 2.1) only without integration of other sensors to ensure the radiometric, geometric and spectral consistencies throughout the selected scenes. Moreover, all scenes were acquired in dry season to reduce the phenological variation and allow for same atmospheric and environmental conditions.

Table 2.1: Wavelength regions and resolution corresponding to each original Landsat band for the selected sensors

Sensor	Bands		Wavelength (micrometers)	Resolution (meters)
Landsat 1-5 Multispectral Scanner (MSS)	Landsat 1-3	Landsat 4-5		
	Band 4 – Green	Band 1 - Green	0.5-0.6	60*[1]
	Band 5 – Red	Band 2 - Red	0.6-0.7	60*[1]
	Band 6 - Near Infrared (NIR)	Band 3 - Near Infrared (NIR)	0.7-0.8	60*[1]
	Band 7 - Near Infrared (NIR)	Band 4 - Near Infrared (NIR)	0.8-1.1	60*[1]
Landsat 4-5 Thematic Mapper (TM)	Band 1- Blue		0.45-0.52	30
	Band 2 - Green		0.52-0.60	30
	Band 3 - Red		0.63-0.69	30
	Band 4 - Near Infrared (NIR)		0.76-0.90	30
	Band 5 - Shortwave Infrared (SWIR) 1		1.55-1.75	30
	Band 6 - Thermal		10.40-12.50	120*[2] (30)
	Band 7 -Shortwave Infrared (SWIR) 2		2.08-2.35	30
Landsat 7 Enhanced Thematic Mapper Plus (ETM+)	Band 1- Blue		0.45-0.52	30
	Band 2 - Green		0.52-0.60	30
	Band 3 - Red		0.63-0.69	30
	Band 4 - Near Infrared (NIR)		0.77-0.90	30

	Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
	Band 6 - Thermal	10.40-12.50	60 *[3] (30)
	Band 7 - Shortwave Infrared (SWIR) 2	2.09-2.35	30
	Band 8 - Panchromatic	.52-.90	15
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Band 1 - Ultra Blue (coastal/aerosol)	0.43 - 0.45	30
	Band 2- Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - Shortwave Infrared (SWIR) 1	1.57 - 1.65	30
	Band 7 - Shortwave Infrared (SWIR) 2	2.11 - 2.29	30
	Band 8 - Panchromatic	.52-.90	15
	Band 9 - Cirrus	1.36-1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60-11.19	100 *[4] (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50-12.51	100 *[4] (30)

*[1] Original MSS pixel size was 79 x 57 meters; production systems now resample the data to 60 meters.
*[2] TM Band 6 was acquired at 120-meter resolution, but products are resampled to 30-meter pixels.
*[3] ETM+ Band 6 is acquired at 60-meter resolution, but products are resampled to 30-meter pixels.
*[4] TIRS bands are acquired at 100 meter resolution, but are resampled to 30 meter in delivered data product.

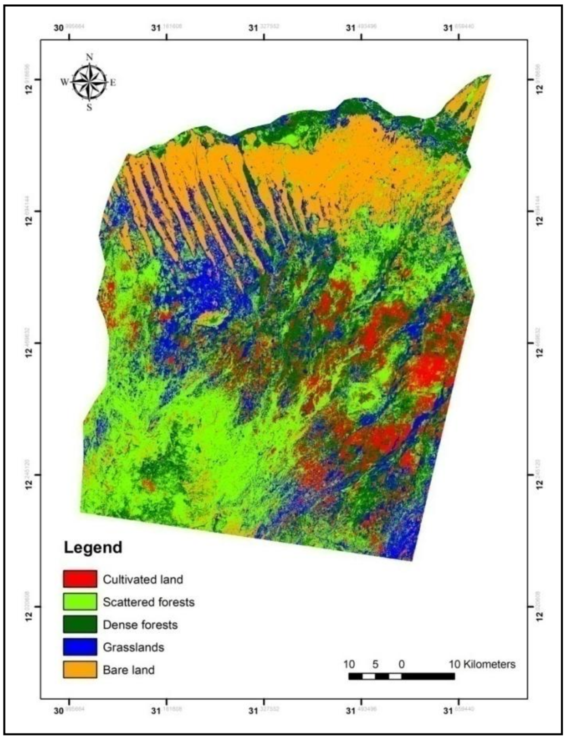
2- Field Survey Data

Ground reference data in image analysis plays important roles to determine information classes, interpret decisions, and assess accuracies of the results (Thapa and Murayama, 2009). In this study, to describe and verify the ground-types adequately, several ground-truthing methods were used. The first way involved the field points or ground-truth. 325 points were gathered during the field visit in July 2015 randomly from the secure areas in the study site represinting different LC types, and to create a “test set” for the classification accuracy. The ground reference points were collected by using GARMIN eTrex Venture HC GPS deviceto record the coordinates of each visited point.

The first field work was planned to be in November 2014 to coincide with the season of acquisition in order to eliminate the variation in natural phenological status and allow for same atmospheric and environmental conditions. But unfortunately, it wasn't possible to collect the required points due to the critical situation of the study area. To avoid the problems mentioned above, the study integrated shapefiles (i.e. points) gathered from FNC of Sudan for the forests.

Stratified random field sampling design was used with a proportional allocation strategy (McCoy, 2005), which has been established from spectral classes generated from unsupervised classification (Fig. 2.2) (the nearest image available before time of field work) to improve the efficiency of sampling by gaining greater control over the composition of the sample as well as to ensure a sound distribution of represented field samples relating to identified LU/LC class categories. These samples were collected mainly by the central coordinates of selected pure segments (polygons) representing both the homogeneous and the heterogeneous landscape environments of the study area. Subsequently, these have been transformed to shapefile, and then were introduced to eCognition software in form of thematic layer to make Training and Test Area (TTA) Masks to be used in subsequent steps of Geographic Object-Based Image Analysis (GEOBIA) paradigm as training and testing objects.

Figure 2.2: LU/LC Classification for the selected site in study area for the year 2011



During the ground reference data collection, ten LU/LC classes were identified representing:

1- Cultivated land: This class includes the lands which are used or cleared to be utilized for seasonal crop production in the rainy season, as well as the areas that are used for commercial seasonal crops (El-Abbas, 2015) as shown in Fig. 2.3 below.

Figure 2.3: Example for cultivated land class

Source: Taken by author (2014)

2- Bare land: The land is not covered by (semi-) natural or artificial cover and has not been developed for other uses (Fig. 2.4). It is, most often, degraded areas (Di Gregorio and Jansen, 2000).

Figure 2.4: Example for Bare land class

Source: Taken by author (2014)

3- Dense forests: Refers to closed forests, where trees, various storeys high, and undergrowth, cover a high proportion of the ground. In land area, more than 0.05 hectares with trees higher than 5 meters and canopy cover of more than 10 percent or trees able to reach these thresholds in situ. (Fig. 2.5). This does not include land that is predominantly under agricultural or urban land use (UNEP, CBD and SBSTTA, 2001).

Figure 2.5: Example for Dense forests class

Source: Taken by author (2014)

4- Shrublands: An area of land which is covered with low trees and bushes (Fig. 2.6), often also including; grasses, herbs, and geophytes (Harden, 2002).

Figure 2.6: Example for Shrublands class

Source: Taken by author (2014)

5- Scattered forests: This class represents the open forests, spanning more than 0.5 hectares; with trees higher than 5 meters and a canopy cover of 5-10 percent, or trees able to reach these thresholds in situ; or with a combined cover of shrubs, bushes and trees above 10 percent and height of 5 m. (Fig. 2.7). It does not include land that is predominantly under agricultural or urban land use (FAO, 2000a).

Figure 2.7: Example for Scattered forests class

Source: Taken by author (2014)

6- Grasslands: This class includes an area in which the natural dominant plant forms are grasses and forbs (FAO, 2000a) as displayed in Figure 2.8.

Figure 2.8: Example for Grasslands class

Source: Taken by author (2014)

7- Rocky area: Cover the areas mixing rocks and soil. Where it is the more biologically active and is richer in organic matter (Fig. 2.9). The two key soil features are its water holding capacity and the quantity of its nutrients and organic matter that sustain plant growth (FAO, 2015).

Figure 2.9: Example for Rocky area class

Source: Taken by author (2014)

8- Horticulture land: Cover the areas that include all trees and annual plants which are intentionally planted for fruits commercial production (Burbank, 2004) as shown in Fig. 2.10 below.

Figure 2.10: Example for Horticulture land class

Source: Taken by author (2014)

9- Settlements: Representing the residential areas ranging from local building material to concrete and bricks houses, trees and small gardens inside the villages are included (Dutta *et al*., 2010) as illustrated in Fig. 2.10 below.

Figure 2.11: Example for Settlements class

Source: Taken by author (2014)

10- Water bodies: The main feature of the class is seasonal streams, which are normally covered by trees or could be bare land during the dry season (Fig. 2.12).

Figure 2.12: Example for Water bodies class

Source: Taken by author (2014)

The second collection way was an observation questionnaire to gather LU/LC information, which focuses on a deep description of LU/LC for each selected site. Furthermore, the study utilized meteorological information, where it was used to gather the spatial characteristics of the region such as; surface temperature, rainfall,… etc, as in annex (1)

In general, the field survey helped to understand the natural sitting of the study area as well as to understand the perception of the local people relevant to this study.

2.2.1.2 Data Pre-processing

The availability of new imagery and technology does not translate to obtaining accurate surface information, as image spectral variability is governed by numerous environmental factors. As a result, the information content in imagery varies depending upon atmospheric, surface composition, topographic, LC structure, and sensor characteristics that collectively determine the nature of the radiation transfer cascade at any particular location in time. These complexities often dictate the need for image pre-processing and radiometric calibration to convert calibrated Digital Numbers (DNs) to absolute units of at sensor spectral radiance, and ultimately to surface spectral reflectance parameters, as many earth science applications are primarily concerned with surface characterization (Bishop and Colby, 2002). Therefore, pre-processing is necessary for extracting and quantifying meaningful information from remotely sensed data (Iqbal and khan, 2014; Naqvi *et al.*, 2014; Butt *et al*., 2015). The typical pre-processing operations in the present study included:

1- Geometric correction

This technique involves modeling the spatial position of the satellite imagery in relation to its actual ground location (Bruce and Hilbert, 2004; El-Abbas, 2015). In LU/LC classification and multi-temporal analysis, the classification accuracy of the thematic output is directly affected by the registration precision. Therefore, GPS ground control points of landmark areas collected from the field covering distinguishable features in the study area were used to correct the geometry of input datasets. Images have been co-registered in Erdas imagine 11 software with 50 GPS points. The Root Mean Square Error (RMSE) achieved in all cases is less than 0.5 of pixel size, which illustrates an adequate precision of rectification.

The spatial dimension of the image used is as follows; the MSS image provides 60 X 60 m spatial resolution, and Landsat 8, TM and ETM+ 30 X 30 m spatial resolution. Accordingly, the Nearest Neighbor technique was used to resample the image to a pixel size of 30 m × 30 m. The output maps projection was Transverse Mercator Projection (UTM/ zone 36 WGS 84 North). Afterward, subsets of the study area were selected.

2- Radiometric correction

Radiation from the Earth's surface undergoes significant interaction with the atmosphere before it reaches the satellite sensor. As a result of this interaction, the detected pixel value by the sensor is affected by the combination of the target surface object and the atmosphere itself. Therefore, it is very important to determine true surface reflectance values and to retrieve the physical parameters of the Earth's surface, including surface reflectance, by reducing atmospheric effects from satellite images. Atmospheric correction is arguably the most important part of the pre-processing of satellite remotely sensed data (Lu *et al*., 2002; Richter and Schläpfer, 2015). Such a radiometric calibration and correction are especially important when comparing data sets over multiple time periods (Hadjimitsis *et al*., 2010). Multi-temporal data used in the present study requires atmospheric correction to reduce the atmospheric effect for accurate quantitative analyses. This is to ensure the differences obtained as a result of image difference rather than atmospheric conditions. QUick Atmospheric Correction (QUAC) atmospheric correction method in ENVI 4.5 software was, therefore, used.

3- Topographic normalization

The satellite imagery from mountainous regions often contains a radiometric distortion known as the topographic effect caused by differential solar illumination of the Earth's surface in undulating terrain. This effect often results in widely varying spectral responses from what are perceived as uniform cover types, which pose several problems in the analysis of digital RS data, especially for image segmentation (i.e., the partitioning of a scene into regions of spectral homogeneity) and automated LC classification (Keating and Colby, 1998). To reduce topographic effect in digital imagery, the study applied transformations using of Lambertian reflectance model in Erdas imagine 11 software by the following equation according to Richter *et al.* (2009).

$$\rho_{\mathrm{H}} = \rho_{\mathrm{T}} \frac{\cos \theta_{s}}{\cos \beta}$$

Where: ρH is a horizontal surface, ρT denote the reflectance of an inclined (terrain), cos β is the local solar illumination angle and cos θs refers to the terrain slope.

This model normalizes the imagery, making it appear as a flat surface instead of topographic data.

4- Image enhancement

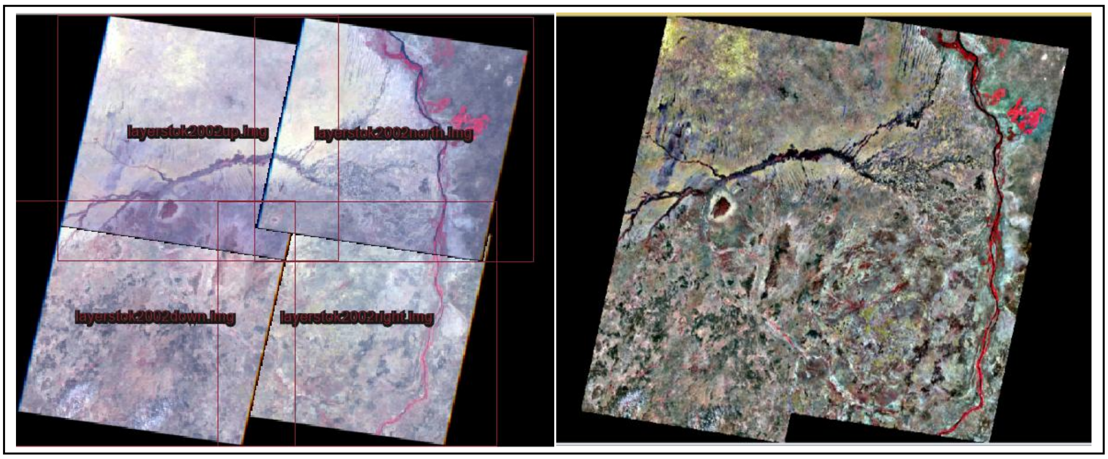
Different methods of image enhancement were used to prepare the raw data so that the actual analysis of images will be easier, faster and more reliable. Three processes are presented below:

a) Filtering and Mosaic Images

The filter operation, to enhance image structures, is common. Due to the large area of the study site, it is needed to obtain a wider field-of-view of a scene. Hence, image mosaicing technique is required to aid for a better understanding of what the images represent. Mosaicing is the process of combining multiple, individual images into a single scene, it can be obtained by understanding the geometric relation between the images (Renuka, 2016). It is one of the techniques of image processing which is useful for tiling a digital image. Most approaches to image stitching require near exact overlaps between images and identical exposures to produce seamless results (Bind, 2013). In the current study, the geocoded images were blending together along user-specified cut lines (polygons) arbitrarily shaped to form one large radiometrically balanced image so that the boundaries between the original images are not seen (Fig. 2.13).

Subsequently, the intensity values of pixels were changed; it was done by calculating grayscale value relations of the neighbouring pixels. Then, the coefficient matrices were used, which cut a small area, or matrix, out of the original image centered on an individual image point. The filter/matrix then had to "run" over the entire image.

Figure 2.13: Example for image mosaicing (image 2002)



In general, image mosaicking applications require both geometrical and photometrical registrations between the images that compose the mosaic (Levin *et al*., 2003). The geometrical registration is usually referred to as image registration and is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints and by different sensors. To geometrically align the images in the present study, the geometric correction was used as referred above.

In contrast, the photometrical correspondence between images deals with the photometrical alignment of image capturing devices. Oliveira *et al*. (2014) indicated, the same object under the same lighting conditions, have to be represented by the same color in two different images. However, even in sets of images taken from the same camera, the colors representing an object may differ from image to image. This poses a problem to the fusion of information from several images. Hence, the problem of how to balance the color of one image so that it matches the color of another must be tackled. Accordingly, to avoid the problem above color correction algorithms (i.e.; image dodging and color balancing) were used for correcting the photometrical disparities.

The visual transition in mosaics is mainly caused by differences in positioning accuracy, image tone and relief displacement of high ground objects between overlapping images (Chen *et al*., 2014). Therefore, Seamline Generation technique (i.e.; Weightd seamline method) was used to address these problems.

2.2.1.3 Image Classification

There is no doubt that an accurate spatial extent of LU/LC data and its dynamics are required for supporting environmental planning, resources management, and public policy decision making. Thus, LU/LC classification is vital because it gives data which can be used as input for modeling and further analyses, especially the one dealing with the environment (Disperati *et al*., 2015). This information grants a comprehensive means of understanding the interaction of geo-biophysical, socio-economic systems behaviours and interactions (Moran *et al*., 2004). One of the most important functions of RS data is the production of LU/LC maps through a process called image classification. This process refers to the task of extracting information classes from a multiband raster image to be used in creating thematic maps (Al-doski *et al*., 2013; Lillesand *et al*., 2015). It requires an understanding of the way materials and objects of interest on the earth's surface absorb, reflect, and emit radiation in the visible, near-infrared, and thermal portions of the electromagnetic spectrum. However, to ensure the success of image classification process, several factors influencing the quality of the final product should be considered including; the availability of quality imagery and the secondary data, an accurate classification process as well as user's expertise of the procedures (Khatami *et al*., 2016; Rwanga and Ndambuki, 2017). The classification process could deal with an individual pixel or meaningful image objects such as GEOBIA, and that distinguishes it from most of the other classification paradigms. From the fundamental tasks in the current study is to manage the huge information derived from satellite imagery in the form of spectral value in addition to texture, shape, and context of the image segment to meaningful LC class categories. Accordingly, the innovative GEOBIA classification approach was applied.

1- GEOBIA

In the past, most of the satellite data applications particularly LU/LC classifications have been created using a Pixel-Based Image Analysis (PBIA) of remotely sensed imagery. PBIA has long been a popular method to classify remotely sensed imagery given its simplicity and high efficiency (Blaschke, 2010). However, recent advances in technology and increased demand of RS applications, the acquisition of Landsat data is steadily increased and it has been widely used for classification (Devi *et al*., 2015; Belward and Skøien, 2015; Phiri and Morgenroth, 2017). On the other hands, the growing availability of these data has created a challenge in images classification, due to its association with a huge amount of detailed features needed to be classified. Where PBIA method cannot take full advantage of the spatial, texture or contextual information found in satellite images thus the results display a "salt and pepper" and that affected the inaccuracy of the classification (Duro *et al*., 2012; Hussain *et al*, 2013; Tewkesbury *et al*., 2015). As a result, GEOBIA techniques have emerged as an alternative analysis framework that can mitigate the weaknesses associated with the past dominant PBIA (Zhang *et al*., 2018). They relate to the conceptual model of geo-objects, which encompasses spatial entities or spatial regions that are represented and analyzed as points, lines or polygons (Radoux and Bogaert, 2017). The advantage of this approach is the capability to define rules for image object identification at various scales using spectral reflectance characteristics, as well as within object texture, context relationships, shapes of features, and ancillary thematic or continuous data of different spatial resolution (Benz *et al*., 2004; Lang, 2008; Blaschke *et al*., 2014). A single set of attributes is assigned to each polygon as a whole, in contrast to pixel-based classification, where each individual pixel is classified (Zhan *et al*., 2005; Schöpfer *et al*., 2008; Hay and Castilla, 2008; Radoux and Bogaert, 2017). It is based on the assumption that image objects offer features at hierarchical spatial levels, and exploit image information more cleverly for mapping LU/LC, as it is much closer to real-world features than discrete pixels (Gamanya *et al*., 2007). GEOBIA is quickly gaining acceptance among remote sensors and has demonstrated great potential for classification

(Zhuo *et al*., 2008). In recent years GOBIA classification for LC mapping purposes using Earth observation data has attracted significant attention (Lang, 2008; Blaschke, 2010; Li and Shao, 2014; Ma *et al*., 2017), where the RS community has undertaken considerable efforts to promote the use of this technology for LU/LC mapping (Blaschke and Strobl, 2001; Blaschke *et al*., 2004; Walker and Blaschke, 2008; Blaschke, 2010). In semi-arid regions, where areas are spatially heterogeneous and with a similar spectral response, LU/LC mapping with remotely sensed data encounters a complexity of problems when applying methods based on spectral information and ignoring spatial information (Chambers *et al*., 2007; De Sy *et al*., 2012; El-Abbas, 2015). Therefore, for this study, the object-based approach has been proposed for discriminating different LC classes based on group pixels with analogous spectral and spatial response, based on predefined criteria to extract features of interest.

2- Image Segmentation

In RS, the process of image segmentation is defined as "an operation that creates new image objects or alters the morphology of existing image objects according to given criteria" (Darwish *et al*., 2003). It is the first as well as the most important step toward GEOBIA process. The goal of this process is to divide the image into meaningful, continuous, and contiguous segments (or image objects).

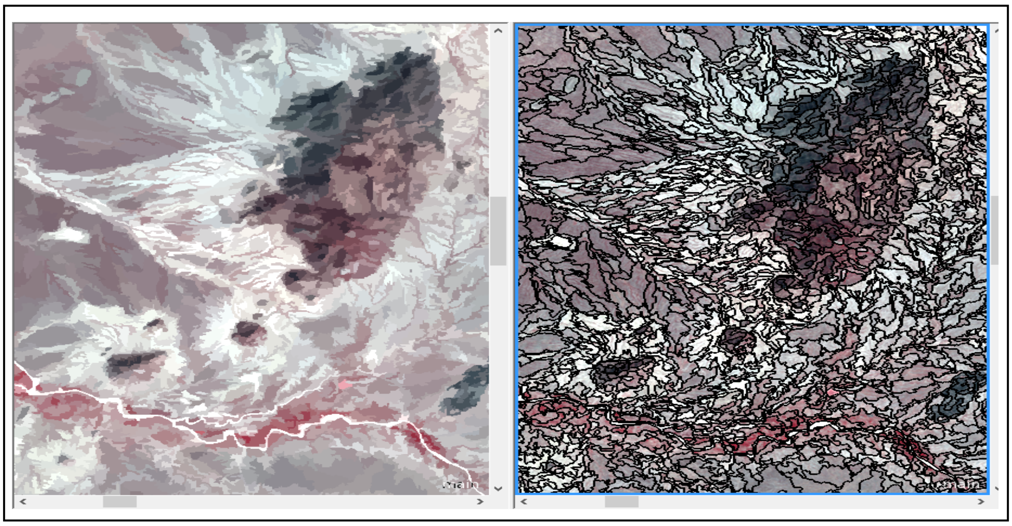
Segmentation principally means the grouping of image elements by certain criteria of homogeneity based on shape, size, color, and pixel topology controlled through parameters set by the user depending on the objective, as well as image quality, bands available, and image resolution. The values of the parameters define how much influence spectral and spatial characteristics of the image layers will have in defining the shape and size of the image objects that correspond to real-world entities within the geographic extent of the image being investigated (Gronemeyer, 2012). The image segmentation decreases the complexity by removing undesired details and then meanwhile provides a new vision of real-world objects which leads to an image with graspable objects. The approaches vary from very simple algorithms based on one feature, such as chessboard segmentation, to very complicated approaches such as a multiresolution segmentation, which has been applied in different fields (Baatz *et al*., 2004).

The segmentation techniques can be categorized into two main domains: knowledge driven (top-down) methods and data driven (bottom-up) methods. The difference between these two approaches is; in the top-down method, the input image is partitioned into many smaller homogeneous regions. It is worth to be mentioned, in this approach, the user already knows what he wants to extract from the image, but doesn't know how to perform the extraction. Therefore, by formulating a model of the desired objects, the system tries to find the best methods of image processing to extract them. Meanwhile, the bottom-up methods assemble objects to create larger objects. As with clustering methods, in the beginning the generated segments are only image object primitives. It is up to the user to determine what kind of real-world objects the generated image objects represent. Bottom-up methods perform a segmentation of the complete image. They group pixels to spatial clusters that meet certain criteria of homogeneity and heterogeneity (Baatz *et al*., 2004). Each image object has a large number of characteristic properties; the so-called object features or attributes. All the generated image objects are linked hierarchically to each other (Baatz *et al*., 2004). That provides the ability to efficiently adapt the extraction of meaningful image object primitives to specific objectives and image data. This has the additional advantage that segments can not only be identified on basis of spectral properties but on a host of other features, as for instance geometrical, textural and class related features.

Different methods in image segmentation may be used such as; statistical classification (Pieczynski, 1992), thresholding (Quy and Polasek, 2014), edge detection (Ren and Li, 2014) and region detection (Gu *et al*., 2009), or any combination of these techniques (Hussin *et al*., 2012; Khurana and Awasthi, 2013). Each method above has its own distinction, e.g., statistical approaches consider both the spectral and spatial information, but ignore spatial explicitness inherent in remote sensing imagery. On the other hand, thresholding of the image pixels value is relatively simple but ignores spatial information. Otherwise, edge and region detection techniques are subjective which depends on the user's determination, while the integration of spatial properties is an advantage in both cases (El-Abbas, 2015).

Multiresolution segmentation strategy was applied to the dataset in the present study as a preliminary step of GEOBIA approaches to create meaningful unclassified image objects (object primitives) and to generate different abstraction levels (Fig. 2.14). This segmentation algorithm characterized as a bottom-up region-merging technique, applying a threshold optimization procedure for image segments, which categorizes the image objects according to a maximum acceptable heterogeneity based on defined threshold to maximize their respective similarity (Baatz *et al*., 2002; Baatz *et al*., 2004).

Figure 2.14: The example segmentation result for the image year 1994 with scale parameter of 15, shape 0.1, smoothness 0.5 (left), Original image without segmentation, (right)



GEOBIA LC classification using Landsat images faces a challenge of selecting the optimal segmentation scale (Möller *et al.,* 2007; Dronova *et al*., 2012). When the segmentation scale is not appropriate, the image can be under or over segmented (Frohn *et al*., 2011). Therefore, each image was segmented into four different segmentation projects in Trimble eCognitionTM Developer 8.7 software as illustrated in Table 2.2. The segmentation started by considering each pixel as a separate object. Subsequently, pairs of smaller image objects were merged to form bigger segments (more pixels). The merging decision is based on local homogeneity criterion, describing the similarity between adjacent image objects. In this sense, each pair of image objects with the smallest increase in the defined criterion was merged. This procedure was developed to extract image objects at various ranges of resolutions (fine or coarse structures) in an appropriate way. To obtain appropriate segments for the desired classes, the segmentation process has been performed by;

a) Defining which bands and thematic layers should be used, and that is due to the influence of the weight image layers in the creation of image objects.

b) Level; it determines whether a new generated image level will either overwrite a current level or the generated objects shall contain sub- or super-objects of a still existing level. The order of generating the levels affects the objects' shape (top-down vs. bottom-up segmentation).

c) Scale parameter; its value affects image segmentation by shaping the size of image objects. This determines the maximum allowed heterogeneity within an object. For a given scale parameter, heterogeneous regions in an image will result in a higher number of objects as compared to homogeneous regions. The size of image objects can be varied by varying the scale parameter value.

d) Colour and shape; these two parameters balance each other, i.e., if color has a high value (high influence on segmentation), shape must have a low value, with less influence. If color and shape parameters are equal, then each will have roughly equal amounts of influence on the segmentation outcome. In general, they affect how objects are created during segmentation and used to determine the combination of the homogeneity criterion. The colour criteria define the overall contribution of spectral values to defining homogeneity. Moreover, it balances the colour homogeneity of a segment, on the one hand, and the homogeneity of shape on the other. The colour heterogeneity is given by following the equation, based on El-Abbas (2015):

$$\mathrm{h_{colour}} = \sum_{c=1}^{n} \mathrm{w_c} * \sigma_\mathrm{c}$$

Where: c is the n band, σ_c the spectral standard deviation of the band c and w the weighting of the n band analogue to the equation above.

While shape is defined by the two parameters: smoothness and compactness, compactness can be used to define the ratio between the parameter of the segment and the square root of its area (number of pixels it contains). It can be derived by the object extent x and the size n, as shown in the equation below, according to El-Abbas (2015):

$$\mathrm{h_{comp}} = \frac{\mathrm{x}}{\sqrt{\mathrm{n}}}$$

Smoothness factor can be used to optimize image objects for smoother borders. Which is given by the object extent x and the extent of the minimum surrounded rectangle r, parallel to the image raster as clarified in the following equation below as well:

$$\mathrm{h_{smooth}} = \frac{x}{r}$$

Table 2.2: Reports the different parameters applied and criterion combinations used

Segmentation settings	**1984**	**1994**	**2002**	**2014**
Image layer weights	1.1.1.1	1.1.1.1.1.0.1	1.1.1.1.1.0.1.1	0.1.1.1.1.1.1.1.0.0.0.0.0.0
Scale parameter	10	15	25	300
Shape	0.1	0.1	0.1	0.1
Compactness	0.5	0.5	0.5	0.5

3- Hierarchical Fuzzy Classification

Information about current LC in Nuba Mountains is very necessary for management and conservation of these areas. Up to the last decade, traditional per pixel classification algorithms were used (e.g. Mohamedain, 2012; Deafalla *et al*., 2012) in extracting LC information there. However, they are poorly equipped to monitor and detect LC in images acquired by the current generation of satellite sensors with adequate accuracy. Where, the pixel might represent a mixture of class covers, within-class variability, or other complex surface cover patterns that cannot be properly described by one class (Kumar and Arun, 2015). Since one class cannot uniquely describe these pixels, fuzzy classification (Foody *et al*., 1992; Foody, 2009) has been developed in contrast to the traditional classification (as noted earlier in section 2.2.1.3 (1) GEOBIA, where a pixel does or does not belong to a class. Hierarchical fuzzy classification, is one of the most important classifications for LC, it's an appropriate strategy which helps to understand the imagery at different levels of abstractness and concreteness to serve different applications (Mohd *et al*., 2012; Kumar *et al*., 2012; Ahmed *et al*., 2017) such as: forest monitoring (Dibs *et al*., 2017), urban planning (Duque de Pinho *et al*., 2011) and riverscape mapping (Demarchi *et al*., 2016). The procedure involves decomposing the image into hierarchical tree structure defining the hierarchical LC structure, followed by generating knowledge rules for each LC type. A fuzzy sets approach (Bonissone, 1980; Aydin, 2004) to image classification makes no assumption about statistical distribution of the data, and provides more complete information for a thorough image analysis consequently reduces classification inaccuracies. It allows for the mapping of a scene's natural fuzziness as well as imprecision (Foody *et al*., 1992; Wang and Jamshidi, 2004).

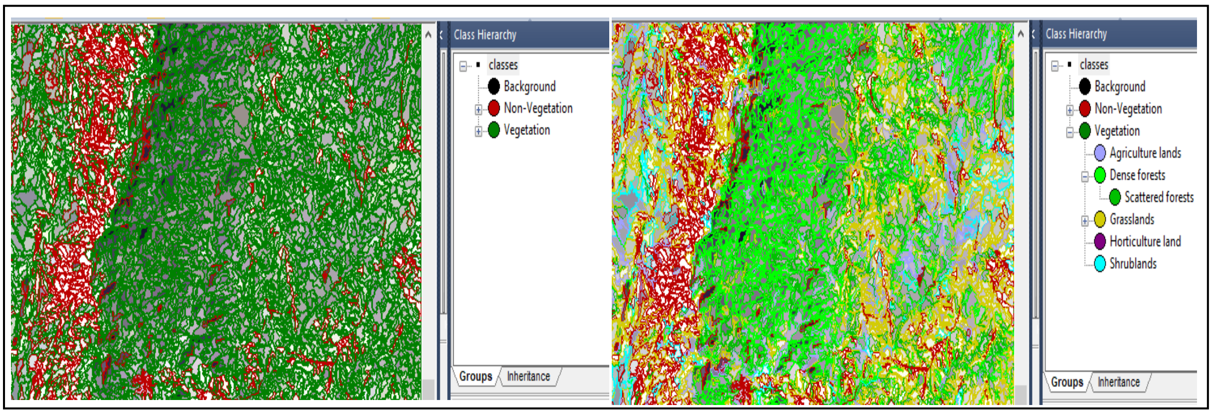
In this study, a GEOBIA hierarchical approach is proposed in order to classify LU/LC and to detect their changes in the Nuba Mountain Region. The method makes use of the fact that LC types and their associated knowledge form a natural hierarchy. A hierarchical classification is a powerful approach in solving classification problems by decomposing the image into a hierarchical landscape structure. This also results in sub-dividing the area into spectrally consistent regions and helps dealing with spectral variability within each subarea. The rule-based classification of the study area was built on three types of knowledge: spectral domain knowledge, it was applied to construct the hierarchical structure of LC classes. Secondly, spectral classification rules based on training data, where the training data helps to generate thresholds to be used later as rules for discriminating and classifying LC categories more accurately. Finally, to support spectral knowledge in the classification of LC, spatial rules based on user experiences were used to increase the resultant accuracy.

4- Fuzzy logic

GEOBIA is considered as an important and new image classification paradigm in RS (Blaschke *et al*., 2014). It provides more meaningful information than pixel-based approach by allowing for less well-defined edges or borders between different classes. The GEOBIA technique allows for using the fuzzy logic (Zadeh, 1965), where each pixel belongs to a class with a certain degree of membership (Amo *et al*., 2004). The membership value of a pixel to a class varies from 0.0 its mean no membership to 1.0 and that means 100 percent complete membership to a class (Gronemeyer, 2012). To generate rules in the fuzzy expert system, there are two common ways; the expert knowledge and training data.

At the present study, the training and testing objects have been declared by selecting representative samples contains meaningful spectral and spatial properties for each class and the confused training objects (critical samples) has been eliminated. Sample object has been defined by the value of 0.95, which mean that 95% of an image object has to be overlapped by the sample area for specific class category derived by the TTA Mask to create a class sample. A hierarchical system was proposed in this study to attain LC classes. The first level was created to discriminate between vegetation and non-vegetation parent classes. Subsequently, the second level of non-vegetation classes aimed to separate water from land classes, which allowed for the separation of one (Water bodies) and three land cover child classes (Bare land, Settlements and Rocky area). Meanwhile, vegetation categories were divided into five subcategories in a hierarchical format, which effectively reduced vegetation type-related confusions, these child classes comprised of; Agriculture lands, Dense forest, Grasslands, Horticulture land and Shrublands respectively in the second level. Furthermore, one child class (Scattered forests) was generated from Dense forest class and it represented in the third levelas can show in Figure 2.15. The next step of research after created a nomenclature for LC, was examine multi-temporal LU/LC changes in the study area.

Figure 2.15: The stratified classification diagram



The figure on the left shows the image classified to the top two parent classes, vegetation and non-vegetation. The figure on the right is the image classified into all six child classes of vegetation.

5- Features

The definition of a feature in GEOBIA is an algorithm that measures various characteristics of image objects, where Image objects within the defined limits are assigned to a specific class. At the same time, image objects outside of the feature range are assigned to a different class or left unclassified (Gronemeyer, 2012). The efficacy of different features varies widely, again depending on objectives, object size, color, texture, and shape properties, and location within the object hierarchy. It can be applied to image objects, an entire scene, or a class. Basically there are two types of features that are extracted from the images based on the application. The first type is object features, which are attributes of image objects such as the geometrical features of each image object. The second one is the global features, which are not represented by an individual image object, such as the number of image objects of a certain class (Lisin *et al.*, 2005; Bosch *et al.*, 2011).

Due to complexity and spectral similarity in semi-arid areas, introducing spatial information as well as spectral information to the classification hierarchy gives valuable features which allow separation of spectrally similar objects (El-Abbas, 2015). Acordingly, logical classification rules were set by referring to expert interpretation knowledge, and a logical procedure was established by making logical inferences. Where the study visually investigated the represented image objects to take a decision for the best features that should be considered to discriminate respective classes. Based on that, the mean layers values have been selected as main features to discriminate between most of the investigated objects. An exception was made using subsequent rules, geometrical features and texture values are used effectively to optimize or correct most of misclassified objects. Multiple features of objects were then calculated to structure data layers in each temporal image. Spectral features were obtained, based on the reflectance of the incident electromagnetic wave of different objects in each band, this includes; spectral signal of objects in each band (i.e., average of spectral signals from all the pixels within the objects), brightness of objects (i.e., average of spectral signals from all the bands) and maximum difference (i.e., maximum variation between spectral signals of all bands). The textural features were applied, as well, including; mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment and correlation. Meanwhile, the shape features that were used consisted of the geometric features of objects, including length-width ratio, compactness, density and shape index. Moreover, normalization via min-max scaling was conducted, which is aimed at reducing the effects of different data expressions owing to various acquisitions and generation conditions (Wang *et al*., 2018). Meanwhile, for the change detection, feature fusion through layer stacking was applied to generate new bi-temporal images with multiple feature layers. This simplified the complex classification process and allowed intricate LC features to be effectively classified.

Field work is usually limited because of time, cost, and difficulty of reaching some places. Therefore, the present study used in addition to the field data Google Earth maps to develop and control the signatures and the accuracy of the classification. As well the study subsequently utilized an improved method for the analysis of satellite images, based on integrating multiple features namely; Normalized Difference Vegetation Index (NDVI), Modified/Normalized Difference Water Index (MNDWI), Soil Adjusted Vegetation Index (SAVI), DEM and Thematic layer. Utilization of these features has been applied mainly to discriminate between different types of vegetation cover and to separate settlements from confused objects relevant to grasses and scattered-forest classes.

a) NDVI

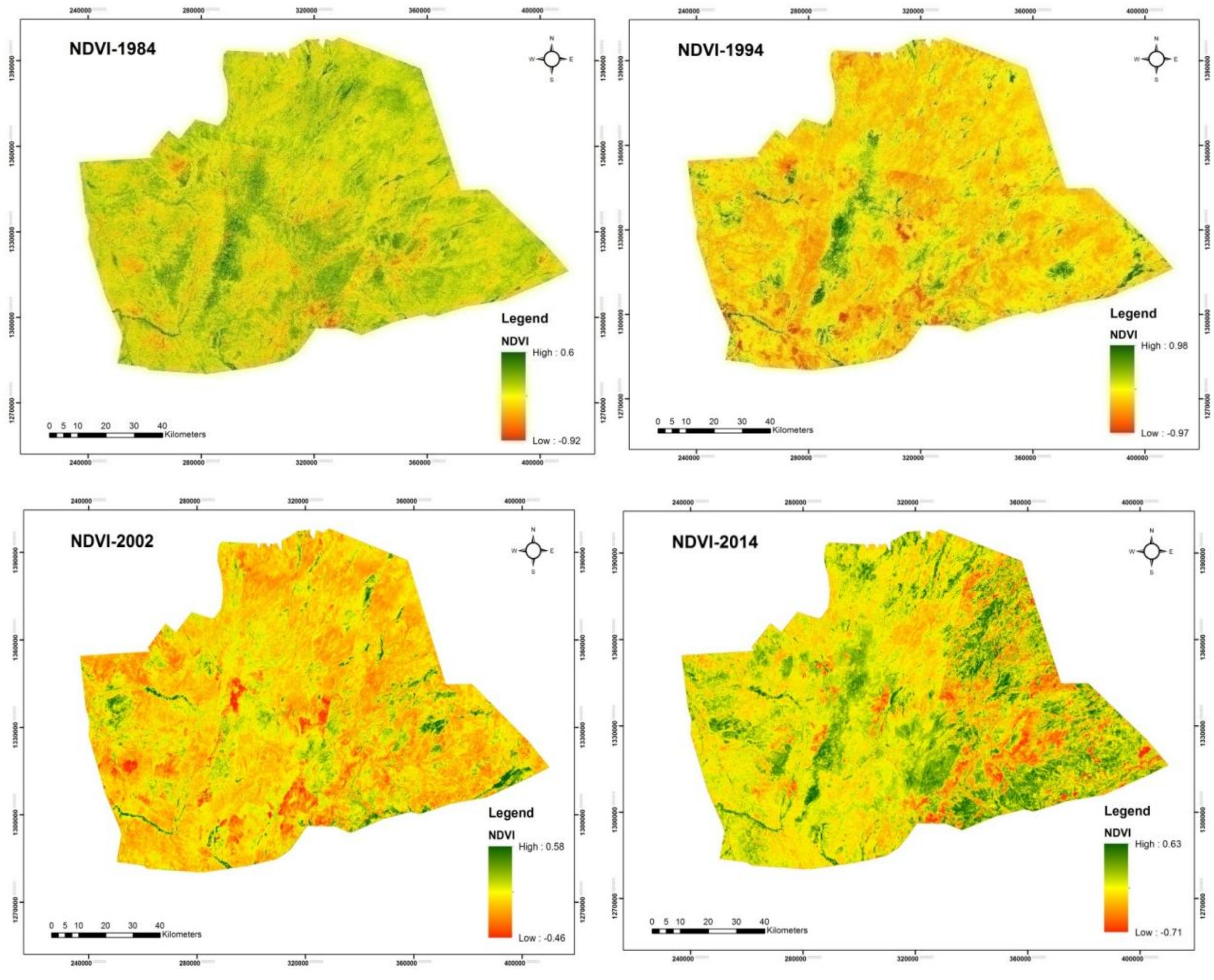
For LC classification, some band combinations of the remotely sensed data are exploited and the spatial distribution such as road, settlements, forests, agriculture lands and water resources are easily interpreteted by computing their NDVI. Li *et al*. (2011) defined the NDVI an index of plant greenness or photosynthetic activity and has a linear correlation between density and distribution of vegetation. It is a simple numerical indicator that can be used to analyze the RS measurements, and is based on the observation that different surfaces reflect different types of light differently (Demirel *et al*., 2010; Rani *et al*., 2015). Where, the vegetation can be distinguished from most of the other materials by virtue of its notable absorption in the red and blue regions of the visible spectrum, its higher green reflectance as well as its reflectance in the near-IR region (Ricotta *et al*., 1999; Bhandaria *et al*., 2012). The NDVI value range from +1.0 to -1.0, the highest value of the NDVI indicates dense vegetation while the lowest value usually indicates rock, sand, or snow (Ghebrezgabher *et al*., 2016). Zhang *et al*. (2009); Ahmadi and Nusrath (2010); Bhandari *et al*. (2012); Rani *et al.* (2015), found that the response of vegetation to the environment is very sensitive and not only affects the climate and ecological balance but has been found to be an effective barrier against natural disasters as well. Therefore, NDVI is widely applied in research on global environmental and climatic change (Gao, 1996). NDVI is calculated as the normalized difference between the red and near-infrared bands, from the following equation, based on (Ghebrezgabher *et al*., 2016):

$$\mathrm{NDVI} = \frac{NIR - RED}{NIR + RED}$$

Where, NIR is the near infrared band value for the segment, and RED is the red band value for the segment.

In the present work, NDVI technique was applied to discriminate the vegetation from other LC as a first step (Fig. 2.16). Following that, it'is utilized to understand the distribution of vegetation throughout the study area, which is significant for enhancing the accuracy of forest and woodland classification change (Rawat *et al*., 2013; Zhang *et al*., 2013; Li *et al*., 2014).

Figure 2.16: Multi-temporal NDVI of the study area



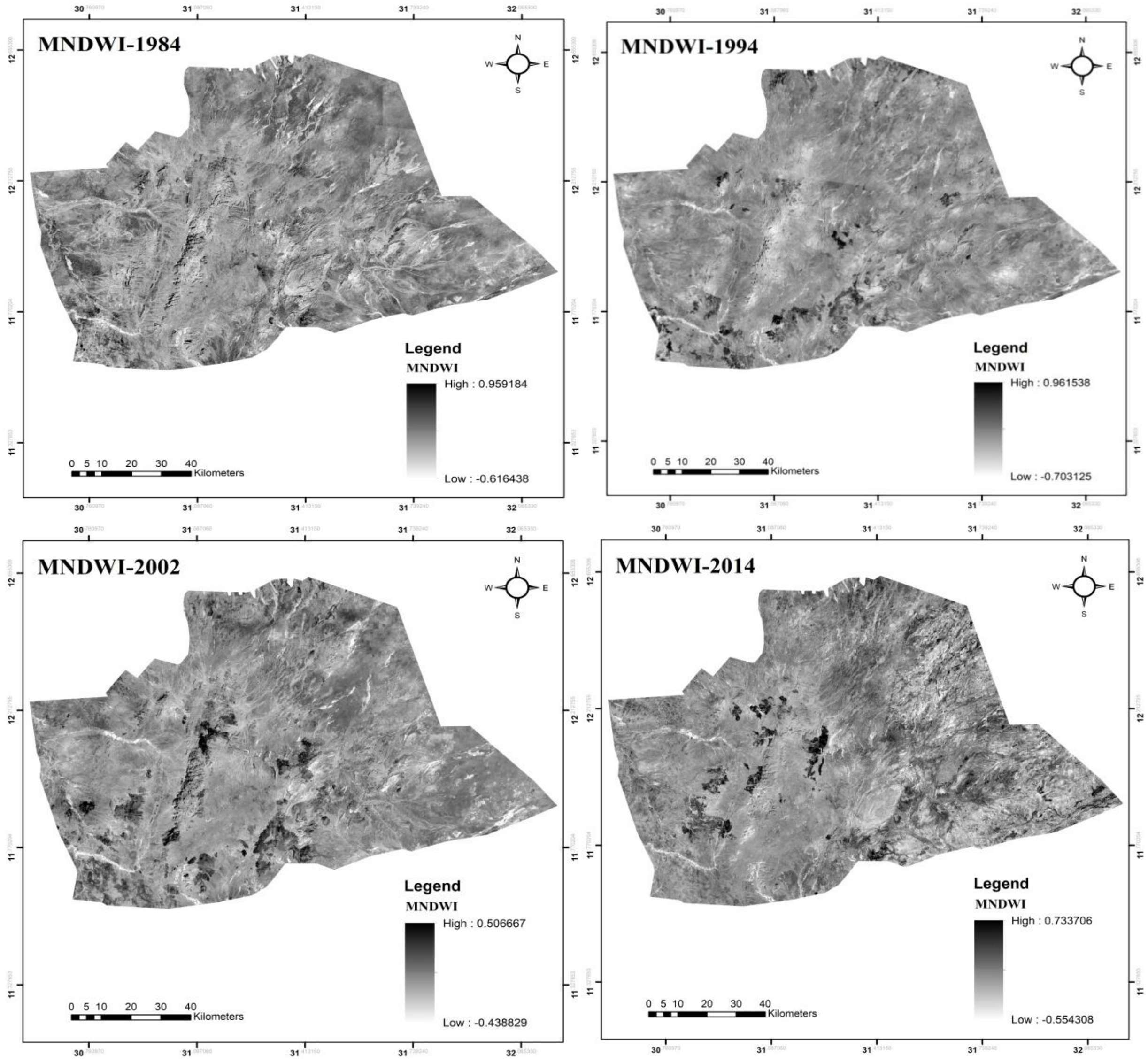
b) MNDWI

Normalized Difference Water Index (NDWI) is a new method that has been developed to delineate open water features and enhance their presence in remotely-sensed digital imagery (McFeeters, 2007). The water body has strong absorbability and low radiation in the range from visible to infrared wavelengths. Therefore, the index uses reflected near-infrared radiation and visible green light to enhance the presence of such features while eliminating the presence of soil and terrestrial vegetation features (Xu, 2006). Recently, several researchers (El-Asmar *et al*., 2013; Aggarwal and Minz, 2013; Zhang *et al*., 2013) have used the Modified/Normalized Difference Water Index (MNDWI) which was modified by Xu (2006) in his study. The value for the MNDWI varies from −1 to 1; the highest value indicates water while the low MNDWI value indicates forest or high vegetation cover (Ghebrezgabher *et al*., 2016). In the current study, MNDWI was used to classify the water body (Fig. 2.17). The MNDWI is explained by the following formula, according to Ghebrezgabher *et al*., (2016):

$$\text{MNDWI} = (Green - NIR)/(Green + NIR)$$

Where, Green is a band in the green wavelength, NIR is a band in the near-infrared wavelength.

Figure 2.17: Multi-temporal MNDWI of the study area



c) SAVI

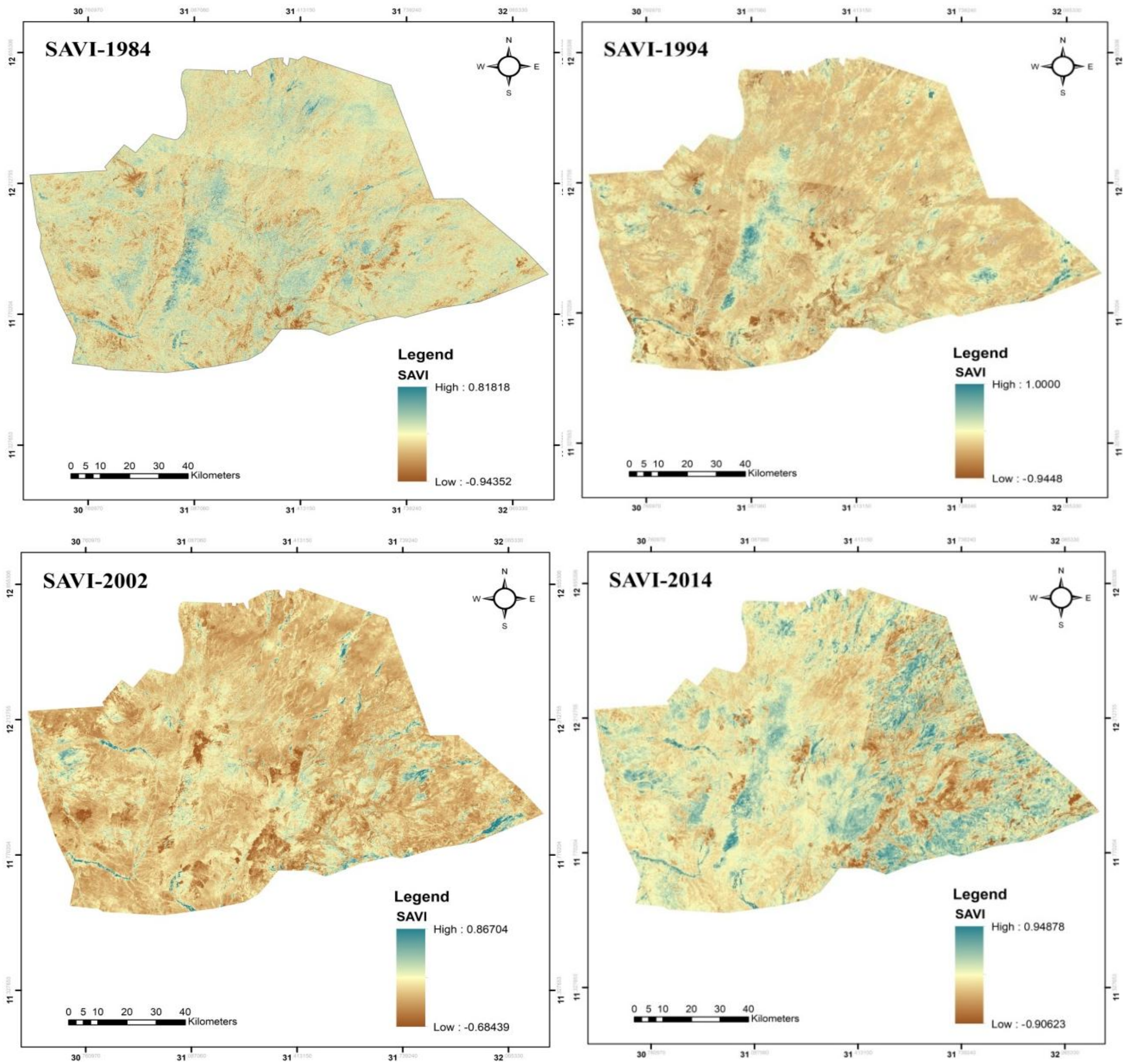
SAVI is used to minimize the effect of brightness reflection that can influence vegetation index values, which is caused by the soil. The SAVI is very useful in arid and semi-arid regions where the distribution of the NDVI value is generally very low or when comparisons are being made across different soil types that may reflect different amounts of light in the red and near infrared wavelengths (i.e., soils with different brightness values).

Based on Huete (1988), the SAVI depends on red and near-infrared spectra, with a constant L factor that is added to the denominator of the NDVI formula to adjust for the effect of soil. The SAVI value ranges from −1 to 1. However, the value of L varies by the amount or cover of green vegetation, where in very high vegetation regions L=0; and in areas with no green vegetation L=1. Generally, an L=0.5 works well in most situations and is the default value used. When L=0, then SAVI = NDVI (Huete, 1988; Gilabert *et al*., 2002; Aggarwal and Minz, 2013; Ghebrezgabher *et al*., 2016). For the present study, the SAVI is very important due to the location of the country in arid and semi-arid zones (Deafalla, 2012). Thus, the SAVI was developed to correct the influence of soil brightness in an area that has a low vegetative (Fig. 2.18). 0.5 was applied as a constant factor (L) to all pixels, except some pixels under high forest cover, where the L factor was zero. According to Ghebrezgabher *et al*. (2016), SAVI was defined as:

$$\text{SAVI} = (NIR - RED) * 1 + L/(NIR + RED + L)$$

Where, NIR is near-infrared band, red refers to the red band, and L is the soil brightness correction factor.

Figure 2.18: Multi-temporal SAVI of the study area

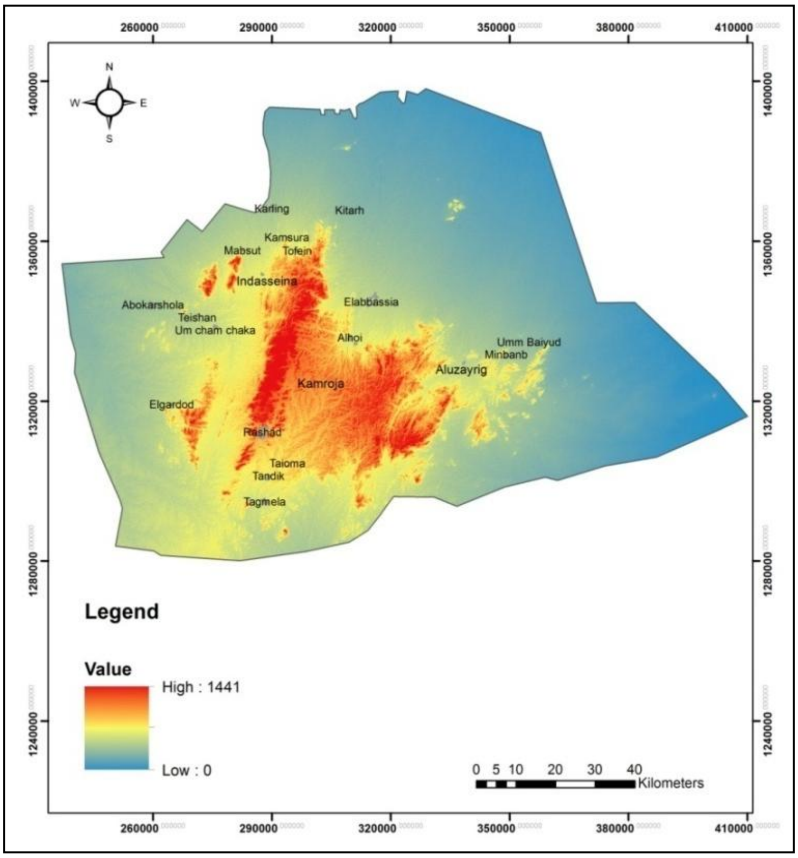


d) DEM

According to Burrough (1986), DEM is defined as "any digital representation of the continuous variation of relief over space". It used to determine terrain attributes such as elevation at any point, slope and aspect. DEM can be created from either sterepairs derived from satellite data or aerial photographs or generated from digital terrain elevation data. DEMs are an integral part of many environmental management applications and are widely used in hydrologic and geologic analysis, hazard monitoring, natural resources exploration, agricultural management etc. (Kumar *et al*., 2017).

In the present study, the difference between the vegetation types was enhanced by using DEM, where it was applied to gather the spatial characteristics of the vegetation cover (density and type) and terrain features. In this section, it was mainly used based on user expert knowledge to separate the vegetation types that have convergent spectral reflectance properties. Based on Lee *et al.* (2004), most classifying methods are based on spectral information and they work well in forest vegetations recognition. But some vegetation types that have similar spectral characteristic are not clearly distinguished by using these methods only. However, DEM was employed as an important criterion in classifying vegetations, based on the geometrical association of specific altitude. Five DEM images provided by the USGS, derived from ASTER data with a spatial resolution of 30 meters and a vertical resolution of 1 m were used to enhance the classification between forests and horticulture land. After DEM images mosaicing, the images were projected to UTM/ zone 36 WGS 84 and resampled to 30 m spatial resolution by using the nearest neighbor technique.

Figure 2.19: DEM in the study area



e) Thematic layer

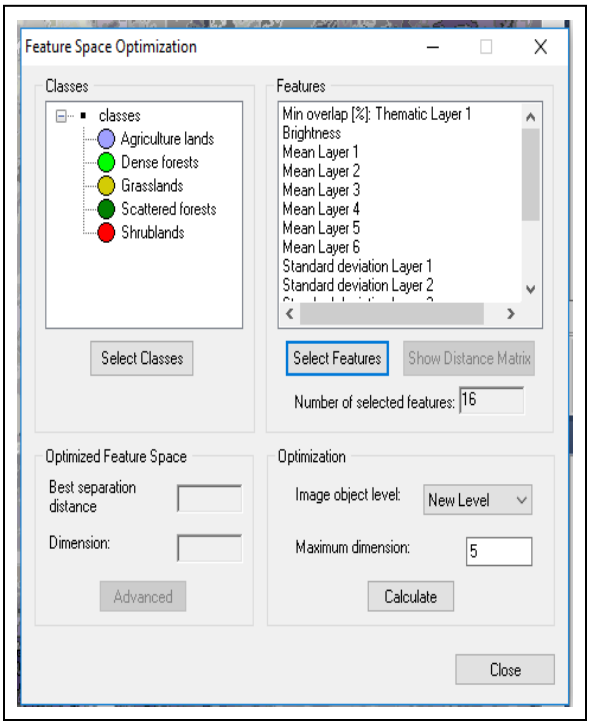
The information about the size, distribution and change of human settlement areas is a critical component in studies of LU/LC change (Wang *et al*., 2010). Many studies such as; Gong and Howarth (1990); Ridd (2006); Hoberg and Rottensteiner (2010), referred to the detection of settlement areas as the basis for numerous applications, e.g. regional planning (El-Abbas and Csaplovics, 2012), the observation of urban expansion (Hegazy and Kaloopb, 2015), or disaster prevention and management (Nirupama and Simonovic, 2002). As the case of the Nuba Mountains, it is very important to monitor the changes of rural settlements in a timely and economically efficient manner. Even so, unfortunately, till nowa numbers of villages have not been mapped. Space- and air-borne RS holds certain advantages in detectingand monitoring the dynamics of settlements, where it allows for study without requiring expensive or time-consuming monitoring campaigns as well as it provides large spatial coverage (Hu *et al*., 2016). Wang *et al*. (2018) referred to the fact that it is not feasible to use high spatial resolution images, to map large areas, due to the lack of spatial coverage and funding limitations, in addition to complexity in their classification process, because rural settlement patterns are highly complicated. Furthermore, their study recommended using medium-resolution imagery, with less expensive satellite data such as Landsat imagery, to map rural settlement based on GEOBIA. Due to their characteristics in classification, GEOBIA has been widely used in mapping the settlement (Shackelford and Davis, 2003; Al-Khudhairy *et al*., 2005; Walker and Briggs, 2007). Settlement areas (particularly those located in rural areas) have a heterogeneous appearance, of digital satellite data, because they consist of a large number of different objects such as houses (with different building material), roads and trees. The variety of these objects results in specific local patterns in the images. These patterns make the spectral classification of such areas very difficult. On the other hand, however, and if they are properly modeled, they can be exploited to improve the classification result. Therefore, to get accurate results, the classification of these objects in the current study was conducted based on Thematic layer that it can be defined as "a spatial representation of analyzed data of elements of the same type" (Blanc, 2013), where it allows rolling up metrics, grouped and colored by geographic boundaries. Thematic layer is very useful for data under conditions of semantic heterogeneity e.g. settlement mapping (Worboys and Duckham, 2002). An assigned class was utilized to delineate the settlements with threshold condition min overlap >= 1 thematic layer (ground points of Settlements site).

6- K-Nearest Neighbor Classification (KNNC)

The past four decades have been marked by different developments in LC classification methods of Landsat imagery, where the introduction of numeric-based pattern recognition algorithms was the basis of modern classification methods such as KNNC model and Knowledge Based Image Classification (KBIC) and many other classification algorithms (Phiri and Morgenroth, 2017). KNNC is one of the most commonly used approaches for digital image classification due to its simplicity, effectiveness, and computational efficiency (Kwon and Lee, 2003; Benz *et al*., 2004; Samaniego and Schulz, 2009; Han *et al*., 2011; Kang *et al*., 2016). The concept of KNNC based on selecting features that will be applied for classifying the image by the user, besides choosing image objects as training areas by selecting representative samples, contains meaningful spectral and spatial properties for each class (Slade, 1991; Radzikowska and Kerre, 2002; El-Abbas, 2015). At this level, KNNC allows partial membership of an object to different classes, and also takes into account the relative importance closeness of each neighbour with respect to the test instance (Jensen and Cornelis, 2008; Jensen and Cornelis, 2011). In subsequent steps, unclassified or wrongly classified objects are assigned to the correct classes by adding samples of known classes and the confused training objects have been eliminated. The advantage of the KNNC approach is that, it's an extremely flexible classification scheme, easily implemented, as well as that the entire image analysis process is contained in eCognition software. Import of field ground samples, choosing input objects features, classification and accuracy assessment are all parts of the built-in workflow of this software (Laliberte *et al*., 2006).

In the present study, classification has been conducted by selecting training objects of each class type. The results, in the KNNC approach, are solely based on the selected samples, therefore sufficient and appropriate samples had to be chosen so that the feature space for each class can be defined accurately (Laliberte *et al*., 2006). For that reason, samples were carefully selected. The input features (bands and indices) have been chosen based on the use of "feature view" and "feature space optimization" tools. Feature view allows for initial visual assessment of the usefulness of a feature by displaying the segmented image in grayscale. Feature space optimization is a tool that evaluates the distance in feature space between the samples of classes, and selects feature combinations that result in the best class separation distance. Numbers of input features were selected for class description based on the feature view and feature space optimization tools as shown in Figure 2.20 below. According to Laliberte *et al*. (2006), it is not advisable to input a large number of features with a limited number of samples, because it is impossible to assess the n-dimensional feature space appropriately with too many features and not enough samples. On the other hand, that could leave out numerous of other potentially useful features. Therefore, proper selection of features is still largely based on the image analyst's experience.

Figure 2.20: Selection of the features used



7- Knowledge Based Image Classification (KBIC)

KBIC is being used successfully in many applications covering a wide array of fields, such as; LU/LC mapping (El-Abbas, 2015), population estimation (Nepali, 2010) as well as the detections of oil spills or landmines (Stefanov *et al.*, 2001). The approach has several advantages including their flexibility with regard to diverse data sources, where it uses the existing auxiliary data (e.g. aerial photographs, DEMs, and multispectral imagery), as a means of developing rules for classification (Skidmore, 1989; Jennings, 2002).

KBIC has undergone a significant development over the past decade, and that is attributed to the availability of RS data and geospatial information, as well as the development of GIS which is used for combined analysis of different spatial information (Lu and Weng, 2007). Phiri and Morgenroth, (2017) indicated that the knowledge-based methods relate LC types to auxiliary data, where vegetation distribution, for example, can be related to the topography of the area, therefore DEM data will be required. The procedure for this method involves developing rule sets which have binding thresholds in relation to particular LC types (Tailor *et al*., 1986; Wang and Newkirk, 1988).

According to Lu and Weng (2007); Phiri and Morgenroth, (2017) in GEOBIA, KBIC is closely linked with image segmentation as the clusters depend on rule sets developed from other datasets apart from spectral information. Recently, different knowledge-based classifiers were developed such as; decision trees method, which uses thresholds from auxiliary data to identify LC types (Li *et al*., 2011; Verhulp, 2017). This study employed a KBIC and constructed a stratified classification model based on user expert knowledge to describe LC classes based on combinations of conditions to interpret objects of interest, which has been well-known as rule sets in eCognition software.

8- Change detection

LU/LC changes especially those occurring by anthropogenic forces is one of the most important components of global environmental change (Jessen, 2005a). The real challenge is lack of enough knowledge about LU/LC patterns, where it is a major impediment to the design of sustainable development strategies as well as it holds the capacity of local governments to implement sound environmental management. It is, therefore, vital that accurate, cost-effective and up to date information on these changes are made available to facilitate the understanding of the link between LC changes and EC to allow planners to make effective decisions (El-Hattab, 2016). The traditional monitoring systems for assessing LC changes, such as conventional terrestrial inventories and geographical surveys, are no longer sufficient (Rokni *et al*., 2015). Satellite-based RS facilitates a cost-effective way for detecting the LU/LC change (Rogan and Chen, 2004; Fan *et al*., 2007; Lu *et al*., 2010a; El- Abbas, 2015) and is extensively used for change detection in recent decades (Lu *et al*., 2004a), as it can locate the spatial distribution, the extent of the change as well as to quantify the trend and magnitude of the dynamics precisely over a vast geographic area in a recurrent and consistent way (Zhou *et al*., 2008a). Digital change detection has been defined by (Singh, 1989; Rogan and Chen, 2004; Jia *et al*., 2016) as a process of "determining and/or describing changes in LC and LU properties based on co-registered multitemporal RS data".

Various techniques have been applied using RS data for LU/LC change detection for many decades such as; change vector analysis (Johnson and Kasischke, 1998), transformation (Yang, *et al*., 2009), classification (Alphan *et al*., 2009) and hybrid methods (Jiao *et al*., 2014). Recently a wide variety of change detection methods have been developed, till now two broad approaches are common; data transformation and change labeling (Johnson and Kasischke, 1998; El-Abbas and Csaplovics, 2012). Basically, the detection of continuous (transformation) and categorical (labeling) changes are known as pre-classification and post-classification methods respectively (El-Abbas, 2015). Pre-classification techniques operate on raw imagery, while post-classification comparison methods detect LC change by overlaying independent sets of classified imagery of different dates (El-Abbas and Csaplovics, 2012).

9- Pre-classification Techniques

The pre-classification techniques, also known as binary change or non-change information detecting techniques (Al-doski *et al*., 2013), include various techniques that directly use the multiple dates of satellite imagery to generate "change" vs. "no-change" maps, but do not specify the type of change (Singh, 1989; Lu *et al*., 2004b). These methods include; Image Differencing (ID), modified image differencing, principal component differencing, multi-temporal Post Change Analysis (PCA), the combination of ID and PCA, change vector analysis, Image Ratioing (IR), modified IR, the combination of IR and PCA, principal components analysis, artificial neural networks and classification tree (Zhou *et al*., 2008b). The basic premise in these techniques is measuring the nature of changes, which means changes in the features of interest that will result changes in radiance or reflectance values (Lu *et al*. 2004b). Most of the pre-classification techniques are identified as the most accurate change detection techniques, because they are straight forward, easy to implement as well as effective inrecognizing and locating change (Sunar, 1998). However, the pre-classification techniques processes require; selection of suitable thresholds to identify changed areas, being sensitive to misregistration of pixels and they cannot provide details of the nature of change or provide a matrix of change information (Lu *et al*. 2004a; Al-doski *et al*., 2013). Previous literature such as; Bayarsaikhan *et al*. (2009); Torahi and Rai (2011); El-Hattab (2016) has shown that image differencing, principal component analysis and post-classification comparison are the most common methods used for change detection. These techniques have been successful and have typically been applied and evaluated in medium spatial resolution satellite images such as Landsat (Long *et al*., 2018).

10- Post Classification Change Detection Comparison

Post-classification comparison is the most common method used for change detection analysis (Al-doski *et al*., 2013; Ayele *et al*., 2018). It is used by many researchers such as (Muttitanon and Tripathi, 2005; Diallo *et al*., 2009; Bayarsaikhan *et al*., 2009; Torahi and Rai, 2011; El-Hattab, 2016). This technique is very advantageous when using Landsat data from different sensors with different spatial and spectral resolutions (long *et al*. 2018), it has been proved an effective way to study LU/LC changes in different areas around the world (Dewidar, 2004; Fan *et al*., 2007; Sun *et al*., 2009).

This approach is based on comparing independently produced classifications of images from different dates (Yuan *et al*., 1998), after that it is required to generate the thematic maps, followed by a comparison of the corresponding labels or themes to locate and classify the changes as well as provide "from-to" change information (Jensen, 2005a; Yuan *et al*., 2005). There are several advantages to this technique, where it minimizes the problems caused by variation in sensors and atmospheric conditions, as well as environmental differences between different dates, since data from different dates are separately classified (Singh, 1989; Lu *et al*., 2004b) and hence reflectance data from those two dates need not be adjusted for direct comparability (Zhou *et al*., 2008b). Furthermore, this technique provides a complete matrix of LC change when using multiple images (Naumann and Siegmund, 2004; Jensen, 2005a; Teng *et al*., 2008).

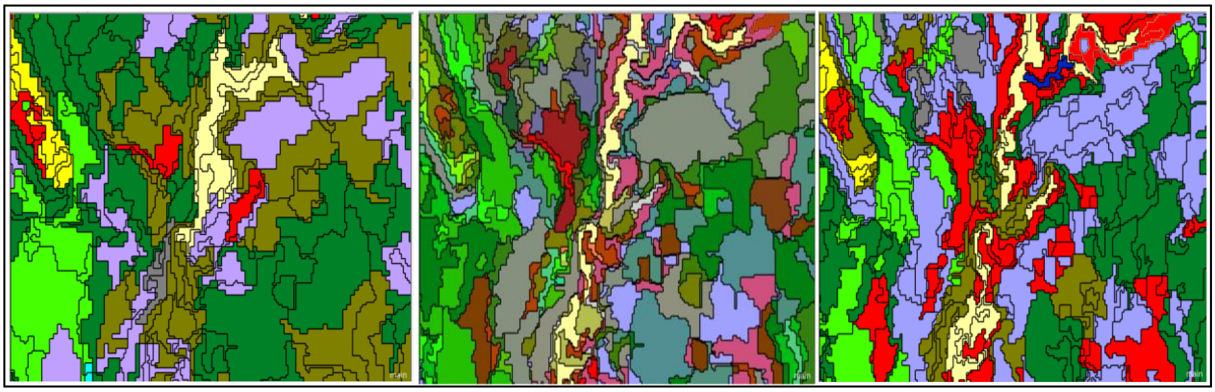
The traditional change detection method, based on pixel-based analysis can be affected by many factors; for example: misregistration between different dates or sensors (Wang *et al*., 2018), the atmospheric conditions (Singh, 1989), limitations of radiometric differences (Lu *et al*., 2004b, Jensen, 2005a), vegetation phenological variability or differences (Lu *et al*., 2002); sensor calibration (Lillesand and Keifer, 1994) in addition to the landscape and topography characteristics of the study areas as well as analyst's skill and experience (Al-doski *et al*., 2013). Geographic Object-Based Change Detection (GOBCD) has demonstrated significant advantages, where it overcomes these problems (Chen *et al*., 2012) as well as considerably improves the accuracy of change detection of multispectral imagery in heterogeneous environments (Im *et al*., 2008; Zhou *et al*., 2008b). Chen *et al*. (2012) defined GOBCD as 'the process of identifying differences in geographic objects at different moments using object-based image analysis'. To simplify, the concept of GOBCD is to extracts the meaningful image-objects by segmenting (two or more) input RS images, which is consistent with the original notion of using change detection to identify differences in the state of an observed "object or phenomenon" (Singh, 1989). Each image object is considered as a single study unit in GOBCD (Wang *et al*., 2018). Based on Blaschke and Hay (2001); Hay and Castilla (2008), a feature of GOBCD is to combining segmentation operation and spatial, spectral and geographic information along with the experience of the analyst with image objects to model geographic entities.

Recently, there is an increasing interest in the application of GOBCD (Blaschke, 2010; Hussain, *et al*., 2013; Wang *et al*., 2018), where numerous studies were done for different purposes such as; quantify LC change, improve spectral classification, reduce the classification error propagation and improvement of the LU/LC change classification accuracy (e.g. Zhou *et al*., 2008a; Hussain, *et al*., 2013; Al-doski *et al*., 2013).

Multi-date post-classification comparison change detection was performed in the present study to investigate LC change in the study area from 1984 to 2014. Then to evaluate the results of conversions, moreover GOBCD was applied to quantify and locate the changes.

Similar to GEOBIA classification, the first step in GOBCD is to perform the image segmentation. However, instead of using multispectral imagery, the multiresolution segmentation was applied after overlay operation between each paired layers of classified objects (i.e., 1984 to 1994, 1994 to 2002 and finally 2002 to 2014 classified maps), in which all objects from the classification layers were split at their intersections and preserved in the resultant object level, as shown in Figure 2.21. The resultant objects from the segmentation were identical to those of overlay operation classification maps. All classification maps for the selected years were used as thematic layers when performing the segmentation. According to Zhou *et al*. (2008b), the borders separating different thematic classes are restrictive for any further segmentation when using a thematic layer, and it is not allowed for the generated objects to cross any of the borders of different LC classes. Consequently, the generated objects were exclusively based on the information of thematic layers by setting the weight of the image layer to 0.

Figure 2.21: Segmentation results of GOBCD for selected years (left: change from 1984 to 1994, middle: change from 1994 to 2002 and right: change from 2002 to 2014) with scale parameter of 30, shape 0.1, smoothness 0.5.



In post-classification GOBCD, many factors that can have an effect on the result such as; the attribute errors and errors in spatial registration (Rogan and Chen, 2004) between the classified maps, which may lead to a significant overestimation of actual change. Hence, object characteristics including LC types for the selected years, spatial relations (e.g. distance to neighbors and adjacency), and shape features were used to create rules for change detection. The choice of the relevant features and their threshold values were determined by combining expert knowledge and quantitative analyses (Zhou and Troy, 2008). Objects with the same types of LC for the selected years were then identified as having no change (No Change) and were separated from those with changes by comparing the LC types obtained from the two thematic layers. In the study area, several types of LC change were considered to be highly unlikely (e.g. Settlements change to other LC types except to bare land). Consequently, 54 classes, including 44 change categories and the 10 class of no change were used in subsequent change detection analysis. They are sorted into five main classes namely; Deforestation parent class which includes12 subclasses, Degraded land parent class, contains 5 subclasses, No change category, includes 10 subclasses, Other change category divided into 13 subclasses and Reforestation parent class which includes 14 subclasses (Annex 15).

2.2.1.4 Accuracy Assessment

Recently, the RS science and application communities have developed increasingly reliable, consistent, and robust approaches for capturing land dynamics to meet a range of information needs related to management, scientific, or policy support activities (Olofsson *et al*., 2014). However, this information requires quantitative accuracy statements to buttress the confidence in the information generated and in any subsequent reporting or inferences made (Olofsson *et al*., 2014). The accelerated usage of these techniques has made the geospatial process faster and powerful, but on the other hand, the increased complexity of their process creates increased possibilities for error (Murty and Tiwari, 2015). Accordingly, an accurate mapping is an important and complex issue that has not yet reached the satisfactory and acceptable level (El-Abbas, 2015). Accuracy assessment or validation is a significant step in the processing of RS data (Stehman and Wickham, 2011). It establishes the information value of the resulting data to a user, where it compares the classified image to another data source that is considered to be accurate or ground truth data (Rwanga and Ndambuki, 2017).

The general accuracy assessment framework was defined by Strahler *et al*. (2006) and Olofsson *et al*. (2014), and it is still applicable to most GEOBIA results. However, GEOBIA validation has its own characteristics (Hernando *et al*., 2012). Accordingly it is necessary to adjust some of the good practices of the general framework for the specific quality assessment of GEOBIA results. These practices depend on the type of geospatial database that is going to be extracted from the image analysis (Radoux and Bogaert, 2017). Based on Khorram *et al*. (1994); Congalton and Green (2009), the most reliable and widely applied method of checking the accuracy of a map is the thematic quantitative site-specific, well-known as confusion matrix or error matrix. A confusion matrix or error matrix is a table that shows correspondence between the classification result and a reference data, assuming that the reference data are correct. It depends on using the ground truth data, results of manually digitizing an image and fieldwork/ground survey results recorded with a GPS-receiver. Alas, there is no unique accepted standard or universal measure for maximum allowable error. Anderson *et al*. (1976) suggested the maximum allowable error is 15% (i.e., 85% overall accuracy), and since that date numerous land classification studies depended on his proposal to cutoff between the acceptance and rejection of the result. Therefore, Congalton and Green, (2009) recommended that accuracy assessment reports must indicate the entire raw error matrix of computed assessment values. These related specific assessment values that are used to estimate the probability of correct class assignments are: error of commission (represent objects that belong to another class but are labeled as belonging to the class), and error of omission (represent objects that belong to the truth class but fail to be classified into the proper class). As well as kappa coefficient (a discrete multivariate) as a compensation for the chance in agreement, in addition to the overall precision or reliability of a classification result (Lang, 2008). Indeed, these values provide the basis to describe the classification precision and the errors as well (Foody, 2002) and have become a standard means of assessment of image classification accuracy (Rwanga and Ndambuki, 2017).

Haque and Basak (2017) noted in their study, the classification accuracy should be done by ground truth points, or by physical appearance in the study site. Accordingly, stratified random sampling was adopted to calculate the classification accuracy of each LC image. At least 60 random points were used to assess the accuracy of every classified image. Classification accuracy assessment in this research was conducted for the four LU/LC images and for the three LU/LC change images (result of LU/LC change images in annexes 12, 13 and 14) based on the reference TTA Mask samples utilizing the best classification result method (Zhan *et al*., 2005; Tiede *et al*., 2006). Additionally, for more accurate result of each class of LU/LC the overall accuracy, producer's accuracy, user's accuracy and Kappa statistics methods (Foody, 2002; Schöpfer and Lang, 2006; Grenier *et al.*, 2008) were applied. These methods are a basic accuracy measure (Liu *et al*., 2007), which is calculated by dividing the correctly classified objects (sum of the values in the main diagonal) by the total number of objects checked (Bharatkar and Patel, 2013). It can be described by the following equation below according to Bharatkar and Patel (2013).

$$\text{Overall accuracy (\%)} = \frac{\text{Correctly classified pixels}}{\text{Total number of pixels}} \text{.......... (1)}$$

Moreover, classification accuracy of individual classes can be calculated in a similar manner by two approaches. The first one is user's accuracy, it is the ratio between the numbers of correctly classified object and the classified totals object of a particular LU/LC class. It can be calculated by the following equation:

$$\text{User's accuracy (\%)} = \frac{\text{Correctly classified pixels}}{\text{Classified total pixels}} \text{ .... (2)}$$

The second method is the producer's accuracy, it can be defined as the ratio between the number of correctly classified object and the reference total object for particular LU/LC class, it can be described by the following equations:

$$\text{Producer's accuracy (\%)} = \frac{\text{Correctly classified pixels}}{\text{Reference total pixels}} \text{....... (3)}$$

Based on Bharatkar and Patel (2013), the most appropriate way of presenting the individual classification accuracies are as follows;

$$\text{Commission error} = 1 - \text{user's accuracy} \text{ .... (4)}$$
$$\text{Omission error} = 1 - \text{producer's accuracy} \text{................ (5)}$$

Kappa coefficient (K) is the measure of agreement of accuracy. Based on Wilkinson (1996); Smits *et al*, (1999); Congalton and Green (2009) to name a few they state that, Kappa analysis has become a standard component of most every accuracy assessment and is considered a requirement in field of RS. Accordingly, it can be calculated based on the equation (6) below.

$$K = \frac{P_0 - P_c}{1 - P_c} \text{ .... (6)}$$

Where:
P0 = proportion of units in agreement. It equals the overall accuracy.
Pc = proportion of units for expected chance agreement.

According to Bharatkar and Patel (2013), the general range for Kappa values are; $K < 0.4$, that means it a poor kappa value; while, if $0.4 < K < 0.75$, it represents a good kappa value, and if $K > 0.75$, it means an excellent kappa value.

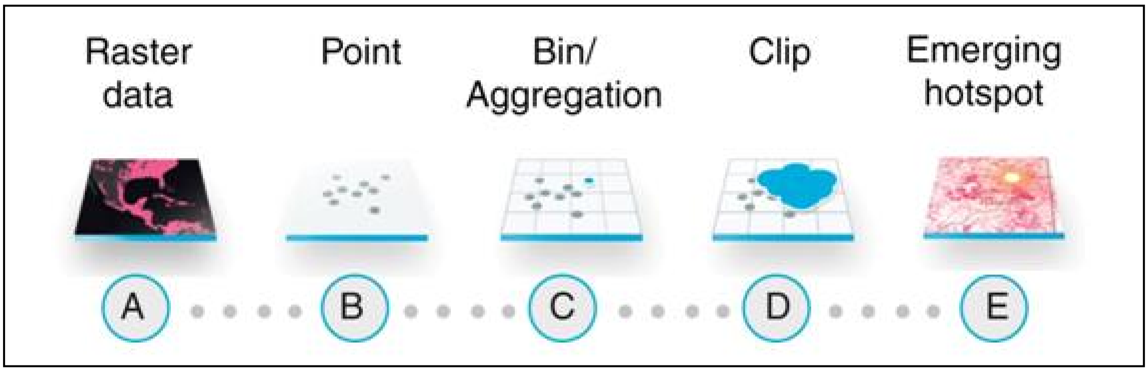
2.2.1.5 Hotspots Analysis

Many studies such as; Aben *et al*. (2012); Isobe *et al*. (2015), have used the term 'hot spot', generically across disciplines to describe a region or value that is higher relative to its surroundings. Based on Getis and Ord (1992), hot spots defined as locations where observed patterns are not likely the result of random processes or of subjective cartographic design decisions; they represent places where there are underlying spatial processes at work. This definition has been extended by Harris *et al*. (2017) to incorporate information about the temporal dimension of the data. In a forest conservation context, there are differences between the terms 'deforestation' and 'forest loss'. WWF (2015) identified the deforestation 'as' broad regions of concern based on expert opinion and scenario analysis where available. Meanwhile, forest loss was defined according to Heino *et al*. (2015) as a 'stand replacement disturbance', meaning the removal or significant reduction of tree cover that can result from a variety of factors globally (Hansen *et al*., 2013). Thus 'deforestation' as defined here does not always equate to forest loss, i.e. conversion of forest to a new, non forest LU (FRA, 2015; Tropek *et al.,* 2014; Harris *et al*., 2017). Therefore, it has more negative impact on the environment. Regarding this matter, Harris *et al*. (2017) defined a hot spot of deforestation as an area that exhibits statistically significant clustering in the spatial pattern of forest loss. The analysis of this technique could be performed at a global scale using one set of standardized parameters across all geographic domains. However, to be relevant for LC policy, Harris *et al*. (2017) recommended that, these analyses will be more useful if they relate to dynamics occurring within specific domains of legal responsibility. Accordingly, to identify deforestation hotspots in the study area, Hotspot analysis tool was applied.

1- Input data and pre-processing

In this analysis, deforestation dominates the forest loss dynamic, observed within the study area that resulted from change detection. The period 2002 to 2014 was chosen. Input data consisted of forest extent and forest loss data produced by the analysis of LU/LC change of the study area as mentioned earlier. These were delivered as raster data at 30 m spatial resolution. Forest deforestation in the original data product that occurred outside the forest extent mask (>5-10 % tree canopy density) was not considered in the analysis. Parallel processing and data management were conducted using Hotspots analysis in ESRI ArcGIS software version 10.1. The Raster data (30 m Landsat pixel scale), were stored in a cloud environment, and then were converted to points. These points were aggregated into space-time bins and point counts were tallied. Subsequent to the analysis, the data was extracted for an area of interest and converted into a net CDF data cube format; for each bin in the cube. Then, the Getis-Ord Gi* statistic was calculated to produce an emerging hot spot map. A summary of the processing steps used in our analysis is shown in Figure 2.22.

Figure 2.22: Summary of Hotspots analysis processing steps



2- Statistical analysis

By evaluating spatiotemporal patterns in forest deforestation, using a statistical measure of the Getis-Ord Gi* statistic (Ord and Getis, 1995), Hotspots analysis tool helps to determine the location and degree of spatial clustering of forest deforestation, where, the Getis-Ord Gi* statistic measures the intensity of clustering of high or low values (i.e. counts of deforestation) in a bin relative to its neighboring bins in the data cube (ESRI, 2016). The sum for a bin and its neighbors is compared proportionally to the sum of all bins. A statistically z score will be significant when the difference between the local sum and the expected local sum is significant, and that is due to randomness (Feltman *et al*., 2012). Getis-Ord Gi* Hotspots analysis determines where the features with high and low Z score and p value tend to form a cluster in the study area. The Getis-Ord Gi* statistic generates Z scores (standard deviations) and P values (statistical probabilities) for each feature which can help to indicate cold and hot spots of events. Z score output represents the statistical significance of clustering for a specified distance, whereas p value indicates the probability that the observed spatial pattern was created by some random process (ESRI, 2016). In the present study, a Z score above 1.97 or below 0.92 means that there is a statistically significant hot spot or a statistically significant cold spot of deforestation at a significance level of P <0.05. The larger a bin's Z-score, the more intense the clustering of values (hot spot). Getis-Ord Gi* hotspots were calculated based on Hansen *et al.* (2013) as the following equation:

$$G_i^* = \frac{\sum_j^n = 1 W_{ij} {}_j^x}{\sum_j^n = 1 X_j}$$

Where, Gi* is the spatial autocorrelation (spatial dependency) statistics of an event 'i' over n events. The term xj defines the magnitude of variable x at event j over all n, while wij defines the weight value between the events i and j that represents their spatial interrelationship. Gi* statistics considers the magnitude of each feature in the dataset in the context of its neighbours' values.

3- Output maps

By default, the Hotspots analysis tool categorizes each bin into one of seven distinct categories that cover a range of scenarios: one category of non-significance along with three hot spot and three cold spot categories, each reflecting a different configuration of spatiotemporal significance (ESRI, 2016). To better understand how each hot spot category is related to deforestation in each village, the resulting hot spot maps for each village were evaluated against filed data, collected by FNC, including intact forest landscapes, locations of tree plantations and protected areas.

2.2.2 Socio-economic Data

For decades, household sample surveys have become a key source of data on social and economical phenomena (UN, 2005). It is the most flexible method of data collection and it provides value information to planners, decision makers, academia, business, and the public (Miller, 2017). Accordingly, Human, social and financial data were collected through a social survey of households; stratified ensure better precision and reduce time, effort and monetary costs. This assessment was conducted during the period of the June to July 2014, followed by a second fieldwork, in July of 2015, to identify the up-to-date situation there. For the household level assessment, standard questionnaires were administered to heads of households. The survey was designed as a cluster sample (a representative selection of villages). The total sample size was 224 questionnaires, 200 for heads of households of non-displaced respondents, while, 24 for displaced people distributed among different units according to the Principle of Population proportional to Size (PPS) in the selected sites. The PPS is a sampling technique for use with surveys or mini-surveys in which the probability of selecting a sampling unit (e.g., village, zone, district, and health center) is proportional to the size of its population. It gives a probability (i.e., random) representative sample. It is most useful when the sampling units vary considerably in size because it assures that those in larger sites have the same probability of getting into the sample as those in smaller sites, and vice versa. This method also facilitates planning for field work because a pre-determined number of respondents are interviewed in each unit selected (McGinn, 2004). Sixteen villages were randomly selected, three, 3 and 10 villages in Rashad, Abokarshola and Elabbassia units, respectively. Furthermore, two refugee’s camps, Abkorshola in Rashad locality, and Jabarona Omdurman locality (Khartoum), with total samples size 24 contributions were covered. The limit of statistical significance (alpha) is 0.05, in a confidence interval of 20. This sampling estimate was increased by 10% to allow for non-response, bias and to account for possible missing or “unclear” data. Due to absence of prior information, on homogeneity (or otherwise) of the characteristics of the population, the size cannot be determined using conventional methods based on standard deviations, as this requires prior calculation of such an statistic. However, it is well established in the literature of survey methods in developing countries, where base data is lacking, that method of stratification and the relatively large sample size will overcome such problems to some extent (Deafalla, 2012). The questionnaire was designed with closed multiple-choice and open-ended questions concerning the basic characteristics of Nuba mountains community, respondents perspectives about different aspects of the LU/LC uses, in addition to identifying main war impacts such as; agricultural situation, livestock conditions, macroeconomic situation, availability of food, food stock, types of food consumed and number of meals per day,…etc.

Despite a number of approaches exist to measuring food security, complex data collection and analysis are impractical till now, especially in emergency situations (Wiesmann *et al*., 2009). This is based on Ruel (2003); Wiesmann *et al*. (2006) and Arimond *et al*. (2008), who indicated that, the data of diversity and food frequency have proven reliable proxy indicators of diet quality and quantity across a range of settings. The dietary diversity and food frequency of households or individuals were correlated with measures of food security (Hoddinott and Yohannes, 2002; Ruel, 2003; Arimond *et al*., 2011; Vaitla *et al*., 2017). Therefore, the data related to food consumption was collected by applying a standardized household questionnaire for both non-displaced and displaced respondents, including the standard World Food Programm (WFP) FCS module to recording both frequencies and quantities of food items consumed in the past 7 days either through purchase, own production or in-kind. The module was develop based on Wiesmann *et al*. (2009), where an additional question about the number of days on which a food item/group was consumed in small amounts only, was appended in the questionnaires in order to test the effect on the FCS of excluding small amounts. The questionnaires were tested in Dar Elsalam unit, rural of Omdurman, Khartoum State, before traveling to South Kordofan State. Furthermore, another questionnaire was applied in Dar Elsalam unit, (were all the community in this unit are Nuban 100%) with the "Nuba's Immigrants" for more than 10 years with a total sample size of 55 contributions. The questionnaire aimed at identifying the new social characteristics of the community. The survey was conducted in Arabic language and the translated version is shown in annexes (3), (4), (5) and (6).

The application of RRA has been quite wide as regards rural development such as; natural resource assessment, health, nutrition, non-formal education, emergencies and disasters, agroforestry, agricultural marketing as well as sociology approaches (Ellman, 1981; McCracken *et al.*, 1988; Crawford, 1997), where it reflects the new thinking about development, needs, and people-oriented responsibilities. A central characteristic of RRA is that it's a highly systematic and structured process, relying on interdisciplinary teamwork and special strategies for data collection and analysis (Crawford, 1997; Cavestro, 2003). In the current study, RRA approaches i.e.; focus on group discussions, interviews and key informants techniques were applied. Focus group discussions were facilitated for 5 different groups from randomly selected locations (separated by sex and age) to identify problems and causes of environmental change along with possible mitigation and adaptation strategies. Participants for the discussions were selected purposively amongst representatives in the communities, as well as various sub-groups within it. Moreover, a short interview with the older ones as key informants was conducted to understand their perception of the trends of LC changes. These informal interviews helped to understand their adaptive nature and resource consumption strategy.

2.2.2.1 Data Analysis

The collected information has been coded, entered, processed and analyzed both in qualitative and quantitative ways. Statistical Package for Social Sciences (SPSS) version 18 was used to analyze the data. SPSS is a statistical package particularly suited to social science and survey data. Summary information of the social – economic characteristics of the study sample was obtained in the form of frequency, percentages, distribution, mean, minimum, maximum, sum and standard deviation by using descriptive analyses. Furthermore, correlation analysis was applied to determine the war impacts on the local community.

Moreover, to gauge both diversity and frequency of food consumption in surveyed areas of the study site, FCS was used. FCS is an index that was developed by the WFP in 1996, which assigns a food security score based on dietary diversity, food frequency, and the relative nutritional importance of different consumed food groups (WFP-FAO, 2008; WFP, 2009; Lovon and Mathiassen, 2014; Vhurumuku, 2014). It utilized based on the idea that the experience of household food deprivation causes predictable reactions, especially in the new life. The FCS was calculated using the frequency of consumption of different food groups consumed by a household during the 7 days before the survey. Where foods were regrouped into eight standard food groups (see Table 2.3 below). Each food group was assigned a weight, reflecting its nutrient density (WFP, 2008; 2009) so that groups rich in proteins have the highest score (e.g., animal protein foods), while food groups with few micronutrients have the lowest (e.g., sugar and oil).

Table 2.3: Food groups and weights

FoodItems	**Food groups**	**Weight**
Maize, maize porridge, rice, sorghum, millet pasta, bread and other cereals	Cereals and Tubers	2

Cassava, potatoes and sweet potatoes	Cereals and Tubers	2
Beans, Peas, groundnuts and cashew nuts	Pulses	3
Vegetables and leaves	Vegetables	1
Fruits	Fruits	1
Beef, goat, poultry, pork, eggs and fish	Meat and fish	4
Milk yogurt and other diary	Milk	4
Sugar and sugar products	Sugar	0.5
Oils, fats and butter	Oil	0.5
Condiments	Condiments	0

The consumption frequency of each food group was multiplied by an assigned weight (Fig. 2.23), that is based on its nutrient content by using the following equation according to WFP, 2008:

FCS = ^{a} staple x staple+ ^{a}pulse x pulse+ ^{a}vegetable x vegetable+ ^{a}fruit x fruit + ^{a}animal x animal+ ^{a}sugar x sugar + ^{a}dairy x dairy+ ^{a}oil x oil

Where:

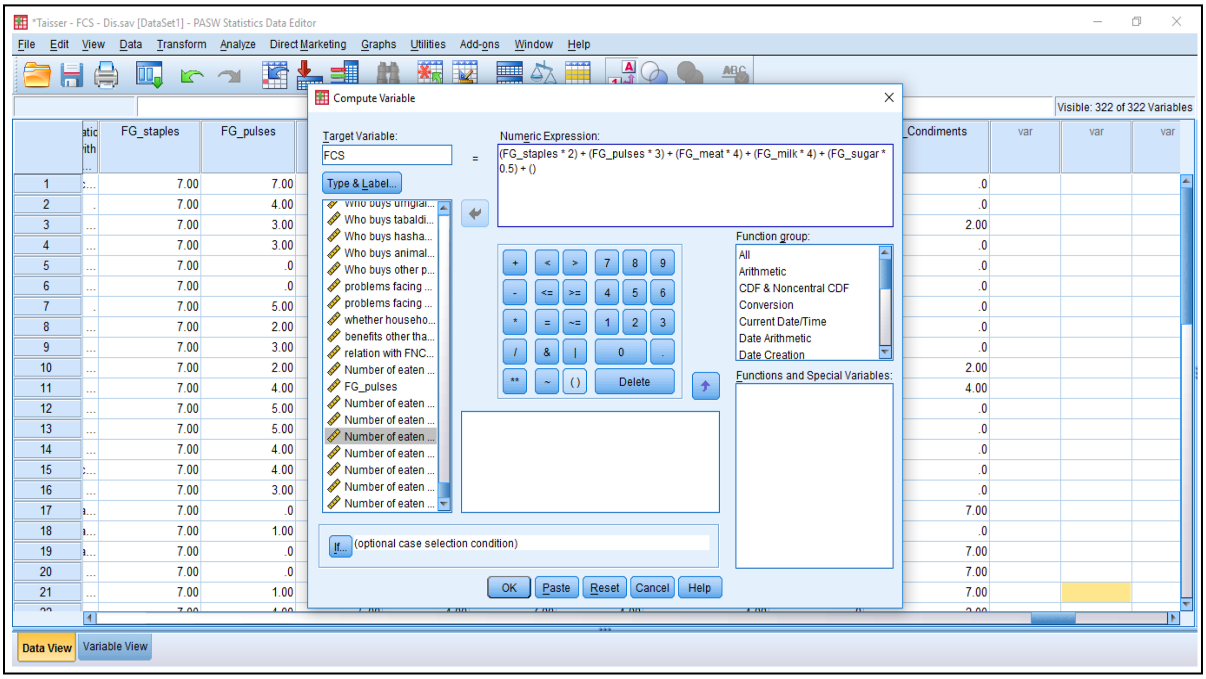
FCS = Food Consumption Score

Xi = Frequencies of food consumption= number of days for which each food group was consumed during the past 7 days.

ai = Weight of each food group.

*(7 days was designated as the maximum value of the sum of frequencies of the different food items belonging to the same food group).

Figure 2.23: The calculation of food group



Descriptive analysis was used to compare estimates of the prevalence of poor and borderline food consumption based on the FCS and calorie consumption per capita. Correlation co-efficients were calculated to quantify the strength of the association between the two variables. As the main interest was on the monotonic relations, the Spearman coefficient was applied, which is based on the rankings of the households and measures the strength of the monotonic relationship. Furthermore, to test for linear and non-linear relationships, the study estimated regression with calories per capita as the dependent variable, including linear, polynomial and log-linear combinations of the FCS.

Subsequently, scores were clustered according to results of the analysis into three groups of household; poor, borderline or acceptable food consumption. A score of 20 is a bare minimum with a score below 20 reflecting a household that is not expected even to eat staples and vegetables on a daily basis and was therefore considered to have poor food consumption. Households with scores between 20 and 35, were assessed as having borderline food consumption, as a score of 35 reflects a household with daily staple and vegetable consumption as well as oil and pulses four times a week, which is considered a minimum for an adequate diet (WFP, 2008; Lovon and Mathiassen, 2014).

Descriptive statistical methods were applied, as well, to assess the prevalence of household food insecurity, access component and to detect changes in the food insecurity situation of a population over time.

2.2.3 Literature review

A formal updated literature review was used to studythe covered area that was because of the difficulties in data collection due to security reasons.

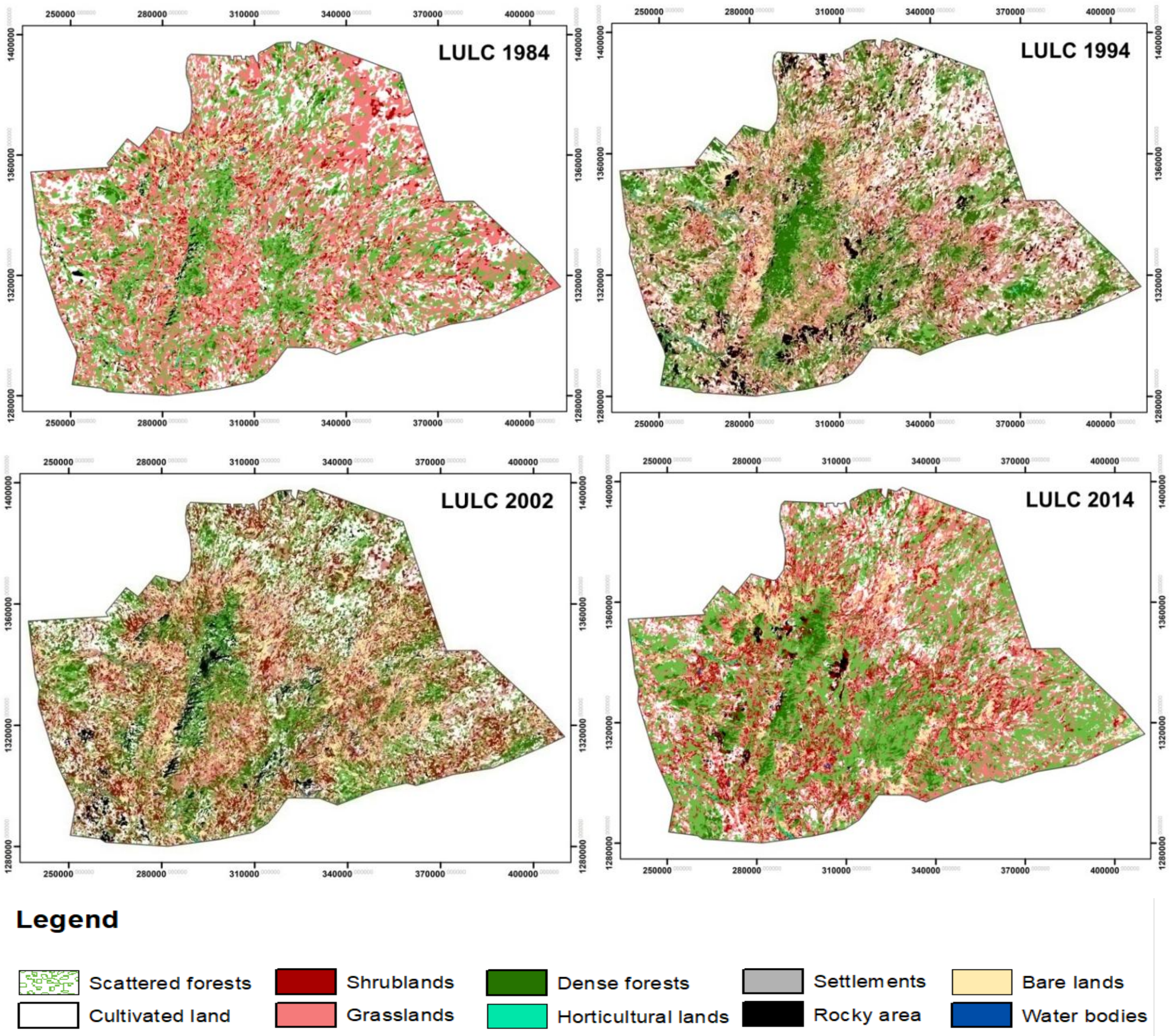
2.3 Results and Discussion

2.3.1 Assessment of LU/LC

In the study site, the main impediment to carrying out the requisite field work was the risk of war. However, satellite sensor data have proven useful for mapping LC, estimating geophysical and biophysical characteristics of terrain features, as well as monitoring changes in LC, especially in conflict areas and post-war zones. Given the increased availability of mid to fine resolution (30 m pixels) satellite imagery since the early 1990s (Stoney, 2006) and the increase of civil wars over the same period (Sarkees *et al*., 2003), this research field holds much potential for assessing the burden of war by identifying and analyzing effects with a view to aid the victims like many cases such as BiH, El Salvador, Vietnam, and the first Gulf War (Brauer, 2000). In this work, the classification scheme was categorized in three levels for a total of two first level classes, nine second level classes and one third level classes. Several objects were inferred and identified by means of logical search and resorting to probabilities by studying and correlating photo-elements and existing knowledge. Using the shape pattern of man-made features, Settlements, Horticultural and Cultivated lands were identified. Settlements whether rural or urban areas, are distinguished by its density pattern. While, Cultivated lands are distinguished by check-board pattern of fields, which indicates the individual field or holdings. Similarly, check-board pattern with wells (Hafer) indicated irrigated croplands. Meanwhile, the irregular pattern of natural features were utilized to identifey the water bodies, and hills. However, the major portion of the study area is occupied by Forest land. In this way taking into account the photo elements, associated features and fieldwork, a LU map has been prepared. Accordingly, the study area was mapped and quantified into ten land features: i.e. Cultivated lands;

Scattered forests; Dense forests; Shrublands; Grasslands, Rocky areas, Bare lands, Water bodies, Horticultural lands and Settlements (Fig. 2.24).

Figure 2.24: LU/LC classes in study site



In this study, no significant water bodies are in the study area, an exception is found during the rainy season with some seasonal valleys (*Wadis*). Therefore, the MNDWI was important to understand the distribution of water bodies and it also helped minimize misclassifications. It succeeded to determine the location of water bodies in the region as clarified in Figure 2.24 above. On the other hand, the SAVI was found to be an important step toward the classification of LU/LC in the study site. It had a significant effect to minimize the soil influences on canopy spectra involving red and near-infrared wavelengths. Where, it shifted the origin of reflectance spectra plotted in NIR-red wavelength space to account for first-order soil-vegetation interactions and differential red and NIR flux extinction through vegetated canopies. SAVI, in the study area, was ranging from 0.08 to -0.09 in (1984), 1.0 to -0.9 in (1994), 0.8 to -0.6 in (2002) and from 0.9 to -0.9 in (2014).

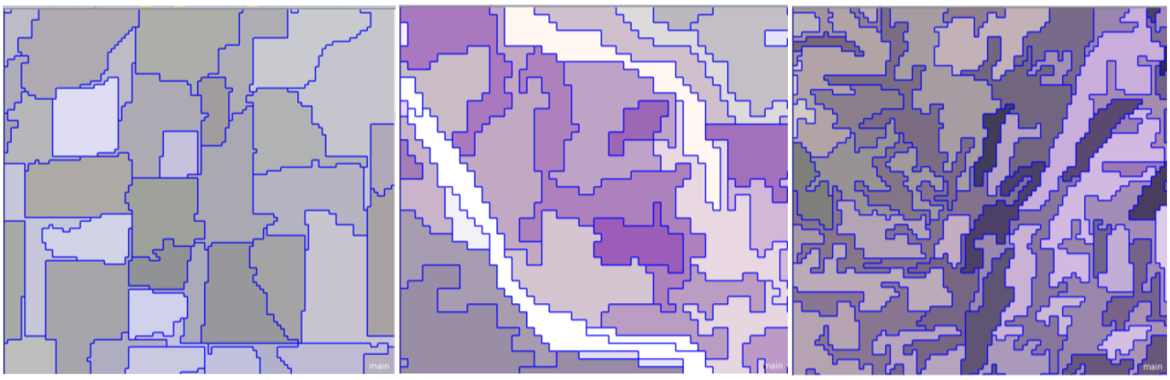
The NDVI in this study demonstrated to have generally positive effects in the classification results for images of good quality. Their values ranged from 0.6 to -0.92 in (1984), 0.98 to -0.97 in (1994), 0.58 to -0.46 in (2002) and from 0.63 to -0.71 in (2014). Areas of the barren rocky area and sand showed very low NDVI values (for example, 0.1 or less), meanwhile water bodies were represented with negative NDVI values (Table 2.4). Sparse vegetation such as shrubs, grasslands as well as senescing crops resulted in moderate NDVI values (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) correspond to dense vegetation such as that found in Dense forests, Horticultural lands, Scattered forest and crops at their peak growth stage. NDVI helped to separate vegetation types from other LC types; however some vegetation classes (i.e. Dense forests and Horticultural lands) have been very difficult to be identified because mixed, sub-pixel size and similar spectral characteristic. Therefore, other classification features such as DEM were used to differentiate between these classes in the area.

Table 2.4: Vegetation indices for images 1984, 1994, 2002 and 2014

Class	NDVI				MNDWI				SAVI			
	1984	**1994**	**2002**	**2014**	**1984**	**1994**	**2002**	**2014**	**1984**	**1994**	**2002**	**2014**
Cultivated lands	0.0381 to 0.0132	0.0320 to 0.0124	0.0555 to 0.0102	0.0413 to 0.0101	-0.1001 to 0.0003	-0.1057 to 0.0520	-0.0221 to 0.0139	-0.0941 to 0.0995	0.0114 to 0.0103	0.1576 to 0.0139	0.0811 to 0.0115	0.0139 to 0.0384
Scattered forests	0.2534 to 0.0902	0.2686 to 0.0974	0.3465 to 0.1551	0.2444 to 0.1855	-0.3604 to - 0.1714	-0.4471 to - 0.2178	-0.2251 to - 0.0853	-0.3432 to - 0.2268	0.0469 to 0.0268	0.7828 to 0.5814	0.3252 to 0.2100	0.5365 to 0.2782
Dense forests	0.5631 to 0.2535	0.8899 to 0. 2687	0.6834 to 0.3466	0.6312 to 0.2445	-0.4590 to - 0.3605	-0.5888 to - 0.4472	-0.3211 to - 0.2252	-0.4113 to - 0.3433	0.0625 to 0.0470	0.8324 to 0.7829	0.5388 to 0.3253	0.7455 to 0.5386
Shrublands	0.0902 to 0.0669	0.0973 to 0.0620	0.1550 to 0.0843	0.1854 to 0.0766	-01713 to - 0.1591	-0.2177 to - 0.2035	-0.0852 to - 0.0504	-0.2267 to - 0.1506	0.0267 to 0.0199	0.5813 to 0.3794	0.2099 to 0.1644	0.0781 to 0.0415
Grasslands	0.0668 to 0.0382	0.0620 to 0.0321	0.0742 to0.0556	0.0765 to 0.0414	-0.1590 to - 0.1002	-0.2034 to - 0.1058	-0.0503 to - 0.0221	-0.1505 to - 0.0941	0.0198 to 0.0115	0.3794 to 0.1577	0.1643 to 0.0812	0.0414 to 0.0140
Rocky areas	0.0039 to - 0.2379	0.0123 to -0.4145	0.0100 to -0.1785	0.0100 to -0.4863	0.0002 to 0.0310	0.0521 to 0.2759	0.0140 to 0.1759	0.0996 to 0.3471	0.0002 to -0.2278	0.0120 to -0.1690	0.0005 to -0.0274	0.0318 to- 0.0150
Bare lands	-0.2378 to - 0.5790	-0.4144 to -0.7194	-0.1784 to -0.3490	-0.4862 to -0.5109	0.0311 to 0.0632	0.4936 to 0.7289	0.2100 to 0.2645	0.4196 to 0.6934	-0.5134 to-0.9435	-0.4979 to -0. 9448	-0.4900 to -0.6843	-0.5814 to -0.9062
Water bodies	-0.5789 to - 0.9201	-0.6193 to -0.9721	-0.3489 to -0.4643	-0.5108 to -0.7142	0.0631 to 0.0959	0.7290 to 0.9615	0.2644 to 0.5066	0.6935 to 0.7337	-0.2277 to -0.5139	-0.2985 to -0.4980	-0.3861 to- 4899	-0.3986 to -0.5813
Horticultural lands	0.6439 to 0.4182	0.9614 to 0.5832	0.6070 to 0.5817	0.6329 to 0.4432	-0.6164 to - 0.4591	-0.7031 to - 0.5889	-0.4388 to - 0.3212	-0.5543 to - 0.4114	0.8181 to 0.0626	1.0000 to 0.8325	0.8670 to 0.5389	0.9487 to 0.7456
Settlements	-0.0131 to - 0.0040	-0.0009 to -0.0211	-0.0340 to -0.0631	-0.0201 to -0.0134	-0.0284 to - 0.0157	0.2760 to 0.4935	0.1759 to 0.2100	0.3472 to 0.4195	0.0102 to 0.0002	0.0138 to 0.0119	0.0115 to 0.0006	0.0383 to 0.0319

Indeed, DEM gave improved classification results and showed a very high capability of differentiating between the mixed classes. The result indicated that, the Horticultural lands are only located in altitude less than 800 m. In contrast to the Dense forests that are located in different altitudes. To avoid mixing these categories of low land, texture values, i.e. the shape, were used, which enhanced the classification result.

Figure 2.25: Different gradient directions for (a) Cultivated lands, (b) Horticultural, (c) Forest lands



(a) (b) (c)

Figure 2.25 above shows an example of a possible evaluation of the texture. These images are processed with ane Cognition operator. Typically, Cultivated land objects contain many edges with one main edge direction (a), whereas in Horticultural objects, the direction of the edges is equally distributed to some extent (b) and in forest objects, several main directions can be found (c). Other texture measures could be, for example, the average length or contrast of the edges. However, several tests have to be performed in order to prove these ideas.

2.3.1.1 LC classification accuracy

The classification accuracy assessment was estimated based on the reference TTA Mask samples utilizing the best classification result method as shown in Table 2.5 below. Settlements class has higher accuracy (100% accuracy) which is attributed to the uniqueness of its spectral value as the remaining areas of the image represent very different spectral information compared to this class. The lowest accuracy has been observed in the water class, with the reported accuracy of 81% for image of 2014. This was confused with Bare lands and Rocky area classes, a confusion attributed to units of pixels within the same class and which has heterogeneous values, due to the increased class variances of spectrum in high resolution imagery. Moreover, another confusion can be observed in the class of Grassland for the image of 2014 as well (86%), which is mainly confused with Shrublands. This is due to the fact that object information contained in these classes is not easily distinguishable. Even during the field visit; the study faced some difficulties to differentiate between these classes.

Table 2.5: The accuracy assessment for images 1984, 1994, 2002 and 2014

Class	Objects				Mean				StdDev				Minimum				Maximum			
	1984	1994	2002	2014	1984	1994	2002	2014	1984	1994	2002	2014	1984	1994	2002	2014	1984	1994	2002	2014
Background	1102	8360	3085	1434	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1
Rocky areas	579	3450	3107	400	0.88	0.99	0.93	0.85	0.159	0.015	0.058	0.112	0.244	0.690	0.426	0.206	1	1	1	1
Bare lands	2346	5959	12459	7280	0.96	0.98	0.97	0.91	0.039	0.016	0.032	0.084	0.628	0.651	0.139	0.104	1	1	1	1
Water	61	558	434	400	0.96	0.98	0.95	0.81	0.029	0.034	0.079	0.217	0.839	0.472	0.602	0.103	1	1	1	1
Dense forests	12597	19785	26817	19770	0.97	0.99	0.97	0.94	0.055	0.014	0.029	0.054	0.110	0.747	0.169	0.104	1	1	1	1
Horticulture land	109	464	234	144	0.97	0.99	0.97	0.94	0.054	0.015	0.069	0.075	0.654	0.736	0.236	0.472	1	1	1	1
Scattered forests	10896	9730	16502	15997	0.98	0.99	0.98	0.95	0.037	0.012	0.029	0.044	0.504	0.812	0.169	0.489	1	1	1	1
Cultivated land	7447	10756	15498	6897	0.97	0.99	0.98	0.94	0.039	0.027	0.020	0.052	0.365	0.873	0.607	0.535	1	1	1	1
Shrublands	2806	2936	13294	8426	0.97	0.98	0.97	0.93	0.035	0.027	0.027	0.063	0.646	0.151	0.236	0.351	1	1	1	1
Grasslands	14063	16655	10111	11804	0.97	0.99	0.95	0.86	0.028	0.014	0.025	0.057	0.605	0.760	0.660	0.188	1	1	1	1
Settlements	103	144	152	126	1	1	1	1	1.174	0	0	0	1	1	1	1	1	1	1	1

The producer's accuracy and user's accuracy measures are useful to evaluate the classification accuracy for individual classes. Where, the accuracy assessment for all LU/LC categories were found, by using these methods, to be good, the only exception was for the class of Rocky areas (for image 1984) and the class of Grasslands (for images 1984 and 2002). The performance was poor to some extent. As shown in Table 2.6, the current finding agreed with the result of best classification result method, in Table 2.5 above regarding the class of Grassland, where it represented lower percentage as well. In general, the overall classification accuracy of both methods resulted in strong and perfect agreement.

Table 2.6: Summary of Accuracy (%) and Kappa statistics of LU/LC maps

LULC category	**1984 Accuracy**		**1994 Accuracy**		**2002 Accuracy**		**2014 Accuracy**	
	Producer's	**User's**	**Producer's**	**User's**	**Producer's**	**User's**	**Producer's**	**User's**
Rocky areas	0.71	1	1	1	1	1	1	1
Bare lands	0.94	1	0.987	1	1	0.98	1	1
Water	1	1	1	1	1	1	1	1
Dense forests	1	1	1	1	1	0.98	1	1
Horticulture land	1	1	1	1	1	1	1	1
Scattered forests	1	1	1	1	1	1	1	1
Cultivated land	1	1	1	1	1	1	1	1
Shrublands	1	1	0.96	1	1	0.96	1	1
Grasslands	0.83	1	1	1	1	0.86	1	1
Settlements	1	1	1	1	1	1	1	1
Overall accuracy	**0.98**		**0.996**		**0.979**		**1**	
Kappa statistics	**0.976**		**0.995**		**0.975**		**1**	

Table 2.6 lists, as well, the overall accuracy and kappa of the LU/LC classification maps. Where, these maps achieved an overall accuracy with values of 98%, 99%, 97% and 100% for years 1984, 1994, 2002 and 2014 respectively. Additionally, the kappa value of 0.97, 0.99, 0.97 and 1 for maximum likelihood classifier of the selected years respectively indicates better classification.

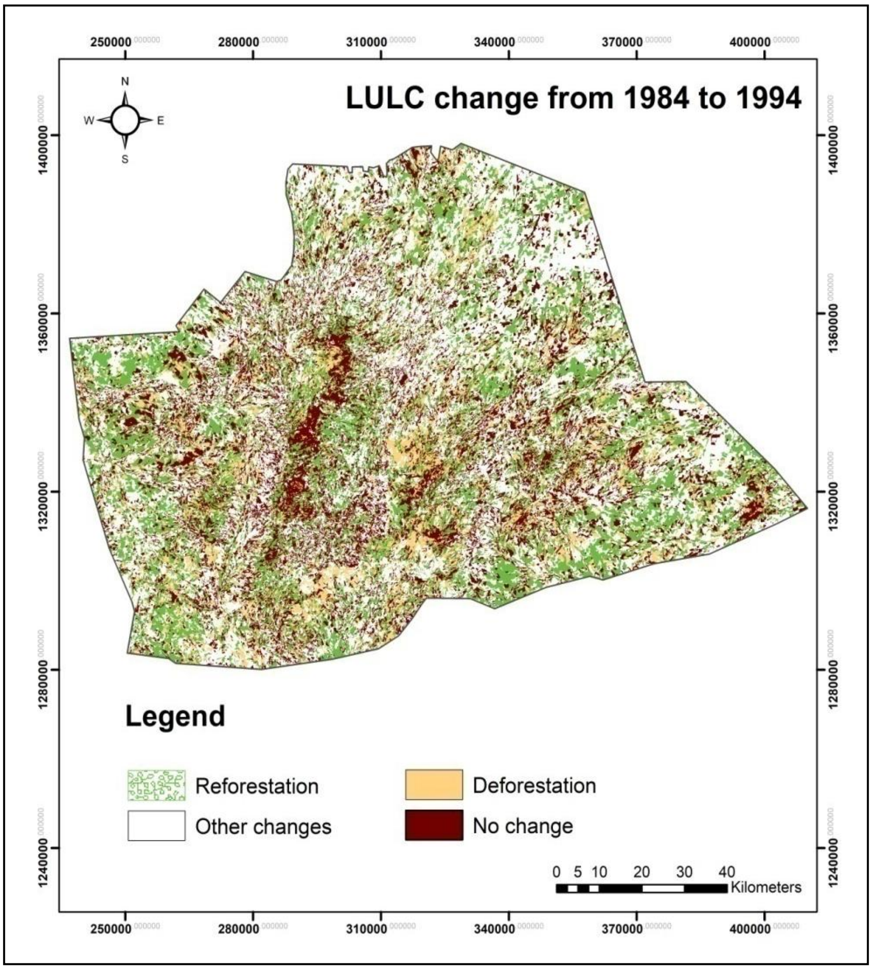
2.3.2 Land classification change analysis

2.3.2.1 Changes of the first period from 1984 to 1994

Unfortunately, the history of the study area during the last decade's shows that it has been exposed to a series of recurring conflicts for years. The cataclysmic Sudanese civil war began in 1983 that pitted the North against the South. Since that date, till end of 1988, the Nuba generally sought to refrain from choosing any sides, despite that, the area has been affected and it was a silent casualty of war and armed conflict, where, the war was a major driving force in changing the rate and patterns of the local LU/LC dynamics.

In 1985, the situation changed when the Nuba people felt distrust and doubted that the government instituted policies aimed to marginalize or eliminate educated Nuba's leadership from participation in the Sudanese polity. Nevertheless, given government neglect and militia raiding, as well as the myriad and not so subtle forms of racial discrimination to which they were subjected, by 1989 many Nuba were allied with the Sudan People's Liberation Army (SPLA), and some had even joined its military (Burr, 1998). The war in Sudan, since the end of 1989, has been characterized by an incremental fortunately in that time military activity and social policy directed against the Nuba peoples of South Kordofan have been nothing short of genocidal. The current results indicated that, the study area has undergone significant LU/LC alterations and transformations since late 1984s as illustrated in Figure 2.26 below.

Figure 2.26: LU/LC change from 1984 to 1994



The initial clustering analysis of the period from 1984 to 1994 showed there is a considerable recovery in vegetation cover during the war period as shown in Figure 2.26 above. Where, Dense forests areas coverage increased approximately to be 206537.9 ha (16.4%) while Bare land decreased to be 100532.7 ha (4.7%). Shrublands, Scattered forest and Grassland areas were declined slightly as well to 59607.1 ha (4%), 225005.4 ha (17.89%) and 356203.3 ha (19.6%) respectively as illustrated in Table 2.7 below.

Relatively, Cultivated lands were increased from 15.7% to 16.5% during that period. It's important to note, there was a huge change in Settlements area, which increased from 1379.0 ha (0.2%) to be 35929 ha (2.9%) in 1994. This is mainly due to the established villages "22 peace units" by Sudanese government in 1992 to house 70,000 returnees and resettlement of 500,000 Nuba internally displaced people (Burr, 1998). Furthermore, the reluctance of Internally Displaced People (IDPs) to return to their rural homes after the war caused an increased demand for land driven by housing needs.

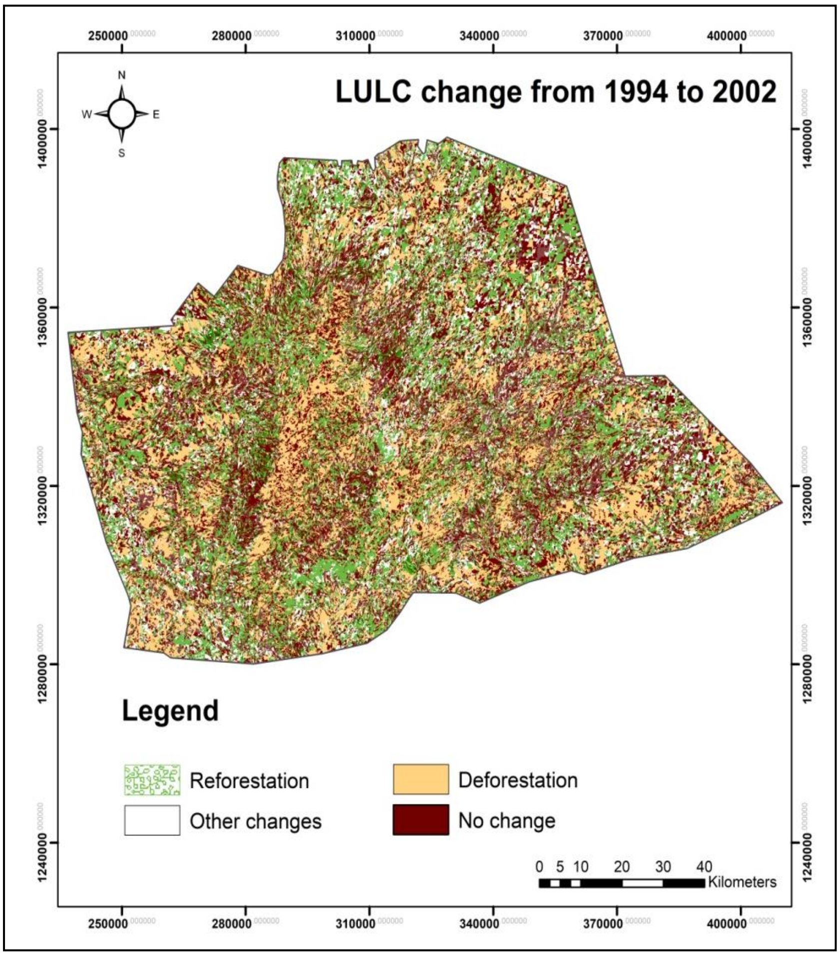
Table 2.7: Change matrix for the first period from 1984 to 1994

	Cultivated land	Bare land	Dense forests	Scattered forests	Shrublands	Grasslands	Rocky areas	Horticulture land	Settlements	Water	Total	%
Cultivated land	112.1	8459.7	45730.2	53607.7	11280.2	61513.8	16466.8	0	0	0	197170.5	15.7%
Bare land	4470.5	15033.4	0	5300.2	5256.1	23114.2	0	0	33550	0	86724.4	6.8%
Dense forests	8491.6	455.3	18149.8	12217.9	0	8060.9	3456.4	2627.6	0	0	53459.5	4.3%
Scattered forests	1468.8	11608.4	65885.8	76152.8	2301	76486.0	17000.5	0	0	0	250903.3	19.9%
Shrublands	15980.5	12150.0	18.2	9400	6315.2	45369.5	0	0	0	0	89233.4	7.1%
Grasslands	99547.2	11152.6	72218.6	66064.1	25196.4	140823.2	73442.6	0	1000	0	489444.7	38.9%
Rocky areas	76999.2	0	3765.0	2262.7	0	835.7	2519.7	0	0	0	86382.3	6.9%
Horticulture land	0	0	770.3	0	0	0	0	1134.4	0	0	1904.7	0.15%
Settlements	0	747.7	0	0	0	0	0	0	1379.0	0	2126.7	0.2%
Water	0	0	0	0	0	0	0	0	0	530.5	530.5	0.04%
Total	207069.9	59607.1	206537.9	225005.4	50348.9	356203.3	112886	3762	35929	530.5	1257880	100%
%	16.5%	4.7%	16.4%	17.89%	4%	28.3%	8.97%	0.3%	2.9%	0.04%	0	100%

2.3.2.2 Changes of the second period from 1994 to 2002

Unfortunately, the analysis of the period 1994 to 2002, detected a pervasive environmental degradation in the area, which revealed an intensive and dynamic rate of deforestation, mainly related to admixture dynamic interactions between social and ecological systems. Many empirical geospatial researches proved that, civil wars and other forms of conflict cause human displacement, especially when such displacement occurs within, rather than across, national boundaries. Civil wars are influential underlying drivers of human-induced environmental change in those environments (Geist and Lambin, 2002; Tejaswi, 2007; Gorsevski *et al*., 2012; Gbanie *et al*., 2018). Several authors (such as; Dudley *et al*., 2002; Witmer, 2008; Wilson, 2014; Mansaray *et al*., 2016) have demonstrated that IDPs crises are contributing to increased LC change rates in areas where IDPs have relocated. These negative environmental consequences compromise the environment's potential to provide ecosystem services for both the IDPs as well as to non displaced people (Gorsevski *et al*., 2012; Baumann *et al*., 2015). In reality, refugee villages that were created to take in those fleeing unstable areas, placed significant stress on the surrounding land and water resources in the study area. That led to uncontrolled exploitation of forest resources and a concomitant increase in LC change. As a result, natural vegetation, like forests, was removed, degraded and substituted mainly by crop fields which covered approximately 299978.4 ha as clarified in Figure 2.27 below.

Figure 2.27: LU/LC change from 1994 to 2002



The results indicate that severe land cover changes have occurred resulting from agricultural intensification, where Cultivated land and Bare land increased in the years 1994 and 2002 to 24% and

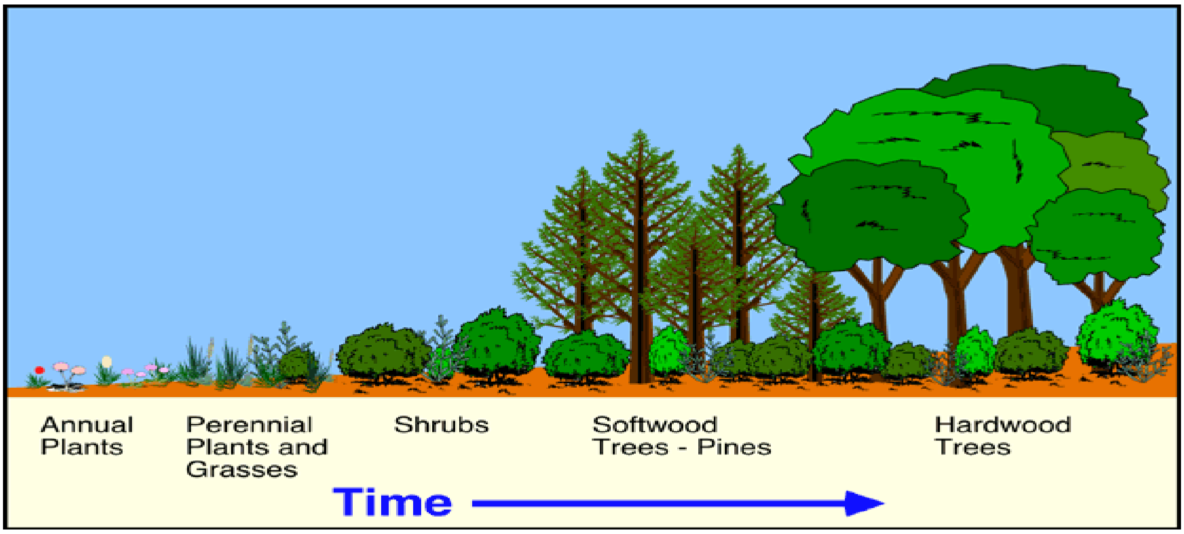
11.40% respectively. This is mainly due to urban and peri-urban agriculture became a major livelihood activity for IDPs to make the region food self-sufficient, especially when the war destabilized food production activities. In contrast, Dense and Scattered forest lands were decreased from 16.4% and 17.89% to be 13.10% and 11.9% respectively (Table 2.8). Indeed, that supports Ghazoul and Evans (2001) who referred to the fact that some types of small-scale agriculture undoubtedly cause deforestation. In fact, these changes directly contributed to the degradation and depletion of renewable resources of the area (Deafalla, 2012; Deafalla *et al*., 2014b). The result of the case study revealed that, the area has been severely hit by sand encroachment, soil erosion especially in the northeast part of the area.

Table 2.8: Change matrix for the second period from 1994 to 2002

	Cultivated land	Bare land	Dense forests	Scattered forests	Shrublands	Grasslands	Rocky areas	Horticulture land	Settlements	Water	Total	%
Cultivated land	94175.5	27296.9	24426.5	6215.2	48484.4	1992.1	4479.3	0	0	0	207069.9	16.5%
Bare land	5514.15	26554.95	0	5987.1	9284.95	11501.15	0	0	638.1	126.7	59607.1	4.7%
Dense forests	52190.1	13697.5	57978	7146.6	38440.4	20753.1	11554.2	4778	0	0	206537.9	16.4%
Scattered forests	43174.0	2301.9	26416.9	48317.72	82985.26	15381.42	6428.2	0	0	0	225005.4	17.89%
Shrublands	17483.9	9845.9	99.65	4400	6589.65	11929.8	0	0	0	0	50348.9	4%
Grasslands	64760.1	59226.6	38360.1	59607.2	70374.2	58220.8	5454.3	0	200	0	356203.3	28.3%
Rocky areas	22680.6	0	16794.8	18368.9	1637.4	14224.6	39179.7	0	0	0	112886	8.97%
Horticulture	0	0	1930.05	0	0	0	0	1831.95	0	0	3762	0.3%
Settlements	0	4258.7	0	0	0	0	0	0	31670.3	0	35929	2.9%
Water	0	0	0	0	0	0	0	0	0	530.5	530.5	0.04%
Total	299978.4	143182.5	166006	150042.7	257796.5	134003	67095.7	6609.95	32508.4	657.2	1257880	100%
%	24%	11.40%	13.10%	11.9%	20.49%	10.65%	5.33%	0.5%	2.58%	0.05%	0	100%

On the other hand, the analysis of the matrix of LU/LC changes demonstrated the rapid decline of Grasslands (10.65%). It was replaced mainly by Shrublands that became (20.49%). Actually this was nearly five times the size of the areas in 1994. That was related to the ecological succession, which is the term used to describe the directional non-seasonal cumulative change in the types of plant species that occupy a given area over time. It involves the processes of colonization, establishment, and extinction which act on the participating plant species (Sahney and Benton, 2008). Fig. 2.28 below is an example for progress in ecological succession.

Figure 2.28: An example for progress in ecological succession



Source: Pidwirny, (2006)

2.3.2.3 Changes of the third period from 2002 to 2014

In this period, the recent changes in the global political economy and environmental systems, as well as local dynamics of the state, have increasingly brought rapid changes in LC, social, institutional and livelihood transformation across broad areas of the study area.

1- The demographic change

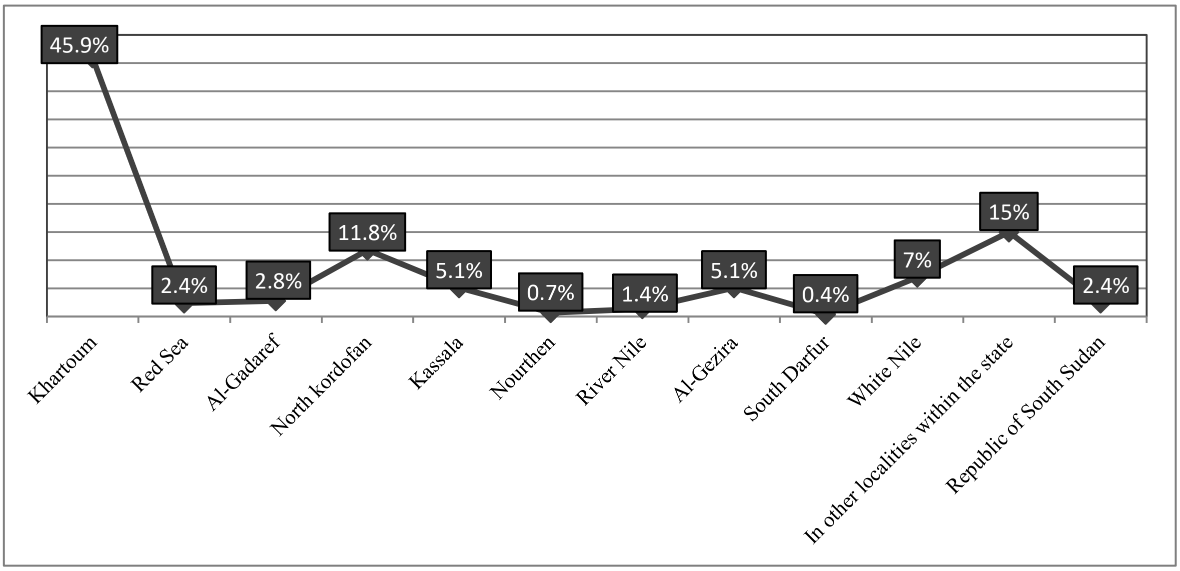
Migration and EC are interrelated, where EC affects migration directly in particular through economic, environmental political drivers (Black *et al*., 2011; Geddes *et al*., 2012; Deafalla *et al*., 2018). The mobility of a large majority of migrants worldwide, moving within their own countries rather than abroad, can take many forms; e.g. moving from one rural area to another, or from rural to urban areas. There are different reasons and causes for migration, often though, the prime motivation is to escape situations of distress caused by food insecurity, poverty, lack of jobs, increased competition for scarce land and water resources, and so on (FAO, 2018a). Till now, despite the decades of world summits, transnational advocacy, and scholarly research, but haven't sufficiently investigated heterogeneous driving forces that lead into the migrations and find suitable solutions.

Environmental, economic, political and social factors have long had an impact on migration flows in Nuba Mountains, as people have historically left places with harsh or deteriorating conditions. However, the scale of such flows, both internal and cross-border, is expected to rise as a result of accelerated EC, with unprecedented impacts on lives and livelihoods. In the study area, unfortunately, the degraded resources, changing livelihoods and conflicts forced the indigenous people migration to other regions such as Khartoum and North Kordofan states (Fig. 2.29), in addition to the Republic of South Sudan with, negative consequences for political stability in the area. The current study supports Thomas and Blitt (1998) who noted that, the absence of a socio-economic adaptation strategy to EC and resource scarcity often exacerbates ethnic conflicts, migrations and insurgencies; and indirectly impacts the international community.

According to the definition of 'migration' by the National Geographic Society (NGS) in 2005, the study identified five patterns of migration in the region:

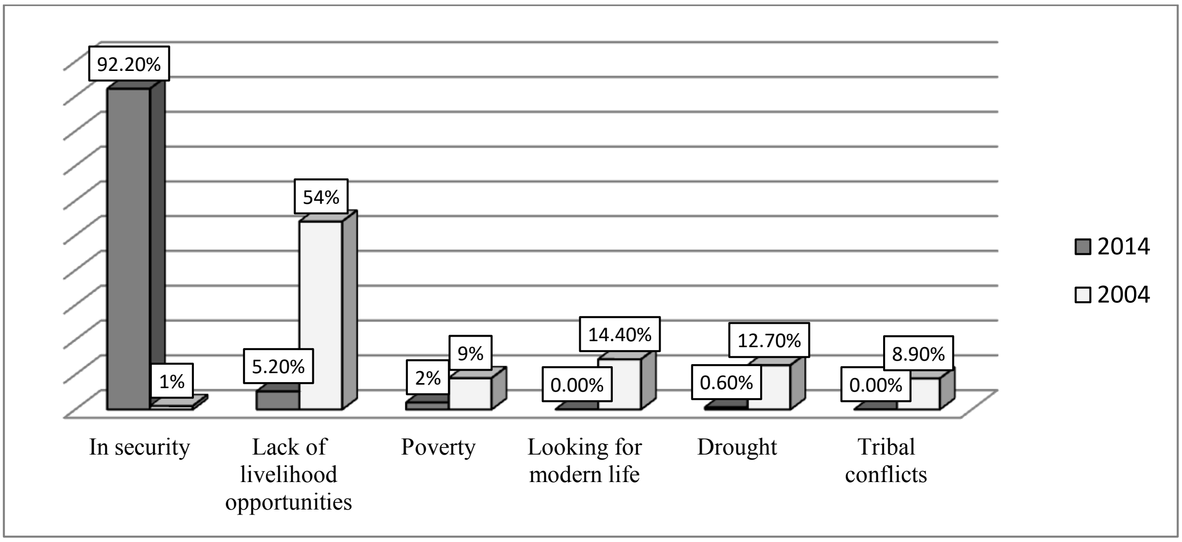
1- External migration (it means moving to a different state, country, or continent);
2- Internal migration (refers to moving within a state);
3- Impelled migration (refers to when people are forced out of where they live by unfavorable circumstances such as warfare or political problems);
4- Return migration (the voluntary movements of immigrants back to their place of origin, this is also known as circular migration);
5- And seasonal migration (moving ineach season, or in response to labor or climate conditions).

Figure 2.29: Rate of migration and mobility from Nuba Mountains to other sites



The underlying causes of respondent's migration in 2004 were totally different than in 2014 (Fig. 2.30), where they were mainly attributed to the lack of livelihood opportunities (54%), followed by drought (12.7%), poverty (9%), tribal conflict (8.9%) and search for modern life (14.4%). The current study agreed with IOM (2005) and Abrha (2017) who noted that, the youth employment crisis pushes millions of people, especially youth, women and men, towards the decision to migrate with the purpose of seeking alternatives to improve their job prospects. Many of them migrate to urban areas and big cities within their countries or seek new opportunities in foreign countries. According to the statistics of UNDESA (2016), roughly 71 million unemployed youth leave their countries of birth to seek employment aboard as international migration.

Figure 2.30: Reasons of migration and mobility in Nuba Mountains



The proportion of young migrants was higher in Nuba Mountains, estimated to be 80.4%, comparing with the proportion of girls and young women who migrated which represented only 19.6%. The average age of men migrants was between 15 to 25 years. Meanwhile, the average ages of girls or women were 20 to 35 years.

Migration is often misperceived as a failure to adapt to the changing environment. Instead, migration can also be an adaptation strategy to climate and environmental change, if managed correctly, because it is an essential component of the socio-environmental interactions (IMO, 2017). Based on FAO, 2016; 2018a, migration has many challenges and opportunities. For example, at the rural level, losses in human capital and agricultural labour may have negative impact on crop production and food availability. Moreover, the labor migration experiences can end up representing either an opportunity or a risk to youthful people and can lead them to decent work, or it's very opposite. That depends on policies and measures supporting them e.g.; provision of better knowledge of the world of work, more and better social protection, education and training for employment, entrepreneurship development, social inclusion and an effective institutional framework (IOM, 2005; Abrha, 2017). On the other hand, migration fostering rural-urban economic linkages, could reduce pressure on resources, enhancing and diversifying rural employment opportunities, and helping the poor to better manage risks through social protection. Furthermore, the leveraging remittances for investments in the rural sector can be effective strategies for improving livelihoods and alleviating distress-induced migration. In addition, the migration can bring new opportunities for immigrants, through participating in higher education, finding a better and decent job, getting a chance to gain professional experience and an opportunity to develop their personal competencies (UNDESA, 2016). The results of the case of Nuba community in Khartoum state were the best example supporting the above studies. The equality (to some extent) of opportunity and treatment of migrants, allowed them to contribute as productive members of the new community at different levels of income, as workers, entrepreneurs, students, and consumers. Moreover, the migration became a productive and empowering experience and opened up new opportunities for them, where migrants, both women and men, gained more skills through education, and/or work experience, and earned higher wages, allowing them to support their families and to contribute to the development of their communities of origin, as well as the societies in which they live and work. For young women, migration allowed them socially empowering benefits, as the recipients of remittances or as breadwinners or students in a new state. In the future, young women may gain decision-making power and experience greater personal autonomy.

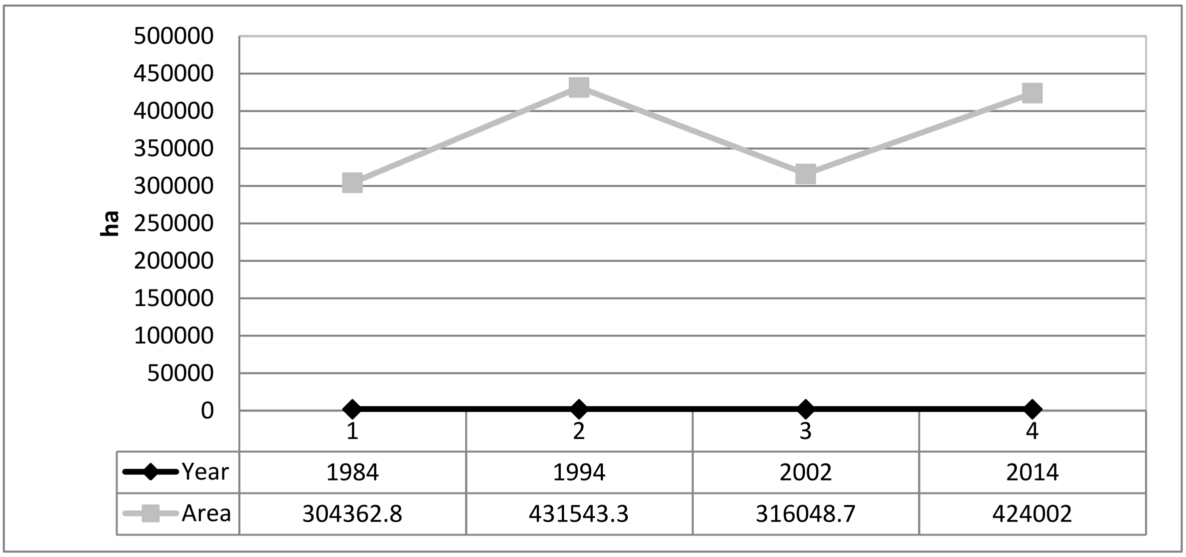
The situation was totally differed in Nuba Mountains since June 2011. Again, the conflict between the Sudanese Armed Forces (SAF) and the Sudan People's Liberation Movement-North (SPLM-N) has broken out in many parts of South Kordofan, causing major destruction of assets, reduced access to farms for cultivation, damage to harvest, diminished agricultural labor opportunities, disruption to livelihoods, civilian displacement, and an uncertain number of deaths according to the Famine Early Warning Systems Network (FEWS, NET) 2011. Displacement and migration rates have increased. The UN Office for the Coordination of Humanitarian Affairs (UNOCHA), reported in 2013, more than 45,077 individuals were estimated to be severely affected and displaced to neighboring states (IFRC, 2013). Unfortunately, this number was increased to be 116,000 in 2014 according to aid agencies and the SPLM-N (UNOCHA, 2014). Meanwhile, 25,900 people in the same period have sought shelter in Government controlled areas, according to the Government of Sudan's Humanitarian Aid Commission (HAC), the International Organization for Migration (IOM) and other aid agencies (UNOCHA, 2014). To date, an estimation of about 600,000 – 630,000 people in south Kordofan have been directly affected and/or displaced by the conflict since the start of the war in 2011(FEWS NET, 2016). In June 2016, The United Nations Refugee Agency warned of the catastrophic humanitarian situation in the Nuba Mountains. Disappointingly, up to date, people are still tragically fleeing violence, most crossing into neighbouring South Sudan, as South Sudan is itself home to some 1.69 million internally displaced people (UNHCR, 2016). In 2016, more than 7,500 refugees arrived in Yida of South Sudan's Northern Unity, nearly 3,000 in May alone. The area is already home to some 70,000 refugees. 90 per cent of new arrivals are women and children (UNHCR, 2016). According to the Office of the UN High Commissioner for Refugees (UNHCR) in 2018, nearly 250,000 Sudanese refugees have fled to South Sudan, mostly to Unity and Upper Nile, since the start of the war in the Nuba Mountains. Disappointingly, the situation now in the Nuba Mountains is worse, since 42.0% of household's states they are currently displaced, 95% of displaced households are fleeing due to fighting. The other causes of migration were 5.2% for lack of livelihood opportunities, poverty (2%) and drought (0.6%). Additionally, 31% of respondents said they had families living in refugee camps compared with 37% in 2013. Furthermore, 80% of households stated that they didn't feel safe at home, compared to findings in 2013 (an increase of 13%). The PCD analysis showed decrease in settlements areas, which became only 0.84% in 2014 (Fig. 2.31) and that was due to shelling and burning of villages in addition to the forced migration. By late April 2014, the situation has become better to some extent, where 30,000 displaced people returned from North Kordofan to several locations in the Abu Karshola locality according to reports from the South Kordofan's Voluntary Return and Reintegration Commission (VRRC) (UNOCHA, 2014). The majority of the returnees were spontaneous, although some returned under the Government organized return process in March 2014.

2- LU/LC

Unlike the analysis during the study period, 1994 to 2002, the investigation of the image in 2014 (Fig 2.24) showed a considerable recovery of the natural resources, due to the abandonment of agricultural lands during the war period. That agreed with Stevens *et al*. (2011); Ordway (2015); Gbanie *et al*. (2018), who have referred to that conflicts sometimes help protect forest environments and their biodiversity, depending upon their nature and location. For instance, the demilitarized zone between North and South Korea has provided a safe haven for migratory birds (Brady, 2008). Similarly, forests along the Thailand-Malaysia border, which remained untouched during periods of insurgency (1960-

1970), have supported abundant wildlife and are being converted into a National Park by the Malaysian Government (McNeely, 2003). The results of changing in LU/LC from 2002 to 2014 reveals that, the natural vegetation has been reforested and modified during the last years, where Forest lands (Dense and Scattered) increased from 316048.7 ha in 2002 to 424002 ha in 2014 (Fig. 2.31 below). The observed increase was due to the transformation of 121097 ha of Cultivated land, 24989.3 ha of Bare land, 5009.75 ha of Horticulture land and 36865.56 ha of Rocky land.

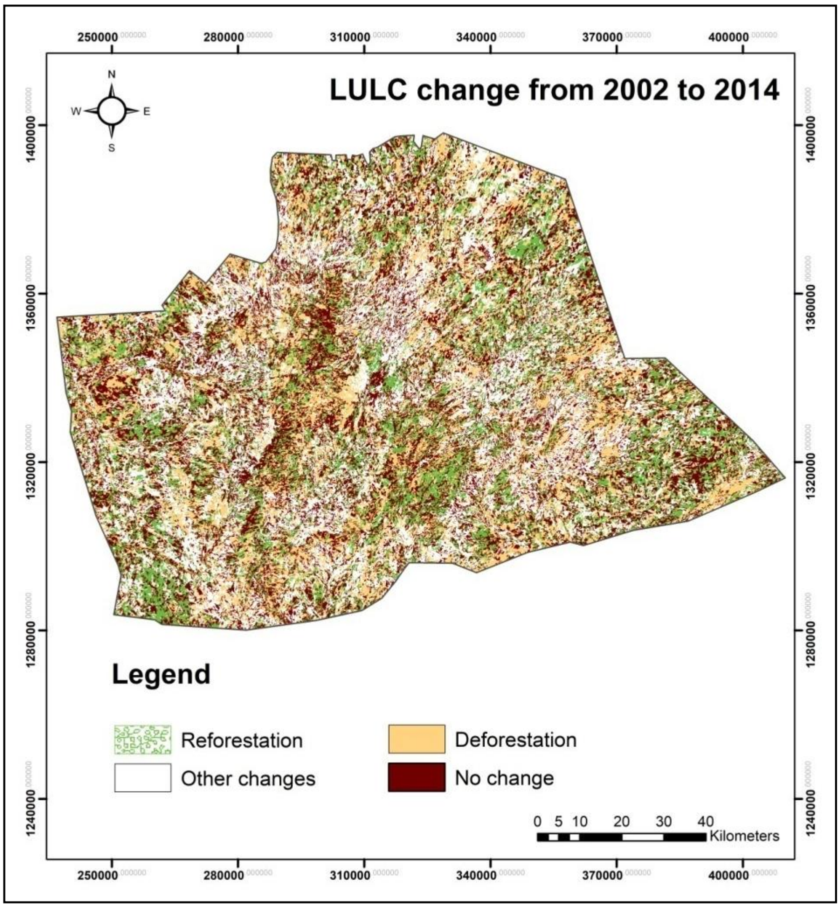
Figure 2.31: Forest lands in study area



Nuba Mountains is rich with various tree species which grow naturally, where the forests cover 33.76% of the study area. The region has diverse and rich vegetation, resulting from the variability in climate, soils and rainfall (Harrison and Jackson 1958; El Tahir *et al*., 2010; Deafalla *et al*., 2018), where the area covered with a mixture of different tree families such as: *Acacia senegal* savanna, broad-leaved savanna woodland *Acacia seyal* and *Balanites aegyptiaca*. Other thorny and broad-leaf non-thorny woody species are also present. The study indicated three types of forest tenure systems in the area; reserved forests, community forest and natural woodlands. The forest reserves in the study areas constitute a basic source of a variety of environmental goods and services most needed by villagers in addition to providing them with critical subsistence, income generation and job opportunity. Furthermore, the forestry and agricultural residues of these communities typify the fundamental source of energy for 96% of citizens around the forest.

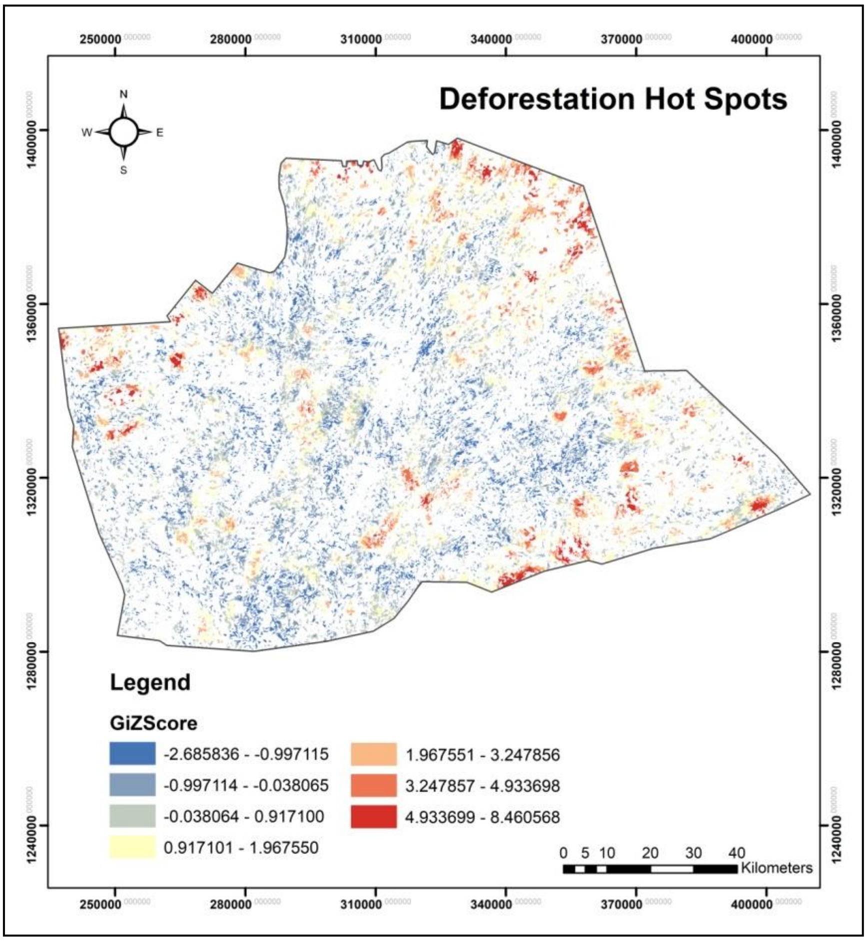
By contrast, as illustrated in Figure 2.32 below, Bare land in the study site has decreased from 11.40% to 9.7%. A huge decrease of Cultivated land and Horticulture land was observed during the study period, where they represented only 13.16% and 0.18% respectively. Generally all this areas became reforested. The analysis, as well, indicated a slight decline in Shrublands (20.06%), with increase in Grasslands that became (20.54%). Actually, this was almost double their area in 2002. Figure 2.32 below shows the LU/LC change dynamics in the study area, 2002 to 2014.

Figure 2.32: LU/LC change from 2002 to 2014



Indeed, economic conditions have a major influence on the situation of forests in terms of exploitation, conservation possibilities and regulations, where poor communities depend heavily on natural resources, as well, it is to be noted that economic development increases the pressure on the environment (FAO, 1994). The results showed a rate of deforestation in some locations, such as the finding in Fig. 2.32 above. For more investigation, Hotspots analysis determined the deforestation hotspots in the study area, as shown in Fig. 2.33 below. Deforestation is a particular concern in Nuba Mountains because the loss of biodiversity is damaging the potential for economic growth, as well as affecting the safety of those inhabitants in terms of food and health (medicinal plants) and limiting their options of survival. Figure 2.33 illustrates that, features with high positive value of z score are specified as the hotspots of deforestation (red) with values ranging between $8.460>z>1.967$, whereas features with low value of z score are specified as the cold spots of no deforestation (blue) with values ranging $-2.685<z<-0.917$. The z score helps to indicate whether the features show a random pattern or they show statistically significant clustering or dispersion, which presents that there is an underlying spatial processes at work. Therefore, for statistically significant positive z score, the higher the value, the more intense the clustering of the hotspot. For statistically significant negative z score, the lower value, the stronger clustering of cold spots. That agreed with Santiago and Kheladze (2011); ESRI, (2013), and Said *et al*. (2018). As to deforestation in this region, spalier, was rampant near more populated areas, roads and water bodies, but even remote areas have been encroached as displayed in Figure 2.33. Forests are cut down for many reasons, but most of them are related to income generation or for basic needs to their families (Allott, 2016). According to group's discussion results, the biggest driver of deforestation is agriculture, with 41.6% as clearly shown in Figure 2.33 below. Farmers cut forests to provide more room for planting crops and livestock grazing. The above finding agreed with Majumder (2015); Allott (2016); Brewbaker (2017), who noticed that often many small farmers in many countries around the world each clears a few acres by cutting down trees and burning them in a process known as slash and burn agriculture. The other causes of deforestation apart from agriculture were: 31.4% brick making, 12.7% over grazing, 8.8% firewood collection, 1.5% fires and 2% logging. Commercial logging usually involves felling of trees of only selected species which fetch better prices. Choudhary (2018) mentioned that, this operation of creaming or removing some selected trees amidst dense forests causes much more devastation than the actual number of trees or the volume of timber removed would suggest. Our findings are consistent with other conflict-environment relationship research such as Dudley *et al*. (2002); Nackoney *et al*. (2014), which found that deforestation through forest-based livelihood activities (fuel wood, charcoal) and informal settlement by IDP residents were major drivers of landscape change at the study area bush interface. In addition to factors above, with a small percentage (2%), the forest loss was due to soil infertility as one of bombing effects.

Figure 2.33: Deforestation hot spots in study area



Sudan, like other developing countries, has weak strategies, policies and legal frameworks that support the sustainability of natural resource (Atta Elmoula, 1985; Tolentino, 1991; Deafalla *et al*., 2015). The criteria of forest resource management were largely carried out informally through local community leaders prior to the colonial era. Since 1986, governments intervened and with drew the managing control from villagers and followed new approaches to manage this resource. The study found that the largest parts of forest benefits were obtained through illegal access, leading to negative impact on forest resources. Moreover, 82.9% of respondents had no relationship with Sudan FNC, meanwhile only 17.1% had this relationship, implying: access to extension services, licenses, establishing relationships, training on awareness, as well as rights and properties. On the other hand, and despite the small area and limited contribution of community forests, farmers possessed a huge experience in the establishment of plantations and their management. Therefore, opposite to the expectations of the government, multiple-use management policy proved to be ineffective in the absence of coordination between all stakeholders.

Although, the study area has heavy rains, there are no permanent watercourses in the area, where the water represents only 0.07% of the land cover as shown in Table 2.9. However, it forms seasonal streams, the most prominent among which are Khor Aldelib, Khor Kadada, Khor Tagmala and Khor Umbrumbita, which carry substantial run-off between July and October. The degradation of farm land hit the poor first, the wealthy monopolized the fertile growing areas known as ‘‘*Wadis*’’ in the study area, which are areas of land with subsurface water, and therefore more capable of producing crops. To overcome these problems of irrigation there, farmers have worked through the rehabilitation and expansion of traditional water harvesting techniques in the area which led to the spread of water harvesting techniques called ‘Hafir’. The Hafir is the local name in Sudan for water reservoir. It is a hollow dug in the ground designed to store water runoff after a rainy season, it can be natural or manmade. The Hafir is usually used in semi arid regions, where rainfall is annual but over short periods, and storage is required for the rest of the year and preferred in clay soils, so filtration is reduced allowing maximum storage and less labour. The water is used by all the community, farmers, nomads, and livestock as well as for domestic drinking water. The numbers of Hafirs in the area were increased during the last years to 22 Hafirs in 1994 from 0 in 1984, the huge spread was in 2002, when the number was estimated to be 90 Hafirs, but unfortunately this number retreated, due to devastation of civil war in some sites, to 79 in 2014. The other water sources in the area are shallow wells and deep boreholes. Water resources of Nuba Mountains were affected during the last years, where groundwater recharge was decreased by soil erosion, precipitation and/or increased temperatures, evaporation and war. Interestingly, the time consumed in a trip of water collection for household uses ranged between 2 to 3 hours in 2003 and increased to 3 to 5 hours in 2008 (Deafalla *et al.*, 2018). Water-related problems are likely to worsen as a result of environmental change during upcoming years.

Table 2.9: Change matrix for the third period from 2002 to 2014

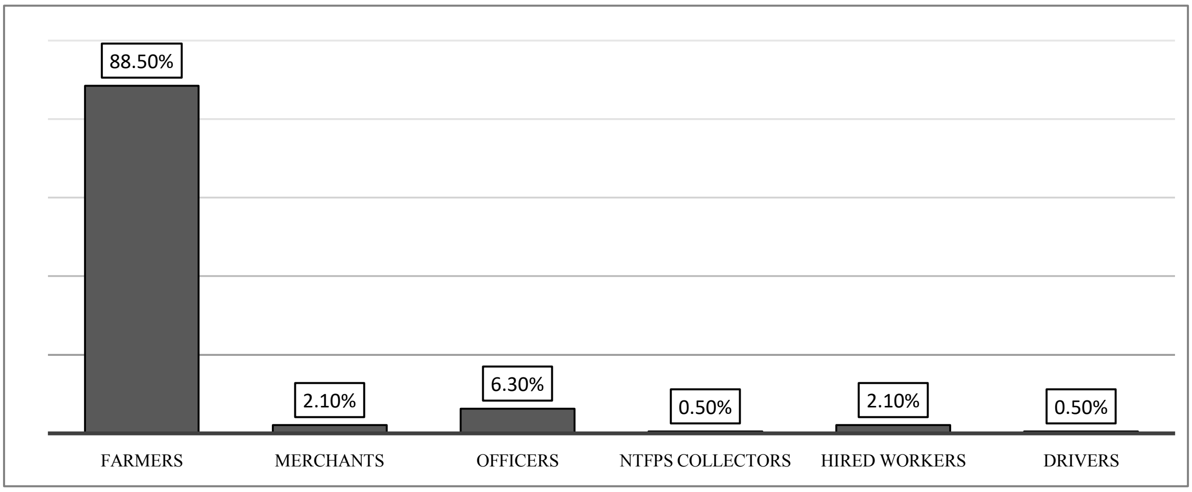
	Cultivated land	Bare land	Dense forests	Scattered forests	Shrublands	Grasslands	Rocky areas	Horticulture land	Settlements	Water	Total	%
Cultivated	61472.8	13883.42	19245.5	101851.5	29783.32	70871.12	2870.7	0	0	0	299978.4	24%
Bare land	7146.8	39767.3	0	24989.3	37783.9	32393.1	0	0	743.7	358.4	143182.5	11.40%
Dense forests	21499.1	9117.0	21172.4	65587.8	19545.4	25640.3	2699.0	745.0	0	0	166006	13.10%
Scattered forests	27967.9	8823.1	13887.8	38110.7	31109	28901.9	1242.3	0	0	0	150042.7	11.9%
Shrublands	28735.5	20151.6	22500	35404	79559.2	71446.2	0	0	0	0	257796.5	20.49%
Grasslands	9577.1	13141	32282.7	7094.9	54619.1	16910.4	377.8	0	0	0	134003	10.65%
Rocky areas	9201.78	0	10985.7	25879.86	0	6992.4	14035.96	0	0	0	67095.7	5.33%
Horticultural land	0	0	5009.75	0	0	0	0	1600.2	0	0	6609.95	0.5%
Settlements	0	17319.1	0	0	0	5338.2	0	0	9851.1	0	32508.4	2.58%
Water	58.2	0	0	0	0	0	0	0	0	599	657.2	0.05%
Total	165659.2	122202.5	125083.9	298918.1	252399.9	258493.6	21225.76	2345.2	10594.8	957.4	1257880	100%
%	13.17%	9.7%	10%	23.76%	20.06%	20.54%	1.68%	0.18%	0.84%	0.07%	0	100%

3- Agricultural Situation

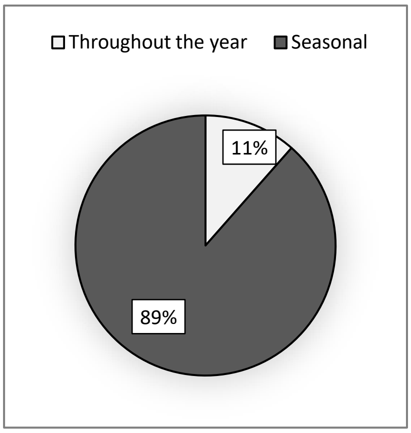
Agriculture and its related activities make up the basic fabric of rural life throughout the world, contributing significantly to the rural economy in terms of employment and business opportunities, infrastructure and quality of the environment (European Commission, 2000). In the study site, the land tenure system has been considered as a major underlying factor behind the use of natural resources, where land is still viewed as a communal resource between the national government in Sudan and farmers. In general, apart from registered freehold land to the government, under the 1970 Amendment of the 1925 Land Settlement Ordinance, traditional farmers and pastoralists tend to regard the land they use as a personal property (UNDP, 2006), where their traditional communal system there allows that every recognized member may establish the right to a piece of particular land (except the registered land of government) by clearance, borrowing, rent, planting trees or tapping Hashab (*Acacia senegal*). And this land is granted by village's Sheikh or by inheritance (Bello, 2014).

Rain-fed agriculture has mainly depended on the natural base of available land and natural water sources from rainfall. Generally, agriculture in the study site is labor-intensive, where 88.5% of the respondents (for both displaced and non-displaced respondents) are farmers, and it provides the main livelihood source. Its seasonality (June to October) pushes households to seek other types of employment during the slack period (Fig. 2.34).

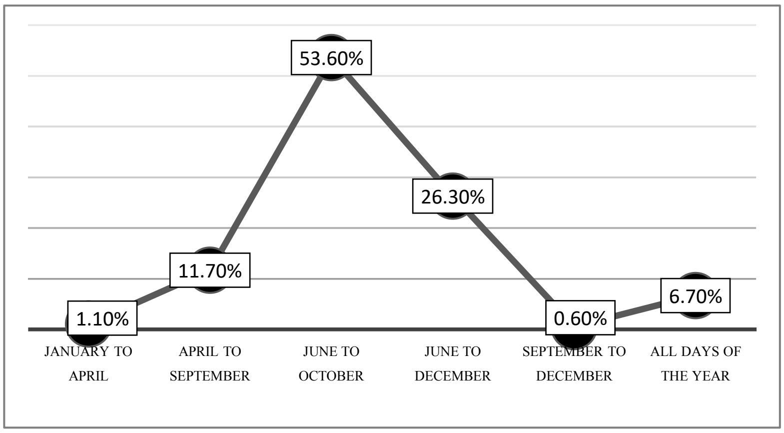
Figure 2.34: Main Occupation



Duration of main occupation



Seasonal Calendar of agricultural activities



Mixed farming is common in the study area, and it is practiced under different subsystems, depending on the availability of the land and the amount of rainfall. The study found that, farmers of the northern and eastern parts of the region cultivate larger areas than the farmers in the western and southern parts. This is mainly due to the availability of land to plant in terms of space, elevation and lighter type of soil. In the northern parts of the area, where the soil is sandy, millet (*Panicun milieaceun*) is grown as the staple crop, with cash crops including sesame (*Sesamum indicum*), groundnuts and karkade (Hibiscus), supplemented by watermelon (*Citrullus lanatus*) as a source of water and animal feed. While, in the southern parts, which have good rainfall and clay soils, rural households produce sorghum (Sorghum bicolor) for subsistence. Additionally, the commercial production takes place there under both large and small mechanized farming. A third important farming subsystem that expanded recently is horticultural production as shown in Figure 2.25 of LU/LC in the study area above, they mainly focused on; mango groves (*Mangifera indica*), followed by Lemon (*Citrus aurantifolia*), Guava (*Psidium guajava*), Bananas (*Musa acuminata*) combining limited vegetable production, grown along khors and wadis and tapping shallow groundwater aquifers. With the exception of large mechanized farming, all of the mentioned farming types combine small-scale livestock raising with forestry production.

The agricultural system of small farmers (outside the registered land) adopted in the study area is based on the shifting cultivation. It is represented in two main forms: First; the fallow cultivation with one to three years, where the field is planted for two out of the three years, with one year rest. This system is mainly found in the central and southern parts of the region. It is commonly adopted among the semi-nomadic farmers, where they use to allow their land to generate fodder for their animals. On the other hand, they benefit from excrement fertilizer that field's soil to retain its nutrients. The second form; is the short-fallow cultivation with only one to two years of fallow, and it is regarded as the most popular, and ideal system of cultivation, particularly among the rural settled groups of the northern parts, where the demand for land is relatively high, and there is an overall increase in the cultivated land to the extent that there is no unoccupied or not allocated land that can be distributed or used by the landless group (Bello, 2014).

The study site is characterized by Mountain farming. It is largely family farming usually run by men and children in collaboration with women. Mountain agriculture has evolved over the centuries in an often harsh and difficult environment and contributed to sustainable development for the local communities (Bello, 2014). The hill farms are small-scalein character. Diversification of crops, integration of forests and husbandry activities with their patches of useable land dispersed at different altitudes, with many different climates and limited use for mechanization, is most effectively carried out by family farms. The cultivating areas are located about 2 km. from the villages, while the far farms are located about 3 to 5 km. from the villages.

Figure 2.35: Mountain farming

Source: Google Earth Source: Internet

Severe and prolonged droughts and loss of arable land due to war, desertification, and soil erosion are reducing agricultural yields and causing crop failure and loss of livestock, which endangers both pastoralists and rural peoples (Deafalla *et al*., 2018). The intercountry conflicts affect agriculture in a variety of ways; this impact also varies with the characteristics of each area's agriculture (FAO, 2000b). Where, in some countries there may be surplus labour in rural areas, in such cases, and regardless of their obvious human cost, war impacts would not necessarily weaken agricultural productivity and output trends. Other cases, like in Nuba Mountains, the circumstances are entirely different, where agriculture is constrained by labour shortages, especially, at seasonal peaks (harvesting, weeding, etc.). Therefore, war casualties or the diversion of men from agricultural production to the armed forces, has undermined the viability of agriculture in the study area. Furthermore, in areas that specialize in labour-intensive export, although these are small areas, war has madean impact on foreign exchange earnings, which may have severe implications for development and food security for all the country. As well as, in some parts of Nuba Mountains, the commercial farming areas depend, at least partly, on labour migration. Unfortunately, war interrupted the established flows of seasonal labour migration, where workers from Nuba Mountains could no longer migrate to jobs in other regions during phases of civil war and, therefore, that damaged productivity of those farms. This disruption also has an effect, where it reduces income in areas that are not directly affected by war.

The war caused changes in the soil structure and soil physicochemical priorities, severely destroyed the vegetation, and formed large dump areas. The operation of heavy machinery also resulted in high soil compaction, large bulk density, deficient soil nutrients and major soil erosion as are shown in Fig. 2.36 below. The study indicated that, for the then current season, fewer households were able to plant crops (12%), and the acreage they were able to plant was also smaller compared to two years ago (median acreage is one third of the size of two years ago) as illustrated in Fig. 2.37. The household land under cultivation for the current season has dropped by 75% that significantly correlated with bombardment (0.044) with Correlation Coefficient (0.175*). Bombardment led to fear of going into fields to cultivate and being exposed to aerial attacks and massive displacement of families.

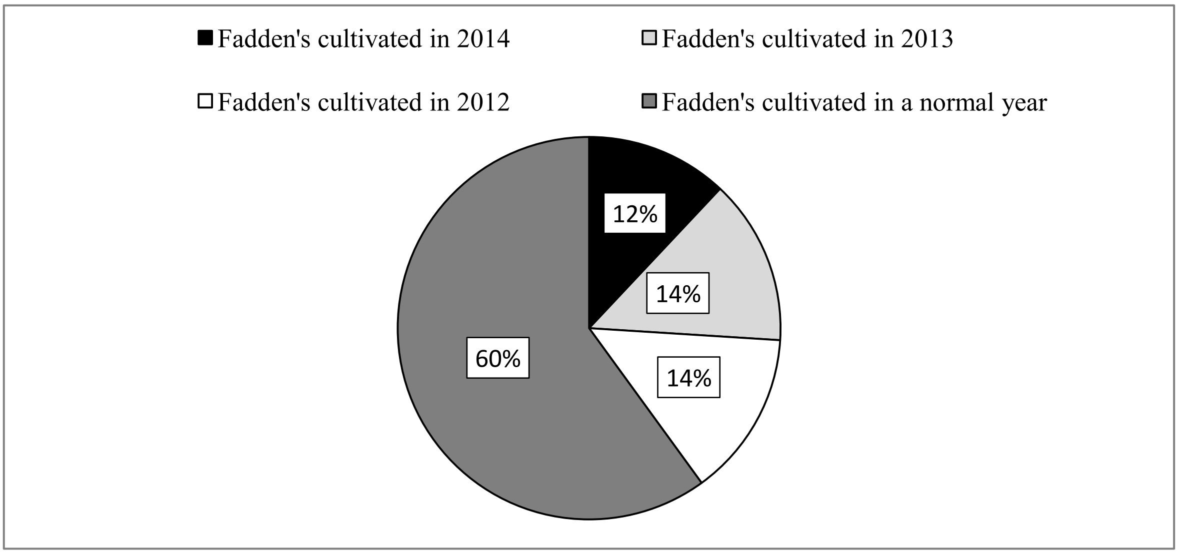
Figure 2.36: Soil erosion in study site resulting from bombardment

Source: Taken by author (2014)

Source: Taken by author (2014)

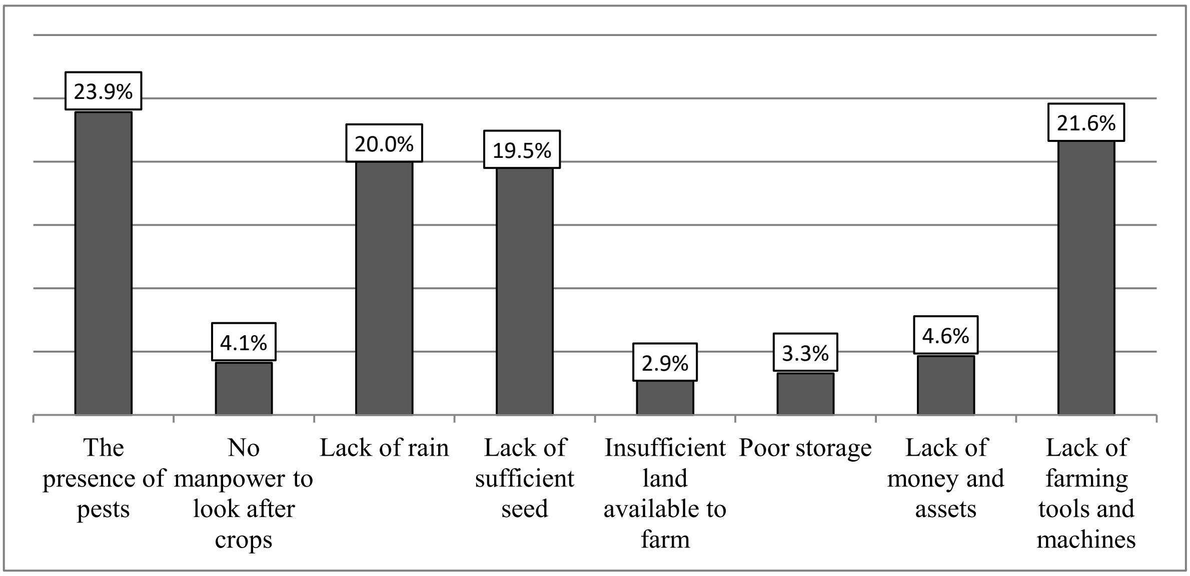
Some of these areas are extremely damaged, and are unfit for cultivation and production of goods. For example in the Abkarshola unit, farm equipment and agricultural crops had been nearly destroyed. Furthermore, in 2015, the late rains resulted in poor harvests in all districts of South Kordofan. According to FEWS NET (2015), grain production of agricultural season 2015-2016 was estimated to be about 40 percent less than the average of the previous five years. The poor crop production was aggravating in 2016 with an average household 2-3 bags of maize for example, compared with 15-25 bags in 2014 (Fig. 2.36).

Figure 2.37: Cultivated area in the study site



Actually, that year, 2018, most farmers on large-scale semi-mechanized farms (located in Sudanese government-controlled areas) were likely to avoid risks associated with farming in Nuba Mountains, due to the potential damage of crops and looting of cultivation equipment and/or the harvested crop itself by SPLM-N as happened during the last years. Crop production is predicted to decline substantially for the season of 2019. This is, as well, expected for the horticultural products namely: Mango, Lemon, Guava and Bananas. As displayed in Figure 2.38 below, the focus-group discussions provided more insights into the agricultural challenges faced by the communities there.

Figure 2.38: The agricultural challenges faced by the communities



4- Livestock conditions

Traditional pastoralism systems based on local resources contribute to the livelihoods of 70% of the world's rural poor (CBD, 2010; FAO, 2014). Nuba Mountains is characterized by a large livestock population, which represents about 30% of the estimated national livestock count (Deafalla, 2012). Livestock production comprises one of the main economic activities in the area. According to the calculations undertaken in this study, 16.8% out of total respondents declared that they rely on livestock to improve their diet and food security. Grazing lands vary according to the characteristics of each area in the study site. Elabbassia, for example, is a wet or rainy season grazing area, while, the situation is different in Rashad, where the grazing is therefore limited, and herders in the area most of the year depend on forest trees as a source of fodder for their livestock. The pastorals, which are mainly, practiced by two groups; the Baggara (cattle raisers) and the Shanabla (camel raisers) nomads, beside a few of Nuba cattle owners used to reside in different areas in the region during the different seasons. Animals are allowed to stay from July through September, however, in practice this is extended until December. This extension period causes conflict with the sedentary herds. Animal husbandry there involves rearing of livestock such as cattle, sheep, goats, and camels. Generally, animals are kept there to serve several functions in the area, including: source of income (30.8%), food source (28.3%), means of transport (6.2%) and (8.2%) labor source (i.e. animal traction), and social prestige (26.5%). Meat and milk produce contributes about 10% - 12% of the needs of the residents and less than 5% for IDPs (Deafalla, 2012). Poor households access milk mainly through kinship support (IOM, 2009; FEWS NET, 2012). Livestock ownership and area cultivated determines one’s wealth. Traditionally, livestock ownership and numbers reflected wealth and prestige in the community. Over the years, many households have lost their livestock through cattle raiding and looting. Recently in the study site, livestock production is being challenged by the vagaries of climate change, political effects and socio-economic pressures. The current condition of livestock is very critical since 65.3% of respondents are poor and 30.5% are very poor. As well as, livestock ownership was limited to one third of the community only. Insecurity along the border of South Sudan is continuing and that contributed to hamper the seasonal migration of nomadic livestock owners and their herds, which affected pastoralist groups in the study area. The current study agreed with FAO (2013), who referred to that focusing of animals in areas with limited resources leads to negative effects, on the health of livestock, and increasing the risk of disease outbreaks. As well, this could also spark intertribal conflict or violence between herders and farmers. The study noted an increase in livestock deaths and an increase in prices. 72.1% of households experienced animal disease outbreaks and they are all having livestock deaths (Fig. 2.39), with 56.8% having lost at least half their livestock.

Figure 2.39: The livestock situation in study site

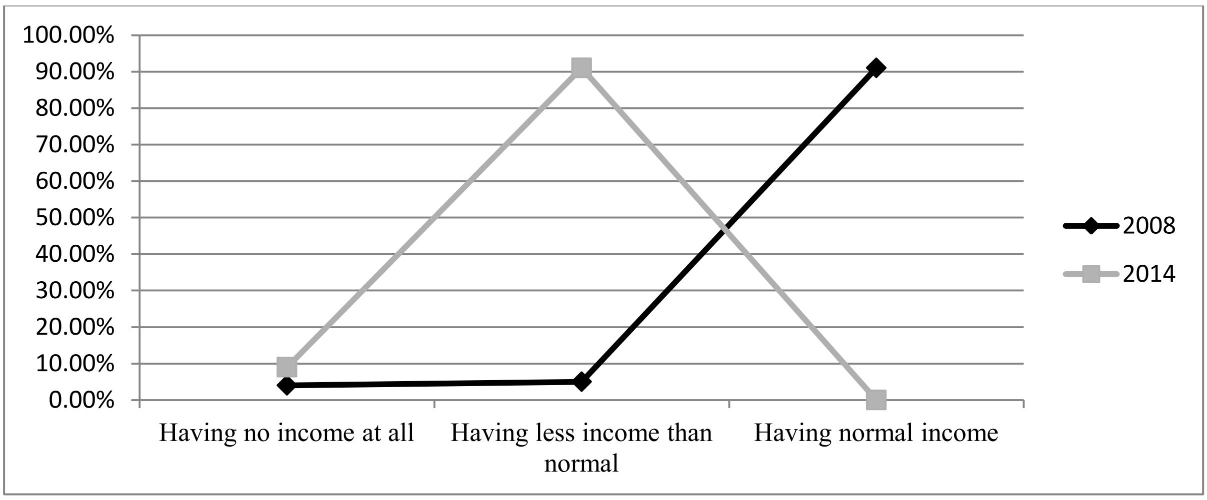
Source: Taken by author (2014)

It is worth mentioning, unfortunately, medicines for livestock are currently not available in the region's markets according to the focus-group discussions. This critical situation for livestock is due to high insecurity around the main seasonal grazing routes in border areas (85%), in addition to the severe pasture and water shortages (15%) due to the unsuitability of the area for drilling boreholes and poor development of other water resources. It is most important to consider that the consequences of the animal's concentration in areas with limited pasture and water lead to overgrazing and can have a longer term negative impact on the quality of the pasture.

5- Extreme poverty

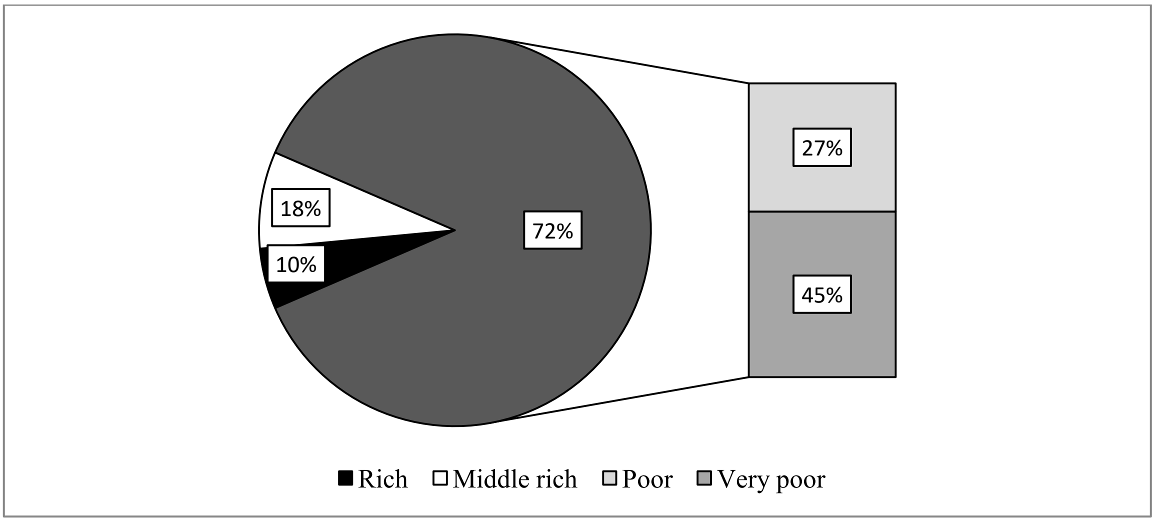
Despite the potentiality of the study area, the poverty level of households is extremely high as illustrated in Figure 2.40 below. Faki *et al*. (2011) have already mentioned that, Kordofan is believed to be among leading states in poverty levels, compared with other states of Sudan. This situation is due to conflicts, weak infrastructure, poor natural resource management, and high dependency on rain-fed agriculture for their livelihoods. Current research agrees on the significant overall negative impact of global environmental change on livelihood, which may even exacerbate other real or potential situations such as discrimination or terrorism and poverty (Thomas and Blitt, 1998). EC impedes poverty reduction; hence it is a key factor for poverty-reduction strategies such as the Sustainable Development Goals (SDGs) and UN's Millennium Development Goals (Lisk, 2009; Deafalla, 2012). Skoufias *et al*. (2011) and Deafalla *et al*. (2014a) mentioned that change in the environment, based on conflicts, might affect the path of poverty. Conflicts have been identified as one of the main causes for the persistence of poverty in many regions of the world (Collier, 2003; 2007), where they impact substantially on economic development and the living conditions of local populations, at the time of the conflict and for many years thereafter (Justino, 2012). However, there is remarkably little systematic understanding of the role of economic factors on the outbreak and duration of civil wars, or the impact of civil wars on the lives of those in fighting areas and on people's ability to escape poverty (Justino, 2012). The majority of respondents in the study area are subsistence poor (72%) and highly dependent on natural resources for daily life and income generation. Additionally, there is a lack of sufficient financial and technical capacities to manage environmental risk, ability to adapt, as well as to access credit and safety nets. Furthermore, 91% of households report having less income than normal and 9% of respondants having no income at all (Fig. 2.40). This effectively precludes the majority of households from the capacity to buy food.

Figure 2.40: Decreased levels of income in 2014



The wealth measure was done according to the number of assets owned (such as large food supply, animals, farms), as clearly shown in Figure 2.41 below. Rich households were understood to be those who own assets (houses and farms), livestock (i.e.; cows, goats, and chickens) those with a large supply of food stock (20 bags or more); those who harvest at least 15 bags and those with one or many wives, children and houses in the same compound. The middle rich households had the same characteristics as the rich households with the difference being a lesser number of assets owned. The poor households were understood to be those with a small number of livestock; those who had to work on other people's farms instead of owning farms; and/or, those who had only small amounts of food in stock (less than 5 bags). The result displayed that, most of the respondents (72%) are very poor as clarified in Fig 2.41 below.

Figure 2.41: Wealth status of households in 2014



6- Water

Currently, there is scarcity in freshwater sources, which is causing tension between the local communities. The main improved water sources reported are boreholes and collected rainwater, while, surface water and unprotected dug wells are the main unimproved water sources used in the area. According to Enough (2014), the daily water use for drinking, cooking and personal hygiene is 117 liters (30.9 gallons) per household, on average, or approximately 15.6 liters (4.1 gallons) per person per day. On the other hand, sanitation and hygiene indicators are very low in the area. Based on UNOCHA (2014) in Rashad town, almost 10,000 people are without access to safe sanitation as latrines provided are enough for only 200 people. 27% of households are using an improved water source as their primary source. Meanwhile, only 18% of the residents have sanitation facilities in their homes.

7- Health statistics

The health situation of the community in the study area is very critical due to low access to medical service and medicines. The withdrawal of some NGOs such as Médecins Sans Frontières (MSF) from the area, due to insecurity, has seriously affected access to primary health care for the local people. 49% of households reported at least one child had diarrhea, in the preceding two weeks, and 69% of them at least had one child with Malaria in the preceding four weeks. Unfortunately, health services are experiencing major challenges in the area, where, national NGOs are already overstretched and international NGOs working in the sector are currently underrepresented (UNOCHA, 2014).

8- Education

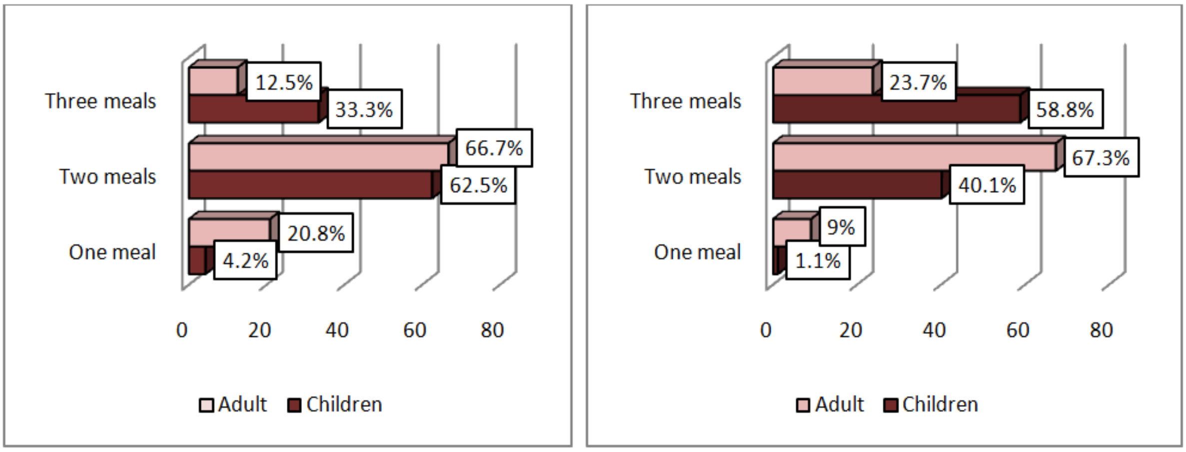
The education level in the study area is very low. Illiteracy between respondents is relatively high (34%), while basic education (38%) and religious schools (Khalwa) (13%) are the main education levels attained by respondents. The numbers of educated peoples with intermediate, secondary, and university levels are low. This could directly be related to the non-existence or limited numbers of schools (55% of respondents), followed by the inability to pay for school fees which was given as the predominant reason (35%), insecurity (30%), in addition to the transportation problem for students living far from the villages where schools are located (10%).

9- Food Insecurity

Food security is a complex sustainable development issue linked to health and nutrition; it is a major public health problem for both developing and developed nations (Endale *et al*., 2014). It has been best defined by the World Food Summit as having access to sufficient, safe and nutritious food (FAO, 1996; Farzana *et al*., 2017). During the past decades, the changing global economic environment has challenged traditional approaches to addressing hunger (Deafalla *et al*., 2018). Over the world and Sudan particularly, considerable progress in fighting hunger over the past decades should be viewed against the backdrop of a challenging global environment: rising unemployment and underemployment rates, volatile commodity prices, overall higher food and energy prices and, above all, the global economic recessions that occurred in the late 1990s and again after 2008 (FAO, IFAD and WFP, 2015). Recently, increasingly extreme weather events and natural disasters such as floods, rising temperatures and droughts have taken a huge toll in terms of economic damage, hampering efforts to enhance food security in Sudan. Political instability and civil strife have added more complexity to this picture. These developments have taken their toll on food security in some of the most vulnerable states, particularly in Nuba Mountains region, while other regions such as central, eastern and northern of the country, have remained unaffected or have been able to minimize the adverse impacts.

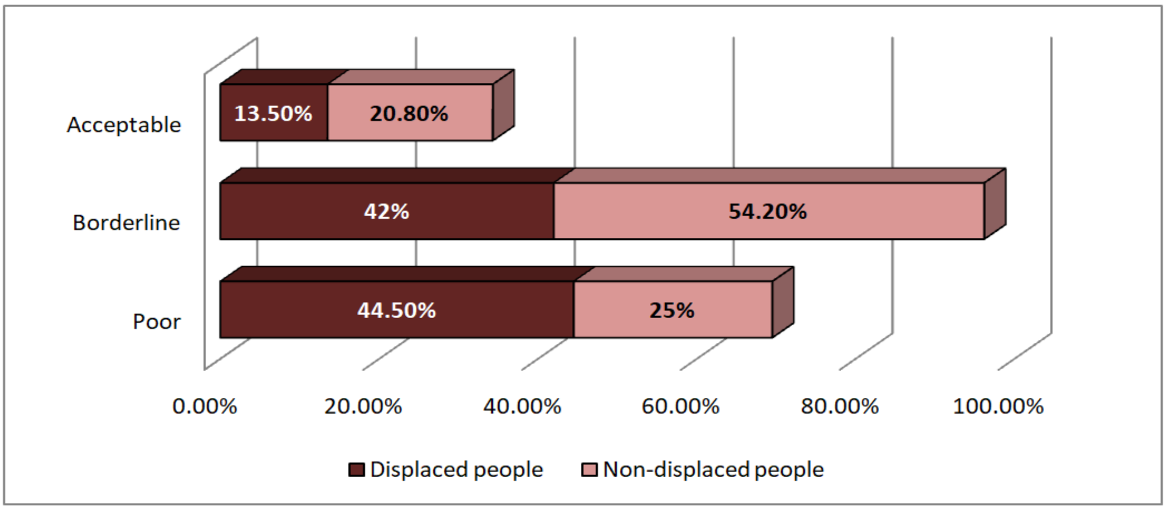
Recently, food insecurity is of greatest concern in Nuba Mountains, where more than 250,000 people now face crisis to emergency levels of food insecurity (FEWS NET, 2016). The South Kordofan and Blue Nile States Food Security Monitoring Unit (FSMU) reported about 242 people, including 24 children, had died in Kau-Nyaro and Werni areas of Nuba Mountains from lack of food and hunger-related illness in eight villages in the second half of 2015 (UNOCHA, 2016). Although, the food security situation is still deteriorating in the study site, the situation somehow was improved to some extend in 2014, where, 35.1% of households survive on one meal a day, compared to 61.5% in 2013, and 57.5% in 2011.

Figure 2.42: Number of meals per day for Displaced people (left) and Non-displaced people (right)



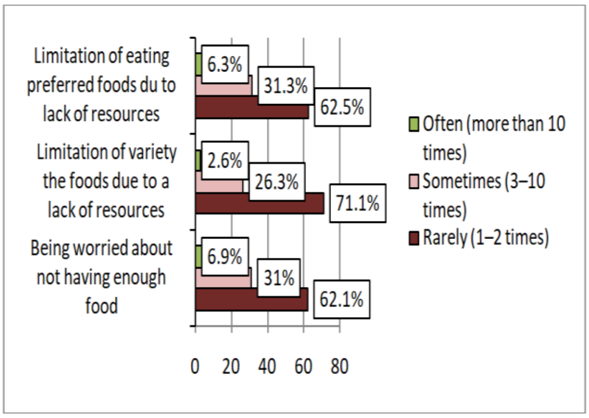
To measure food security, the food consumption score test was used to gauge both diversity and frequency of food consumption over a week. Results reveal that 79.2% of the non-displaced households and 86.5% displaced household have unacceptable consumption levels (Fig. 2.43).

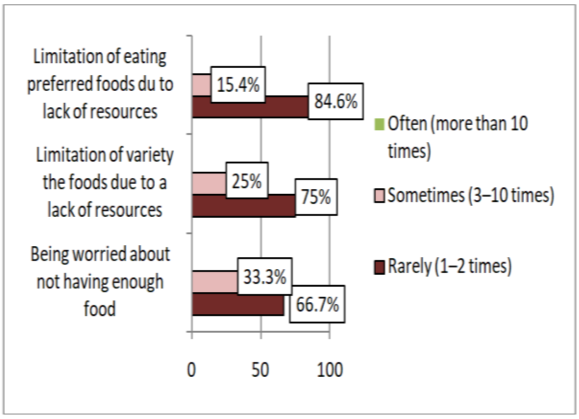
Figure 2.43: Food consumption score status in 2014



Additionally, households consume food in low feeding frequency with poor diversification. Current household food stocks were found to be extremely low for both displaced and non-displaced households. Approximately 6.9% of households stated they did not have enough food to last even a week (see Fig. 2.44).

Figure 2.44: Number of meals per day for Non-displaced people (left) and Displaced people (right)



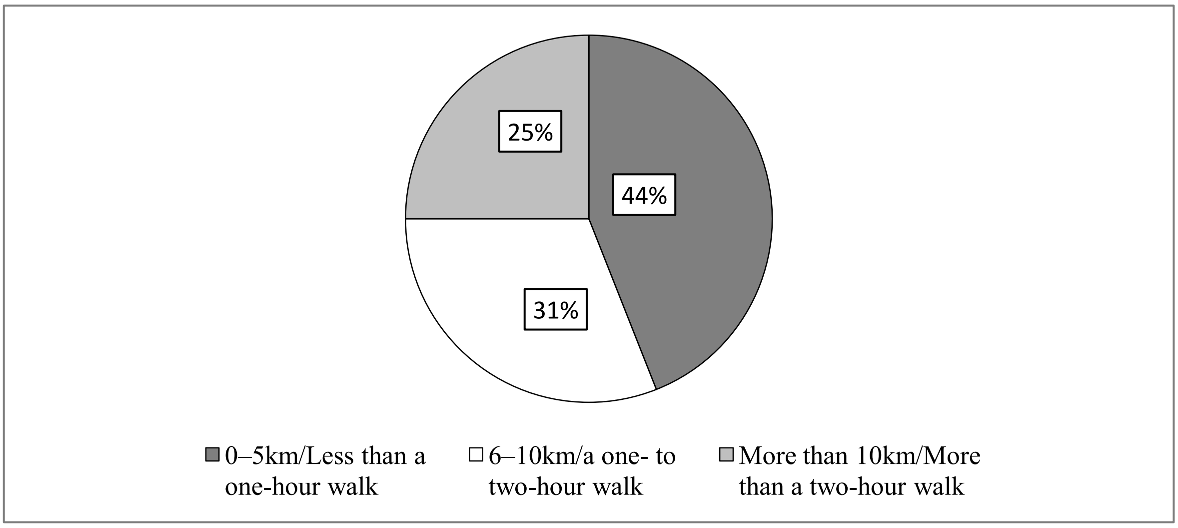


Humanitarian access for aid organizations in Government areas has improved in Nuba Mountains over the past ten months, although from a low base. According to UNOCHA (2014), some 20,000 of the newly displaced people, mainly women and children, in Government-controlled areas have received varying degrees and forms of assistance, mainly food and nutrition. This includes 10,178 new IDPs in Rashad town. Even that, food insecurity is expected to deteriorate through the scenario period of the upcoming months, as households exhaust coping strategies due to current restrictions on humanitarian access, no access to markets, trade flows, poor rainfall, limited food production and population movements. The net result of all these factors are extreme hunger during the "lean season" and perhaps even worse to come in 2018 if the situation continues under these circumstances.

10- Accessibility to market

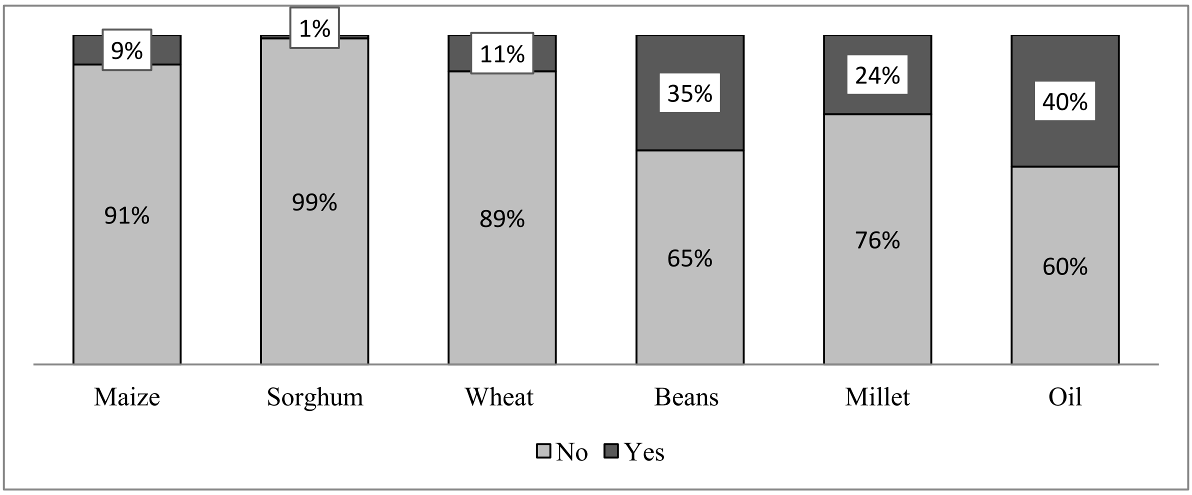
The ongoing conflict has further limited access to local markets and availability of commodities at the markets, prompting widespread displacement in search of food. The household survey noted that market accessibility decreased significantly during the rainy season, and 44 percent of households had to walk one hour to reach weekly markets as shown in Figure 2.45 below.

Figure 2.45: Accessibility to market



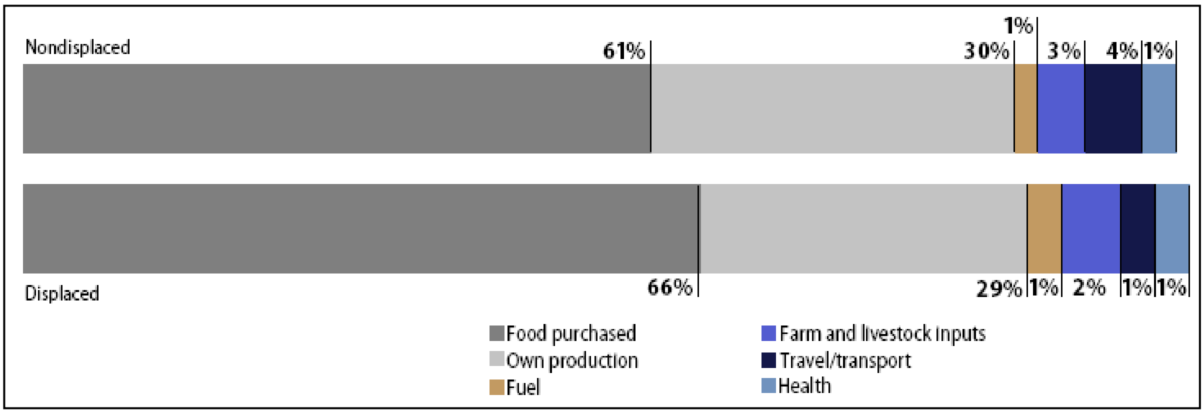
The availability of goods, including primary commodities, appeared to vary widely across markets. 24.1% of households reported availability of a variety of goods in markets, while 75. 9% only had a few locally produced food items for sale. Primary commodities such as maize and sorghum were less widely available than goods such as beans and oil (see Fig. 46).

Figure 2.46: The availability of some commodities in local markets



The continuous increase of inflation led to devaluation of the local currency. During the last years till now, and due to the impact of conflict on oil production, the Sudanese government faced shortfalls in foreign currency to fund imports of essential commodities. In July 2014, the official inflation rate was 46.8%, and the unofficial black market exchange rate was over SDG 11 per Euro, more than double of the official Bank of Sudan exchange rate, while in July 2018 unofficial black market exchange rate was over SDG 55 per EURO. Actually, the fall in the official exchange rate masks the true size of the fall in purchasing power as prices for locally produced, imported food and the non-food items have increased in local currency terms. Concerning the high prices of these products, they are driven by the reduced supply to markets due to the poor production, as well as restricted market access in areas affected by conflict in South Kordofan (Fig. 2.47). The study indicates that there is an increase in all the commodity prices: i.e. nominal sorghum prices reportedly between 1-1,5 EURO per Malwa, an increase of over 100% higher than last year and 130% above the five-year average and about 75% above the reference year (2009/2010); and millet prices in June were 96% higher than last year and 150% above the five-year average.

Figure 2.47: Household expenses



11- Coping strategies for food insecurity

In connection to food insecurity, any community adaptation of new techniques or alteration of regular behavior is executed that translates to coping strategies (Farzana *et al*., 2017). Historically, household resilience has been characterized by a number of fairly regular behavioral responses or techniques which translated to coping strategies with crises moments when the resources are limited or absent (Maxwell, 1996; Maxwell and Caldwell, 2008). Based on Kyaw (2009), households adopt coping strategies in the early stages of food insecurity, which however vary based on cultural and geographical differences (Maxwell and Caldwell, 2008). For example, in the phase of idiosyncratic shocks such as food price hike or natural disasters, households may employ food or non-food based coping strategy or a combination of both to protect their basic needs (FAO, 2008; Ruel *et al*., 2010). Therefore, to complement the current understanding of different coping strategies implemented by the Nubian households, the study surveyed the population's strategies for coping with food insecurity. Gathering NTFPs, and hunting, as a food stock, were the most widely and frequently used coping strategies, where, 71.3 percent of households used this strategy, an average of 4.5 days per week. At the same time 12.6 percent of households depend on the harvesting immature crops, they used this strategy an average of 3.5 days per week. 9 percent of households reduced their number of meals eaten in a day. This strategy is used 3.1 days per week on avaerage. Meanwhile, 7.1 percent of households limit portion sizes of meals, and use this strategy an average of 2.8 days per week. The current results agree with finding by Enough (2013), in their assessment to other parts of South Kordofan state, that the most common food-insecurity coping strategies overwhelmingly involved collecting wild food, hunting, or harvesting immature crops.

CHAPTER THREE

The Nature and Value of Local Ecosystem Services Based On NTFPs

General overview

Due to overemphasis on timber production in past decades, NTFPs were neglected by foresters and policy makers leading to lack of attention on their values, although their uses are less ecologically destructive than timber harvesting. Based on the findings in chapter two, chapter three discusses at length the importance of NTFPs for the Nubian communities as a basic and successful strategy to EC adaptation. The chapter introduces the core concepts to the study: NTFPs, poverty, livelihoods, sustainability and rural development. After identifying the types and locations of these products, the detailed literature study and discussion elaborates and justifies the dimensions which can provide insight into NTFPs values. These values cover the food security, income generation, tradition medicine, local industries, bioenergy and other services. It concludes with a discussion of the effect of demographic change and associated cultural change on NTFPs uses.

3.1 Introduction

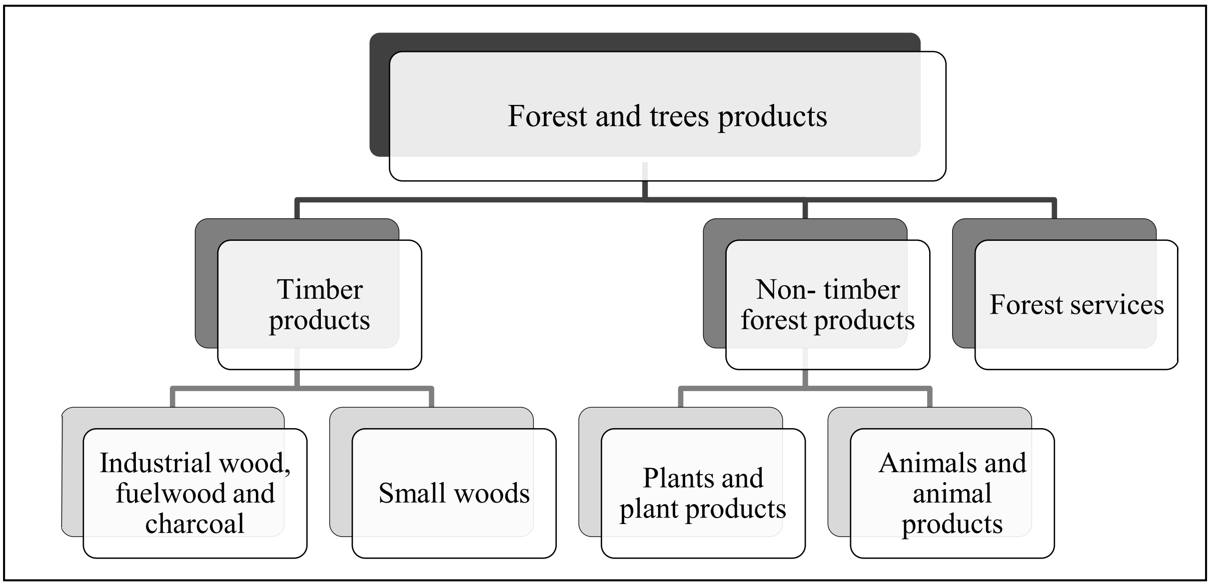
3.1.1 Definition and Classification of NTFPs

Non Timber Forest Products (NTFPs) refers to ‘‘goods of biological origin other than wood, derived from forests, other wooded land and trees outside forests’’ (FAO, 1999a; 2009). According to Shiva and Mathur (1996); Akinyerni *et al.* (2003); IGSSS (2016), these products are also known as Minor Forest Products (MFPs) or Non-Wood Forest Products (NWFPs). It covers all products obtained from plants of forest origin and host plant species yielding products in association with insects and animals or their parts and items of mineral origin except timber. The term NWFPs excludes all woody raw materials. Consequently, timber, chips, charcoal and fuel wood, as well as small woods such as tools handle, household equipment and carvings, are excluded. NTFPs, in contrast, generally include fuel wood and small woods; this is the main difference between NWFPs and NTFPs (FAO, 1999b; Deafalla, 2012).

Unfortunately, till now there is no internationally and globally accepted classification scheme, specifically designed for NTFPs (Vantomme, 2003; Deafalla, 2011). That is due to the lack of a clear definition and a consistent classification of NTFPs, which leads to the perpetuated long-standing institutional neglect of NTFPs. Clear definitions, with their related well defined terms, on products gathered from forests, wild sources, or from any other type of land, are product classification systems applicable to NTFPs which are an essential prerequisite to elaborate and use (Vantomme, 2001; Vantomme, 2003). Product classification systems are the basis for compilation and aggregation of production and trade statistics on NTFPs, where, good statistical data on, the contribution of this sector to national economies, and for the elaboration of appropriate policies and regulations governing its sustainable development, are essential to value. Furthermore, the definition and classification of NTFPs are crucial and affect policies at state and national levels. For instance, rural Indian communities are given usufruct rights and access to naturally fallen branches for fuel wood, however, cutting of wood is not allowed, as it is considered as timber, and thus belongs to the state. Similarly, the Indian Forest Act defines bamboo as timber, and its only harvested and traded by the government (IGSSS, 2016).

FAO (1999a) suggested a preliminary classification of forest and tree products as can be shown in Fig. 3.1 below. On the other hand NTFPs are classified as good as possible, in several countries, through their existing national product classification systems such as; International Standard Industrial Classification of all economic activities (ISIC) of the United Nations Statistical Division (UNSD), Standard International Trade Classification (SITC) of the UNSD and Harmonized commodity description and coding System (HS) of the World Customs Organization (WCO). These international systems often form the basis for further elaboration of more detailed regional and national product classification systems (Vantomme, 2003). Recently, although several countries have made considerable progress in elaborating product classification systems for NTFPs for use at their national level, these national systems are not comparable among countries and not easily adaptable as a basis to gather statistics data of NTFPs at the regional and international level. Therefore, based on FAO (1995a) nomenclature and definitions need to be rationalized, as a first step at the international level. A scheme for standard international classification of NTFPs can be built on, and harmonized with, the existing classification systems, such as ISIC and SITC. Actuality, the acceptance of such a classification can help to build linkages for better statistical systems and databases on NTFPs and better recognition of their importance (Vantomme, 2001; Deafalla *et al.*, 2014c).

Figure 3.1: Preliminary classification of forest and tree products



Source: FAO, (1999a)

3.1.2 Importance of NTFPs

NTFPs play an indispensable role in the daily lives and overall wellbeing of rural and urban people, all over the world. FAO in 2014 estimated that, 80 percent of the comunitiesin developing countries use NTFPs to meet some of their health and nutritional needs (FAO, 2018b). Large number of rural people, particularly those living in forested areas, depend on NTFPs for various levels of uses. At the subsistence level, NTFPs are major sources for food, medicines, fodder, gums, fiber, and construction material (Falconer, 1990; FAO, 1995a; Clark and Sunderland, 2004; Shacleton and Shackleton, 2005; KSLA, AAS and FAO, 2005; Ahenkan and Boon, 2011a). As well, these products are more accessible to the poor (Saxena 2003; Deafalla *et al.*, 2012). Arnold (2002) stated that ‘‘NWFPs are particularly important in reducing the shortages suffered during the 'hunger periods' of the agricultural cycle as they help to even out seasonal fluctuations in the availability of food''. Furthermore, many of NTFPs are important traded commodities at local, national, regional and international levels, providing employment and income at each level (Peters, 1996; Ros-Tonen, 1999; van Andel, 2000; Marshall *et al.*, 2003a; Ahenkan and Boon, 2011a; Deafalla *et al.*, 2013), where they provide in developing countries alone, approximately of 17 million full-time jobs in the formal sector and another 30 million in the informal sector. Moreover, they provide 13 to 35% of all rural non-farm employment (Duong, 2008; Abdulla, 2013); and as well, these products are a significant part of the economy of many countries especially in sub-Saharan Africa, where they contribute to foreign exchange earnings (van Andel, 2000; Shiva and Verma, 2002; Ahenkan and Boon, 2011b). In Sudan; as an example, over 13 % of the foreign exchange earned is generated from the Gum arabic trade alone (Tieguhong and Ndoye, 2004). In addition, NTFPs constitute a poverty trap, a safety net, or a potential, but an underutilized resource, for rural development and poverty alleviation (Ros-Tonen *et al.*, 1995; Clendon, 2001; Belcher, 2005; KSLA, AAS and FAO, 2005; Marshall *et al.*, 2006; Ahenkan and Boon, 2010; Deafalla, 2011; Deafalla *et al.*, 2014c). Moreover, NTFPs play a significant role in supporting biodiversity and other conservation objectives (FAO, 1995a; Charlie and Sheona, 2004; Marshall *et al.*, 2006), where, it can be harvested by using simple technologies with relatively little impact on the forest environment (Myers, 1988; Neumann and Hirsch, 2000; FAO, 2008; Ahenkan and Boon, 2011a).

In recent years, NTFPs started to gain considerable importance in Sudan due to many reasons such as: the exponential development in the use of NTFPs in many industries and medicine. Besides, the use of NTFPs, as food and drink, are becoming more familiar. Moreover, these products are particularly important during the critical periods of droughts and famine (e.g. the famine of 1982 some of the NTFPs were the only available food stuff). In addition to that, NTFPs are developing a good market value, as well; public awareness is increasing about their socio-cultural use (Sulieman and Eldoma, 1994; Deafalla, 2012; Deafalla *et al.*, 2014c). However, these products are not adequately treated, and there are no clear mechanism and extension services to improve their quantity, through afforestation and/or to improve their quality through development of best practices of pre and post- processing of collected NTFPs (KSLA, AAS and FAO, 2005). Furthermore, there is a huge lack of reliable data on the geo-location of the trees species, their production and trade and on the number of people involved, which makes it hard to assess the effective contribution of NTFPs to rural livelihoods (Chikamai and Tchatat, 2004). Besides above mentioned, they usually involve a low-value product, which makes them less attractive to larger forestry entrepreneurs. Significance, in general, and economic value, in particular, is rarely taken into account in land use planning or in assessing Gross Domestic Product (GDP). This is somehow due to the subsistence or local market nature of most of the commodities, which often go unrecorded in official national statistics, and partly due to the previous tendency where emphasis was on wood/timber and NTFPs, which were considered only as incidental (FAO, 1995b). Obviously, there is a serious lack of research based on RS integrated with GIS techniques as well as the technology development related to NTFPs, in addition to lack of clear and appropriate policy support for NTFPs development, in spite of their positive attributes and potentials in Sudan in general, and in the study area particularly. Therefore, the current study is attempting mapping the NTFPs species and investigating the role of these products for the Nuba communities to help in designing sound, valid management and policy guidance.

3.2 Research Methods

The data were collected by different methods namely; multi source social- economical-ecological data, RS and GIS techniques, to cover a wide range of research topics necessary to achieve the objectives.

3.2.1 Socio-economic Data

Human, social and financial data were collected through social survey of households; stratified sampling was used to represent different geographical areas and different income groups. This was to ensure better precision and reduce time, effort and monetary costs. The anthropometric survey was designed as a cluster sample (a representative selection of villages). Sixteen villages were randomly selected, three, ten and three villages in Rashad, Elabbassia and Abo Karshola localities, respectively (Annex 2). The sample size was 279 questionnaires, 200 for head of households distributed among different units according to the PPS (Table 3.1 below). 24 contributions gathered from two refugee's camps, Abkorshola camp in Rashad locality, and Jabarona camp in Omdurman locality. Additionally 55 contributions from Nuba's Immigrants in Dar Elsalam unit, rural of Omderman, Khartoum State to raise understanding of the relations between patterns of local-level economic and demographic changes on NTFPs.

The appropriate sample size for a population-based survey was determined largely by three factors: (i) the estimated prevalence of the variable of interest (means dependence on NTFPs), (ii) the desired level of confidence and (iii) the acceptable margin of error (IFAD, 2008).

The sample size required was calculated following using equations (1 to 5) according to IFAD (2008). Total sample size was calculated using equation (1)

$$n = \frac{t^2 \text{ x } p(1-p)}{m^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

n = required sample size
t = confidence level at 95% (standard value of 1.96)
p = the estimated prevalence of the variable of interest (means dependence on NTFPs)
m = margin of error at 5% (standard value of 0.05)

Proportion of Head of the household (x) was calculated by equation (2)

$$x = \frac{H}{T} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where:

H = number of Head of the Household (HHD) for each village's

T = total of Head of the household

Samples proportion (N) was calculated by equation (3)

$$N = x \times z \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where:

x = proportion of Head of the household

Z = total of sample size (200).

The sample was further increased by 5% (margin of error at 5% standard value of 0.05) to account for contingencies such as non-response or recording error = Samples equal.

Samples equal (S) =

$$N+\frac{Nv}{L}\times 100\times 0.05 \ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Where:

Nv = samples proportion for each village in every cluster.

L = total of N for the cluster of village.

Finally, the calculation result was rounded up to the closest number that matches well with the number of clusters (3 clusters for 16 villages) to be surveyed. The final sample size (N) for each cluster was then divided by the total number of villages (3, 10 and 3 for Rashad, Elabbassia and Abo Karshola respectively) to determine the number of observations per cluster = final samples size.

Final sample size (F) was calculated by equation (5)

$$\frac{N}{R}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5)}$$

Where: R= number of clusters.

Table 3.1: Sample size distribution

No.	Village name	Population	Households (HHD)	Proportion of HHD	Samples proportion	Samples equal	Final Sample size
	Rashad Unit						
1	Tomorrow	832	202	0.03	9	10	14
2	Um shotur	1102	222	0.03	9	10	14
3	El Muzlagan	150	214	0.03	9	10	14
Total		2084	638	0.09	27	30	42
	Elabbasia Unit						
1	Elabbasia	15604	2690	0.36	109	112	14
2	Totah	752	150	0,02	6	6	12
3	Al Tamada	755	151	0.02	6	6	2
4	Eldebikaya	700	140	0.02	6	6	14
5	Tofain	602	120	0.02	5	5	14
6	Jabal Nimre	212	41	0.01	2	2	10
7	Gardod Alzibel	939	157	0.02	6	6	14

8	Jabal Elahmar	517	96	0.01	4	4	14
9	Ahoo	1650	321	0.04	13	13	14
10	Abo Jamous	215	37	0.01	1	1	10
Total		21946	3903	0.53	158	161	118
	Abo Karshola Unit						
1	Karling	2670	445	0.06	18	19	14
2	Elhoger	2918	453	0.06	18	19	12
3	Um Baraka	2661	440	0.06	18	19	14
Total		8249	1338	0.18	54	57	40
Total	**Rashad locality**	**32279**	**5879**	**0.8**	**239**	**248**	**200**

The final sample size was changed where some villages were replaced due to security and logistic reasons in Rashad and in Abo Karshola localities during the field visit, as can be shown in Figure 3.2 below.

Figure 3.2: Risk of conducting fieldwork in study area 2014

Source: Taken by author (2014)

Source: Internet

The questionnaire was designed with closed multiple-choice and open-ended questions concerning social characteristics and respondents perspectives about different aspects of the NTFPs activities. The aim is to identify main NTFPs collected, consumed and marketed by households; and ranking their importance according to criteria of mostly collected, most valuable in terms of financial returns, most consumed, the time and frequency of collection trip. The limit of statistical significance (alpha) is 0.05, in confidence interval at 20. This sampling estimate was increased by 10% to allow for non-response bias and to account for possible missing or "unclear" data. Structured questionnaires were used in face-to-face interviews of individual and household members, free listing and key informants techniques were applied, besides using a slightly modified version of the questionnaire to interview national traders. This data was integrated with other data from 2008 (322 questionnaires) to help in comparing between the past and current situations of NTFPs.

The survey was conducted in Arabic language and the translated version is shown in annexes (3) and (6). The questionnaire was tested in Dar Elsalam unit before the travel to South Kordofan State.

3.2.1.1 Methods of data analysis

The collected information was coded, entered, processed and analyzed, both qualitatively and quantitatively, by using SPSS version 18.

IVI method (Giliba *et al*., 2011 and Penanjo *et al*., 2014) was used to reflect the cultural significance of species and use category. The importance value was calculated according to Ballal *et al.* (2014):

$$\text{IVI} = ni/N$$

Where:

IVI= importance value index for a species (or use category); and ni = number of informants who consider that species (or use category) most important. Meanwhile, N refers to the total number of informants.

The total IVI for the NTFPs was calculated by summing up the IVIs of each studied species (Ballal *et al.*, 2014). Then, the overall IVIs were ranked to reveal the most significant species. While, the relative contribution of a NTFPs to income generated from trade of total forest products was calculated in percentages.

Furthermore, descriptive statistical analyses were applied to analyze data concerning social characteristics and respondents perspectives about different aspects of the NTFPs production activities. Summary statistics of the socio-economic characteristics of the study sample was obtained in the form of frequency, percentages, distribution, mean, minimum, maximum, sum and standard deviation.

3.2.2 Remotely sensed and GIS data

Increasing realization of the fact that forests not only provide multiple benefits to mankind but also help in conserving the environment has created global concern for their protection and conservation (Roy and Tomar, 2000; Rai, 2012; Rai, 2013). However, if these resources have not been managed in a sustainable or equitable manner, this leads to environmental degradation (Singh *et al*., 2002; Rai, 2009; Rai and Lalramnghinglova, 2010a; Rai and Lalramnghinglova, 2010b; Rai and Lalramnghinglova, 2010c; Rai and Lalramnghinglova, 2011a; Rai and Lalramnghinglova, 2011b; Rai, 2012). In this direction, vegetation mapping may be a primary requirement for various management and planning activities at the landscape level (Singh *et al*., 2002; Xie *et al*., 2008). With the advent of RS, the scope of effective planning and management of natural resources has considerably widened (Melesse *et al*., 2007; Maurya *et al*., 2013). The use of satellite data permits timely and accurate information on very short repetitive cycles needed for monitoring (Roy *et al*., 1996; El-Abbas, 2015). It is observed that remotely sensed data can meet many of the information needs for proper forest management in short time and at low cost (Chaudhary, 2003). Researches in forest resource, using RS images, have provided very useful decision-making support and provide policy frameworks for their sustainable management. Methodologies have been developed towards this end by various authors such as (Franklin and Peddle 1984; Tiwari *et al*., 1990; Kandya *et al*., 1992; Kaur *et al*., 1994; chaudhary *et al*., 1999; Babu *et al*., 2002; Sihag *et al.*, 2015). In the present study, the trees that are harvested in the study area grow naturally with no apparent management intervention. Besides that, there is a serious lack of information and research regarding the location and types of these trees. For forest trees type mapping, therefore, it is very important to provide the required data, based on forest inventories. Decision makers will, thus, be able to make decisions to improve and manage forests in a sustainable way.

3.2.2.1 Data

1- Image type used

The RapidEye is a commercial RS mission by the German company RapidEye AG, launched in August 29th, 2008 (El-Abbas, 2015). It offers a data source containing an unrivaled combination of large-area coverage, frequent revisit intervals, high resolution and multispectral capabilities (RapidEye user's guide, 2010). Three RapidEye products are available; Level 1B, 3A and B3. The study utilized the 3A product, because it has undergone a range of pre-processing stages that include the application of radiometric, sensor, and geometric corrections. It is also aligned to a cartographic map projection (usually UTM) with the default geometric correction based on GCPs. The intention of the ortho-correction process is to remove distortions inherent in imagery. The process ensures the satellite image conforms to a map projection, and includes correcting for terrain displacement (Watt and Meredith, 2011). The sensor observes the Earth's surface in five spectral bands. These bands simultaneously record the reflected energy from the Earth's surface in the blue (band 1) with spectral range from 0.44 to 0.51µm, green (band 2) ranging from 0.52 to 0.59 µm, red represented in (band 3) with spectral range 0.63–0.685 µm, red edge (band 4) ranging from 0.69 to 0.73 µm and near-infrared (band 5) with spectral range 0.76–0.85 µm. It is important to note that, RapidEye is the first high-resolution multispectral satellite system incorporating red-edge band, which is sensitive to vegetation chlorophyll content (Schuster *et al*., 2012). That makes this system different from, and privileged among the other multispectral satellite systems (Schuster *et al*., 2012; Ustuner *et al*., 2014). All these five bands shave the same calibration coefficients (Tapsall *et al*., 2010). High-resolution Rapideye imagery have been successfully utilized in several studies such as; monitoring LU/LC (Park *et al*., 2018), detecting changes (Zhanga *et al*., 2017), forest mapping (Saito and Sakaguchi, 2013) and in water studies (Tetteh and Schönert, 2015).

In the current study, five RapidEye scenes, located in path/row: ranging from 174/051 to 173/052, taken on October 12, 2012 and October 11, 2013, were acquired for the identification and mapping of tree species in Nuba Mountains. The imagery is delivered in a Geo-Tiff format enabled to be integrated in GIS environment and thus to be overlaid with existing GIS datasets by applying the appropriate coordinate transformation. The Geo-TIFF file was scaled from 12-Bit to 16-bit dynamic range for delivering ñ, the dynamic range, which determines the number of discrete levels of information. The 16-bit image provides 65536 levels (Watt and Meredith, 2011). Radiometry and Color Balance were 5-Band GeoTiff; calibrated radiance-at-sensor (Watt/m 2 sr-1 µm-1) with 0% cloud cover. The pixel size was rescaled from 6.5 meter to 5.0 meter. The five spectral bands were utilized. These bands measure discrete band widths (wavelengths) that are positioned to minimize atmospheric effects and are optimized to allow water penetration, discrimination of vegetation types and plantation vigor.

2- Field Survey Data

As mentioned previously (see Section 2.2.1.1 (2) above), ground truthing allows image data to be related to real features and materials on the ground (Thapa and Murayama, 2009). This enables calibration of RS data, as well as aids in the interpretation and analysis of what is being sensed. A dataset constituted of 270 geo-referenced GPS points that were utilized adequately to describe and verify the species of trees across the study area, as well as to create a "test set" to assess classification accuracy. This dataset comprehends the result of field survey performed in 2014. However, in the survey during that period, no specific and well-defined statistical sampling design was used. Therefore, in 2015 the botanical survey was developed and modified (Annex 1).

3- Ancillary Data

To help in the classification, additional data related to climate and temperature was collected. Furthermore, 65 points were randomly gathered, during the field visit in July 2015, from the study site, to identify the soil types, and to create a "test set" to assess classification accuracy.

3.2.2.2 Image Pre-processing

For the selected images, several pre-processing steps are required prior to analyzing satellite images such as ortho-correction, atmospheric and topographic corrections. These processes were undertaken in ENVI, GRASS and Erdas imagine 11 softwares and are designed to produce standardized image products from which quantitative analysis such as LC mapping, monitoring, and detection of change can be performed.

1- Geometric correction

To correct the geometry of input datasets, GPS ground control points of landmark areas collected from the field covering distinguishable features in the study area were used. Images have been co-registered in Erdas imagine 11 software with 50 GPS points. The RMSE achieved in all cases is less than 0.5 of pixel size, which illustrates an adequate precision of rectification. The output maps projection was Transverse Mercator Projection (UTM/ zone 36 WGS 84 North). Afterward, subset of the study area was selected.

2- Atmospheric Correction

To achieve accurate results of multi-temporal satellite imagery and adjacent scenes, it is essential to remove the scattering and absorption effects of the atmosphere. The Second Simulation of Satellite Signal in the Solar Spectrum (6S) algorithm (Vermote *et al*., 1997), developed by Vermote *et al*., in 2006, was used in the present study to correct the atmospheric effects. The model is widely used and accepted for estimating the propagation of electromagnetic radiation in the atmosphere, especially for high resolution images (Mahiny and Turner, 2007; Balthazar *et al*., 2012; Burns and Nolin, 2014; Mannschatz *et al*., 2014). The 6S simulates satellite observations, accounting for varying target heights of a realistic definition of custom or standard atmospheric, aerosol and visibility models. Variables for defining these models, for a specific date and time, are generated from a number of RS sensors (e.g. AIRS, MODIS and MISR). Atmospheric conditions are simulated for the image date using a customized atmospheric model defined by the mean water vapour and ozone values over the scene from the daily atmospheric data collected for the image date. The visibility is defined using the mean Aerosolmoptical Depth (AOD) value over the scene from the daily atmospheric data collected for the image date. Based on Watt and Meredith (2011), the 6S implementation allows imagery to be scaled to 16 bit unsigned integer values. This is then converted to reflectance using available parameters. The resulting image represents calibrated energy returned from the field of view as detected at the top of the atmosphere.

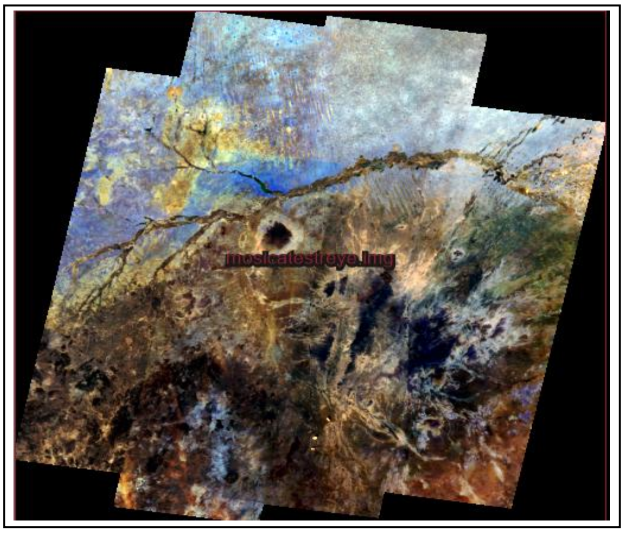
3- Topographic normalization

The topographic effects in hilly or mountainous terrain areas can be reduced by applying a correction to adjust the reflectance for each pixel to a horizontal surface. The C-correction method that was defined in Riaño *et al*. (2003); Wei *et al*. (2008); Richter *et al*. (2009) was applied for correcting the topographic effects. The DEM was resampled to match the 5-metre RapidEye image using nearest neighbour interpolation. Slope and aspect are derived from the DEM for input into the C-factor correction. These parameters are entered into a correction tool developed in ENVI to apply the topographic correction to each band in the selected RapidEye scenes.

4- Mosaic Images

At the completion of the pre-processing, the individual images were mosaicked to produce a single coverage (Fig. 3.3), which can then be ingested into ArcMap and used as inputs to run the customized ArcGIS and eCognition routines. Color correction algorithms (i.e.; image dodging and color balancing) were used for correcting the photometrical disparities. Seamline Generation technique (i.e.; Weightd seamline method) was used to avoid visual transition during the mosaicking process.

Figure 3.3: Image mosaicking



3.2.2.3 Image Classification

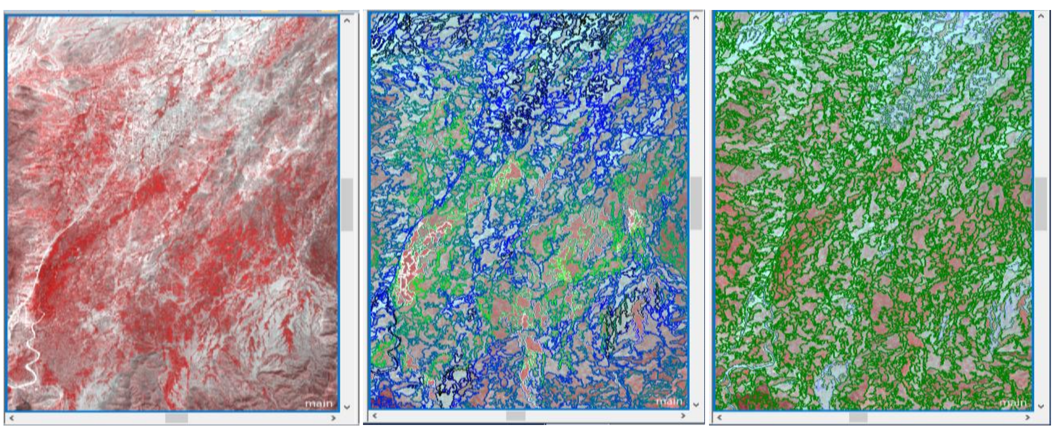
1- GEOBIA

When using high resolution, the spectral information in an image is spatially heterogeneous and the pixel no longer corresponds to the object. This is due to the size of the pixels, where they are significantly smaller than the object concerned (Blaschke, 2010; Blaschke *et al*., 2014). Several researchers such as; Kressler *et al*. (2003a; 2003b); Lennartz and Congalton (2004); Ivits *et al*. (2005); Yan *et al*. (2006); Dupuy *et al*. (2012); El-Abbas (2015), have pointed to the limited accuracy of this method of classification, where "salt and pepper" effects result from isolated pixels responsible for this drawback. GEOBIA has proven to be an effective way of solving this problem and it provides most accurate results (e.g.; Willhauck *et al*., 2000; Oruc *et al*., 2004; Yan *et al*., 2006; Whiteside *et al*., 2011; Radoux and Bogaert, 2017). Furthermore, this approach provides complex information on various scales, through multiple segmentations with different parameter settings. As well, it's able to filter out meaningless information and assimilate other pieces of information into a single object (Gronemeyer, 2012). Recent advances in GEOBIA have revolutionized the processing of high to very high spatial resolution RS data such as Rapideye, IKONOS, QuickBird and Radar, providing effective computer-assisted classification techniques, for which results come close to the quality of manual image-interpretation. This is much faster as well, cheaper and reproducible over large areas (Durieux *et al*., 2008; Tormos *et al*., 2012; Makinde *et al*., 2016; Ma *et al*., 2017). Accordingly, this study used bi-temporal high spatial resolution imagery for tree species classification based on GEOBIA.

2- Image Segmentation

Multiresolution segmentation algorithm in Trimble eCognition TM Developer 8.7 software was applied to generate image objects from the pan-sharpened RapidEye image. This segmentation algorithm was characterized as a bottom-up region-merging technique, starting from one-pixel objects, larger objects were generated by merging smaller ones with a series of iterative steps (Baatz *et al*., 2004; Li *et al*., 2015a). Parameters that were used as input for the segmentation algorithm included: (1) weight of each input layer; (2) scale parameter; (3) color/shape weight; and (4) compactness/smoothness weight (see section 2.2.1.3 (2). In this study, all of the five spectral bands of RapidEye image were used as input. The weights of color and its compactness were set as 0.1 and 0.5, respectively, in order to balance the difference of spectral/shape heterogeneity between forests and other classes. For the Forests class, the segmentation algorithm was performed at two levels, with different scales, 800 for the first and 400 for second level (Fig. 3.4), to create objects that are connected to each other in the class hierarchy of contextual features. Each hierarchical level contained groups of objects, which were created to maximize the variability between different levels, while minimizing the variability within them (Baatz *et al*., 2004; Kosaka *et al*., 2005; Jain and Jain, 2006; El-Abbas, 2015). As well, each level contained different information details, which have been achieved by suitable scale parameters at each level represented in Figure 3.4. That allowed expressing each class and/or object in the respective level by one or more fuzzy sets (Padwick *et al*., 2010; El-Abbas, 2015; Li *et al*., 2015a). An image object domain has been used to link between the segmented object and the classification scheme through defined level, objects and fuzzy sets.

Figure 3.4: Image segmentation results for RapidEye with different scale factors; a) Original image (without segmentation), b) segmentation result with scale parameter of 800, shape 0.1, smoothness 0.5 and c) with scale parameter of 400, shape 0.1, smoothness 0.5.

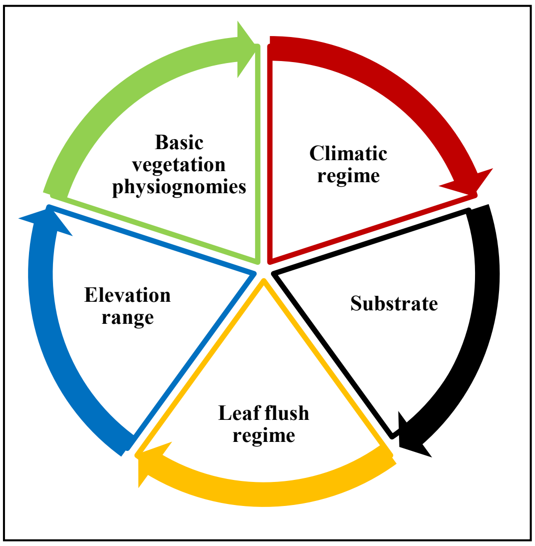


(a) **(b)** **(c)**

3- Hierarchical Fuzzy Classification

Several researchers such as: Benz *et al*., (2005); Dupuy *et al*., (2012); Do *et al*.,(2016); Ma *et al*.,(2017), proved in their studies that, the fuzzy classification improves class description, by using understandable linguistic concepts built from expert knowledge. As well, this facilitates fusion of heterogeneous multi-source information including non-image data. Therefore, the current study proposes a method combining this kind of knowledge and feature extracted from RS images to generate tree species map. The method consists of three steps to decompose the image into a hierarchical tree structure. The first is to extract features such as; spectrum information, texture, and geometry shape from RapidEye images, through training samples by using KNNC. The second step is to derive environmental knowledge which illustrates vegetation distribution. Soil types, temperature, precipitation and landform are chosen as the main environmental factors controlling vegetarian species. Landform indexes such as elevation, slope and aspect are derived from high resolution DEM. The third step is to define tree species using decision tree method with environmental knowledge and feature extracted from RS images, which is based on user expert knowledge, to describe forest vegetation classes by using Trimble eCognitionTM Developer 8.7 software. The study visually investigates the represented image objects to make a decision on the best features that should be considered in order to discriminate respective classes. Based on that, the mean layers values have been selected as main features to discriminate between most of the investigated objects. An exception was made using subsequent rules (Fig. 3.5) geometrical features and texture values are used effectively to optimize or correct most of misclassified objects. Multiple features of objects are calculated to structure data layers in RapidEye image. Spectral features are obtained based on the reflectance of the incident electromagnetic wave of different objects in each band. This includes; spectral signal of objects in each band (i.e., average of spectral signals from all pixels within the objects), brightness of objects (i.e., average of spectral signals from all bands) and maximum difference (i.e., maximum variation between spectral signals of all bands). The textural features are applied as well including; mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment and correlation. Meanwhile, the shape features that are used consist of the geometric features of objects, including length-width ratio, compactness, density and shape index. Moreover, normalization via min-max scaling was conducted, which is aimed at reducing the effects of different data expressions owing to various acquisitions and generation conditions (Wang *et al.*, 2018). Additionally, feature fusion through layer stacking was applied to generate new bi-temporal images with multiple feature layers. This simplified the complex classification process and allowed intricate trees features to be effectively classified (more details about the classification steps are given in section 2.2.1.3 (3). The Figure 3.5 below shows the main criteria of species classification.

Figure 3.5: The main criteria of species classification, it's adopted and developed from Oliveira-Filho (2009; 2015)



In the present study, the training and testing objects have been (declared) by selecting representative samples contains meaningful spectral and spatial properties for each class, and the confused training objects (critical samples) have been eliminated. Sample object has been defined by the value of 0.95, which means that 95% of an image object has to be overlapped by the sample area, for specific class category, derived by the TTA Mask, to create a class sample. As mentioned earlier, the study area consists of both man-made and natural entities, accordingly, a hierarchical system was proposed in this study to attain forest vegetation classes. The natural area is composed of forests orchards, shrubs, agricultural fields and grass. Remaining regions are covered with water, roads and settlements areas. Therefore, it would be a good strategy to divide the whole study site, at a first level, into two classes as vegetation and non-vegetation due to its heterogeneous nature. Decomposing the area into such two classes, as a first level, would help to eliminate errors arising from mixed pixels, in non-vegetation area from further levels. Subsequently, the second level involves further decomposition of vegetated area, which effectively reduces vegetation type-related confusions. It allows for the separation of one forests class and one Non-forested area that (composed of; Cultivated lands, Grasslands, Horticulture land and Shrublands child classes) in the third level. The forests class involves forest feature-related classifications such as; forest physiognomies, trees structure and leaf flush regime as can be shown in Figure 3.5 above, which allowes for the separation of nine species classes.

The classification was based on different hierarchical attributes;

a) NDVI and Normalized Difference Red edge index (NDRE)

The absorption features related to chlorophyll content are generally controllable in the spectral reflectance patterns of forests in the visible spectrum (Fyfe, 2003a; 2003b; Freitas *et al*., 2005; Watt and Meredith, 2011). In contrast, the spectrum in the near infrared region is generally influenced by water content and the contribution of other organic material. Previous research (e. g. Wiegand *et al*., 1990; Hatfield *et al*., 2008; Cammarano *et al*., 2014) has shown that individual spectral bands such as the green, red and spectral ratios that include NIR, correlate well with the degree of canopy closure, and are effective for separating forest from non-forest. Indeed, for this study band ratios are of particular interest and very important as they provide an effective way to improve the classification. Accordingly, NDVI was used in this study. Moreover, as the study mentioned earlier, a new feature in RapidEye sensor is the Red Edge band, which allows better estimation of the ground cover and chlorophyll content of the vegetation (Haboudane *et al*., 2002; Vinal and Gitelson, 2005; Tapsall *et al*., 2010). It has been successfully used for classification of vegetation, forestry and agricultural areas recently (Eitel *et al*., 2011; Schuster *et al*., 2012; Tigges, 2013; Löw *et al*., 2013; Ustuner *et al*., 2014). Accordingly, NDRE ratio was calculated by the following equation (Barnes *et al*., 2000) to identify and separate out species:

$$\text{NDRE} = (R_{band5} - R_{band4})/(R_{band5} + R_{band4})$$

The visual interpretation was based on the shape, size and site of trees.

Table 3.2: Displayed NDVI and NDRE of RapidEye imagery results for the current study

Tree	NDVI	NDRE	Similar trees spectral reflectance range
Acacia Senegal	0.37- 0.22	0.26- 0.17	*Acacia polyacantha, Sterculia setigera, Acacia mellifera, Dalbergia melanoxylon, Azadrachta indica, Khaya senegalensis, Ailanthus excels, and Terminalia spp.*

Grewia tenax	0.39- 0.22	0.25- 0.35	*Combretum hartmannianum, Anogeissus leiocarpus, Boswellia papyrifera, Acacia polyacantha,* and *Sterculia setigera*
Balanites aegyptiaca	0.30- 0.16	0.22- 0.14	*Acacia oerfota, Boscia senegalensis* and *Acacia seyal*
Acacia nilotica	0.28- 0.23	0.19- 0.16	*Hyphaene thebaica* and *Piliostigma reticulatum*
Adansonia digitata	0.33- 0.20	0.24- 0.20	*Guiera senegalensis* and *Albizia amara*
Ziziphus spina-christi	0.24- 0.21	0.20- 0.17	*Diospyros mespiliformis*
Tamarindus indica	0.36- 0.30	0.22- 0.14	*Azadrachta indica, Khaya senegalensis, Ailanthus excels, Acacia mellifera,* and *Dalbergia melanoxylon*

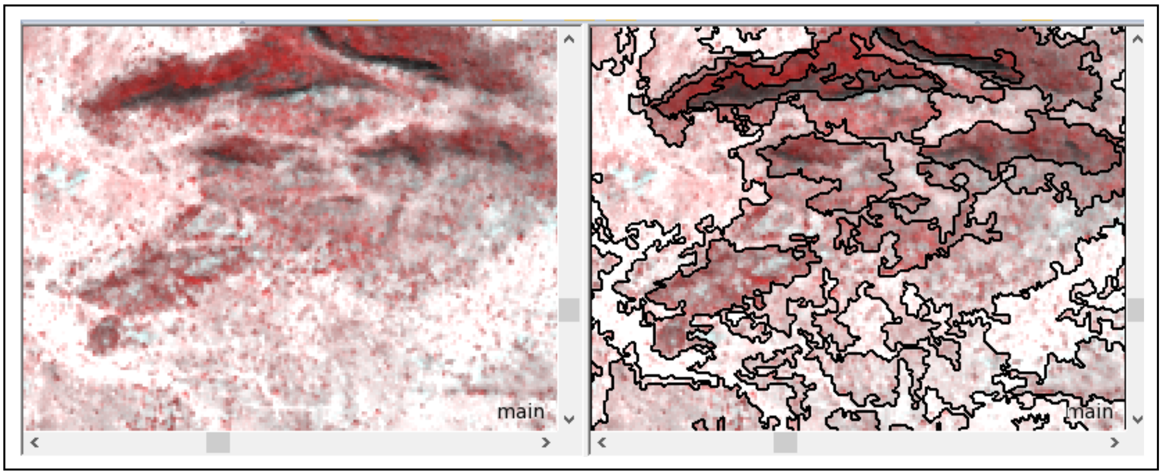
Unfortunately up to date, NDRE of RapidEye imagery has been investigated in a few studies in semi-arid regions (Eitel *et al*., 2011; Marx, 2013). Therefore, it is necessary to explore the potential use of vegetation indices of RapidEye imagery for forest classification. In reality, the current study will help, as well, to examine the ability of vegetation indices derived from original spectral bands of RapidEye imagery in forest classification in those areas.

b) Soil

Accurate and detailed spatial soil information is essential to governments and development partners for sustainable land use and management as well as environmental modeling and risk assessment (Vågen *et al*., 2005; Bationo *et al*., 2007; Sachs *et al*., 2010; Lahmar *et al*., 2012; Niang *et al*., 2014). Based on Xu and Zhuang (2007); Wang *et al*. (2016), identification of the soil types is a very important aspect of forest vegetation classification, because it plays a main role in the distribution of vegetation cover and, as well, determines the type of vegetation that grows in a certain area (Mohamad, 2011; Peng *et al*., 2017). Accordingly, mapping the soil needs identification of a number of elements, which are of major importance for soil survey such as: land type, vegetation, LU, slope and relief (Manchanda *et al*., 2002; Li *et al*., 2015b). As mentioned earlier, soil samples were collected represening 65 sampled plots in the study area. At each sample plot, three soil samples were randomly collected using the cutting ring from the surface layer (0-20 cm) for assessment and determination of the soil physical properties, including the soil water content, soil bulk density, soil total porosity, soil texture, soil organic matter, and rock content. All of the samples were serially numbered and stored in soil-bags for further analysis. For logistical reasons, the study unfortunately couldn't make the required laboratory analysis; therefore the results of laboratory analysis for each class were assessed based on Massoud (2007) and Elgubshawi (2008). To support their findings, the study utilized the RS approach for mapping the soil, which has comes up with promising secondary data source for improving digital soil mapping at all scales (Manchanda *et al*., 2002; Forkuor *et al*., 2017). The use of RS techniques in soil mapping has been found to be cost effective and less time consuming compared with traditional soil mapping approaches (Barnes and Baker, 2000; Dobos *et al*., 2001; Metternicht and Zinck, 2003; Mulder *et al*., 2011). The knowledge-based digital soil mapping, by means of fuzzy logics, is an accurate option for spatial prediction of soil properties (Zhu and Band, 1994; Zhu *et al*., 1997; Menezes *et al*., 2014; Menezes *et al*., 2018). Accordingly, RapidEye imagery has been used for mapping the soil types of Nuba Mountains. Visual interpretation was based on colour, shape, size, shadow, texture, pattern, free carbonates, salinity, organic matter, moisture, site and association (Annex 18).

Due to the complexity of soil compositions, and their corresponding spectral signatures, direct connections between soil properties and their spectral responses could not be constructed (Deng *et al*., 2015). To address this problem, GEOBIA approach was adopted using Trimble eCognitionTM Developer 8.7 software. In this approach as mentioned earlier, images need to be segmented before classification, for which a multiresolution segmentation algorithm (Baatz and Schape, 2000) was used to extract spectral, textural and contextual information as attributes for soil classification (Fig 3.6). The criteria used to define the objects, according to the respective spatial and spectral attributes, was a scale parameter equal to 15 and shape/compactness criteria equal to 0.1/0.5.

Figure 3.6: Image segmentation (left: Original image without segmentation and in right: segmented image)



The classification was conducted based on user experience and by selecting the training objects of each class type, which were carefully selected. To further alleviate the confusion between soil and other land covers, multiple features were used to improve the analysis namely:

1- Brightness Index (BI)

The classification of bare soil areas, fallow lands, vegetation with marked background response are enhanced using this index. In RapidEye imagery, BI uses the Red (R), Green (G) and Blue (B) bands, to represents the difference in reflectance values between soil areas as shown in the following equation based on Ray *et al*. (2004):

$$\mathrm{BI} = ((R^2 + G^2 + B^2)/3.0)^{0.5}$$

Thus it is a good indicator for separating areas of vegetation from areas of soil (Jin *et al*., 2016). In the current study, BI was employed to identify areas where soil is the dominant background or foreground material.

2- Redness Index (RI)

The soil characteristics are composed of organic material, granular mineral, moisture, texture, chemical components and soil cover material etc. Based on Banerjee *et al.* (2014), the soil spectral reflectance depends on soil characteristics, mainly on soil moisture and hydroxyl ions. So RI has been calculated, based on Red (R), Green (G) and Blue (B) bands, to idntify the hematite content of the soil using equation according to Forkuor *et al.* (2017):

$$\mathrm{RI} = R^2/(B + G^3)$$

3- Coloration Index (CI)

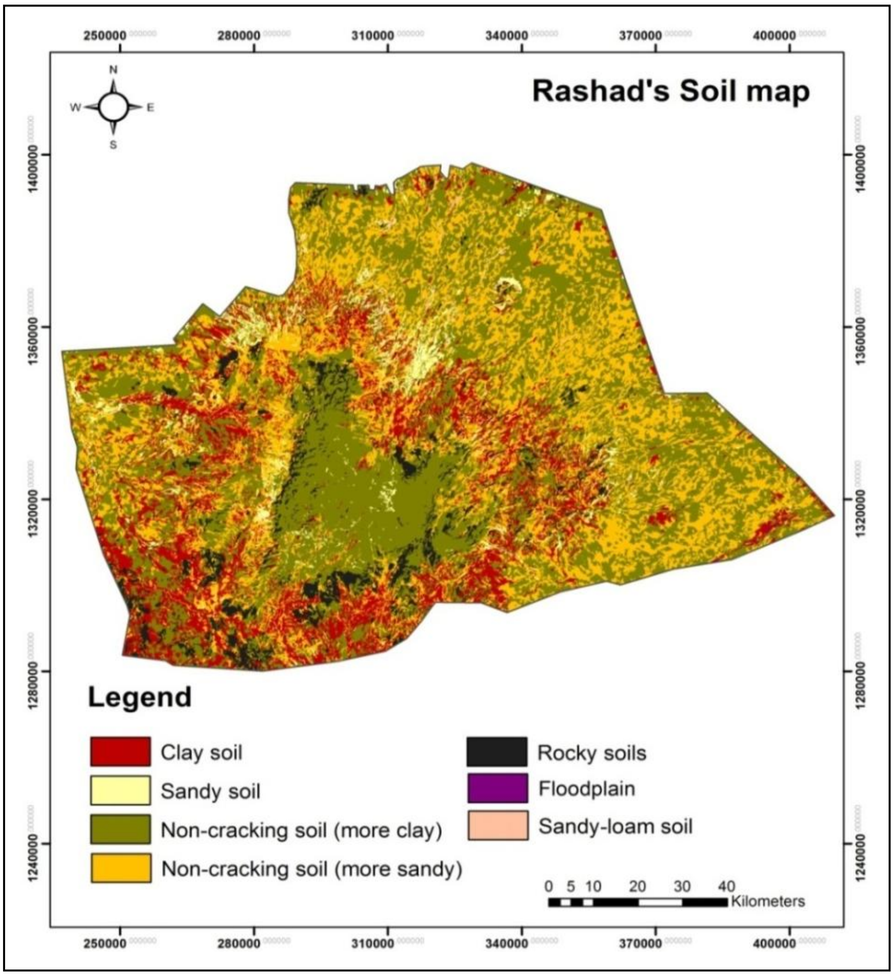
Soil color has been used as one of the key attributes to differentiate and classify soil types in many region (Moritsuka *et al*., 2004; Moritsuka *et al*., 2014: Forkuor *et al*., 2017), therefore, CI was applied to detect the soil color by utilized the equation below based on Ray *et al*. (2004):

$$\mathrm{CI} = (R - G)/(R + G)$$

Where; (R) is a Red band and (G) is a Green bands

The classification schemes for the study area based on user experience and spectral indices (Annex 19) were result in seven soil types' classes, five main classes and four sub classes based on American systems namely; Clay soil, Sandy soil, Rocky soil and Non-cracking soil that divided into: Non-cracking soil (more clay) and Non-cracking soil (more sandy). The last class was soil under water bodies, it was divided into: Floodplain and Sandy-loam soil as shown in Fig 3.7 below.

Figure 3.7: Soil types in Nuba Mountains



Determination of the different classes of inorganic particles is identified by size. The Atterberg's scale is used according to Elgubshawi (2008), with seven classes of particles (Table 3.3).

Table 3.3: The characteristics of each soil class

Soil type	Size range (mm)
Clay	< 0.002 µm
Sandy	< 2 to 0.63 µm
Non-cracking soil (more clay)	< 0.02 to 0.0063 µm
Non-cracking soil (more sandy)	< 0.2 to 0.063 µm
Rocky soil	< 0. 03 to 0.02 µm
Floodplain	< 0.0063 to 0.002 µm
Sandy-loam soil	< 0.063 to 0.2 µm

Accuracy assessment or validation is a key component of any study employing RS data. It is an important part of any classification project. Where, this step essentially determines the quality of the information derived from remotely sensed data. In the current study, best classification result method was applied to test the soil map accuracy. The result was satisfying, where all the classes recorded high percentage as indicated in Table 3.4 below.

Table 3.4: Accuracy assessment of soil map

Class	Objects	Mean	StdDev	Minimun	Maximum
Clay soil	9752	0.9433178	0.04642608307	0.1462936	1
Sandy soil	3006	0.9271318	0.06667027332	0.3364266	1
Rocky soil	4261	0.8797023	0.1046534	0.2274884	1
Non-cracking (more clay)	24891	0.9326528	0.05977634427	0.2074174	1
Non-cracking (more sandy)	17810	0.9328343	0.04682698178	0.226	1
Floodplain	32	0.8352309	0.1855172	0.1022199	1
Sandy-loam soil	348	0.9232935	0.07338409677	0.5203438	1

c) DEM

The classification of RS image mainly depends on the radiometric value difference of vegetations (Jing *et al.*, 2009). In many cases, it is hard to classify the vegetation types due to the phenomenon that the different species have similar spectral value and the same species with different spectral signatures. Particularly in the mountain areas, the problem is more serious because of complex topography. According to Lee *et al.* (2004); Xu and Zhuang (2007), the integration of spectrum combined with elevation information is very useful for recognizing and classifying the tree species. The fusion of DEM data can not only correct the topography distortion, but can also improve the classification accuracy. DEM was employed as an important criterion in classifying forest vegetations, based on spectral character, and its association with particular elevation. Five DEM images, provided by the USGS, derived from ASTER data with a spatial resolution of 30 meters and a vertical resolution of 1 m, were used. After DEM image mosaicing, the images were projected to UTM/ zone 36 WGS 84 and resampled to match the 5-metre RapidEye by using the nearest neighbor technique.

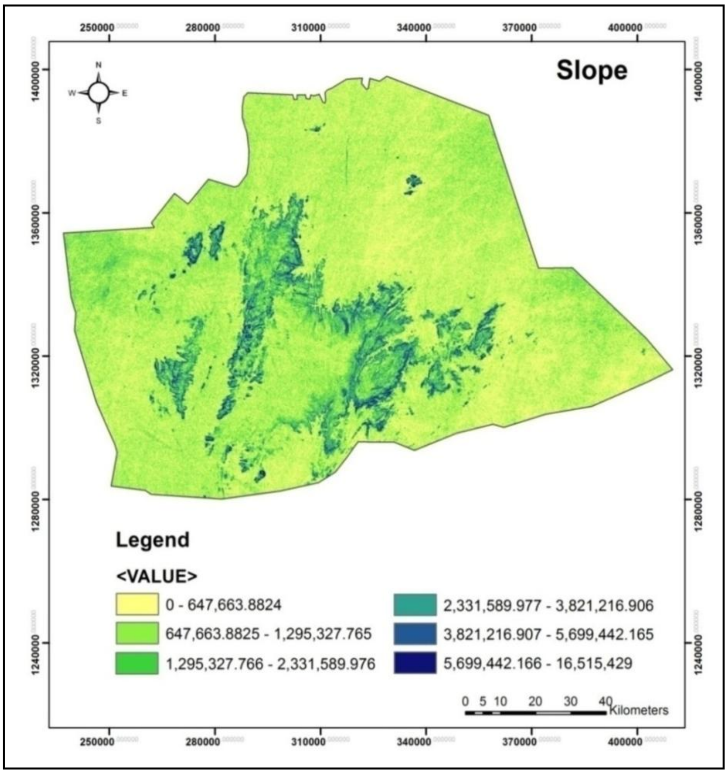
d) Slope

The landscape variations in vegetation are strongly related to topographic factors (Burke *et al*., 1989; Li *et al*., 2015a). Several studies have indicated that the correlation between the diversity of species is essentially related to the slope position and altitude. For example, in Nevada, USA, the shrub land vegetation patterns frequently show a strong correlation with the slope position (Nettleton *et al*., 1986). Another case, in Wondo Genet of Ethiopia, the tree density is negatively related to the elevation, slope, and slope aspect in the remnant moist Afromontane forest (Kebede *et al*., 2013).

Slope is the first derivative of elevation, and it is the rate of change of elevation in any direction. According to Alexander (2001), it is defined as the angle between a tangent to the surface and a horizontal (geoid-parallel) surface. Based on Walsh (1980); Oliveira-Filho (2009; 2015), slope is one of the main environmental factors that lead to spectral reflectance variation of vegetation types. Therefore, the current study used the slope to help in classifying forest vegetation types. Slope units were extracted from a DEM using a break of slope rule on downslope profiles. Each slope unit is an aggregated object of contiguous pixels and is summarized with five suites of variables: shape, topography, topographic variability, spectral characteristics, and variability in spectral characteristics.

Slope units were extracted from a DEM using a break of slope rule on downslope profiles (Fig. 3.8). Each slope unit is an aggregated object of contiguous pixels and is summarized with five suites of variables: topography, shape, spectral characteristics, and variability in topographic as well as in spectral characteristics.

Figure 3.8: Slope in study site



e) Climatic factors

Climate (namely; temperature and precipitation) is the single factor that exerts the largest influence on vegetation distribution and its characteristics on a global context (Prentice, 1990). Thus according to their impacts, deserts, tropical forests, savannas, and other types of vegetation are determined. On many time and spatial scales climate and the vegetation interact bidirectionally (Salazar, 2007). Where, climate change has affected the global distribution of vegetation from the distant past, and conversely, changes in the distribution and structure of the vegetation influenced climate (Nobre *et al*., 2007). One clear manifestation of such interaction is the global pattern of vegetative land cover and climate. Therefore, the study inserted these factors in form of thematic layers to help in the classification of forest vegetation distribution. The climatic data were downloaded from the National Center for Environmental Information (NOAA) official website (https://www.ncdc.noaa.gov/).

3.2.2.4 Map Validation

As stated earlier in section 2.2.1.4, accuracy assessment is an important and essential step in the classification process. In the present research, as suggested by Congalton in (1991) and used in other studies e.g. Tormos *et al*. (2012); Dupuy *et al*. (2012), ground based data is assumed to be 100% correct in accuracy assessments, therefore, reference data was taken to assess the accuracy of using the same schemes utilized in the classification efforts. 15 samples were taken from each class to classify the image. The overall accuracy, producer's accuracy, user's accuracy and Kappa statistics methods (Plourde and Congalton, 2003; Jensen, 2005b; Manandhar *et al.*, 2009) were conducted. These terms have been explained in detail in section 2.2.1.4. It was derived from the error matrices and was used to find the reliability and accuracy of the maps produced. Additionally, for more accurate result of each class, the best classification result method (Zhan *et al*., 2005; Tiede *et al*., 2006) was also applied.

3.3 Results and Discussion

3.3.1 The most important NTFPs in the Study area

Although there are 7,000 cultivated plant species around the world (Martin *et al*., 1998; Hammer and Khoshbakht, 2005; Raman, 2006), food security has become increasingly dependent on a small number of crops (Altieri, 1999; Borlaug, 2002; Saied *et al*., 2008). Nevertheless, an extrapolation by FAO (1999a; 2001) indicates that a number of 18,000-25,000 wild-collected species are used as food. Among those, indigenous fruits trees play a significant role in the livelihoods of rural people, especially for those living in the dry regions (Maydell, 1989), where crop failure often results in poor nutrition of the local communities (Maxwell, 1991; Saied *et al*., 2008). Although such plants are considered as neglected or underutilized at the global level, they have important uses at the local or national level (Maydell, 1989; Hammer *et al*., 2001; Adhikari *et al*., 2004; Gebauer, 2005; Ahmed and Sati, 2018). They are important genetic resources in global efforts to maintain biodiversity (Grivetti and Ogle, 2000) as well as they are part of local and regional agriculture and food procurement systems (El-Siddig *et al*., 1999). In many parts of Sudan, wild plant genetic resources are common in the normal diet, but are especially important during famine periods (Gebauer *et al*., 2002; Robinson, 2005; Ahmed and Sati, 2018). However, their potentialities are neither exploited nor fully appreciated and their contribution to farmers' livelihoods is not sufficiently acknowledged in poverty reduction strategies (Schreckenberg *et al*., 2006; Saied *et al*., 2008), in spite of the obvious interest of local people in such indigenous plants for food, additional income generation, livestock feed, folk medicine, energy, and for their role in soil conservation such as the stabilization of sand dunes (Gebauer *et al*., 2007). The development of alternative crops to improve the range of commodities available is needed, in order to meet the needs of an increasing world population (El-Siddig *et al*., 1999; Deafalla, 2011). This is particularly important for crops which can withstand harsh conditions such as drought, heat and salinity stress. NTFPs play important roles in the daily life of households in the study area. Like in other rural areas in the region, many poor people in the study area live in conditions where a nearby forest is the only accessible source of livelihood. The accessibility and availability of rich forest resources in Nuba Mountains regions facilitated the widespread reliance of households on these resources to meet their subsistence needs and commercial purposes. Results of the current study showed that, almost all of the households (97.5%) attain their needs from direct collection of NTFPs from scattered trees and shrubs surrounding their settlements.

The study site is rich with various tree species which grow naturally. However, the current research focused on much precious species according to local knowledge, namely; *Ziziphus spina-christi, Balantites aegyptiaca*, *Adansonia digitata*, *Tamarindus indica*, *Acacia nilotica*, *Grewia tenax* and *Acacia senegal* (Annex 17). Table 3.5 below clarifies the most important products that were used in the study area for livelihood subsistence and categorize them according to their manner of uses.

Table 3.5: The most important NTFPs in Study area

Scientific Name	**English name**	**Local Name**	**Family**	**Local Name of fruits**
Ziziphus spina-christi	Christ's Thorn Jujube	Seder	Rhamnaceae	Nabag
Balanites aegyptiaca	Thorn tree, Soapberry tree, Soapberry bush, Desert date, Egyptian myrobalan, Egyptian balsam or Zachum oil tree	Heglig	Zygophyllaceae	Lalob
Adansonia digitata	Baobab	Tabalde	Malvaceae	Gounglayes
Acacia nilotica	Babul, Thorn mimosa, Egyptian acacia or Thorny acacia	Soont	Fabaceae	Garad
Tamarindus indica	Tamarind	Aradeib	Fabaceae	Aradeib
Grewia tenax	White cross-berry	Godiem	Tiliaceae	Godiem
Acacia Senegal	Gum arabic	Hashab	Fabaceae	Gum arabic

Reliance on NTFPs is mandatory because of scarcity or insufficiency of alternative products. In this respect, the high IVIs of NTFPs for; food, medicine uses, income generation and small wood products (including; raw materials for local industries, building materials, fire wood and charcoal) as clarified in Table 3.6.

Table 3.6: Ranking of NTFPs according to their IVIs

Species	NTFPs					Small wood products	Total	Rank
	Fruits and seeds	Bark	Gum	Animal Feeding	Total			
Ziziphus spina-christi	0.91	0.68	0.00	0.54	2.13	0.73	2.86	1
Adansonia digitata	0.93	0.80	0.00	0.30	2.03	0.77	2.8	2
Balanites aegyptiaca	0.86	0.48	0.00	0.60	1.94	0.81	2.75	3
Tamarindus indica	0.93	0.63	0.00	0.55	2.11	0.60	2.71	4
Acacia Senegal	0.18	0.48	0.98	0.43	2.07	0.35	2.42	5
Acacia nilotica	0.15	0.28	0.63	0.73	1.79	0.56	2.35	6
Grewia tenax	0.98	0.30	0.00	0.48	1.76	0.52	2.28	7

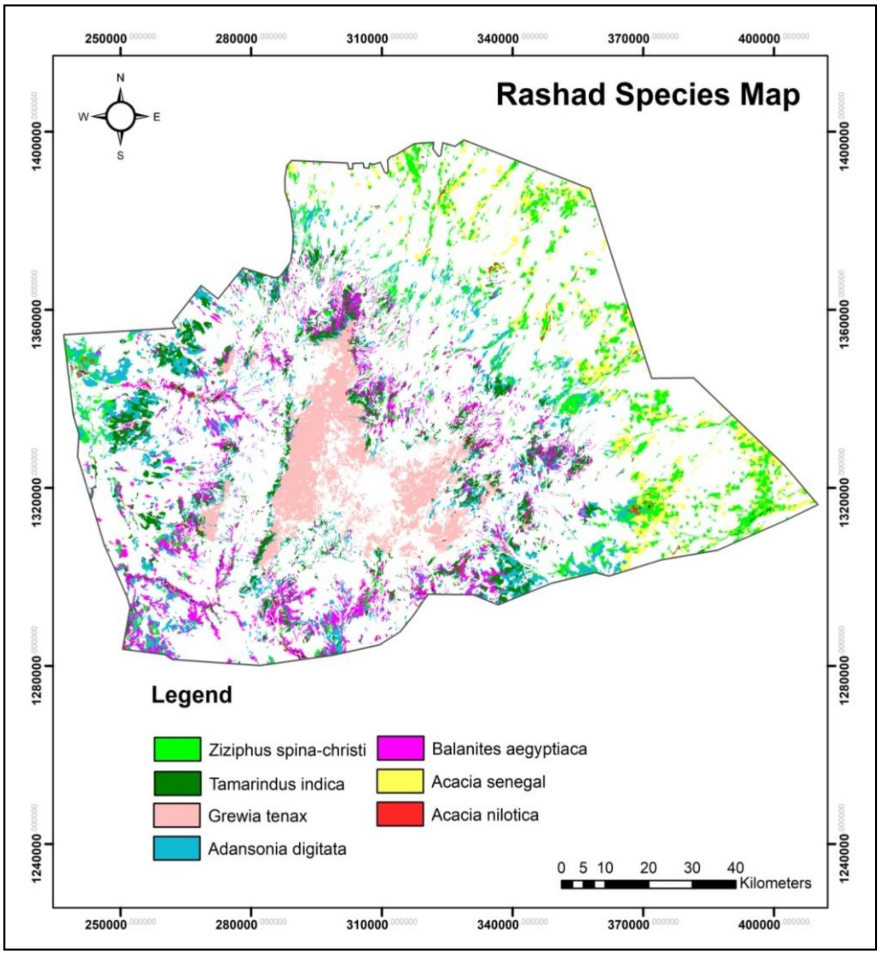
3.3.2 Trees Location

In the present research, by using the tonal variations based on NDVI and NDRE, the vegetation status of the area was identified. Vegetated areas have a relatively high reflection in the near infrared, and a low reflection in the visible range of the spectrum. However, a spectral-based classification scheme, due to some similarities between classes (Table 3.2), has led to ecologically senseless species vegetation classes. Tree types, in that classification, had near or similar spectral characteristic and could not be distinguished clearly, therefore, classification processes tackled other criteria namely; rainfall and temperature, topography, slope, elevation and soil type. By using these features, it was possible to assess spectral separability for every pair of land cover/vegetation class signatures, in order to progressively rearrange the classification scheme to guarantee higher spectral homogeneity and coherence within each final class. One of the main factors in the determination of the vegetation distribution, as well as the type of vegetation that grows in a study area, was the soil. However, the distribution of forest vegetation, in Nuba Mountains, is primarily governed by climatic and edaphic factors and this is reflected in the diversity of forest types. Accordingly, vegetation type is gradually or drastically changed and distributed; from relatively poor, followed by medium and dense stands of different tree species and shrubs, as rainfall increases to south.

In the northern parts, the vegetation cover consists of scattered acacia trees such as; *Acacia senegal* and *A. nilotica,* where, the mean annual rainfall is 300-400mm, and the slop ranges between 1, 295, 327.766 to 2, 331, 581. 959. *Acacia senegal* is found at elevations up to 483 meters, widely in north and northeast parts of the study area. The current results agreed with Bown (1995); Bein *et al*. (1996) who noted that, in their studies, the tree grows best in a moist, well-drained, and neutral to acid soil. In the study area it is found to be on non-cracking soil (more clay). The tree is an important source of income for the local people, therefore, it is natural that it is found, as well actually being cultivated, near villages. Meanwhile, *A. nilotica* was found in flooded areas on alluvial soils along streams.

The genus Ziziphus is known to be drought tolerant and very resistant to heat (NAS, 1980; Paroda and Mal, 1989). It is found in desert areas with very low rainfall (Jawanda and Bal, 1978; Maydell, 1986; Martin *et al*., 1987; Saied *et al*., 2008). In the study site, *Ziziphus spina-christi* is found, as well, in alluvial plains with deep soils at altitudes up to 400 meters. It grows along the edges of ponds and *Wadis* where groundwater is available.

Figure 3.9: Tree species map



In central and southern part of the study site (Fig. 3.9), Balanites woodland are found, where *Balanites aegyptiaca* dominates this type of vegetation. It's a low-rainfall woodland savannah with annual rainfall ranging from 350 to 600mm, located on clay soil with elevations up to 521 meters with slop ranging from 2,331,589.977 to 3, 821,216.906.

In the hilly areas, where the elevation reaches up to 1340 meters, and slope ranges between 5,699.442 to 8, 542, 150, *Grewia tenax* is abundant. It is found on very dry sites, in sandy and rocky soils, while, Baobab are found on the north facing slopes, sheltered from cold southern winds with elevation ranging from 1020 to 1240 meters. It tolerates poorly drained soils with heavy texture, but it does not existin deep sand and it prefers sandy topsoil overlying loamy subsoil (Huxley, 1992). It's found in sandy soils overlying loam and with a high water table with an annual rainfall of 300-500 mm. However, Baobab was found, at its best, at approximate altitudes of 450-600 m.

Meanwhile, *Tamarindus indica* is found in central, western and southern parts of study site, with few representations in the other parts. It is located in areas that have high rainfall, with annual rainfall in the range 600-700mm. Based on Whistler (2000) and Barwick (2004), the tree grows in a range of soils such as; clay, loam, sandy and acidic soil types, which suggests it's tolerant of saline conditions. It is found on non-cracking soil (more sandy) and elevations up to 1,500 meters.

3.3.2.1 The classification accuracy assessment

The key element of a quantitative accuracy assessment is the creation of an error matrix (Congalton, 1991). According to Congalton (2001), "it is a square array of numbers organized in rows and columns which expresses the number of sample units (i.e. pixels, clusters of pixels, or polygons) assigned to a particular category, relative to the actual category" as indicated by the reference data in Table 3.7. Columns of the confusion matrix correspond to the classes of objects in the validation set that belong to the ground truth samples, while rows correspond to which classes the image objects have been assigned to any of the classes in the image. The diagonal shows the objects that are correctly classified. Objects that are not assigned to the proper class do not occur in the diagonal, and give an indication of the confusion between the different species class in the class assignment. Furthermore, the off-diagonal elements in the rows of the confusion matrix, divided by the total number of objects assigned to the RapidEye image class corresponding to the row, represent the commission errors and describe the confusion between that image class and the other species class. The commission errors describe the chance that an object, which has been assigned to a particular class, actually belongs to one of the other classes.

Table 3.7: Error matrix of the classification data

User Class	***Acacia senegal***	***Tamarindus indica***	***Adansonia digitata***	***Balanitesa egyptiaca***	***Acacia nilotica***	***Ziziphus spina-christi***	***Grewia tenax***	**Sum**
Acacia Senegal	65	0	0	0	1	0	1	67
Tamarindus indica	12	74	0	0	0	0	0	86
Adansonia digitata	0	0	48	0	0	0	0	48
Balanites aegyptiaca	2	0	1	64	2	0	0	68
Acacia nilotica	6	0	0	0	41	0	1	48
Ziziphus spina-christi	3	0	0	0	0	24	0	27
Grewia tenax	14	0	2	0	0	0	28	44
Unclassified	20	2	4	1	0	2	0	29
Sum	122	76	55	65	44	26	30	

The total objects classified for each particular species class, and the number of objects found corrected through ground truth samples, along with the total number of reference objects from reference data set, were computed and tabulated as presented in Table 3.8 below for each classifier. Moreover, by using the formulae equations 2 and 3, as described in section 2.2.1.4 for (computing the tree species class wise users and producers accuracy for all classifier), were considered and presented in Table 3.8 as well. The user's accuracy is found highest in case of *Adansonia digitata* (100%), meanwhile the *Ziziphus spina-christi* recorded the lowest percentage (64.8%).

Similarly, producer's accuracy also reflects the exact classification of particular tree species classes and the matching of correctly classified objects by classifier in comparison to ground truth samples. Table 3.8 clarified that, this accuracy also gives better results for *Balanites aegyptiaca*. The study as well, noted that *Tamarindus indica* is better classified in all classification method, while *Acacia senegal* gives very poor producer accuracy as compared to other tree species classes. Indeed, the result is not satisfactory; this may be due to the reasons of misclassification of some of training objects of *Acacia senegal,* such as *Grewia tenax* or *Tamarindus indica,* and this is due to the similarity of trees spectral reflection.

The overall accuracy for species map was 82.4%, with the corresponding kappa statistics of 80%. As previously noted in section 2.2.1.4, kappa coefficient above 75% may be interpreted as better classification than would be expected by random assignment of classes (Vieira *et al*., 2010). As shown in Table 3.8, the overall accuracy and kappa coefficient are comparatively more for maximum likelihood classifier, where both represented approximately the same percentage of trees species map.

Table 3.8: Classification accuracy assessment

	Acacia senegal	***Tamarindus indica***	***Adansonia digitata***	***Balanitesa egyptiaca***	***Acacia nilotica***	***Ziziphus spina-christi***	***Grewia tenax***
Producer	0.5327869	0.9736842	0.8727273	0.9846154	0.9318182	0.923	0.933
User	0.9701493	0.961	1	0.7901235	0.8541667	0.6486486	0.875
Hellden	0.6878307	0.93673203	0.932	0.8767123	0.8913043	0.762	0.9032258
Short	0.5241935	0.9367089	0.8727273	0.7804878	0.804	0.6153846	0.8235294
KIA Per Class	0.4556852	0.9685673	0.8583529	0.9814364	0.9241176	0.9165490	0.9284958
Totals							
Overall Accuracy	**0.8245243**						
KIA	**0.8**						

On the other hand, as in all species, the overall agreement of best classification results method is relatively high, with most of the confusion occurring in *Adansonia digitata* and *Acacia senegal* classes as clarified in Table 3.9 below. This result consists of outputs of Table 3.8, regarding these two products as well.

Table 3.9: Classification accuracy assessment based on best classification results method

Class	**Objects**	**Mean**	**StdDev**	**Minimum**	**Maximum**
Background	8360	1	0	1	1
Acacia Senegal	1211	0.815	0.1098720	0.4715775	1

Tamarindus indica	2841	1	0	1	1
Adansonia digitata	2660	0.982	0.4633149	0.2528453	1
Balanites aegyptiaca	3382	1	0	1	1
Acacia nilotica	537	1	0	1	1
Ziziphus spina-christi	932	1	0	1	1
Grewia tenax	4261	1	0	1	1

3.3.3 Potentiality of NTFPs to Poverty Alleviation and Food Security

NTFPs are of primary significance for subsistence and /or income, at the household and village levels in rural forested areas (Chettleborough *et al*., 2000; Ghosal, 2011; Fadl, 2015; Pandey *et al*., 2016). Forest-dependent people generally rely on NTFPs, especially when livestock browsing in forests, during the dry season, or for displaced people during emergency periods such as; famine, floods or war. This contributes to the diverse survival options of rural people by providing buffers against environmental and economic adversities (Arnold, 2002; Ahmed *et al*., 2012; Kajembe *et al*., 2014).

The importance of NTFPs, in the study area, can take several forms of benefits. These can represent products that are collected directly for subsistence to enhance their direct needs of foods, medicine, raw materials for local industries and livestock feeding, or those for sale in order to earn an income. Roles of the NTFPs, in survival and poverty alleviation, were tackled in this research. Most of harvested NTFPs were used as foods, medicine and nutritional supplements (Table 3.10). On the other hand, the limited quantities of products collected for livestock feeding, reported here, may refer to the strategy of their direct grazing on the tree's fodders and fruits instead of products collection.

Table 3.10: Uses of NTFPs

Product	**Status**	**1**	**2**	**3**	**4**	**5**	**6**	**1&2**	**1&3**	**2&3**	**1, 2&3**	**7**
Ziziphus spina-christi	Non-displaced Households	86.2%	0.7%	2.9%	0%	0.4%	0%	0.7%	6.6%	0%	0%	2.5%
	Displaced Households	85.2%	0.4%	2.9%	1%	0.2%	0%	0.5%	5.2%	0.5%	1%	3.1%
Balanites aegyptiaca	Non-displaced Households	22.9%	2.8%	26.4%	0.7%	0.5%	0%	0.7%	29.2%	5.5%	9%	2.3%
	Displaced Households	20.9%	2.6%	26.7%	0.9%	0.4%	0%	9.8%	28%	5.3%	1.8%	3.6%
Adansonia digitata	Non-displaced Households	3.6%	6.4%	20%	0%	0.7%	0%	2.1%	6.4%	40.7%	17.9%	2.1%
	Displaced Households	3.1%	95	20%	0%	0.7%	0%	19.2%	4.8%	39.4%	1.9%	1.9%

Acacia nilotica	Non-displaced Households	0%	0%	91.3%	1%	2.9%	0%	1%	0%	1%	1%	1.9%
	Displaced Households	1%	0.6%	89%	1.3%	1.3%	0%	0.5%	1.3%	2%	1%	2%
Tamarindus indica	Non-displaced Households	3.9%	7%	33.3%	0%	0.8%	0.8%	0%	5.4%	43.4%	3.1%	2.3%
	Displaced Households	4.4%	11.1%	31%	0%	0%	0.8%	4.4%	3.9%	42.2%	0%	2.2%
Grewia tenax	Non-displaced Households	1%	20.8%	29.7%	0%	0%	0%	0%	5%	39.6%	4%	0%
	Displaced Households	1.5%	17.3%	28.7%	0%	0%	0%	3.7%	4.4%	39.7%	4%	0.7%
Acacia senegal	Non-displaced Households	8.3%	0%	60.4%	0%	0%	0%	2.1%	16.7%	6.3%	4.2%	2.1%
	Displaced Households	11.7%	0%	63.6%	0%	0%	0%	3.9%	13%	3.9%	2.6%	1.3%

Legend: (1) Foods, (2) Drinks, (3) Medical Uses, (4) Animal Feeding, (5) Raw materials for local industries, (6) Cosmetic and (7) For All Uses.

According to Elasha *et al*. (2009); Deafalla (2012), through the experience of forest communities, forestry professionals have recently rediscovered the great importance of NTFPs (ranging from food, fruits and fibers, dye stuffs, flavors and medicines) for meeting people's needs. In recent years, a growing body of scientific research has suggested that, given certain basic conditions, NTFPs can help communities to meet their needs without destroying the forest resource (FAO, 1995a; Deafalla *et al.*, 2012). Furthermore, the study found that some NTFPs were consumed throughout the year by the rural households. These usually occur at the end of the dry season, they are also valued during peak periods of agricultural work from June to October and when less time is available for cooking also. As described in Table 3.10, NTFPs play an important role in the prevention of malnutrition, where their importance is proved, in reducing the shortages suffered during the hunger periods of the war, as they help to even out seasonal fluctuations in the availability of food. Although the quantities of forest foods involved may be small, their nutritional contribution is often critical, especially when cultivated foods are unavailable.

Rural communities in Sudan, especially in the central and western parts of the country, often rely on *Z. spina-christi sp*. to fulfill their food and energy needs (Gebauer, 2005; Saied *et al*., 2008). *Z. spina-christi sp*. fruits play an important role in food security of Nuba people, where more than 85% and 86% for both displaced and non-displaced households respectively, are depending on it (Table 3.10). Fruits are consumed either fresh or dried. The mealy fruit has a pleasant, sub-acid taste, somewhat resembling dried apples (Facciola, 1998). The leaves provide valuable animal forage and fodder under open grazing conditions (Miehe, 1986; Bunderson *et al*., 1990; Verinumbe, 1993), it is widely used in the study site. This is especially important during the dry season, when grazing is limited. Small branches are used as dry season fodder, for camels and goats, and later used to make thorn fences for house. The study indicated that, the respondents collect honey from flowers of *Z. spina-christi* trees, it has an excellent flavor and is normally sold at a price higher than that derived from flowers of other trees.

Furthermore, the trees are used as raw materials in local small industry such as; tool handles, fence posts, bedstead legs, walking sticks, roofing beams, doors and windows. It is hard and heavy and is known to resist termites (Sudhersan and Hussain, 2003). While, the twigs are used as a source of fuel and they produce excellent charcoal. Although the important role of this plant is in food security, little research, however, has been conducted on the rich nutritional content of its fruits and leaves (Nour *et al*., 1987; Berry-Koch *et al*., 1990; Eromosele *et al*., 1991; Saied *et al*., 2008; Deafalla, 2011).

Balanites aegyptiaca has numerous attributes which make it one of the most popular plants across the African continent and especially in the areas where they grow. Where, many parts of the plant are used as famine foods (Deafalla *et al*., 2012; Okia, *et al*., 2013; Fadl, 2015). In Nuba Mountains, *B. aegyptiaca sp*. is considered valuable because it produces fruit even in dry seasons. The tree has high nutritional value consisting of 45 to 46% oil (Fadl, 2013), 64 to 72% carbohydrates (Abu-Al Futuh, 1983), 1.2 to 1.5 % protein (El nour *et al*., 1985) and 40% sugar (Suliman and Jackson, 1959). The most important parts are the fruit pulp and kernel that contain saponin (Fig. 3.13), which has wide industrial and medicinal values (FAO, 1985; Farid *et al*., 2002; Beit-Yanai, 2010; Elfeel and warrag, 2011). The fleshy pulp of both the unripe and ripe fruit is edible and eaten dried or fresh. The oil extracted from the kernel is rich in saturated fatty acids and is used in cooking and treatment. It is very similar to sesame and groundnuts oils in quality and quantity (Abu Al-Futuh, 1983). Oil is extracted by crushing the hard woody shells of the kernel by stones, grounding by native mortars and stirred slowly in boiling water, and then the oil is separated from the water and boiled again to remove the remaining water as shown in Figure 3.10 below.

Figure 3.10: *Balanites aegyptiaca* Oil extraction

Source: Internet

The seed remaining after the oil has been extracted is commonly used as animal fodder by displaced households. For Muslims seeds are used as rosaries (Fig. 3.11). The leaves are eaten raw or cooked as a vegetable. While, the twigs are used as tooth brush, as well, fresh twigs are burnt in order to keep insects away and for lighting. In addition to the above mentioned, the tree are also used for shade and raw materials as; Quran tablets (looh), building materials, life fences, and hand tools (Fig. 3.11). Small branches are used as firewood.

Figure 3.11: Muslims rosaries (left), local industries (right) from *Balanites aegyptiaca sp*.

Taken by author, 2014 Taken by author, 2014

Adansonia digitata sp. is an emblematic, culturally important and physically majestic tree. It is truly multipurpose tree and it contributes to the livelihood of many populations in Africa as a source of food, fiber and medicine (Wickens, 1982; Codjia *et al*., 2001; Sidibe and Williams, 2002; Chadare *et al*., 2009; De Caluwé *et al*., 2010a). For example, the roots are boiled and eaten in many part of Africa in times of famine (Bosch *et al*., 2004; Deafalla, 2012). In Sudan it is made into a milk-like drink called 'gubdi' (Bosch *et al*., 2004). The powdered fruit flesh is added to cold liquid, thus preserving vitamins. In coastal Kenya and Tanzania the pulp-coated seeds are coloured and sugar-coated and sold as sweets (Bosch *et al*., 2004). The seeds are used to adulterate groundnuts and may be used as a coffee substitute. In Africa and India, the leaves of baobab are used either fresh as a cooked vegetable or dried and powdered as an ingredient of soups and sauces (Obizoba and Amaechi, 1993; Yazzie *et al*., 1994; Kabore *et al*., 2011; Rahul *et al*., 2015). In Nuba Mountains, Baobab is an important food and medicinal tree (Deafalla, 2012). Where, the seeds, leaves, roots, flowers, fruit pulp and bark of baobab are edible. Leaves are used in the preparation of salad, while, seeds are used as a thickening agent in soups, as well, they are fermented and used as a flavoring agent. The fruit consists of pulp and large seeds embedded in the dry acidic pulp and shell, the pulp is used widely (Annex 17) to make porridges and beverages as well as for different types of food. Recently, various studies such as Gruenwald, (2009); De Caluwé *et al*., (2009); Kamatou *et al*. (2011); Rahul *et al*. (2015), referred to Baobab as a "super fruit" based on its nutritional value (e.g. vitamin, fatty acid, mineral). Baobab fruit pulp has very high vitamin C content (280-300 mg/100 g), which is seven to ten times more than oranges that contain 51 mg/100 g (Täufel *et al*., 1993; Vertuani *et al*., 2002; Manfredini *et al*., 2002). In addition to that, it contains a high percentage of ascorbic acid, about 337 mg/100 g (Eromosele *et al*., 1991; Gebauer *et al*., 2002; Gebauer*,* 2003). Chadare *et al*. (2009) demonstrated that the consumption of 40 g of baobab pulp provided 100% of the recommended daily intake of vitamin C in pregnant women (19-30 years). Furthermore, beside using the tree for shade, it is used as raw material for local industries, as shown in Figure 3.12. The tree is characterized by a large amount of bark and fiber, therefore it used in manufacturing ropes. Respondents obtain fibers, either from the trunk, branches or root bark, by the removal of the outer bark after cutting it, in the desired location, with a sharp machine, then begin removing fiber and after obtaining the amount required, the fiber is placed in the water for two or three days to remove the juice from them. After being discharged from the water, they are exposed to the air, to evaporate water, and then used to make ropes. These ropes are used in weaving local beds (local name is: *Angraeb*) and chairs (local name is: *Banbar*), connecting animals, string, cords for musical instruments, snares, loin cloths, sacking, baskets, mats, waterproof hats and buckets halters for camels. Moreover, in the study area, the Baobab plays a vital role in water storage during the dry season, where a hollowed trunk is carved out in 3 to 4 days. A medium-sized tree holds 400 gallons while a large tree could contain about 3,000 gallons, and the inner fibers in the trunk help to purify the water. The water stored in them is said to remain sweet for several years, if the hollow is kept well closed. Baobab trees have a specific importance to local people in the study site; it is the place in the village where the elders meet to resolve problems.

Figure 3.12: Local industry from Baobab

Taken by author, 2014

Acacia nilotica sp. has different uses, but in the study area it is widely used, just as a source of fodder, and as a fence, shade and fuel tree. Leaves and pods of *Acacia nilotica* are an excellent fodder, rich in protein, meanwhile, the bark is used for tanning and dyeing leather. The flowers yield a honey of good quality. The twigs are used as a toothbrush. Moreover, it plays basic roles in the local industries such as; small furniture, tool handles, roofing beams, doors and windows. In the Blue Nile of Sudan, the pods of the plant are added to ponds to kill snail species that carry schistosomiasis without affecting the fish. Meanwhile, in India it is used as sizing material for silk and cotton, and the bark is used in paper manufacture. They also use the gum collected from the trunk and branches in paints and medicines. As well, the bark is used, especially in Bengal and Bangladesh, for dyeing cotton and wool. In Tanzania the inner bark and the thick fruit pulp are boiled in water and drunk as a tea. In eastern Java of Indonesia sprouted seeds are consumed as a vegetable, and well-roasted seeds are mixed with coffee. In Nigeria, the Hausa people use roasted seeds as a food flavouring (Fagg and James, 2005).

Tamarind sp., a tropical fruit found in Africa and Asia, is highly valued for its pulp (Van den Bilcke *et al*., 2014). Besides being a rich source of sugars, Tamarind fruit is an excellent source of vitamin B (Ajayi *et al*., 2006), contains carotene and vitamin C (De Caluwé *et al*., 2009). It is rich in pectin, organic acids (Grollier *et al*., 1998), and also contains Carbohydrates (674g / kg) (Morton, 1987; Hughes, 1999) and exhibits high antioxidant capacity (De Caluwé *et al*., 2010a). Tamarind leaves are rich in minerals, such as potassium, phosphorus, calcium and magnesium, and a source of vitamin C and ß-carotene (El-Siddig *et al*., 2006). Tamarind seeds are rich in protein and minerals, such as calcium, phosphorus, magnesium and potassium (Van der Stege *et al*., 2011). They can, thus be an important food source (El-Siddig *et al*., 2006; De Caluwé *et al*., 2010b; De Caluwé *et al*., 2011). *Tamarindus indica* is one of the indigenous fruit tree species that traditionally contributes to food security and ecosystem stability in developing countries around the world (Ebifa-Othieno *et al*., 2017). For example in India, the fruit pulp, mixed with a little salt, is a favorite ingredient of the curries and chutneys, popular throughout the country (Ambasta, 1986; Hocking, 1993). Sometimes it is mixed with sea-salt, and used to polish silver, copper and brass (Purseglove, 1982; Hughes, 1999). Flour from the seed is made into cake and bread (Gebauer, 2003). Roasted seeds are claimed to be superior to groundnuts in flavor (Bole, 1999). As well, the seed contains pectin that can be used for sizing textiles (Garrity, 2001). Furthermore, the seeds are boiled and mixed with gum to produce strong wood cement (Orwa *et al*., 2009). In the southern states of India, cooked seeds of Tamarind tree are fed to draught animals regularly (Kibon and Orskov, 1993). In Pakistan, beside their uses in food (in curries and pickles), apiculture, ornamental, fuel and charcoal, the tree are used as ornamental plants in parks, along roads and riverbanks (Sheikh, 1993). Meanwhile in Africa, *Tamarind sp*. is a host of one of the wild silkworms (Hypsoides vuillitii). Both leaves and bark are rich in tannin. The bark tannins can be used in ink or for fixing dyes and for tanning (Maydell, 1990; Rosa, 1993; Garrity, 2001). Leaves yield a red dye used for dyeing fabrics, which is used to give a yellow dye (FAO, 1988a; Gebauer, 2003). The young fruits are very sour, and are used to acidify the meat and fish (Johns and Stevenson, 1979). Moreover, the Tamarind husk is used as a replacement as a fruit in Senegal, if there are no fruits available (Van der Stege *et al*., 2011). Flowers are used in soups and sauces and for salad as well (Nowak and Schulz, 1998). It is a good source for honey production (Morton, 1987). The second grade honey is dark-colored. The tree provides good firewood with calorific value of 4 850 kcal/kg, it also produces excellent charcoal (Grieve, 1995). Because of its resistance to storms it used as a windbreaker. It is used, as well, for general carpentry, wheels, hubs, wooden utensils, agricultural tools, mortars, boat planks, toys, panels (Orwa *et al*., 2009). Its amber colored seed oil, which resembles linseed oil, is suitable for making paints and varnishes as well as for burning in lamps. There are many different recipes for refreshing drinks around the world. In some African countries, the juice obtained from the fruit pulp is mixed with wood ash to neutralize the sour taste of the tartaric acid. In eastern countries of the continent, the pulp is cooked and made into a porridge called ‘ugail’ made from sorghum or maize flour or dissolved to make a sweet drink (El-Siddig *et al*., 2006). In Ghana, the pulp is mixed with sugar and honey to make a sweet drink (FAO, 1988a; 1988b). In Benin, adding chilli pepper to the juice before drinking has been reported (Van der Stege *et al*., 2011). However, the most common method is to add sugar to make a pleasant acid drink. In the study area, *Tamarindus indica* was highly valued by the majority of the respondents, where, it was favored and extensively consumed by the Nuba population. Tamarind is valued mostly for its fruit, especially the pulp, which is eaten fresh or dry. The majority of respondents (95%) reported that, they prefer taking it dry. It can be eaten alone or as favorite ingredient in food preparation such as; juice, jam, syrup and candy. Moreover, the acidic pulp is used for a sweetened light porridge is prepared by the addition of flour to *Tamarindus indica* drink and served during the fasting month of Ramadan. The juice is regarded as a good thirst-quencher. The beverages are prepared by soaking the fruits in water for 3-4 h followed by hand pressing, sifting then sweetening. The extended crown of the Tamarind offers shade so that it is used as a rest and consultation tree in villages, as well as, it provides shelter for many animals. The foliage has a high forage value, though rarely lopped for this purpose because it affects fruit yields. The tree is used as raw materials in local industries such as; wheels, hubs, wooden utensils, agricultural tools, mortars, and panels. Women use the bark in cosmetics.

Acacia senegal is a very important tree in Sudan, where it contributes substantially to the country’s exports and, thus, to the revenues of the farming communities of gum belt in the study area (Deafalla, 2014). It is a multipurpose tree. In the gum belt countries, it has different uses. For example, seeds are traditionally used for human nutrition in Rajasthan (Ram *et al*., 2014). Moreover, the tree yields fuelwood of good quality used as a charcoal. Its wood is used for small-scale construction purposes such as; agricultural implements, utensils, poles and fence-posts. The bark and the roots provide fiber and make strong ropes and fishing nets (Duke, 1983; Orwa *et al*., 2009). In Africa, the foliage and pods are an important fodder source for sheep, camels and goats. Flowers provide valuable nectar to bees for honey production (Orwa *et al*., 2009). Being a very drought-resistant tree, it is planted for sand dune fixation, windbreakers and shelter belts in arid regions (Deafalla, 2014). Furthermore, Gum arabic has many commercial uses: food (flavour fixative, emulsifier, stabilizer of dairy products), pharmaceutics (these two sectors representing 60-75% of the use of Gum arabic), and industrial products (inks, pigments, polishes) (Gardens, 2016). Gum arabic was reported to have antidotal effects as it can destroy many alkaloids (Duke, 1983). Several thousand tons of Gum arabic are internationally traded every year, mainly in Europe and the United States of America (Gardens, 2016). The findings suggest a difference in the way *Acacia Senegal* is used between study site and other regions. It important to note that, in spite of the multi benefits mentioned above, the main use of the tree in the study site, is the harvest of Gum arabic for food, medicinal and income generation purposes. It can be eaten alone after it is directly obtained from the stems and branches of *Acacia senegal*. As well, it used to increase the viscosity of the solution or food, even if used in very low concentration. According to respondents, the Gum arabic has a nutritional quality besides it help in digestion. The tree produces good firewood from falling branches; it is preferred by respondents and is used as coal.

Fruits and other parts of *Grewia tenax* contribute significantly to the food and energy needs of the rural populations around the world, in multiple ways (Abdelmutti, 1991; Ahmed *et al*., 2012). The fruits have a number of uses and they are most valued for their high nutritive values, most important, as the main source of food during famine (Mabry-Hernandez, 2009). Its leaves and twigs are palatable fodder for livestock. At the national level, it constitutes an important contributor to improving the nutritional contents of rural and urban people in Sudan (Abdelmutti, 1991; Ahmed *et al*., 2012; Deafalla *et al*., 2014c). As a result of the factors mentioned above, *Grewia tenax* is one of the valuable plant species in the study area. Godiem fruits of *Grewia tenax* have a high carbohydrate in liquidized form and a great amount of iron, protein, vitamins, potassium and calcium (Groff *et al*., 1995; Aboagarib *et al*., 2014; Ali *et al*., 2016). The acid-flavoured fruits have a flavour somewhat like hazel nuts (Facciola, 1998). The respondents reported that they eat it fresh or keep it for later usage. Its juice is regarded as a good thirst-quencher, especially during the hot season. Beverages are prepared by soaking the fruits in water for 3-4 h or overnight followed by hand pressing, sifting then sweetening. The fruit pulp is often mixed with juices of other local utilized fruit trees such as *Adansonia digitata* and *Tamarindus indica*. A light porridge is prepared by the addition of flour or custard to Godiem drink and served during the fasting month of Ramadan. As well, the sweetened porridge is served to pregnant and lactating women to improve their health and lactating abilities. It is locally called Nesha, which is thin and is prepared by boiling millet flour and fruit pulp of Godiem and adding custard to the mixture.

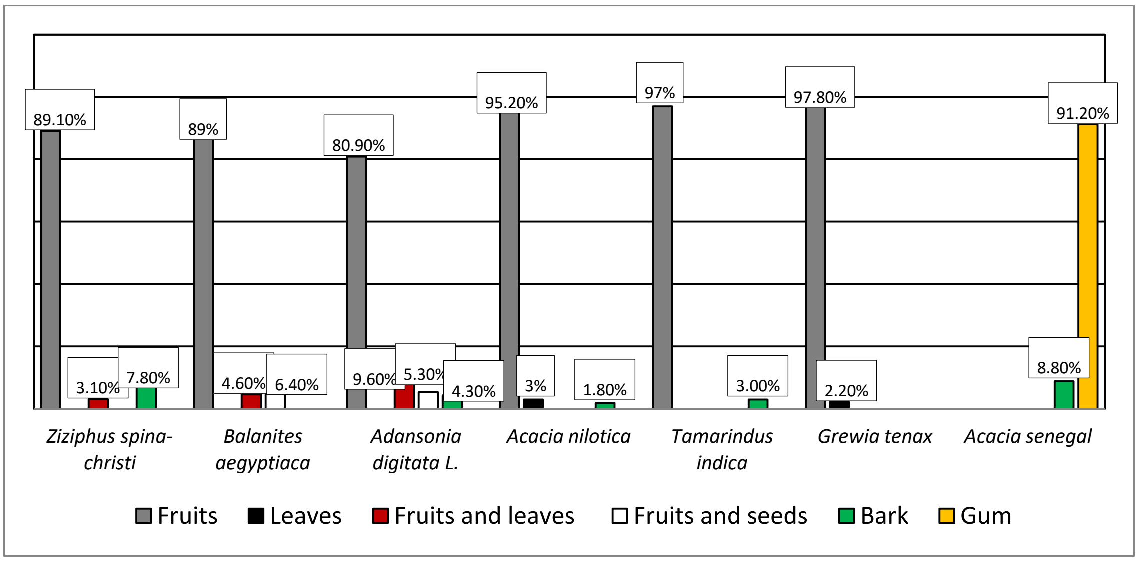
3.3.4 Potentials of NTFPs in Medical Uses

In the past three decades, there has been a growing awareness of the importance of NTFPs especially for food and medicinal uses (Deafalla and El-Abbas, 2012). From historical records (e.g. Al-Razi and Ibn Sina at 9th to 12th century AD and Australian aborigines) several uses of the medical plants were mentioned. From ancient time, a revolution of the medicine was in progress by bringing new drugs of plant and mineral origin into general use. Recently, there has been growing interest in folk medicine or traditional medicine as also known in many cultures, which increased appreciably in most developed countries (Nelson-Harrison *et al*., 2002; Abdullahi, 2011), where it is referred to as Complementary or Alternative Medicine (CAM). For instance, 70% of the population in Canada and 80% in Germany have used traditional medicines as CAM treatment (WHO, 2008; Shewamene *et al*., 2017). A cooperative approach, by various scientific areas (e.g. ethnobotanists, ethnopharmacologists, physicians and phytochemists), is thereby essential to encourage and develop medicinal plants research (Gilani *et al*., 2005).

Medicinal plants are not only a major base for health care systems in many communities, but can also help in the conservation of biodiversity and the discovery of new medicines. Moreover, enhancement of the life quality, of the rural poor societies, might be achieved by recovery of the knowledge and practices associated with these plant resources (Almeida *et al*., 2006). In Sudan, medicinal plants play important roles in the daily life, especially in rural areas, where the vast majority of them has no access to modern medicine and relies heavily on traditional cures (Robinson, 2006; Saied *et al*., 2008). Through its long history, the Sudan has witnessed the intermixture and fusion of several cultures, Pharonic, Christian and Islamic along with the local indigenous cultures. With this unique history, vast variety of climate and various tree species (at least 60 medicinal and aromatic plants, which either occur naturally or are cultivated), traditional medicine, together with use of medicinal plants, became an important part of the cultural inheritance of the country (El-Kamali and El-Khalifa, 1999; Elkhalifa *et al*., 2006; Deafalla and El-Abbas, 2012). There is a lack of information regarding traditional medicinal uses, treatments and prescription of plants in the country, which threatens their existence. Knowledge about this is orally transmitted through generations, and even nowadays, documentation is still poor (Gurib-Fakim, 2006). Today the traditional medicinal plant knowledge is facing serious threats, however, due to the strong influence of modernization theory, culture change and the western worldview (Voeks and Leony, 2004), which has contributed to undermining traditional values among young people (Giday *et al*., 2003; Deafalla, 2011). Moreover, they are largely neglected by governments and scientists.

NTFPs have traditionally occupied an important position in the socio-cultural, spiritual and medicinal arena in the daily lives of households' in the Nuba Mountains. Like in other rural areas in the region, many of poor people, in the study area, live in conditions where a nearby forest is the only accessible source of livelihood, where they attain their needs from direct collection of medical plants from forest or areas surrounding their settlements. Treatment of illness by traditional medicines is a fundamental part of health care in the study area, and it has played a vital and important role for centuries. The study found that, these products were use in medication in almost all the households interviewed. Different parts of these plants, which included; seeds, fruits, leaves and bark were used as shown in Fig 3.13 below.

Figure 3.13: Common medicinal part used of NTFPs

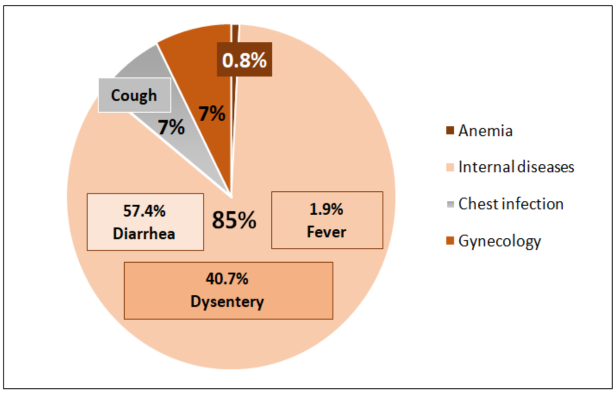


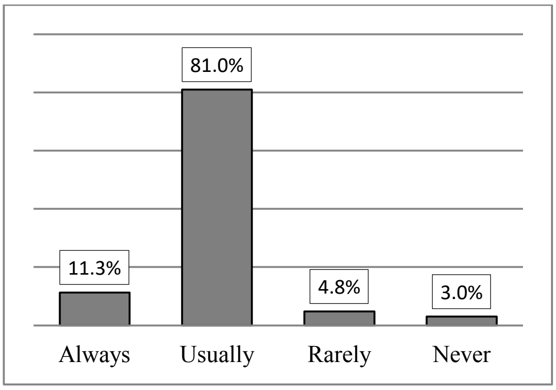
The contribution of these medical plants in treatment as follow;

1- *Adansonia digitata*

Indeed, throughout Africa, the Baobab is regarded with awe by most indigenous people; some even consider it bewitched (Wickens and Lowe, 2008) and commonly used in traditional medicines. The various parts of the plant are used as a panacea, that is, to treat almost any disease but specific documented uses include the treatment of Malaria, Tuberculosis, Fever, Microbial infections, Diarrhoea, Anaemia, Dysentery, Febrifuge, an immunostimulant, Toothache, etc. (Breyer-Brandwijk and Watt, 1962; Adesanya *et al*., 1988; Abbiw, 1990; El-Rawy *et al*., 1997; Wyk and Gericke, 2000; Brendler *et al*., 2003; Tapsoba and Deschamps, 2006; Wickens and Lowe, 2008; De Caluwé *et al*., 2010a; Nguta *et al*., 2010; Kamatou *et al*., 2011). The ways Baobab is used, varies from one country to another, for example, a decoction of the bark is used in Congo to bathe rickety children, while in Tanzania it is used to treat Toothache (Bosch *et al*., 2004). Meanwhile, in Ghana, the bark is used as a substitute of quinine, in cases of Fever (Dweckm, 1996). Stem bark and fibres lining the fruit husk are used to treat Amenorrhoea. The pulp is used in the treatment of hot flushes in Benin (Wickens and Lowe, 2008). In Messina, the powdered seed is given for hiccough in children (Jayaweera, 1981). A root decoction is taken with food in Sierra Leone for strength (Bosch *et al*., 2004). In Malawi Baobab juice called 'dambedza' is served as a cure for hangovers and against constipation. In Zambia a root infusion is used to bathe babies to promote a smooth skin (Wickens, 1982). In the study site, almost all parts (fruits, leaves, bark and seeds) of the tree are used in traditional medicine. Where, several plant parts have interesting anti-oxidant and anti-inflammatory properties (De Caluwé *et al*., 2010b; Kamatou *et al*., 2011; Rahul *et al*., 2015; Usman and Asan, 2017). Seed oil is renowned for healing attributes and has been used by practitioners of traditional medicine, in particular, for cleansing the uterus and other Gynaecological uses. An aqueous extract of the fruit is used to treat Anemia and microbial infections such as; Diarrhea and Dysentery (Fig. 3.14). The leaves and fruit pulp are used as febrifuge to treat Fever as well as an immune stimulant. The study indicated that, fruit uses in Cough treatments were mainly for displaced people.

Figure 3.14: Diseases treated by *Adansonia digitata* and its frequency of uses for treatment

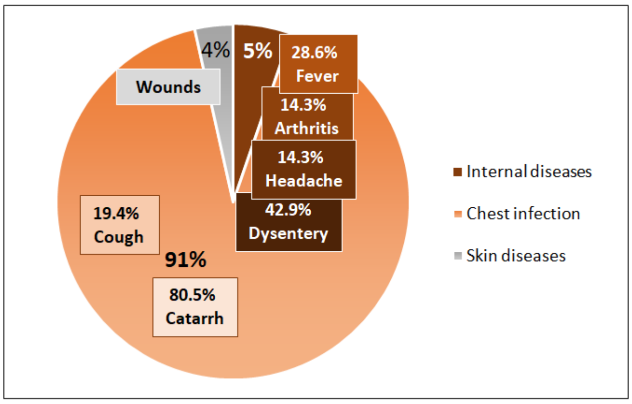


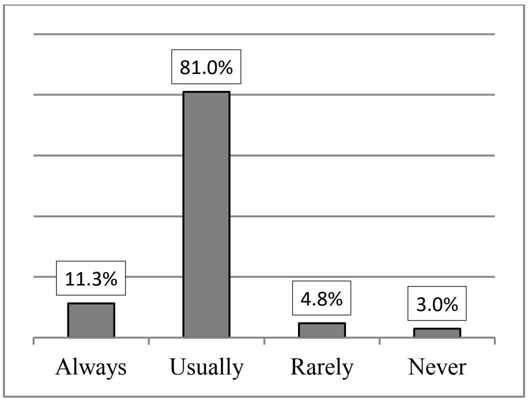


2- *Acacia nilotica*

Acacia nilotica has an inspiring range of medicinal uses with potential anti-oxidant activity, where, it's used widely in the study site to treat chest infections and cough. That agreed with many studies such as (Rizk and El-Ghazaly, 1995; Khafagi, 1999; Kambizi and Afolayan, 2001; Nazif *et al*., 2001; Abuelgassim, 2013; Gmaraldeen *et al*., 2016) conducted on *A. nilotica* (fruits), which proved to have potent activities against clinically isolated bacteria (e.g. Gram negative bacteria Escherichia coli, Shigella flexneri, Salmonella typhi, Pseudomonas aeruginosa, Klebsiella pneumonia, Gram positive bacteria, Listeria monocytogenes and Bacillus cereus) in vitro and was considered as treatment of several bacterial and viral infections. Around the different cultures of the world, almost all the plant parts are used in treatment. For example, In Middle East, Africa, China and Pakistan, bark gum is useful in various diseases such as; Cough, Diarrhea, Ulcers, Tuberculosis, Tonsillitis, Pneumonia, Gonorrhea, Smallpox, Boils and eruptions of the skin, Eye diseases, Spongy and bleeding gums, Leucorrhea, Wounds and Tumors (Khan and Nkunya, 1990; Ruffo, 1991; Zhou *et al*., 2011; Vikrant, 2012; Srineeraja, 2017). As well, pods are used to stop bleeding from bites of leeches. In China and India, powdered gum is also given in Dysentery and Diabetes. The fried gum is considered a nutritive tonic, particularly in sexual debility. It also soothes inflamed membranes of the pharynx, alimentary canal and genito-urinary organs. It is prescribed for chest complaints. Meanwhile, tender shoots top are used to treat Cough (Paul, 2010; Zhou *et al*., 2011). In the study site, there are various forms of seeds uses in treatment (Fig. 3.15), where they are made like tea, by boiling with Hibiscus in water, and drinking or sucking alone, or burning in form of incense then inhaling to treat Cough, sore throat and catarrh. Another form of uses is where seeds are eaten with yogurt, after triturating, to treat Diarrhoea. Although, the decoction of bark is a strong antioxidant astringent anti-inflammatory, it is useful in sore throat, Skin diseases, as an astringent for Diarrhoea and Leucorrhoea and is used in many countries (Paul, 2010; Srineeraja, 2017), but it is not used in the study site. Instead, they used the decoction of seeds to promote wound healing, for washing ulcers, to stop bleeding from Wounds and to treat Headache, Fever and Arthritis.

Figure 3.15: Diseases treated by *Acacia nilotica* and its frequency of uses for treatment

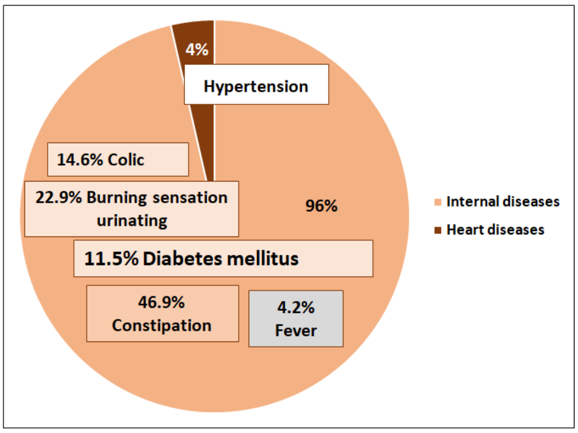


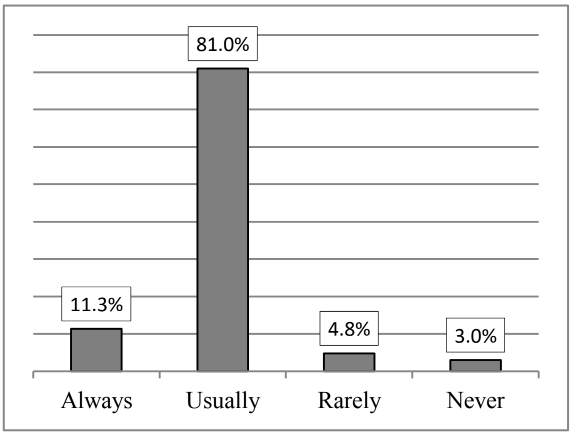


3- *Balanites aegyptiaca*

It is a widely distributed African plant of higher medicinal interest (Kamel, 1991; Gnoula *et al*., 2008; Obidah *et al*., 2009; Khalil *et al*., 2016). For example, in East Africa, fruits are used to treat Dysentery and Constipation. The seed oil is used to treat Tumors and Wounds (Khalid *et al*., 2010). As well as used as laxative, treatment of Hemorrhoid, Stomach aches, Jaundice, Yellow fever, Syphilis, Epilepsy, treat Liver disease and as a Purgative (Ojo *et al*., 2006; Beit-Yannai *et al*., 2010). Meanwhile, the bark is used in the treatment of Syphilis, Round worm infections, and as a fish poison. In some countries like Sudan, it used for Malaria treatment, where in vitro anti-plasmodial test of the dichloromethane and methanol (ME) extract of stem bark of the plant showed anti-malarial activity (Kamel *et al*., 1991; Kwuosa *et al*., 1993; Ndabaneze *et al*., 1994). The aqueous leaf extract and saponins isolated from its kernel cakes have antibacterial activity, therefore, the leaf infusion is used as an antiseptic to clean Wounds and quicken their healing (Bashir *et al*., 1984; Zarroug *et al*., 1988; Chothani and Vaghasiya, 2011). Seeds are used as anthelmintic and purgative. Ground seeds are given to camels to cure Impaction colic (Doughari *et al*., 2007). It is widely used as well as anthelmintic. Root is used in various folk medicines for the treatment of Abdominal pain and as purgative, while the bark is employed as a fish poison and also as a remedy for Malaria and Syphilis. The root, bark, kernel, and fruit have been shown to be lethal to mollusks (Khan, 2009). According to Beentje (1994), there are different uses for *Balanites aegyptiaca sp*. in Kenya, where the root infusion is used as an emetic. For asthma, about 10 gm of seed powder is taken, with a glass of water in the morning for 10 days (Jagtap *et al*., 2009). To avoid unwanted pregnancy, tablets are prepared from roots, mixed with Ferula asafoetida powder and Piper betle leaf; juices are taken once with water for 9 days, soon after the menstruation (Vijigiri and Sharma, 2010). In Egyptian folk medicine, the fruits are used as an oral anti-hypoglycemia (Kamel, 1998) and an antidiabetic (Chothani and Vaghasiya, 2011). Meanwhile, in Sudanese folk medicine, it is used to treat Jaundice (Kokwano, 1976; Deafalla *et al*., 2012) and for Malarial treatment (Kamel *et al*., 1991; Kwuosa *et al*., 1993; Ndabaneze *et al*., 1994; Deafalla, 2011). Furthermore, debittered kernel is used as snacks or mixed with honey and used to increase the male sexual drive (Elfeel and Warrag, 2011). While, in Senegal, Nigeria, Morocco, and Ethiopia, *B. aegyptiaca* is taken as a purgative for Aolic and Stomach ache. In Chad, to remove intestinal worms, the fruits are dried and mashed in millet porridge and eaten (Nkunya *et al*., 1991). In Libya and Eritrea, the leaves are used for cleaning infected Wounds. The use of the kernel oil for treatment of Wounds has been reported from Nigeria (Breyer and Brandwijk, 1982; Chothani and Vaghasiya, 2011). In Somalia, the root bark is crushed and mixed with cold water, filtered as a contraceptive. This preparation is repeated for three days and one glass is drunk three times daily for three days, the method is used in Nigeria as well, but they use a mixture of dried leaves powder of *B. aegyptiaca* and *Ricinus communis* mixed with water (Oliver-Bever, 1986; Chothani and Vaghasiya, 2011). In the study area, an aqueous extract of the *Balanites aegyptiaca* fruit is used mainly as facilitation of bowel movements with inactive colon (Fig. 3.16), and to treat Fever, Jaundice and Hypotensive, Burning sensation urinating and removeal of intestinal parasites (e.g.; Schistosomiasis). Furthermore, it is used as an anti-hypoglycemiato increase the body blood sugar level. Additionally, the fruits are also dried and mashed in millet porridge and eaten to treat and manage Diabetes conditions. The seed oil is used as a laxative, and as a treatment of Headaches, Stomachaches, and Jaundice.

Figure 3.16: Diseases treated by *Balanites aegyptiaca* and its frequency of uses for treatment

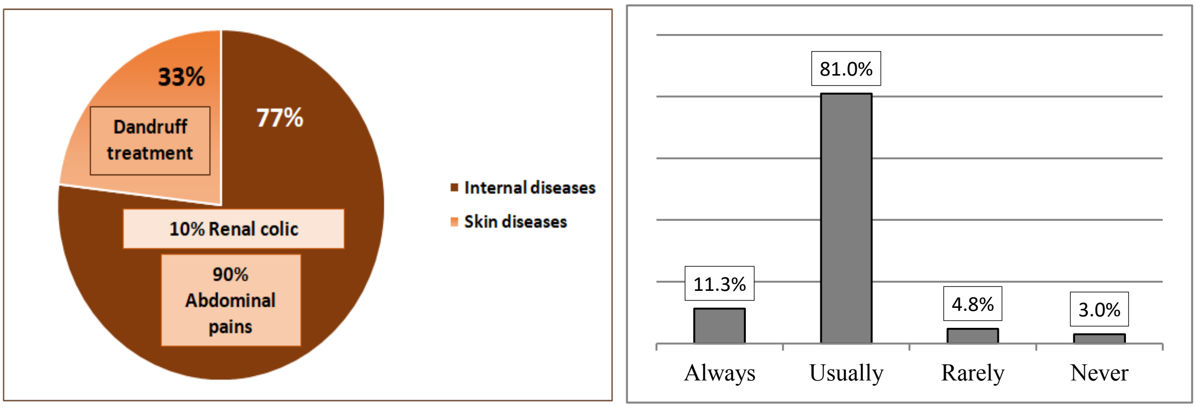




4- *Ziziphus spina-christi*

Although this plant has important roles in traditional treatments, the effects of *Ziziphus spina-christi*, however, has been rarely researched (Nazif, 2002; Harami *et al*., 2006). Based on Said *et al*. (2006); Saied *et al*. (2008), the *Ziziphus spina-christi* has many medicinal properties such as; anti-hypoglycemia, anti-hypotensive, anti-inflammatory, antimicrobial, antioxidant, anti-tumour, a liver protective agent and as an immunesystem stimulant. It is widely used for treatment in different parts of the country. For instance in central Sudan, the powder of the twigs is used externally to treat Rheumatism and scorpion sting (El-Kamali and El-Khalifa, 1999). Meanwhile, in Northern Kordofan the poultice of the powdered leaves is used to heal swellings and macerated roots are used as an anti-purgative (El Ghazali *et al*., 1997). Furthermore, in the eastern part of the country, the roots are reported as a treatment against Headaches, while spines and ashes are applied to heal snake bites. Moreover, boiled leaves are applied against Diarrhoea. In the White Nile state, the bark decoction is used to treat intestinal spasms (El Ghazali *et al*., 1994), and this is the same culture that is found in the study area, regarding the uses of the bark, where 21% of the respondents, from both displaced and non-displaced households, used the same method. The leaves of *Ziziphus spina-christi,* in the study site, are boiled in water and used as an antispasmodic to treat Abdominal pains and Renal colic treatments as shown in Figure 3.17 below. Another use for boiled leaves, is where it is used as a shampoo and applied to the hair to soften and soothe it and for Dandruff treatment.

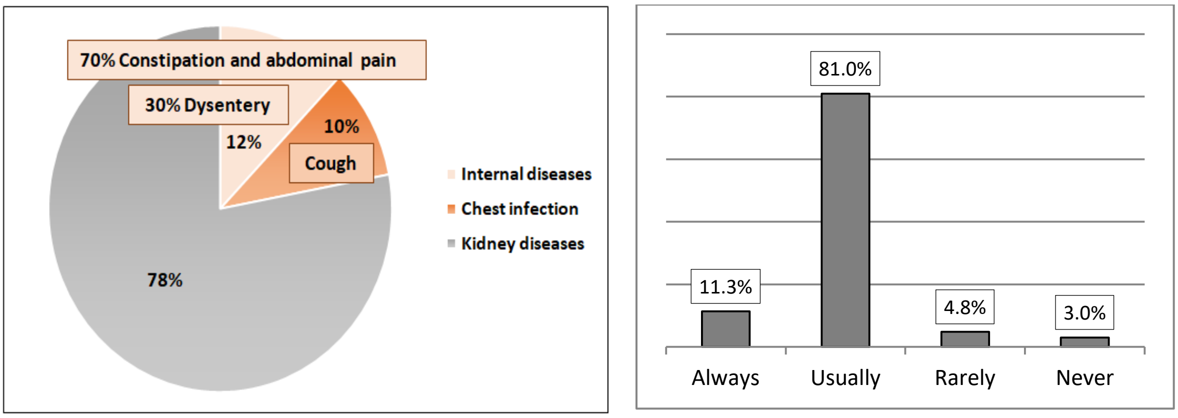
Figure 3.17: Diseases treated by *Ziziphus spina-christi* and its frequency of uses for treatment



5- *Acacia senegal*

Gum, is the main part of the tree used in treatment. For centuries, Gum arabic anti-inflammatory properties were taken advantage of in folk medicine, where it was used internally to treat Inflammation of intestinal mucosa, Chest infections, Cough, and externally to cover inflamed skin (Gamal el-din *et al*., 2003; Deafalla, 2012). As well as, it has been used as an oral hygiene substance by many communities in the Middle East and North Africa (Tyler *et al*., 1977). Gum arabic also proved highly effective in the treatment of Kidney disease (Ali *et al*., 2004; Ali *et al*., 2013). Recently, it has been widely used in pharmaceutical and food industries as an emulsifier and stabilizer (Ali *et al*., 2009). Gum arabic is used by households to treat Kidney diseases, especially for kidney stress or to remove kidney stones (Fig. 3.18). It is eaten alone or mixed with water then drunk. It is easily soluble in water and forms solutions over a wide range of concentrations. Moreover, it is taken, by the same method, to treat severe bacterial infections and stomach diseases such as; Constipation, Abdominal pain and Dysentery. Meanwhile, 8.80% of respondents used the bark as an astringent to treat colds and Diarrhoea.

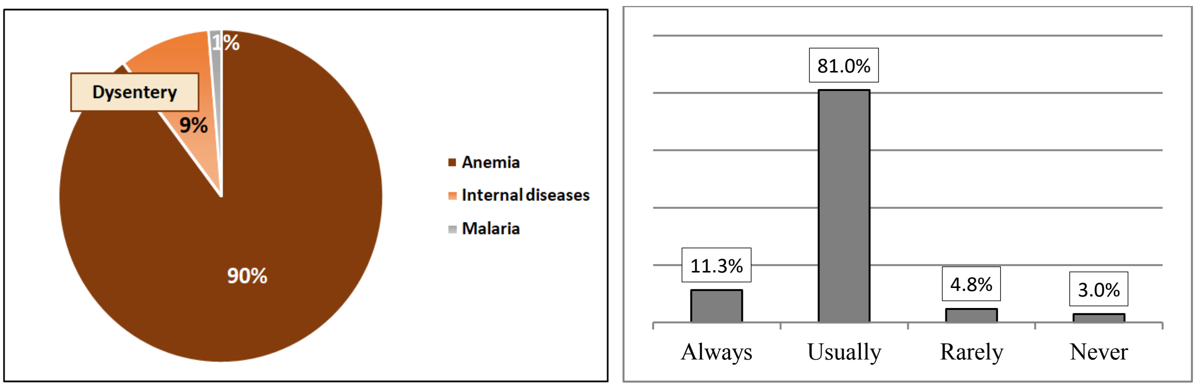
Figure 3.18: Diseases treated by *Acacia Senegal* and its frequency of uses for treatment



6- *Grewia tenax*

Indeed, *Grewia tenax* is a plant that has been used in popular medicine in various ways in different countries. Roots are used to treat Jaundice, Pulmonary infections and Asthma. Root and fruits are useful in treatment of Osteoporosis, Tissue and Wound healing. Leaves are used against Trachoma, Tonsillitis, Infections and are used as a poultice to treat swelling. A preparation of *G. tenax* fruit powder mixed with milk is given for the treatment of bone fracture and swelling. Decoction and fruit juice are used for their tonic and anti-anemic properties. Fruits are small berries, round, orange sweetened and they may be consumed either fresh or dried (Dod, 1978; Aboagarib *et al*., 2014). In Sudan *Grewia tenax* is taken to heal Anemia and as an iron supplement for anemic children (Deafalla *et al*., 2014c). As well, it used to treat Flesh irritation and Skin inflammation for both human beings and animals (Aboagarib *et al*., 2014). In the western part of the country, it is fed to pregnant and lactating women to improve their health and milk production (Gebauer *et al*., 2007; Abdualrahman *et al*., 2011). In the study site, fruits decoction and fruit juice of *Grewia tenax* are mainly used (Fig. 3.19) to heal Anemia, due to the large amounts it contains of iron (Maydell, 1990), as mentioned earlier. Small percentages (1%) and (9%) of respondents, take the decoction and fruit juice to treat Malaria and Dysentery respectively.

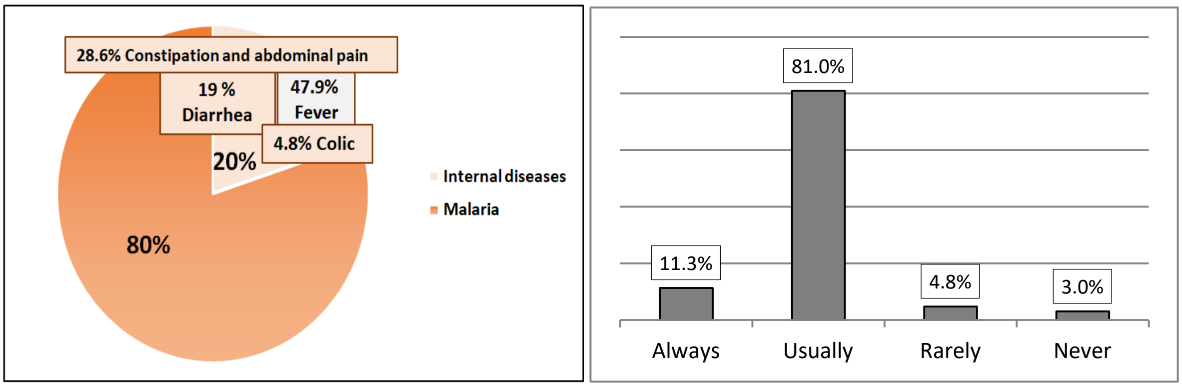
Figure 3.19: Diseases treated by *Grewia tenax* and it frequency uses for treatment



7- *Tamarindus indica*

Tamarindus indica is used as traditional medicine in India, Africa, Pakistan, Bangladesh, and most of the tropical countries (Havinga *et al*., 2010). Every part of the plant from root to leaf tips is useful for human needs. In India, leaves and pulp are crushed and applied on swollen joints, which provides great relief and reduces inflammation (Zohrameena *et al*., 2017). It is used as well, either gargled or drunk as Tamarind juice to treat Sore throat (Asase *et al*., 2005; Vyas *et al*., 2009). It is used for treating constipation, gall disorders and liver problems among others (Aida *et al*., 2001). In the African context, the fruits are used as laxative or febrifuge throughout the Sahel and Sudan ecological zones (Having *et al*., 2010). Tamarind bark used to treat Malaria (Pierre *et al*., 2011). It can also be administered as a decoction against Asthma and Amenorrhea (Orwa *et al*., 2009). The fresh stem bark and leaves are often involved in the treatment of Wounds, Stomach disorder, General body pain, Jaundice, Yellow fever and as a blood tonic and skin cleanser (Komutarin *et al*., 2004). They used as decoction especially in central West Africa. As well as, the ash of bark used to Relives sores, Ulcers, Boils and rashes. The bark is used to treat Diarrhea in West Africa, while, the leaves are used as well for this purpose in East Africa. Young leaves used in fomentation for rheumatism, applied to sores and Wounds, or Administered as a poultice for inflammation of joints to reduce swelling and relieve pain. Leaves extracts exhibit anti-oxidant activity in the liver, and are a common ingredient in cardiac and blood sugar reducing medicines (Maiti *et al*., 2004). A sweetened decoction of the leaves is good against Throat infection, Cough, Fever, and even intestinal worms (Orwa *et al*., 2009). Filtered hot juice of young leaves and a poultice of the flowers are used for Conjunctivitis. The pulp used as a massage is used to treat Rheumatism, as an acid refrigerant, a mild laxative. Meanwhile, powdered seeds are given to cure Dysentery and Diarrhea. In study area, the main uses to *Tamarindus indica* in treatment is tread the Malaria (Fig. 3.20), by using the bark, either boiling with water or take alone as powder. The bark stored as dried powders in closed bottles to use later. While, a sweetened or normal decoction of the fruits used to treat Fever, Diarrhea, Colic and Constipation abdominal pain.

Figure 3.20: Diseases treated by *Tamarindus indica* and it frequency uses for treatment



Actually, the therapeutic use of medicinal plant is becoming popular because of its inability to cause side effect and antibiotic resistant microorganisms, that beside the lack of medical support, where the hospitals are available only in large cities. This result support the World Medicines Situation (2011), that found between 70 and 95% of world population in developing countries depends on traditional medicines for primary health care and in modern medicine as well (Deafalla and Dafa-Alla, 2012) where nearly 25% were based on plant derived drugs (Tripathi, 2002; Radha *et al*., 2013).

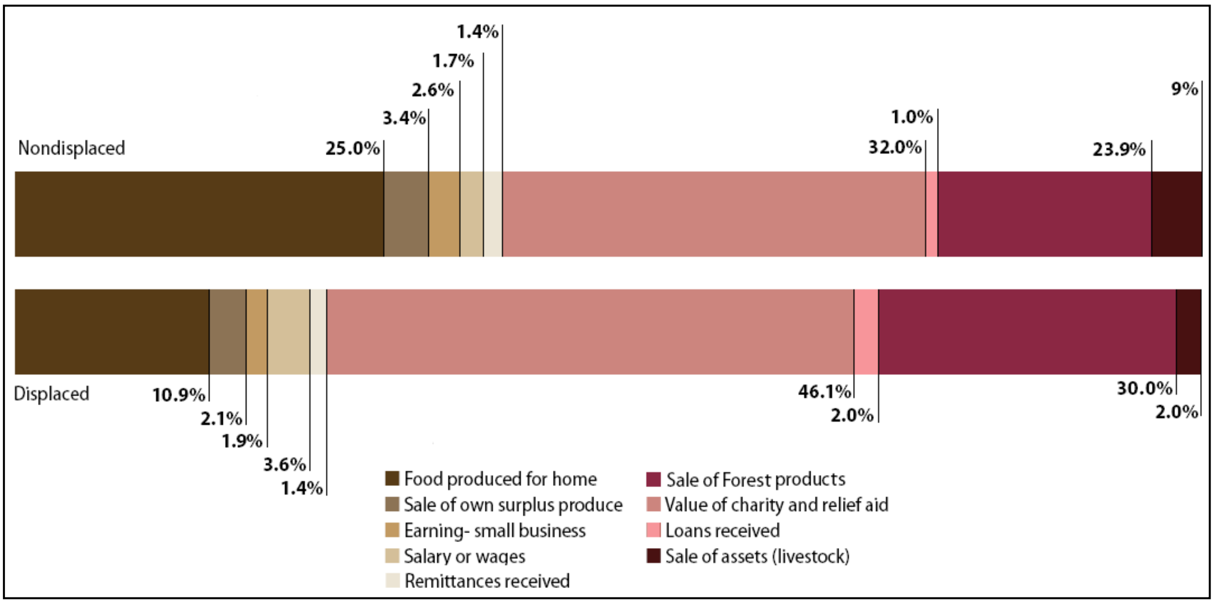
The results show that, the women usually rely more than men on traditional medicine representing 65% to 35% respectively. Although international estimates vary considerably there appears to be increasing traditional medicines use in maternity, with research from different world regions showing that up to 87% of women are using some form of traditional and complementary therapies (Adams *et al*., 2009; Sibbritt *et al*., 2011; Frawley *et al*., 2013; Shewamene *et al*., 2017). In rural Africa, women usually prefer traditional health practitioners such as traditional birth attendants to biomedical health care professionals (Nelms and Gorski, 2006; van der Kooi and Theobald, 2006). That make uses of traditional and complementary medicines for maternity related health complaints is common there (Frawley *et al*., 2015; Johnson *et al*., 2016). On the other hand, women in Western Societies use CAM for various conditions including (but not limited to): the treatment of Premenstrual tension (Girman, 2003), Pregnancy related problems (Skouteris, 2008), Back pain (Broom, 2012), Infertility (Rayner, 2009), Postmenopausal symptoms (Lunny and Fraser, 2010), for induction of Labor (Allaire, 2000). In the study area, the use of plant preparation as sources of drug are based on the experience and superstitions passed from generation to generation, virtually by the word of mouth.

3.3.5 Role of NTFPs in Employment and Income Generation

NTFPs are an important tool in addressing poverty issues for marginalized, catchment forest dependent communities, by contributing to livelihood outcomes including food security, health and wellbeing and income from selling these products (Wong *et al*., 2001; Deafalla *et al*., 2014c). In economic bases the NTFPs play an important role in of income generation to rural household in many parts of the world (Wong *et al*., 2001; Ingram *et al.*, 2012), especially for poor and may provide them the only source of personal income (FAO, 2010). NTFPs also offer an expanding livelihood options and accumulation of wealth and assets required to reduce livelihood problems in rural areas such as food and income (Dewees, 2013; Kajembe *et al*., 2014). The example of India indicates that, NTFPs contribute about 50 percent of forest revenue and 70 percent of income through export (Sekar *et al*., 1996; Enters, 1997). They also contribute 10 to 40 percent of income to the 50 million tribal households in India (Sekar *et al*., 1996; Enters, 1997), while about 200-300 million villagers depend on NTFPs to varying degrees (Shiva, 1995). Another case, in Malaysia rattan collection has been estimated to contribute 14.8 percent of the economic activity of residents in the swamp forests. Even in North American forests, NTFPs have been shown to provide significant additional income and even opportunities for small entrepreneurs (Thomas and Schumann, 1993; Shelly and Lubin, 1995; Emery, 1998). Furthermore, in times of economic and climatic uncertainty, NTFPs and the forest within which they are found, make a significant contribution to the resilience of rural forest dwellers' livelihoods (Dewees, 2013; Malleson *et al*., 2014).

In investigation on the role of NTFPs in household welfare in the study site, the study has found that such products are among the top sources of household income, where, the money earned from collecting, selling or processing forest products has an indispensable contribution to household income. These findings support the theory that NTFPs are an important component to rural livelihoods, where it buffers against risks and shocks and reduces livelihood vulnerability through the provision of cash in times of need (Neumann and Hirsch, 2000; Marshall *et al*., 2006; Arnold *et al*., 2011). The annual income of a household from collection of NTFPs, in this research, was estimated as Euro 1075. These products contribute by more than 23.9% and 30% of the household's income for non-displaced and displaced responds respectively (Fig. 3.21).

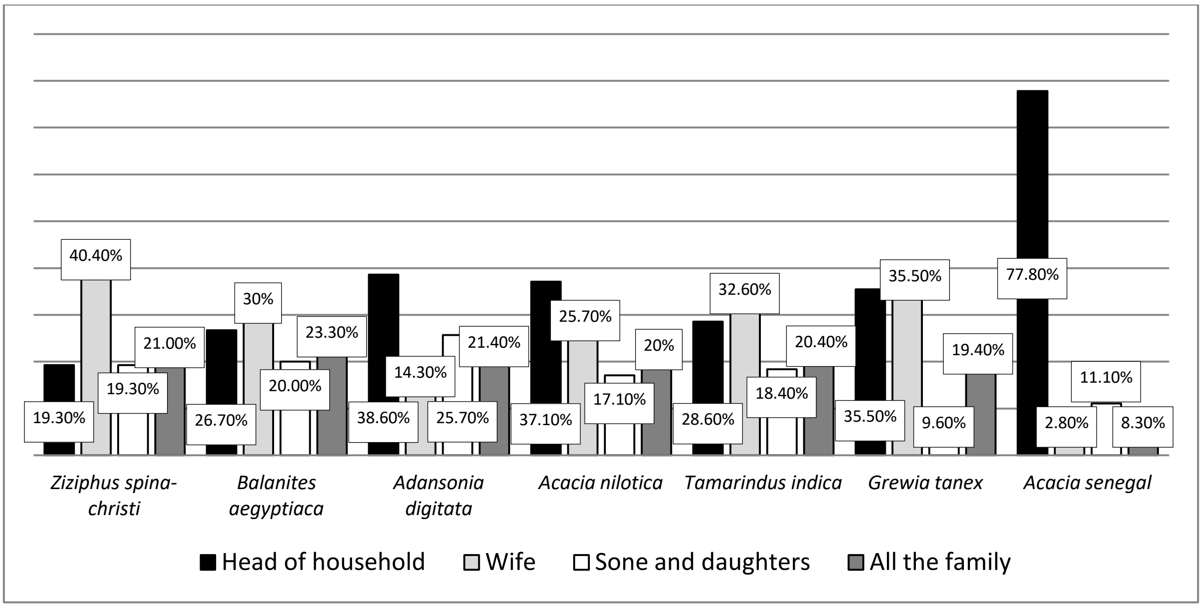
Figure 3.21: Household income



The results agree with Awad (2000); Salih (2000); Deafalla (2011); Deafalla (2012) who have pointed out that NTFPs could play a vital role in rural areas, where resources are meager and the weaker categories in the community cannot migrate to seek employment elsewhere or cannot engage in the more labor demanding activities. For example; In Indonesia, the rattan industry alone provides employment for 200,000 people (Haury and Saragih, 1995). More than 320,000 people are involved in NTFPs production in Vietnam (Tien, 1994) and in Bangladesh NTFPs provide employment for nearly 300,000 people (Basit, 1995). Moreover, in India, 1.6 million person-years are generated in the NTFPs sector (Gupta, 2000; Dattagupta *et al*., 2014). The study showed that, NTFPs provide employment opportunities for youth, women and elderly members of households. That could be supported by the relative importance of NTFP's collection being the single most important secondary occupation in the area where 59% of displaced households and 36% of non-displaced households were involved (Fig. 3.22).

Many of NTFPs are important traded commodities at local, national, regional and international levels, providing employment and income at each level, especially where the majority of the poor people, find NTFPs activities attractive due to the low technical and financial entry requirements, freely available resource base and instant cash in times of need (IFAD, 2008; Kassa and Yigezu, 2015). The most important role of NTFPs is its provision of self-reliance, employment and food security to local economy (Schreckenberg and Marshall, 2006; Deafalla, 2012), where, both women and children, often from the poorest households, can obtain a major source of their subsistence from a diverse set of forest products, including many of the same products sold for cash income (Oksanen *et al*., 2003; Deafalla, 2011). The study indicated that, NTFPs provided the cash-generating opportunities for the women, elderly and children as shown in Figure 3.22 below, where, all members of household participate in collection of NTFPs. It is found; however, as shown here, the wife plays an important role in products collection, except, Gums, *Acacia nilotica* and *Adansonia digitata* collection, which seem to be the job of the household head.

Figure 3.22: The family member who's collecting the NTFPs

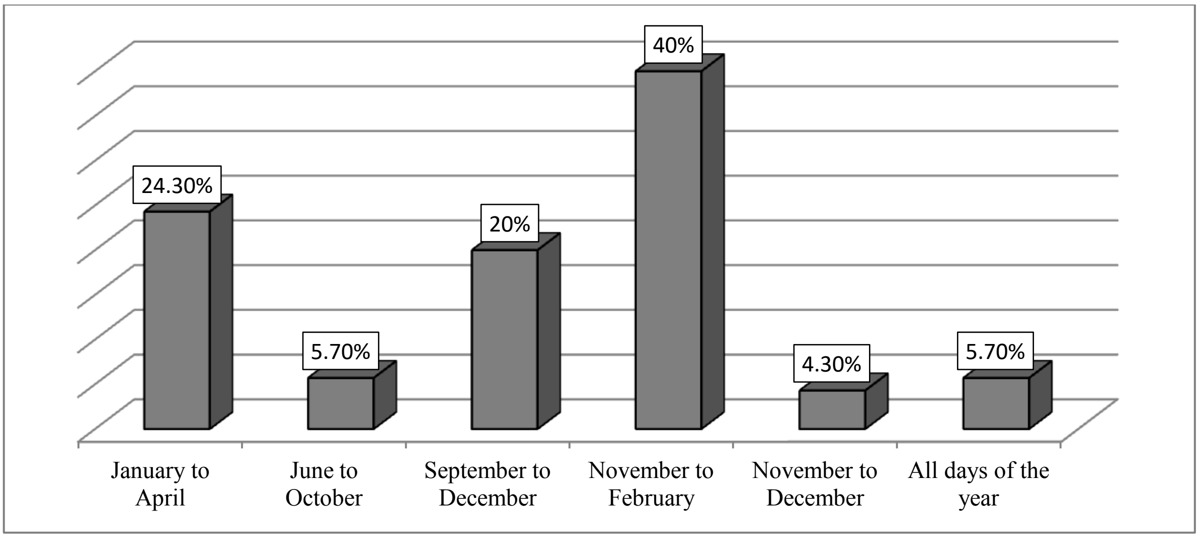


In rural communities, ease of access and low entry thresholds as well as lack of other options, women depend on forest gathering activities for income generation more than men (Arnold, 1994). Where, women are responsible for the household activities that involve forest-based foods and medicine, as well as fuel wood. In this respect NTFPs are particularly important to women because they can be combined with regular family and household tasks (FAO, 1995b), thereby allowing women to combine these income earning activities with other household chores such as child care (Arnold, 1994; 2000; Arnold *et al.*, 1994). Women in the study area earned income from limited sources such as agriculture (mainly crop production) and forests (NTFPs). Unfortunately, there are limited economic opportunities in the study area which hindered the women from diversifying their sources of income. As a result, the women living at the proximity of the natural forest depend highly on the forest to extract many NTFPs (Fig. 3.23).

Figure 3.23: Contribution of NTFPs for income generation to Women

The results agree as well with Adam (2006) who referred that, NTFPs must be considered as provider of employment during the summer and winter seasons, when other alternatives (rain-fed agriculture) are unavailable. From Figure 3.24 below, most activities of the collection were during November to February.

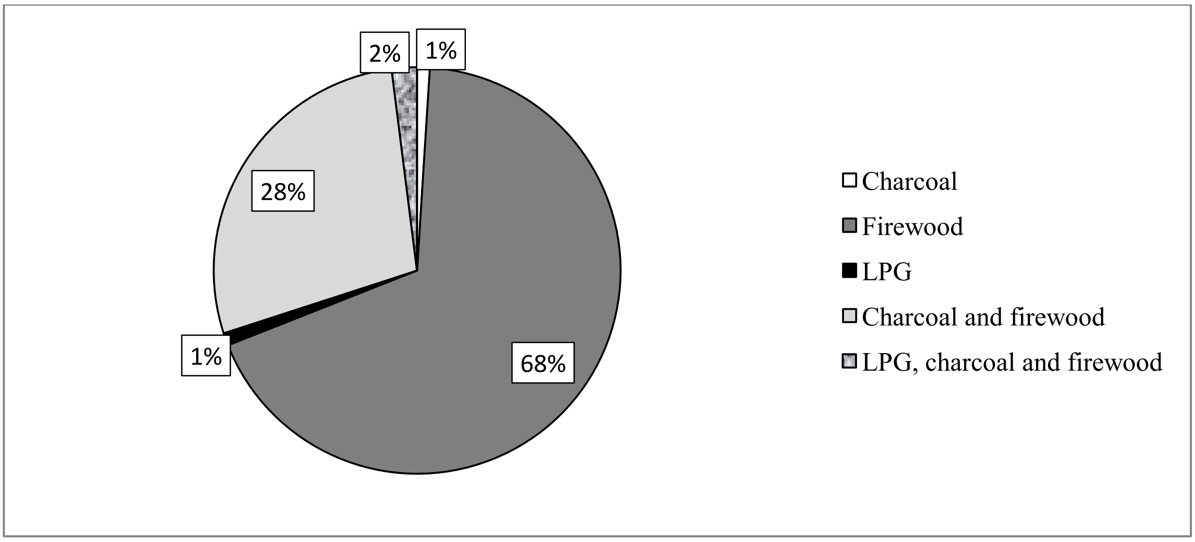
Figure 3.24: Duration of activities of NTFPs collection



3.3.6 Bioenergy

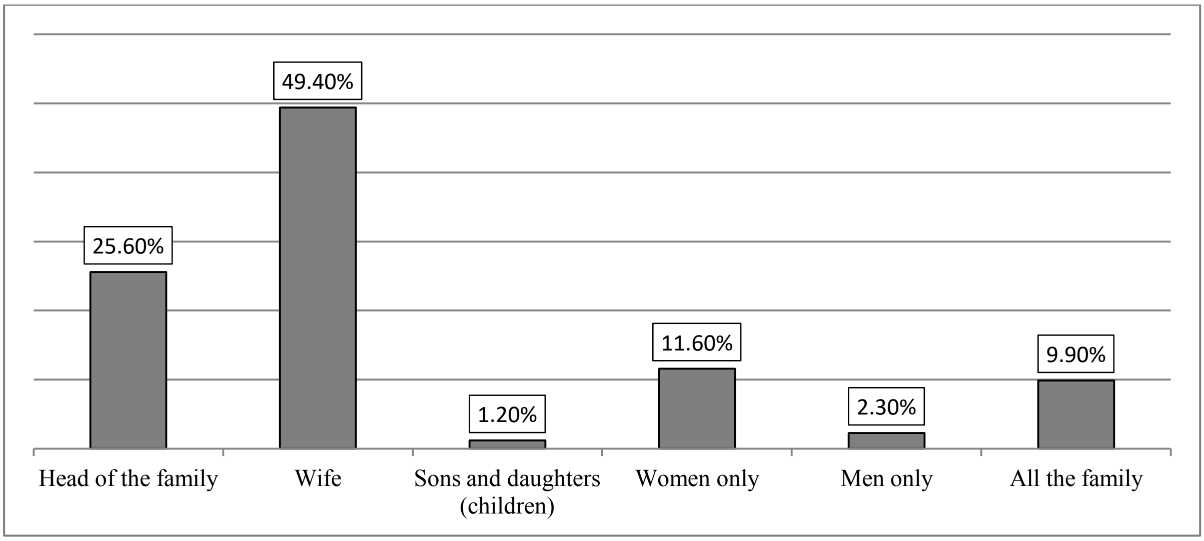
Woodfuels (in all its forms firewood and charcoal), comprise the predominant source of energy for rural populations in developing countries, and are likely to continue to do so (Arnold, 1979; Ramos and Albuquerque, 2012). The study showed that, firewood was the main source of fuel and provides the basic need of households regarding the energy (Fig. 3.25). Locally and nationally there is a need for managing and improving the consumption of fuelwood as a means of forest conservation. This is confirmed by the findings of Adam (2006), a survey of energy use in household sector (2001) which revealed that 82% of households in the rural sector use fuel wood as a source of energy. Additionally in most of the states, the percentage of households using fuel wood is more than 90%.

Figure 3.25: Type of energy used by household



Results showed that, approximately the average of more than three quarters of households (79%), obtained their needs from direct collection of the firewood from scattered trees and shrubs surrounding their settlements. Meanwhile, 15% bought it from village's market, while 6% used both above choices. Results indicated that, the family member, most involved in collection of firewood, was the wife (Fig. 3.26). This result is compatible with the findings of Falconer (1990) and Deafalla (2011), they states that, the gender dimension in fuel wood collection is signified as women do most of it. This is not surprising as fuel wood is an important input in food preparation, which is women's duty in most of households in most African regions. Refugees use what is readily available and familiar to them. Although energy use is dependent on camps and their locations, findings show that the main source of fuel for many IDPs in refugee households is firewood and charcoal. In refugee camps, the task of collecting firewood and cooking falls on women. Having little access to clean and sustainable solutions, women and young girls leave the camp premises in search for firewood, they spend as much as 3 hours each day gathering firewood for cooking. Women and girls have to walk farther and farther as trees within the vicinity have been cut down, increasing the risk of harm. This trend is similar across many refugee camps.

Figure 3.26: Family members who collect fire wood



Preferred tree species for energy wood were *Acacia millefera*, *Acacia Senegal*, *Diospyros crassiflora* and *Acacia seyal*, but most of households use all species available in the area. The study shows that, the type of cooking stoves used were the Ladaya (three-stone) (Fig. 3.27), iron and clay stoves represent 25.1%, 24.1% and 20.6% respectively. The traditional Ladaya stove, although it is simple and inexpensive has biggest problems of less efficient energy use and many health problems for humans, as a result of smoke emissions and household air pollution. Many women, and children nearby, are exposed to long lasting health problems, such as lung or eye diseases (Deafalla, 2012). Unfortunately, in the study site, in addition to safety hazards, women and children are also exposed to detrimental health issues from using harmful fuel sources.

Figure 3.27: The traditional Ladaya stove used by households

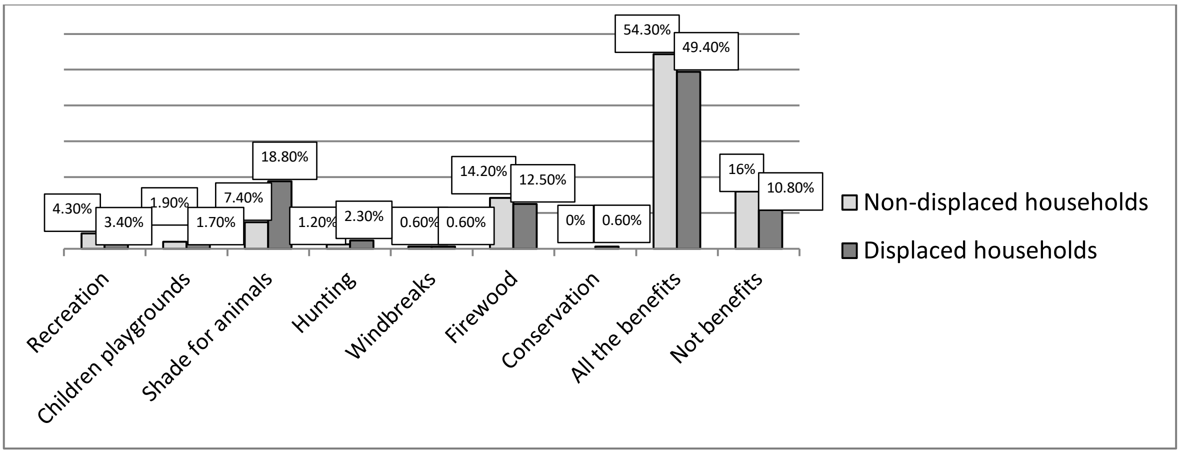
Source: Taken by author (2014)

The current study supported Menduma and Njenga (2018) who concluded that, there were linkages between energy access and food security, where access to energy influences dietary choices and nutrition. 13% percent of displaced households surveyed reported having to skip meals during the previous week because they did not have enough fuel to cook with. In the same survey, 8% percent of households reported undercooking meals in the same period for the same reason.

3.3.7 Other Contributions of NTFPs

The rural areas of Sudan, as well as much of its urban areas, rely on forests. Nuba Mountains Region constitutes an important area of forest resources in the Sudan, where forests play significant roles in the economy, through the provision of a variety of goods and services (Deafalla *et al*., 2014c). They are mainly source of sawn timber, fuel wood, charcoal, animals shade and construction materials from local to national levels, in addition to many other NTFPs as a main source of income and livelihood for the rural poor people (Deafalla, 2011; Deafalla, 2012). Forest resources in the study area contribute significantly to various domestic needs; where they had important contributions in increasing/maintaining fertility of soils and providing fodder and shade to domestic animals, and thereby food crop and livestock productivity and sustainability (Fig. 3.28). That, beside the significant roles of trees in creating amenable microclimate e.g. shade, recreation, children playgrounds and for hunting as well as windbreaks. In addition to the well-known role of forests as protectors of flora and fauna biodiversity that is as important as ever. All these various forms of contributions have a considerable value in improving food security.

Figure 3.28: Other Contributions of NTFPs



3.3.8 Importance of NTFPs for immigrants

The NTFPs play important roles in the livelihoods of millions of rural and urban people across the globe (Anonymous, 2009; Areki and Cunningham, 2010; Asfaw *et al*., 2013; Pandey *et al*., 2016). As well, they fulfill multiple functions in supporting human well being. Many policy makers, urban land managers and city residents, however, tend to completely overlook this fact (Jahnige, 2000). Indeed, NTFPs provide important economic, nutritional, recreational, educational, healthand cultural benefits to residents, and represent an over-looked value for the immigrants. All respondents (100%) consisted of people from indigenous groups. They are Nuba (62.4%), Tagaly (25.2%), Messiria (1.8%), Rizeigat (1.8%), Beni Halba (1.8%), Four (1.8), Kenyna (1.8%) and Kamely (3.4%). The study has documented that all immigrants in urban areas use and even sell a variety of NTFPs. The findings confirm the important role of NTFPs in providing household security and income. Where, 30.8% take it as a food and 23.9% as a drink. High percentage 28.8% for medical uses, while 0.5% only in cosmetic, 5% for selling and 11% for all uses. They obtain these products by bring them from Nuba Mountains, when they visit there, or by receiving them from their families and friends. The focus-groups discussion participants have point out that they use these products for their nutritional, health, house construction, or other needs at the same ways above. The study agreed with (Sofowora, 1993) who referred to local knowledge of NTFPs transfer by inheritance, where the main sources of expert knowledge and skills on dealing with these products were experience and superstitions, passed from generation to generation, virtually by the word of mouth. Moreover, they showed that there is no influence of age in using these products.

CHAPTER FOUR

Value Chain of NTFPs

General overview

The current chapter proceeds to emphasize the "impacts" theme, this time looking at the heterogeneous factors affecting NTFPs value chain. Moreover, detailed literature study and discussion on using a value chain approach to value NTFPs in which environmental, socio-institutional and economic aspects are taken into account to indicate their 'real' value. Subsequently, the practical aspects of measuring and valuing NTFPs market chains are highlighted and presented in a checklist. Additionally, the study touches upon the importance and gathering of primary and secondary data, and its analysis to weaknesses and strengths of NTFPs market chain valuation. That is to provide a common understanding of the terms in the valuation of NTFPs market chains. The study concludes with a discussion of the prediction of dependency scenarios of NTFPs and forest density. This is critical in empowering actors in the chain, and informing regulators, policy makers and development agencies to make interventions that will have sustainable and equitable implications.

4.1 Introduction

The growing integration of the global economy in this new era, has provided the opportunity for substantial economic and income growth for many of the world's population. For the citizens of the developing world, it contains the promise of potentially increasing the rate and scope of industrial growth and agricultural production, as well as upgrading their manufacturing and service activities, the possibility of reaping higher incomes and the improved availability of better quality and increasingly differentiated final products economic growth in their countries. They understand that without sustained economic and industrial growth, there is little hope of addressing the poverty and inequality that is so pervasive. They, therefore, view the growing integration of the global economy as an opportunity for entering into a new era (Kaplinsky and Morris, 2001).

In developing countries, most poverty reduction strategies are predicated on improving agricultural production and promoting market access and integration of smallholder producers in formal market exchange (Nang'ole *et al*., 2011). Value chain approaches have been utilized by development practitioners and researchers alike to examine the inter-relationships between diverse actors involved in all stages of the marketing channel and to capture the interactions of the increasing market dynamics and complexities in those countries (Kaplinsky, 2000; 2004; Schmitz and Knorringa, 2000; Dolan and Humphrey, 2000; Fitter and Kaplinsky, 2001; Ponte, 2001; Giuliani *et al*., 2005; Bair and Peters, 2006; Pietrobelli and Saliola, 2008).

Kaplinsky and Morris (2001), defined the value chain as a description of the full range of activities which are required to bring a product/good or service from conception to its end use and beyond, through the different phases of production involving a combination of physical transformation and the input of various producer services, delivery to final consumers, and final disposal after use. It is simply a framework for trying to understand how the world works, and does not exist in the sense of their having a tangible reality (Mitchell *et al*., 2009). It can be expressed, in a general form, as described in Figure 4.1 below.

Figure 4.1: The value chain description

Sources: AIMS, 2016

In the real world, value chains are much more complex than this. Where, the approach is rooted in production and exchange. As well as it focuses much less on overarching theories and unrealistic assumptions, and more on a practical approach towards supporting specific target groups to access particular value chains (Mitchell *et al*., 2009).

Value chain analysis provides important insights to improve the productive sector and plays a key role in understanding the need and scope for systemic competitiveness (Kaplinsky and Morris, 2001; Nang'ole *et al*., 2011). Value chain analysis can be used to formulate competitive strategies, understand the source(s) of competitive advantage, and identify and/or develop the linkages and inter relationships between activities that create value, where by its concentration on inter linkages allows for an easy uncovering of the dynamic flow of economic, organisational and coercive activities between producers, within different sectors, even on a global scale (Kaplinsky, 2001). Moreover, it overcomes a number of important weaknesses of traditional sectoral analysis which tends to be static and suffers from the weakness of its own bounded parameters. For in restricting itself to sectoral analysis, it struggles to deal with dynamic linkages between productive activities that go beyond that particular sector, whether they are of an inter-sectoral nature or between formal and informal sector activities (Kaplinsky, 2004).

In developing countries, mapping the flow of inputs goods and services in the production chain, provides a framework to analyze the nature and determinants of competitiveness in value chains in which small farmers can participate. It also provides the basic understanding needed for designing and implementing appropriate development programs and policies to support their in-market participation. Indeed, recently many development interventions utilized the value chain approach as an important entry point for engaging small farmers especially, individually or collectively, in high value export markets (Rich *et al*., 2009).

In recent years, commercialization of NTFPs has been widely promoted as an appropriate means of developing forest resources (Lawrence, 2003). This reflects a growing recognition of the contribution made by many NTFPs to rural livelihoods, both in terms of supporting subsistence and as a means of generating financial income (Belcher, 2003). At the same time, because harvesting of NTFPs is generally considered to be less damaging to forest resources than timber extraction, NTFPs exploitation is widely believed to be relatively compatible with forest conservation (Peters, 1996; Belcher, 2003; Newton *et al*., 2006). Thus, commercialization of NTFPs potentially offers a means of achieving both conservation and development goals concurrently (Plotkin and Famolare, 1992; Counsell and Rice, 1992; Marshall *et al*., 2003a; Deafalla, 2011), by increasing the value of forest resources to local communities (Dickinson *et al*., 1996).

Nowadays, the value chain analysis has emerged on the new research agenda for NTFPs with focus on rural studies. Increasingly it is acknowledged that dependency and links to forests go beyond village boundaries. NTFPs contributes significantly, not only to the livelihood of rural residents (Neumann and Hirsch, 2000; Angelsen and Wunder, 2003; Sunderlin *et al*., 2005), but also to the livelihood of migrants (Ambrose-Oji, 2003), national exchequers (Chamberlain *et al*., 2004), as well as the global economy (Leslie, 2005). By focusing on the whole range of activities and relations associated with production, exchange, transport, distribution of a particular commodity (Ribot, 1998; Kaplinsky, 2001) and the value chain approach (Kaplinsky, 2001) as a useful tool, will lead to new practical insights in the markets (Gereffi and Frederick, 2010).

The NTFPs value chains are complex, with multiple stages and actors involved in the process of getting a product from forest to consumer. They are also dynamic and change over time. Information about the quantity and quality of the product, price and their market is very important, particularly at the household and/or NTFPs collector level. In addition, analysis of socio-economic and socio-ecological factors that effect collection, consumption and trade of these products, is important for understanding the local dynamics that influence the harvesting and marketing of NTFPs at the household level. Our hope is to reveal gaps in knowledge, on the roles of these factors on NTFPs, to improve the existing dearth of literature on the issue, as well as to help the process of policy and strategy formulation and to develop appropriate interventions. To achieve that, the study aimed to identify the value chain of these products. That beside to model different natural, topographical, human, social, physical, and financial factors, as well as their interactions affected NTFPs commercialization, from upstream to downstream of value chains, to assess the performance of the value chain and its efficiency in supplying markets and consumers; in addition to simulating and predicting the dependency scenarios of NTFPs and forest changes to evaluate their impact on poverty alleviation and uses for the future prediction of microstructure of rural livelihood.

4.2 Research Methods

4.2.1 Socio-economic Data

The household survey was conducted using structured interviews among households who collect or trade each of the selected NTFPs. The questionnaire was designed in part one to identify factors that affect the decision of an individual or household to collect, consume and market NTFPs in the study area. These include gender structure of the family, family size, education level, main occupation, types of material building and energy types used by household in study area. Part two aimed at identifying the different cultural and technological aspects of NTFPs adopted by different communities in utilizing, harvesting and storage of these products. In total, 224 household collectors and 50 household traders were interviewed in villages, local markets as well as markets in North Kordofan, White Nile and Khartoum States, where the collection and trading of the selected NTFPs are concentrated (Annexes 3 and 7). Furthermore, a market survey, based on it, was used to obtain quantitative data on prices, taxes and quantities sold (Annex 7).

This data were integrated with other data from 2008 (322 questionnaires) to help in the comparison between the past and the current situation of NTFPs, as well as to be used in simulation model.

Moreover, the specific trade data was obtained from statistics of local and international trade data and through purposive interviews at different levels of trading chain (merchants, agents, FNC, Ministry of Environment, Forestry and Physical Development and Ministry of Foreign Trade Sudan) and at different areas which covered value chains of these products (based on Deafalla, 2011) namely; South Kordofan (Rashad and Elabbassia localities), North Kordofan (Um Rawaba and Alrahad localities), White Nile (Kostiy locality) and Khartoum States (Omdurman, Bahri and Khartoum localities).

4.2.1.1 Data Analysis

Descriptive statistical analyses were applied to analyze data concerning social characteristics and respondents perspectives about different aspects of the NTFPs value chain activities. Furthermore, Spearman Rank-Order (SRO) correlation and Pearson Correlation Coefficient (PCC) were applied to describe, test the relationship between these factors and to estimate the probability of participation of households in collection of NTFPs, and moreover the relative magnitudes of such probabilities. This was based on different socio-economic/ecological factors (ethnicity, gender, education, age, main occupation, duration of the main occupation, war, migration, markets ....etc.) that affect such activities.

4.2.2 GIS Data

In Tobler's first law of geography, every phenomenon is related to every other phenomenon in space at form of a spatial pattern, where near or localized phenomena are more related than distant or global ones (Nkeki and Osirike, 2013). A spatial pattern is a perceptual structure, placement, or arrangement of objects on earth, as well as it includes the space in between those objects (Jamhuri *et al*., 2016). Patterns may be recognized because of their arrangement, maybe in polylines or by a clustering of points. The comparison of spatial patterns is a fundamental task in geography and quantitative spatial modeling, which has been used by analysts, scientists and other professionals for planning, managing and estimation. Over the past decades, the global method of accessing and studying the relationships and spatial associations, was very weak. The traditional regression method has been used by several researchers, but there is a serious lack of information about location and attribute data for example, besides weightage values that are not taken into account, as well. Indeed this weakness has stemmed the advancement and development of strings of local spatial statistical models, often referred to as disaggregate statistics. Recently, with the growth of data being collected with a geospatial element, there is an increased interest in analyses requiring spatial pattern comparisons (Long and Robertson, 2017). The local spatial statistical models are designed to capture both spatial association and diversity (heterogeneity) simultaneously. Indeed, the "one model fits all" syndrome that characterized global statistical techniques has motivated modern geographers and other spatial analysts to model and explore the local pattern of relationships that exist between variables.

Fotheringham *et al*., (2002) distinguished between global and local statistics in their study, where, they described local statistics as a spatial disaggregation of global statistic, which is computed at the individual level and yielded multi-valued results. On the other hand, global statistics refer to the overall average values of a data set, which is assumed to represent the situation in every part of the study region and often yields a single-valued result. Based on their classical counterpart, contemporary geographers now recognized that every location has an intrinsic degree of distinctiveness even from the closest location in a spatial component or system. However, the most prominent disaggregate spatial statistical techniques available for empirical analysis, include geographically weighted regression originally designed by Fotheringham *et al*., (2002); local Moran's index (Anselin, 1996); local indicator of spatial association (Anselin, 1995); local Gi* Statistics (Getis and Ord, 1992); local chi-square (Rogerson, 1999) and the variogram cloud plot (Haslett *et al*., 1991). Now, the use of these local spatial statistics has become widespread and prominent especially among spatial analysts, geographers, medical practitioners as well asphysical and social scientists. This is due to it is fast becoming an established fact that global statistics can no longer satisfy contemporary policy needs (Nkeki and Osirike, 2013).

The objectives of the study, in this chapter, are to explore, analyze and predict the spatial relationships that affect NTFPs collection, using geostatistical analyst tools. Using disaggregate statistic to test and model such relationship, is a rich and viable methodology for the study of NTFPs, as it is associated with household food supply (ESRI, 2013). The study utilized ESRI ArcGIS software version 10.1 for computation, exploratory analysis, mapping and visualization. It was chosen because it presents numerous extensions for spatial statistical and geostatistical modeling. OLS, GWR and spatial autocorrelation analysis were used to map spatial pattern, test relationships, geovisualize and to check for redundancy among the explanatory variables. These models allow the pattern of association to be visualized on a map and all statistical values to be spatially represented on raster maps.

4.2.2.1 OLS

OLS is a global statistical model for testing and examining relationships between variables. It is defined by Hutcheson (2011) as ‘‘a generalized linear modeling technique that may be used to model a single response variable which has been recorded on at least an interval scale’’. The model relies on determining the dependent variable (Y) by producing unbiased minimum sum of error square in Y in regards to the independent variable X (Shrestha, 2006). For unbiased observations, the prediction should be equal to the expected value of the dependent variable for a particular set of data (Fernandes and Leblanc, 2005). OLS is based on a set of assumptions: normality, homogeneity and independence of residuals (Montgomery *et al*., 2001). It uses a single equation to estimate the relationships between the dependent variable and the explanatory variable(s) and assumes stationarity or static relationship across the study region. Based on Nkeki and Osirike (2013), the OLS model's equation for this analysis is presented as:

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

Where: Y refers to the dependent variable, X are the explanatory variables, β_0 is the intercept, meanwhile β_1 is Coefficients and E: Random error term.

The technique may be applied to single or multiple explanatory variables and also categorical explanatory variables that have been appropriately coded. In ecological applications for example, it is (a far and away) the most widely-used regression technique for forest monitoring (Peterson *et al*., 1987; Fassnacht *et al*., 1997; Salvador and Pons, 1998; Tunner *et al*., 1999; Cohen *et al*., 2001; Geyrlo *et al*., 2002; Zhang and Shi, 2004; Berterretche *et al*., 2005).

In this study, the OLS was used as a diagnostic tool and for selecting the appropriate predictors (with respect to their strength of correlation with the criterion variable) for the GWR model. It can automatically check for multicollinearity (redundancy among predictors). Feature datasets were added as location data and were arranged as dependent variables and factors of influence on the dependent variables, which were fixed as explanatory variables. The result will be attributed with spatial pattern map, coefficient value and R^2 value. The coefficient value describes to better understand of location samples as statistically significant, while R^2 value explains the significant fraction between 0.0 and 1.0. The analysis used locations of NTFPs demand as dependent variable and heterogeneity such as; area of village, risk level, income, elevation, census, distance to market, distance to road, precipitation and temperature as independent variables (Fig. 4.2). The multicollinearity was assessed with the variance Probability and Robust Probability of the OLS. If the Probability and Robust Probability values are greater than 0.05, it therefore indicates the existence of multicollinearity among the predictors.

Figure 4.2: Testing different explanatory (spatial relation) variables to model and simulate NTFPs

Model_NTFP_colleciont

Shape *	Class_name	Area_ha	quant	Aver_dist	Sum_Area	Risk_leve	Income	Ico	Elevation	UniqID	Dist_3	Area_	Risk_	Census	dis_to_mar	dis_to_roa	precipi	Pre
Polygon	Elabbassia	384.75	1856	3.0842	1045.49	7	2148240	482	51.64	7	3.32	839.38	1	15604	0	0	567	5310
Polygon	Rashad	344.25	6760	2.1857	4509.2	12	1964030	300	111.27	17	2.214	4481.2	1	12102	0	0	750	4152
Polygon	Kamroja	20.7	9331	1.1319	4738.65	17	1941538	159	72.09	12	1.671	4937.6	2	517	10.1	0	569	4508
Polygon	Indasseina	20.7	5067	3.61	5908.39	51	1877745	192	87.48	6	3.681	5671.1	10	600	28	0.45	558	2206
Polygon	Elgardod	27.18	1272	3.99	2537.28	69	830722	299	111.85	16	3.31	2662.1	13	939	26.1	0	570	1407
Polygon	Abokarshola	114.12	72	2.6131	2965.41	77	598249	314	34.1	8	3.019	2883.0	15	10960	0	0	650	8568
Polygon	Tandik	58.86	6695	1.9076	3072.87	51	1838231	281	68.36	19	1.793	2871.9	17	600	10.6	1.7	703	6480
Polygon	Teishan	23.85	4363	2.1593	3125.79	52	1210344	169	100.9	9	2.318	2871.9	18	2918	4.4	8.1	651	7549
Polygon	Aluzayrig	16.65	1950	3.58	2556.77	58	1522156	242	63.37	15	3.619	2839.1	19	659	26.3	5.7	565	4868
Polygon	Umm Baiyud	27.36	27	4.975	1414.78	89	466443	168	73.35	13	5.054	1287.5	21	690	40.3	0.61	565	2182
Polygon	Taioma	5.4	4463	2.63	2924.71	63	1453913	301	36.81	18	2.95	2691.9	22	832	11.3	6.9	700	985
Polygon	Um cham chaka	47.88	312	3.9283	1348.85	79	841075	364	28.11	10	4.093	1237.8	35	5989	0	3.7	650	280
Polygon	Karling	57.24	330	4.8749	2871.63	76	51059	238	28.47	1	5.137	2518.4	37	2670	35.1	12.6	560	1056
Polygon	Kitarh	26.46	537	5.5898	2739.63	79	687005	286	37.32	2	5.624	2610.9	38	5150	24.8	12.1	550	1566
Polygon	Mabust	10.53	946	4.1692	2327.51	81	39934	771	111.42	4	3.961	1983.8	40	412	27.2	2.7	589	6726
Polygon	Tofein	21.51	750	2.4976	2421.63	83	947704	239	103.59	5	3.091	2295.1	41	602	23.9	0.89	558	2237
Polygon	Tagmela	95.85	2370	3.0782	3643.01	82	1124813	158	42.9	20	2.865	3595.7	41	10102	17.7	1.1	715	2331
Polygon	Kamsura	12.51	622	4.3854	3418.76	85	44337	322	84.17	3	4.724	3177.5	43	517	28.4	2.3	580	1947
Polygon	Minbanb	57.6	169	1.9345	1413.38	93	853020	173	71.42	14	2.371	1429.9	47	755	34	6.3	565	4456
Polygon	Alhoi	40.14	1544	2.3854	1089.17	93	988897	260	71	11	2.51	1291.0	49	1650	9	2.8	569	3886

20 (0 out of 20 Selected)

Model_NTFP_colleciont

4.2.2.2 Moran's Index(Moran's I) and Spatial Regression

For more than twenty years, the theory of spatial autocorrelation has been a key element of geographical analysis (Chen, 2013). Spatial Autoregression (SAR) is one type of commonly used spatial models which take into account the effects of spatial autocorrelation by assuming it as an intrinsic part of the ecological process (Legendre and Legendre, 1998; Anselin, 2005). It plays an important role in geographical analysis and has ability to predict a value of an outcome variable based on values of explanatory variables (Stieve, 2012). Although there are various correlation measurements, but there are two are widely used. One is Moran's I (Moran, 1948), and the other, is Geary's coefficient (Geary, 1954). The former is a generalization of Pearson's correlation coefficient, and the latter is analogous to the Durbin-Watson statistic of regression analysis. Compared with Geary's coefficient, Moran's index is more significant to spatial analysis (Chen, 2013). Stieve (2012), defined Moran's I as a ''test for spatial autocorrelation, which examines whether a phenomenon is clustered or not'', its values ranging from +1 (positive autocorrelation) and -1 (negative autocorrelation).

In the current study, autocorrelation statistic was applied to detect whether there is spatial autocorrelation or clustering of the residuals which violate the assumption of OLS. Progressively, the spatial independency of the NTFPs was assessed by using the global spatial autocorrelation coefficient Moran's I. This is defined by the equation according to Nkeki and Osirike (2013):

$$1 = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - y^-)(y_i - y^-)}{(\sum_{i \neq j} \sum_{wij}) \left[\sum_{i=1}^{n}(y_1 - y^-)^2\right]}$$

Where: n represents the total number of villages (polygons), I and j depict the various villages, y and yj is the residuals of location i and j respectively, while y is the mean of the residual and wij represents a spatial weight matrix for measuring spatial proximity between i and j locations.

4.2.2.3 GWR

The global modeling techniques, such as OLS linear and other nonlinear models cannot detect spatial variation and relationships within geographic entities. As a result, intrinsic relationships may be obscured and spatial association between variables in a region is concealed (Nkeki and Osirike, 2013). Such incomplete information derived from global statistics, when adopted for addressing policy issues, may be counterproductive. To strengthen this weakness, statistical geographers (Brunsdon *et al*., 1996; Fotheringham *et al*., 2002) recently came up with GWR, which has been introduced to solve such problems related to spatial non-stationary (Brunsdon *et al*., 1996). It is a technique designed to explore spatial non-stationarity or heterogeneity in geographic dataset which global statistical models cannot explain the relationship between sets of variables into it (Nkeki and Osirike, 2013). This regression method modelling the local relationships between the predictors and an outcome of interest, it capable of handling various relationships of variables in local spatial patterns for modeling, examining, monitoring and decision making (Fotheringham *et al*., 2002; Shrestha, 2006). Such analysis is conducted within a single framework, where the final outputs of the analysis provide a variation of variables in local spatial patterns and a map of the spatial variation in relationships (Fotheringham *et al*., 2002; Luo *et al*., 2009; Jamhuri *et al*., 2016). The recent integration of GWR into ESRI ArcGIS has further increased the quality of output. For example, GIS-based GWR has spatial capability of displaying the parameter estimates and coefficient of determination regarding all variables in a raster surface and vector map respectively for easy and quick visual interpretation of relationships and the detected spatial patterns. GWR has an immense application in almost every domain, including ecological and RS studies (Foody *et al*., 2003). For instance, it used to analyze the forest structural attributes collected from the field measurements and spectral response extracted from the coincided remotely sensed imagery (Foody *et al*., 2003; Lu *et al*., 2004a). Khamis (2012); Netrdová and Nosek (2016) used it to analysis the regional unemployment rate in Europe. While, Shi *et al*. (2006) engaged GWR to investigate the effects of local spatial heterogeneity on multivariate relationships of white-tailed deer distribution, using LC patch metrics and climate factors. In addition, Hu *et al*. (2015) used it to improve the ecosystem service in Fuzhou City, China. On the other hand, Gao and Li (2011) applied GWR to examine spatially non-stationary and scale-dependent relationships between urban landscape fragmentation and related factors. Clement *et al*., (2009) used GWR to analyze the factors that drive the afforestation in Northern Vietnam. Meanwhile, Propastin *et al*., (2008), applied it to investigate the impact of scales on prediction of rainfall uncertainty. Besides that, Wang *et al*., (2005) applied GWR analysis to estimate the Net Primary Production (NPP) of the Chinese forest ecosystems. The underlying tenet of GWR is that, parameters are estimated anywhere in the region of study given a criterion variable and one or set of explanatory variables which have been measured in a known location (Charlton and Fotheringham, 2009). Where, it generates an equation for every component in the dataset by calibrating each one using the target feature and its neighbors. In this respect, nearby features produce a higher weight in the calibration than distant features (Scott and Janikas, 2010). This approach may likely uncover spatial relationships or associations neglected by OLS (Nkeki and Osirike, 2013). The model multiplies geographically weighted spatial matrix consisting of geo-referenced data. The matrix defines the neighborhood spatial relationships between villages and aid the detection of spatial variation in the relationship among the variables. The traditional global regression framework can be represented in the following equation:

$$\mathrm{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n + \varepsilon \qquad (1)$$

Where: Y: Dependent variable, X: Explanatory variables, while β_0: Intercept, β_n: Coefficients and ε: Residuals.

The basic GWR model as developed in (2) by Fotheringham *et al*., (2002) is estimated as:

$$Y_i = \beta_0(u_{i,} v_i) + \sum_k \beta_k\,(u_{i,} v_i) X_{ik} + \varepsilon_i \qquad (2)$$

Besides standard regression notation, the term (ui, vi) denotes the geographic coordinates of the *i^th^* point in space. Hence, equation (2) yields i local regressions over each sample point, and a total of i*k regression coefficients.

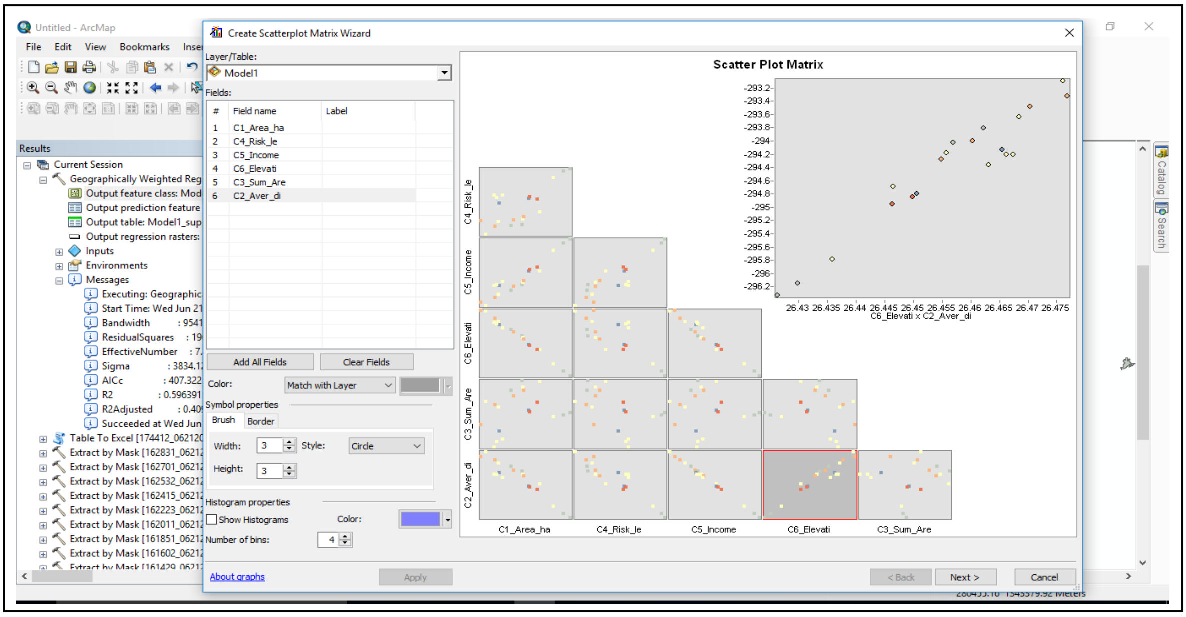
If the relationships do not exhibit spatial variability, (2) coincides with (1). Under standard regression assumptions, both equations can be solved by the OLS method, which includes a spatial weight for (2). The major output from GWR model for each observation (settlements) is a set of parameter estimates (local coefficients for each explanatory variable) and associated diagnostics (standard errors, Cook's D statistics, local R, statistic, and local standard deviation) that can be visualized within a GIS platform (Charlton and Fotheringham, 2009; Fernandez *et al*., 2013). The series of maps often generated are vital tools for understanding the level of spatial relationship and show locations were each predictor exhibit stronger influence on the dependent variable.

GWR was originally developed for the analysis of spatial point data to allow for the interpolation of values that are not included in the data set. It is applied under the assumption that the strength and direction of the relationship, between a dependent variable and its predictors, may be modified by contextual factors. In this application, spatial units (settlements) vary in size and shape over the study area. Consequently, an adaptive kernel was preferred to allow the automatic specification of appropriate distance or number of nearest neighbors. This allows the spatial context (Gaussian kernel) as a function of feature density to vary in extent, where, it constructs a smaller spatial context, where the feature distribution is denser and larger spatial context from one handand distribution is sparse from the other hand. Shahid and Bertazzon, (2015) defined the bandwidth of adaptive kernels as the number of nearest neighbors forming each local area. Based on Brunsdon *et al*., (1996), the weight inside the bandwidth reaches a monotonical zero as the distance increases. The study used Akaike information criterion to select the optimal bandwidth according to Weisent *et al*., (2012). The bandwidths of 50 nearest neighbours were used in both regressions.

4.2.2.4 Simulation Modeling

Simulation modeling methods are used to understand dynamic complex systems and to predict the outcome of change (Ingalls *et al*., 2008; Shahidand and Bertazzon, 2015). In this study a simulation system dynamics model was specified in ArcGIS software version 10.1. The simulation model was structured around the GWR NTFPs model. The study used the scatter plot matrix graph to compare the datasets to look for patterns and relationships to be used in simulation as shown in Figure 4.3 below.

Figure 4.3: Scatter plot matrix



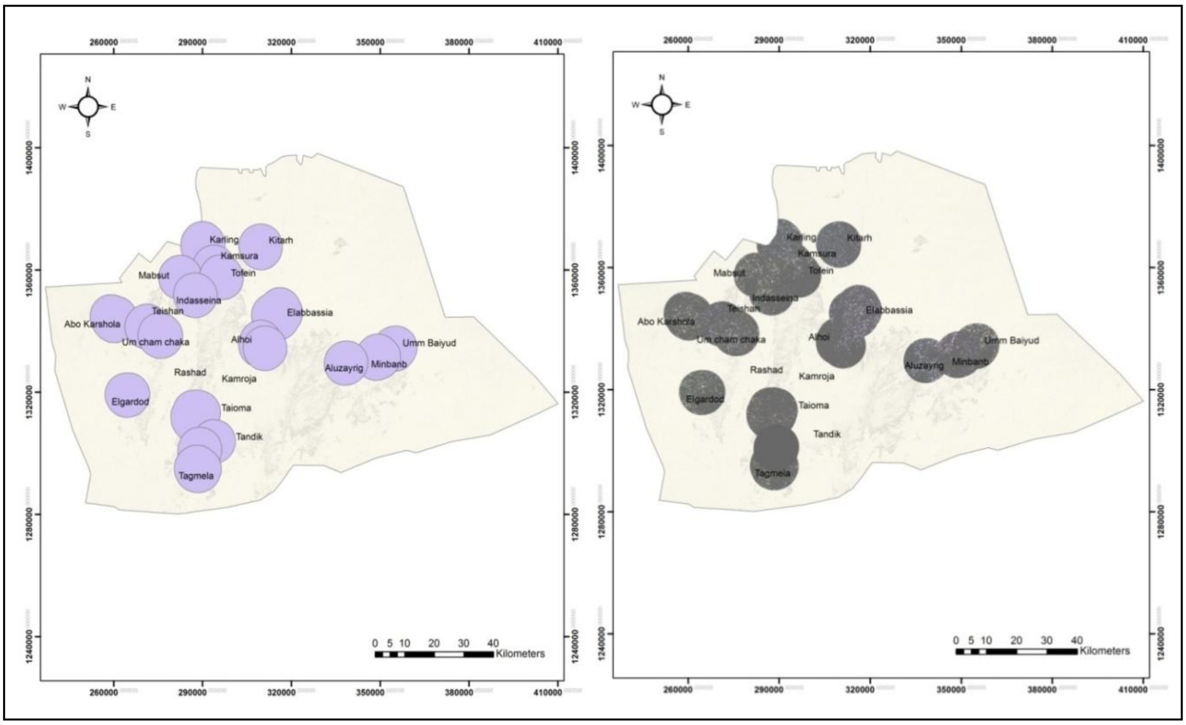
After testing variables, three major categories resulted from GWR analysis, which were identified and selected for the analysis as explanatory variables, namely; risk level, sum of the forest area and average of distance (Table 4.1).

Table 4.1: Predation variables test

FID	Cond	LocalR2	Predicted	Intercept	C1_Aver_di	C2_Sum_Are	C3_Risk_le	StdError	StdErr_Int	StdErrC1_A	StdErrC2_S	StdErrC3_R	Source_ID
0	10.29649652	0.843882389	1566.614626	4724.114086	-782.6667712	0.932057594	-40.11443514	852.0304408	1383.322209	303.6810344	0.252544544	13.84064505	0
1	9.36540762	0.861910805	1056.165889	4564.28265	-847.6164746	0.999700717	-35.55921859	911.0529936	1366.478692	281.5248902	0.243481496	13.35760715	1
2	9.932657338	0.854116766	2182.876683	4804.929291	-846.8362893	0.950125288	-38.15596727	667.3982946	1377.113899	301.1486013	0.250475349	13.7789465	2
3	10.64587234	0.836010589	1947.076709	5165.725759	-846.957162	0.907716363	-41.61539401	597.2484157	1353.228595	291.0818289	0.249526368	13.21069819	3
4	9.686018959	0.861642323	2801.51873	4840.819149	-888.5246338	0.964472723	-36.74295258	466.6991707	1376.269256	300.65545	0.249450527	13.78350821	4
5	10.33938494	0.845086658	6726.252129	5225.781499	-910.7613132	0.925306628	-39.45233956	914.6939833	1345.889607	288.4316851	0.247385018	13.13761446	5
6	8.462794295	0.895977207	2206.001918	4713.100886	-1022.822859	1.094924877	-30.38511827	1156.904792	1387.630077	284.5015731	0.251237018	13.46159025	6
7	11.70755418	0.817123815	4868.129312	5853.823565	-906.1205415	0.843384457	-45.44183088	660.9162822	1356.16284	289.4921196	0.249116141	12.99020812	7
8	11.36813132	0.82516536	5310.031606	5803.844224	-949.2877514	0.86464202	-43.14386398	585.5405094	1344.053841	286.146518	0.246634405	12.83652777	8
9	11.2298722	0.829995089	1407.785362	5840.249803	-990.4515234	0.873983043	-41.72489446	777.6005038	1338.774893	284.9982513	0.24510511	12.76757062	9
10	8.592544525	0.916735307	2237.670397	5292.697498	-1260.849873	1.096427036	-26.6494914	602.2520779	1402.474932	312.8454788	0.255475739	13.73069201	10
11	8.72777296	0.912419475	8568.351485	5228.242048	-1236.308159	1.105785513	-26.97308995	818.361237	1390.031203	303.1440878	0.254675131	13.47137937	11
12	9.709189213	0.869272081	985.3486609	3938.414853	-746.4320325	1.169318071	-32.67122462	1095.592624	1418.06996	291.604586	0.258216925	13.16588291	12
13	9.715963028	0.871128184	2331.181185	4003.515347	-770.0897467	1.172528136	-32.40605383	582.3780514	1412.476198	290.2139935	0.257181471	13.07191175	13
14	9.621427334	0.875199709	3886.040197	4162.196685	-827.5637279	1.170242281	-31.77535982	692.3232695	1398.609183	284.7607452	0.255212227	12.92812524	14
15	12.13641808	0.822240784	4456.146699	6497.208387	-1106.892819	0.817912891	-42.66437697	768.2648968	1381.488178	302.2866264	0.247860215	13.32304756	15
16	12.02797077	0.857528851	7549.808259	6959.626826	-1439.635488	0.850396003	-33.29418224	763.0371519	1430.565788	334.4576851	0.246689977	13.49919937	16
17	13.06279859	0.884692907	4152.649858	7769.765901	-1753.905627	0.80927571	-28.25380589	649.0924578	1680.325934	413.0820175	0.270885782	14.73819367	17
18	13.15275535	0.868969712	6480.570752	7744.1305	-1667.266518	0.785129199	-31.11641948	696.3194116	1654.074782	402.5638815	0.269624359	14.93494225	18
19	13.73822139	0.871137771	4508.978114	8114.565624	-1741.752816	0.740413313	-31.1652987	441.510626	1799.339112	435.186149	0.288134238	15.85590288	19

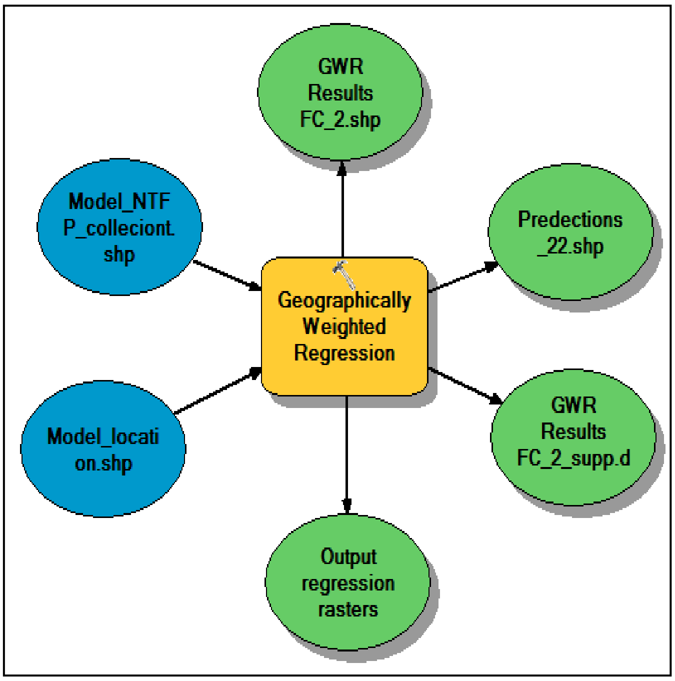
The dependent variable in this model is the quantities of NTFPs collected in the years 2008 and 2014. These statistical values were entered into the prepared GIS vector polygon map as non-spatial data. To visualize the spatial distribution of such data, hotspots were selected to calculate the elevation and density of forest (Dense and Scattered forest), based on the class of forest which resulted from the analysis of image 2014 for the selected villages in the study area.

Figure 4.4: Buffer zones created to calculate the forest density (right) and the elevation (left) within specific distance to settlements.



Once the simulation model was tested in equilibrium village, interventions were introduced. The GWR model results were inspected to identify neighbourhoods, where community's forest dependency is high, on the one hand, and the collect of NTFPs is low and significantly associated with selected variables on the other hand. The local NTFPs quantities collected interventions were simulated on the selected 19 settlements, based on two alternative scenarios: a 0 to 10 points (low/negative), and a 10 to 20 points (high/positive) increase in risk level, while all the two explanatory variables are modifiable at some scale. Based on the quantities collected of NTFPs data for the years 2008 and 2014, the model ran a simulation from 2014 to 2030. After this initial intervention, GWR models were re-run on the new collected NTFPs values, and the quantities collected were still significantly associated with risk level. The same steps were done to simulate the local forest density. Based on the area of forest, for year 2014, the model ran a simulation from 2014 to 2030. After this initial intervention, GWR models were re-run on the new density forest values, and as well the density was still significantly associated with average distance for each village. Figure 4.5 below, shows the complete simulation model with all the GWR coefficients and variables.

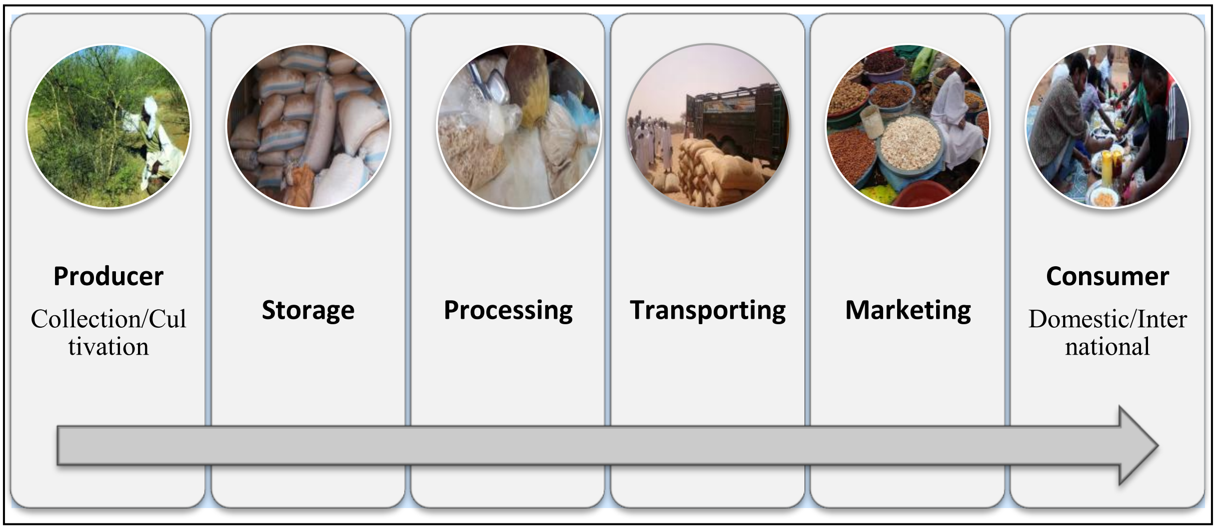
Figure 4.5: The model's framework



4.3 Results and Discussion

NTFPs value chain, in the present study, can be broken down into several sub-sets of activities (Fig. 4.6) including; production, collection, processing, storage, transporting, marketing, and sale. The current finding agreed with Belcher and Schreckenberg, (2007); Deafalla, (2011); Deafalla, (2012) who have indicted in their review the sub-sets activities of NTFPs commercialization and NTFPs value chain.

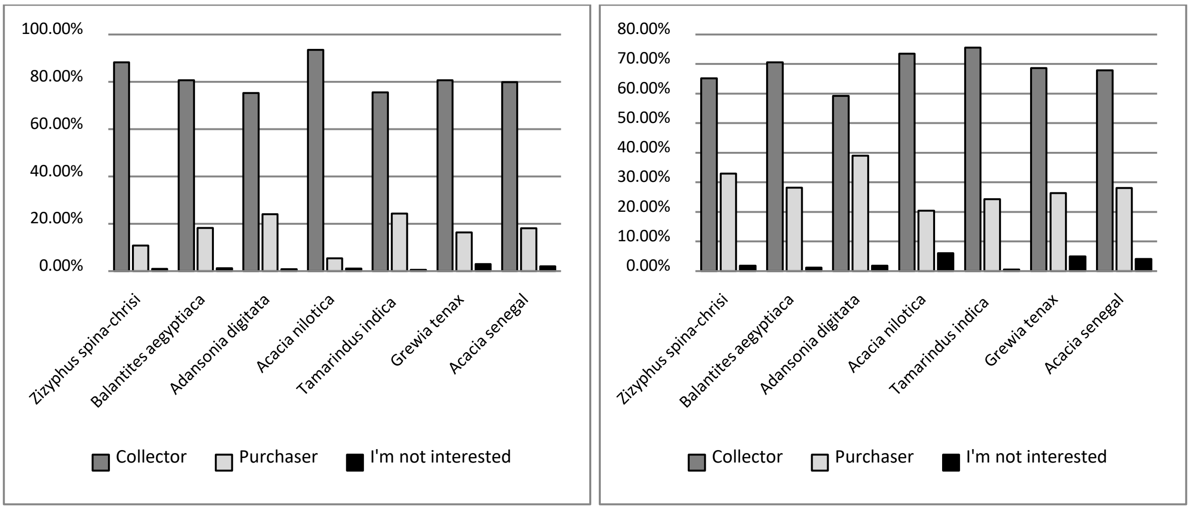
Figure 4.6: Production-to-consumption NTFPs systems



4.3.1 Collection

The largest quantity collected was found to be from *Zizyphus spina-chrisi* (50%), followed by *Adansonia digitata* (21%) and *Balantites aegyptiaca* (16%), this is related to the high demand for these products. Meanwhile, *Tamarindus indica* and *Acacia nilotica* represented only 6% and 1% respectively. On the other hand, although prices of *Acacia senegal* and *Grewia tenax* are high, their collected quantities were smaller, compared with the other products. Which represent only 3% and 1% respectively, and this is directly related to the difficulties of product collection due to the fact that the distance of forests are far from the location of villages.

Figure 4.7: Source of NTFPs for each product for Displaced Households (left) and Non-Displaced Households (right)



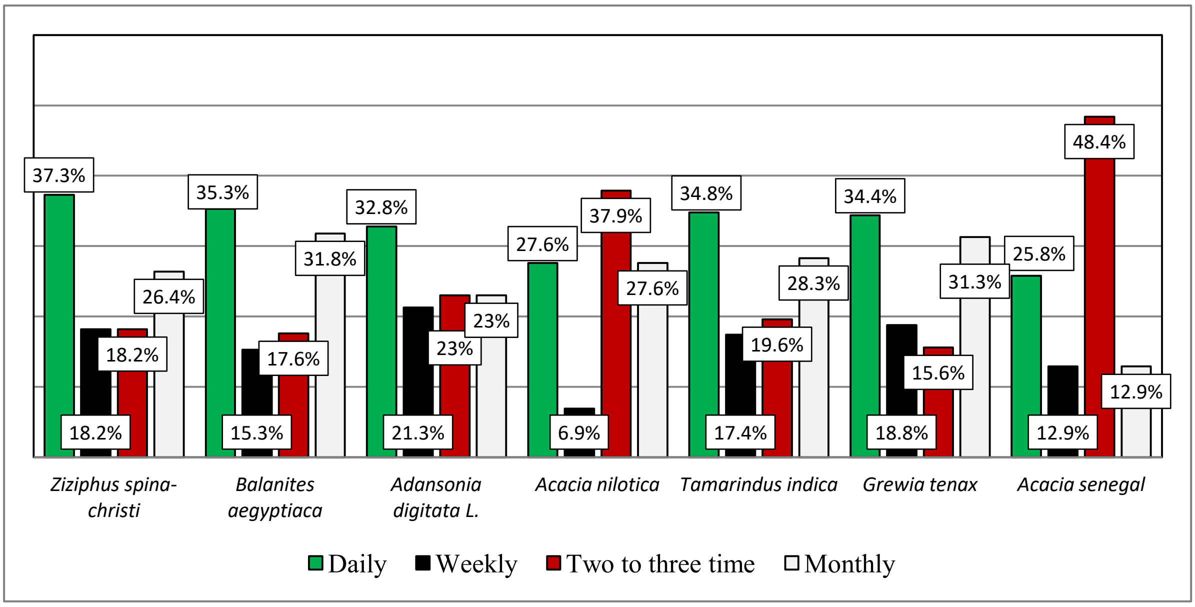
The study indicates that, the quantities collected by displaced household were higher compared with non-displaced household (as shown in Table 4.1 below). This can be explained by the fact that the location of their campus is in the high mountains, where rich forest resources are available and accessible.

In the primary stages of forest product value chains, women often take on roles that they take account of the socio-cultural environment in which they live, as well as their physical capacity (Purnomo *et al*., 2011; Shackleton *et al*., 2011; Shackleton *et al*., 2012). That agreed with the current search finding, where the study found that women are often responsible for NTFPs collection, for example, *Zizyphus spina-chrisi*, *Balantites aegyptiaca*, *Tamarindus indica* and honey (Fig. 3.24 in chapter three). Where this involves spending long times in far remote areas or specific techniques, the collection is done by men.

The frequency of NTFPs collection was daily for all products, the exception was for *Adansonia digitata*, *Grewia tenax*, and *Acacia senegal* represented in Fig. 4.8 below. The time spent in a trip of collection of *Zizyphus spina-chrisi*, *Balantites aegyptiaca*, *Tamarindus indica* and *Acacia nilotica* ranged between (2hr: 55 minutes to 2hr: 97 minutes). While *Acacia senegal* needed 2hr to 2hr: 48 minutes. The products that needed the longest collection time were *Adansonia digitata* and *Grewia tenax* which took about 3hr: 05 minutes. This is directly related to difficulties of product collection due to the long distance to the collection sites and harsh topography, where these particular species are located, as mentioned earlier (Annex 21). For non-displaced households, distance to place of collection of all NTFPs products ranged from 2.32 to 2.78 kilometer except for *Acacia senegal* that was at adistance of 1.92 kilometers (Annex 22), while, the situation differed with displaced households, where the distance to place of collection of all the NTFPs products ranged from 0.52 to

1.50 kilometer. That was due to the fact that they collected the products during their trip from their camps in mountains to/from towns.

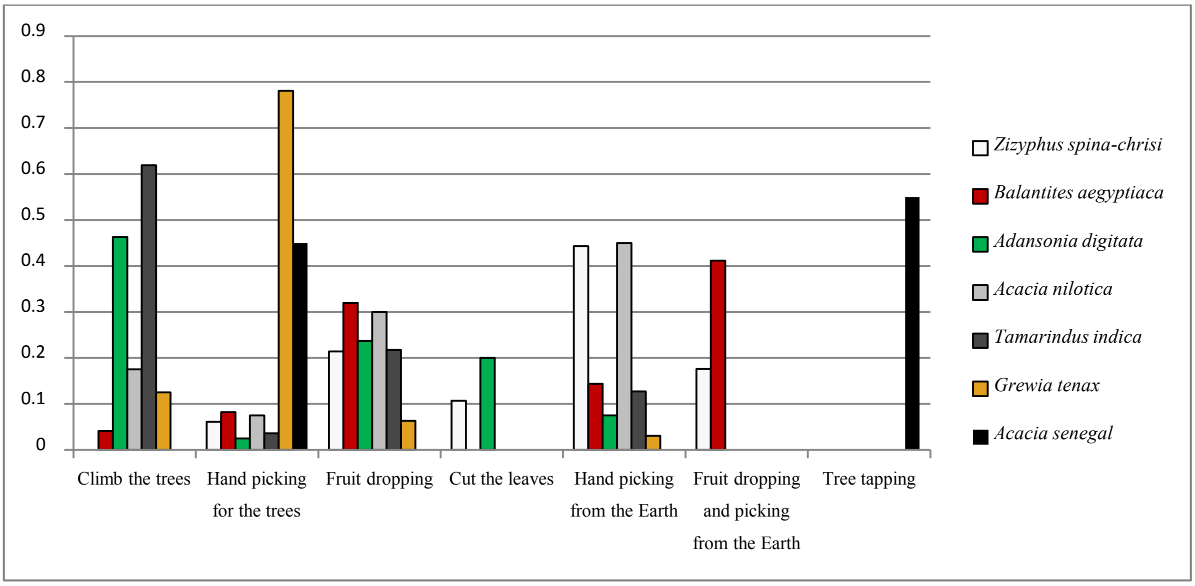
Figure 4.8: Frequency of NTFPs collection



The study showed that, the collection of *Zizyphus spina-chrisi*, *Balantites aegyptiaca*, *Adansonia digitata* and *Acacia nilotica* is taking place during the period from November to December. *Tamarindus indica* was collected in January to February. Meanwhile, *Grewia tenax* was collected during the period from September to October. The *Acacia senegal* collection was done during January and February, 18.2% of households practiced collection from September to December (Annex 23).

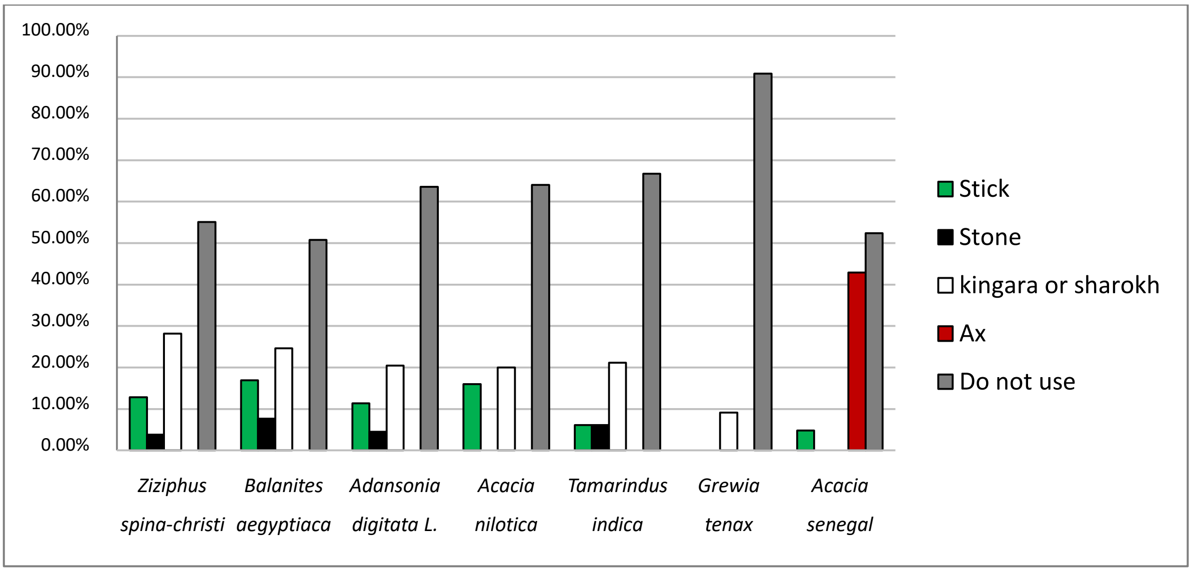
The techniques used in extraction of the concerned NTFPs in the study area showed great variations among different NTFPs and respondents as presented in Figure 4.9 below.

Figure 4.9: Methods applied for products collection



Deafalla (2012), in her research reported that, the harvesting techniques of forest products have direct effect on forest and can result in severe environmental damages, when devoid of careful planning and management. For instance, in the Congo Basin, the bush meat crisis is directly linked to commercial hunting for the meat of wild animals; it is an example of serious environmental impacts of NTFPs use and trade (FAO, 2005). The study agreed with Duong (2008), who described the positive impact of NTFPs to forest conservation as "harvesting of NTFPs usually has a lower impact on the forest ecosystem than timber harvesting and can provide an array of social and economic benefits, particularly to community operations, and can therefore be an important component of forest ecosystem management". The study revealed that, there were no advanced harvesting techniques used for the harvesting of various NTFPs in the study area. Very simple tools and no external inputs were used. In addition, most of respondents don't use any tools for harvesting of NTFPs.

Figure 4.10: Tools used for products collection



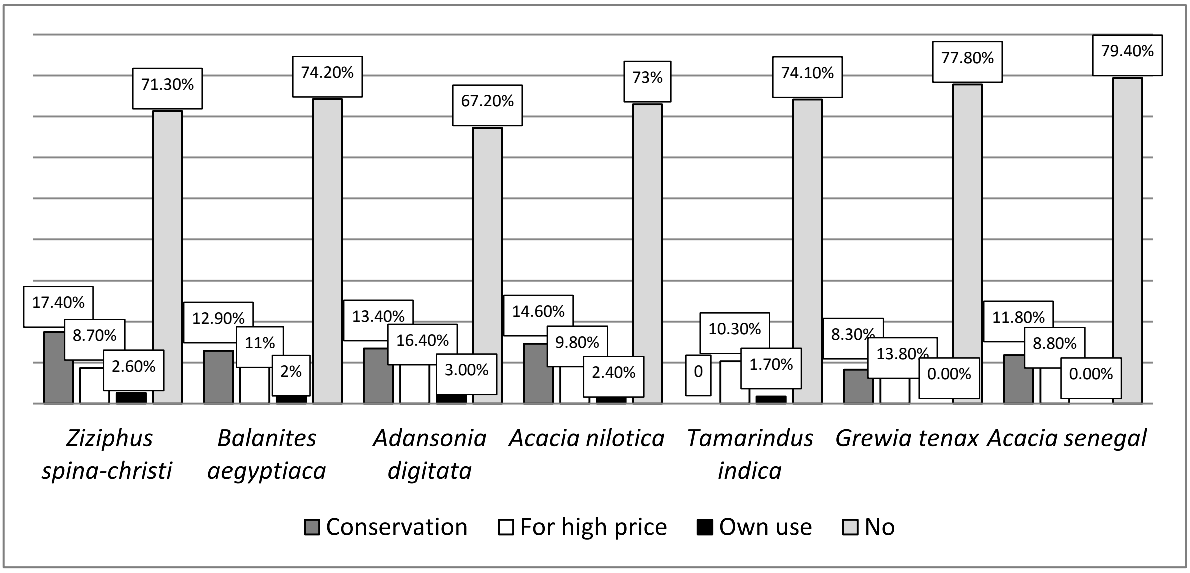
The main problems facing the NTFPs collection were; the war (15.2%), followed by the long distance (13.3%), natural climatic conditions (7%), lack of transportation (7%) and 'All of these reasons are true' (4%). In contrast, 53.2% of households responded that they are no facing any problems in the collection of these products.

On the other hand, a considerable number of households preferred to purchase the NTFPs due to their inability to collect, due to reasons of security (3.2%), health reasons (22.3%), customs and traditions (16.5%), far distances to the nearest forest (3.2%), and (54.8%) have no interest to collect these products. Elabbassia, Rashad and Um Baraka were the main markets for NTFPs's buyers followed by village's market and Tabassa (Annex 20).

4.3.2 Processing and Storage of NTFPs

Post harvesting practices e.g. drying, processing, storage and packaging can make a major difference in the price and quality of product (Pandey *et al.*, 2016). Women play significant roles in the processing stages, although these roles are often informal and so are not recognized (Shackleton *et al.*, 2012). In many developing countries, in the processing stages women are often given the most labour-intensive tasks, and the tasks that require dexterity and patience. Jobs involving this kind of work tend to be part-time, require less skill and are poorly paid. For example, in Zambia, women monopolise homestead taverns where they make and sell honey beer (Shackleton *et al*., 2012), where, they work at home and the money they earn contributes to the cost of educating their children. Another case is from Namibia, where the introduction of mechanical fruit presses meant that men took over collecting and processing marula fruit into juice.This was previously done only by women (Shackleton and Shackleton, 2005). Results revealed that most respondents (89.9%) don't store or make any processing for NTFPs collected. Meanwhile, 10.1% of respondents store these products and crush the fruits of Sider and Tabaldi to powder for selling. The main reasons for storing NTFPs were conservation, achievement of higher prices and for own later use (Fig. 4.11).

Figure 4.11: Reasons of NTFPs storing



This result agrees with the findings of Belcher and Schreckenberg (2007) who state, that small scale NTFPs producers are often at a disadvantage in marketing their product because they produce small volumes of inconsistent quality in relatively remote areas. If their product is perishable they have the additional pressure of having to sell the product before it spoils. Investment in post-harvest storage and processing can extend the economic life of the harvest, reduce some of the urgency for selling, and allow for the collection of larger volumes at one time and in one place by a single producer or by a group of producers. In this way producers can gain considerable bargaining power, and create efficiencies in the overall market. Likewise, investment in value-added processing, in the production area, can pay off. Concentrating on the valuable component of the product can greatly reduce transport costs and lead to greater profits for producers. In many cases, the first step is to communicate consumer requirements to producers. In the study area the source of expertise in collection, handling and storage methods and the use of products is inheritance. In addition, 91% of respondents did not participate in any extension services programs or capacity building workshops to deal with managementof products. A need arises for improving existing tools, introducing improved ones, training and availing better storage and utilization facilities. Investments in value added processing and transportation is badly needed. Most important, however, is the adoption of management systems that sustain the resource base as well as the yield.

4.3.3 Transport Modes

NTFPs haulage to the point of delivery in markets is traditionally carried out by various types of transportation namely; Truck (Lorry), bicycle, Cart (Caro), donkey and self-transportation (going by foot). The study found Trucks is the main transportation method used in normal times as well as in times of rain or war (Annex 24), which fits well, to some extent, with the topographic and soil condition in the study area. However, the problems of trucks are; in the poor, or absent in some cases, links between roads and villages, with the local and the regional markets. Most of the villages in the study site are normally completely cut-off from the rest of the country, during the rainy season, due to the muddy soil type which inhibits vehicles. Additionally facing the looting or land mines, as well as in times of war the availability of trucks becomes scarce. Meanwhile, Caro and donkey or self-transport are used, especially when the quantity sold of NTFPs is small. Transport cost was about 1.8 to 3.65 (Euro) for every sack and sometime about 4.55 € to 5.5€ especially for *Acacia Senegal*.

4.3.4 Trading and Marketing

Table 4.2 below clarifies the quantities collected, consumed and sold by households. However, the percentages are variable among different NTFPs. *Zizyphus spina-chrisi* represented the highest percentage of sold quantity (50%), followed by *Adansonia digitata* (24%), while 15% for *Balantites aegyptiaca*, about 6% *Tamarindus indica*, 3% for *Acacia senegal*, 1% *Grewia tenax*, and 1% *Acacia nilotica* from the quantity sold.

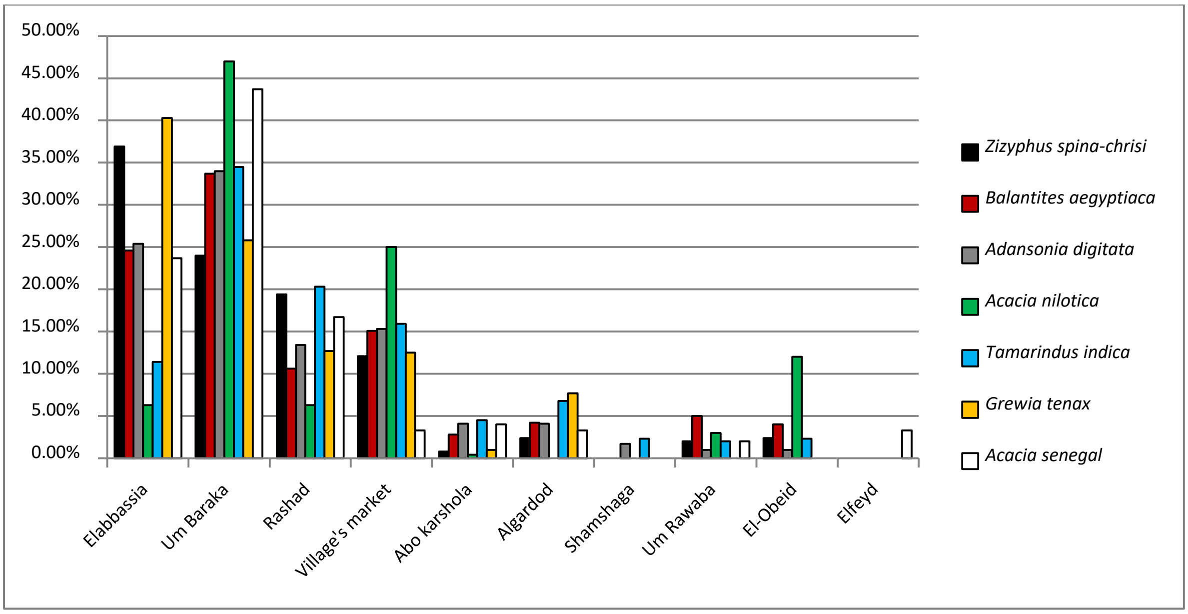
Table 4.2: Quantity of NTFPs collected, consumed and sold (kg)

Products	Status	Quantity collected from NTFPs (kg)	Quantity consumed of NTFPs (kg)	Quantity sold of NTFPs (kg)
Zizyphus spina-chrisi	Non-displaced Households	168550	107185	61365
	Displaced Households	94275	4275	90000
Balantites aegyptiaca	Non-displaced Households	53800	37815	15985
	Displaced Households	40867	2259	38608
Adansonia digitata	Non-displaced Households	73480	53510	19970
	Displaced Households	35578	1561	34017
Acacia nilotica	Non-displaced Households	4410	360	4050
	Displaced Households	23987	200	23787
Tamarindus indica	Non-displaced Households	20325	10545	9780
	Displaced Households	43561	368	43193
Grewia tenax	Non-displaced Households	3695	1290	2405

	Displaced Households	45671	345	45326
Acacia senegal	Non-displaced Households	10609.5	5554	5055.5
	Displaced Households	39271	147	39124

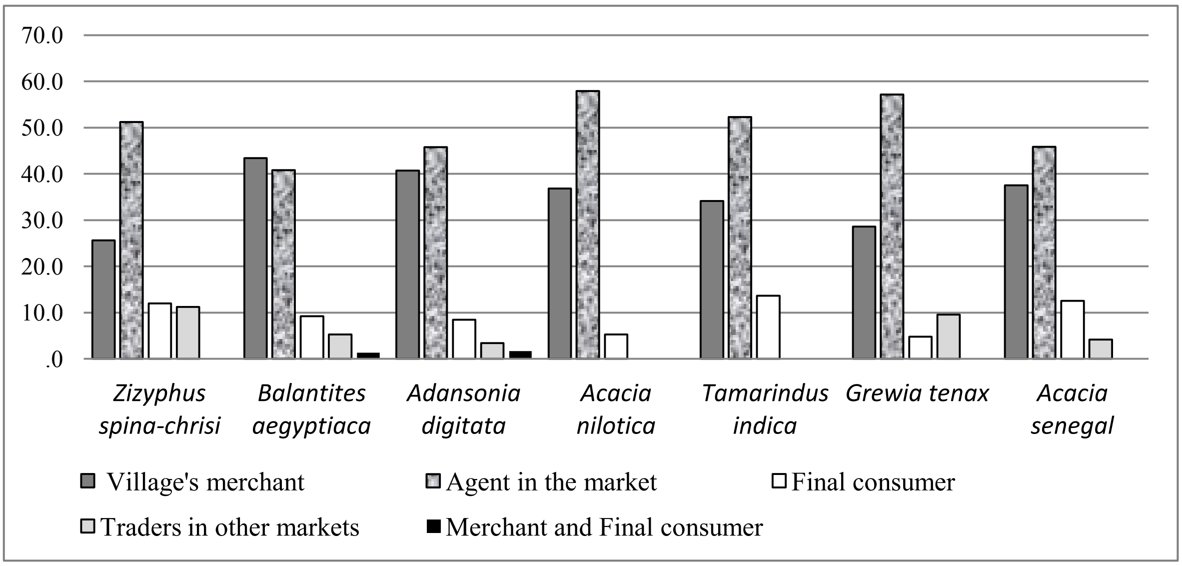
In Nuba Mountains, fruits of these trees are found in most local markets throughout the year, especially *Zizyphus spina-chrisi* which ranked among the most important NTFPs in Sudan according to FAO (1997). Elabbassia market is the main market for sale of NTFPs in the study area, namely, *Zizyphus spina-chrisi*, *Balantites aegyptiaca*, *Adansonia digitata*, *Tamarindus indica*, *Acacia senegal* and *Acacia nilotica*. This is directly related to geographical location, followed by Um Baraka, the second-biggest market in the study site, after Rashad market. All products were also sold in the village market (Fig. 4.12).

Figure 4.12: Main market of each product



In study area, the market of NTFPs is extremely disordered and unstructured. At present forest dwellers collect NTFPs and sell it to local traders, who in turn sell it to the urban centre and finally reach to consumers as clarified in Fig. 4.13 below. Unfortunately, the general pattern in much of the literature on NTFPs such as Neumann and Hirsch (2000); Deafalla, (2012); Amusa *et al*. (2017) who indicated that, the relationships between collectors and traders particularly the middlemen or intermediaries, are economically exploitative. The distribution channel from forest collector to urban wholesaler consists of 3-5 agents in the market speak the language of the tribals and in many cases shell out loans as advance payment for NTFPs. They have great influence on the marketing process of NTFPs as they are able to provide local people with essential resources and services. This agreed with Taha *et al*. (2015) in their study. On other hands, these intermediaries hustle the tribal, cheating them on weights and rates as tribals mostly count in traditional scales and are unfamiliar with the metric measure. The tribals have to sell their material as they need the money to buy weekly supplies.

Figure 4.13: Buyers of NTFPs in the study area



Yet most communities living surround forest have poor access to markets, insufficient capital to invest in improving their livelihoods and little or no bargaining power when selling their products in markets. Due to lack of direct access to markets, they depend on intermediaries to sell their products, reducing their share of the income. There were at least four levels of intermediaries between the collectors/gatherers and processing centre or the main markets in Khartoum state. Ghosal (2013) reported that, marketing of NTFPs through formal channels are a complicated task in the Global South because of the lack of suitable infrastructure and the influence of intermediaries. Strengthening the formal marketing process, on the one hand, can reduce the exploitation of forest products while improving the socio-economic status of forest fringe villagers.

At the local markets, production varies across products, locations and individual households. The relative importance of each differs from product to product, which may not occur sequentially and some may even be repeated or omitted for particular products, this agreed with Marshall *et al.* (2003b); Shackleton *et al*. (2007); Belcher and Schreckenberg (2007). These products are sold and bought many times, adding value at each step, before reaching the consumer and/or final user. In general, the relationships between actors in the value chain of these products, from the collectors, middlemen, traders to wholesalers, vary from one state to the other. In addition, the roles and returns on profit to actors in the chains changed over the time of study and that were mainly related to the Sudanese currency inflation.

Investigation of the marketing channels of NTFPs has shown that pricing of products is largely decided by the market intermediaries. Although our study did not explore the profit margin distributed along the market chain, several related studies have shown that collectors have the smallest profit margin in the NTFPs market chain (Mhapa, 2011; Piya *et al*., 2011). Furthermore, NTFPs collectors are unorganized and dispersed, where trading is done individually. Moreover, they have lack in knowledge and skills for product transformation. Necessary marketing information, to gain leverage in the market, is lacking; as well, there is a lack of related business assets, such as storage and transport (Ahenkan and Boon, 2011). Indeed the interaction of these factors leads to low returns and exploitation for NTFPs collectors. The present findings on NTFPs related market knowledge agree with the report of Kar and Jacobson (2012) working on trade in NTFPs in Chittagong Hill Tracts of

Bangladesh and are consistent, as well, with Amusa *et al*. (2017) who studied the socio-economic factors influencing marketing of NTFPs in south-western Nigeria.

There is a striking note in the practice of intermediaries putting demand with the collectors before NTFPs collection and advancing payment in form of credits. This has been observed to tie the collectors to the apron-spring of the traders through debt or patron client type relationships, this agreed with (Neumann and Hirsch, 2000). Therefore, Piya *et al*. (2011) suggested that, shortening the marketing chain would leave more of the NTFPs value in the hands of the collectors. Most respondents are quite aware of the shortcomings of the system, but did not have the capital or the connections to remedy the situation.

Generally, market constraints often reduce the bargaining power of the poor harvesters supplying the products (Bhattarai *et al*., 2003). Insufficient and poor transportation services, as well as product distribution within the forest, were the major constraints for the collection and marketing.

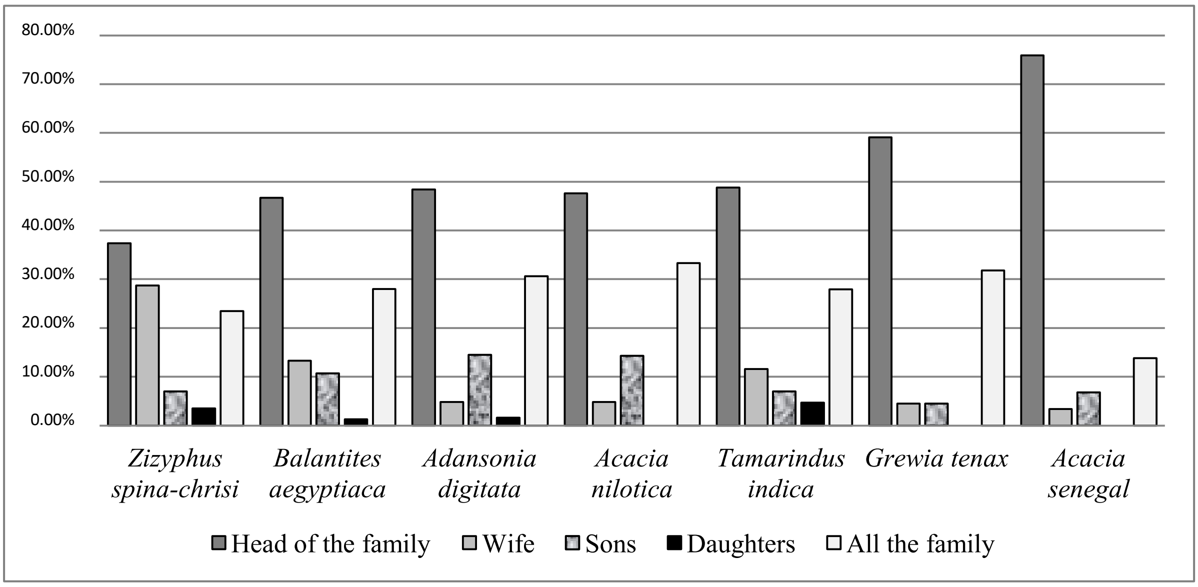
Despite the important values of the products, however there is a variation in price, the market value of NTFPs not only varies with season, but with the availability of the products and demand (Table 4.3).

Table 4.3: Products prices

Products	N	Highest Price (SDG)	LowestPrice (SDG)	Mean	Std. Deviation
Grewia tenax Price for (kg)	33	65	60	4.9	2.3
Acacia senegal Price for (pound)	34	60.5	58	2	1.6
Adansonia digitata Price for (kg)	80	53	50	2.7	1.2
Tamarindus indica Price for (kg)	59	50	45	2.2	1
Zizyphus spina-chrisi Price for (kg)	128	46.5	40	1.6	0.9
Balantites aegyptiaca Price for (kg)	96	46	40	1.4	0.72
Acacia nilotica Price for (kg)	19	7.5	3	1.3	0.78

The results found that there is an influence of some socio-economic factors on NTFPs marketing by households. According to the marketing experience factor, the main member who sells NTFPs was head of the family. This clarified in Figure 4.14 below. In many developing countries, sometimes the only way women in remote rural communities can earn any cash is by trading NTFPs in local markets. However, women’s roles in trading and marketing forest products are also often not part of formal value chains and are likewise overlooked. In the study site, the study showed that, women's economic opportunities for trading and marketing of NTFPs remain restricted by the rigid cultural patterns, tradition and social norms (Fig. 4.14).

Figure 4.14: Member of household concerned with marketing of NTFPs



The tradition and social norms represented (84.5%), following by 'there is no experience in selling' (9.10%) and 'no particular reasons' (6.40%), particularly women in age between 15 to 35 years. Unfortunately, the low profile of women in trading and marketing means initiatives to promote trade in NTFPs do not factor in how they can benefit women (Neumann and Hirsch, 2000; Hasalkar and Jadhav, 2004; Schreckenberg and Marshal, 2006).

4.3.5 Modeling the heterogeneous factors affecting NTFPs

4.3.5.1 Impacts of the Socio-economic factors in NTFPs

Recently, socio-economic benefits of service roles of forests are recognized, but have not been properly integrated in forest management for sustainable development (FAO, 2003). However, especially in most developing countries, estimates of socio-economic values of NTFPs are not available. Where they are available, they are normally underestimates. There is a vast array of NTFPs being traded locally and nationally. In Africa, for example; an assortment of fruits, spices and medicines from various open-air markets, for poverty alleviation, are traded, though there is not much information to demonstrate this. However, when local people are well organized they can often generate more income from NTFPs activities (KSLA, AAS and FAO, 2005). In the Sudan, research on NTFPs is limited. Socio-economic research is even scarcer and is usually related to Gum arabic (El Abass, 2009; Mohammed, 2011; Deafalla and Dafa-Alla, 2012) and on some resins (El Abass, 2009). Other studies such as FAO and FNC (1995); El Amin and Ballal (1996); Deafalla *et al*. (2014c) provided description data on production and consumption of NTFPs. The objective of this research is to identify the socio-economic factors that affect collection, consumption and trade of these products. It is hoped to reveal gaps in knowledge, on the roles of these factors on NTFPs, to help processes of policy and strategy formulation and to develop appropriate interventions. The study examined many factors that could affect NTFPs collection. Some of them haven't any influence in the household decision to collect NTFPs, such as Age of responders, household size, market and tribe (Annex 25). In contrast, the most commonly recurring factors that affect levels of dependency on these products were: Gender, education, main occupation, duration of the main occupation, distance of villages and migration.

1- Influences of Gender

Analyzing value chains from a gender perspective provides an understanding of the roles that women and men they are play. Many studies supported the relationship between gender and resources management for example (Meinzen-Dick and Zwarteween, 1998) that suggests, the extent to which differences between men and women influence resource utilization and control patterns, decision-making power and livelihood strategies. That, beside the culture and tradition, religious beliefs, accepted divisions of labour and authority, household and family responsibilities, and physical abilities that also play a large part in determining what men do and what women do (Shackleton *et al*., 2012). For example, Campbell *et al*. (1997) stated that in Ethiopia, men like taking risk and hence are more likely to go to the forest and collect NTFPs compared to women. In contrast, Opaluwa *et al*. (2011) reported that in Nigeria females are more likely to collect NTFPs than their males. In the study area, some joint forest gathering activities do exist between men and woman, but the control has been observed by men on collection of these products. In general, women tend to fill lower paid and less responsible positions in value chains of these products than men. The study showed, in Table 4.3, there is a positive significant influence that affects the household decision to participate in NTFPs as a collector or a producer by gender; the only exception was on collection of *Acacia nilotica*.

2- Educational levels of households

Level of education is a significant indicator of the society's stock of human capital and refers to the years of education that an individual has completed (Little, 2003; CIPD, 2017). In all socio-economic studies education is included to measure the level of socio-economic development in the area, where it is an important contributor to productivity growth of the countries (Upendo, 2013). As shown in Table 4.3 below, the result agrees with Adhikari *et al.* (2004); Kamanga *et al*. (2009) who affirm that the education level of rural communities can influence their reliance on NTFPs production or trading. They find that households such as in Africa and in Nepal with higher education levels generally have more reliable sources of income opportunities and generally wider asset bases. The result indicated the significant influence of responder's education in *Balantites aegyptiaca* and *Adansonia digitata* collection.

3- The Main occupation and its duration

Dependence on these products, in study area, throughout the year, is affected by the type and duration of the main occupation as well as accompanying household needs (Table 4.3). Several large-scale studies showed the positive link between wealth status of households and NTFPs dependence (e.g.; Angelsen and Wunder, 2003), where the poor are more dependent than ever and basically derive a larger share of their overall needs from forest products and activities. That dependency varies according to season (Arnold, 1994). The result indicated the significant influence of these factors in *Zizyphus spina-christi*, *Balantites aegyptiaca* and *Acacia nilotica* collection. The study clarified that, most of responders were displaced from other localities of South kordofan state and their main occupation was to work as hired workers, in the form of farmers and livestock keepers, which directly affected, as clarified in Table 4.4, the collection of these products.

Table 4.4: Socio-economic Factors that affect collection of NTFPs

Products	**Gender**		**Education of head household**		**Education of wives**		**Main Occupation**		**Duration of the main Occupation**		**Distance of villages**		**Migration**	
	Correlation Coefficient	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**	**Correlation Coefficient**	**Sig. (2-tailed)**
Zizyphus spina-chrisi	0.012	0.885	.137	.086	.010	.912	.091	.257	.017	.836	.281	.000	.282	.001
Balantites aegyptiaca	.009	.920	.172	.048	.028	.783	.147	.095	-.112	.206	.004	.004	.312	.001
Adansonia digitata	-.074	.449	.150	.130	.156	.151	-.041	.688	.044	.666	.275	.206	.328	.005
Acacia nilotica	.347	.004	.132	.177	.113	.420	.430	.000	-.358	.004	.394	.022	-.028	.859
Tamarindus indica	.027	.781	.191	.062	.270	.013	.120	.228	-.038	.706	-.038	.000	.431	.000
Grewia tenax	-.020	.848	.096	.389	.244	.035	.104	.323	.035	.742	.073	.476	.092	.455
Acacia senegal	-.025	.822	.093	.212	.171	.174	.123	.282	-.087	.445	.213	.053	.101	.445

4- Distance of villages

As shows in Table 4.4 above, the distance from homestead to the source of NTFPs has negative and significant relationship with collection of *Balantites aegyptiaca* and *Acacia nilotica*. Indeed the current result consistent with Opeluwa *et al*., (2011) who reported in their study on determinants of NTFPs collection and utilization in Nigeria, where revealed that the distance separating the households to the source of NTFPs negatively affected their decision to collect NTFPs. It suggested that households residing close to the source of NTFPs are more likely to collect NTFPs or to acquire higher amount of NTFPs. On the other hand, the present findings, regarding other products, agreed with Adhikari *et al*., (2004), who found that increase of distance does not eventually affect household decision to collect NTFPs, such as firewood in Nepal, indicating that as distance to the source of collection increases household still collect firewood because it is not easily substituted by other source of energy in that area.

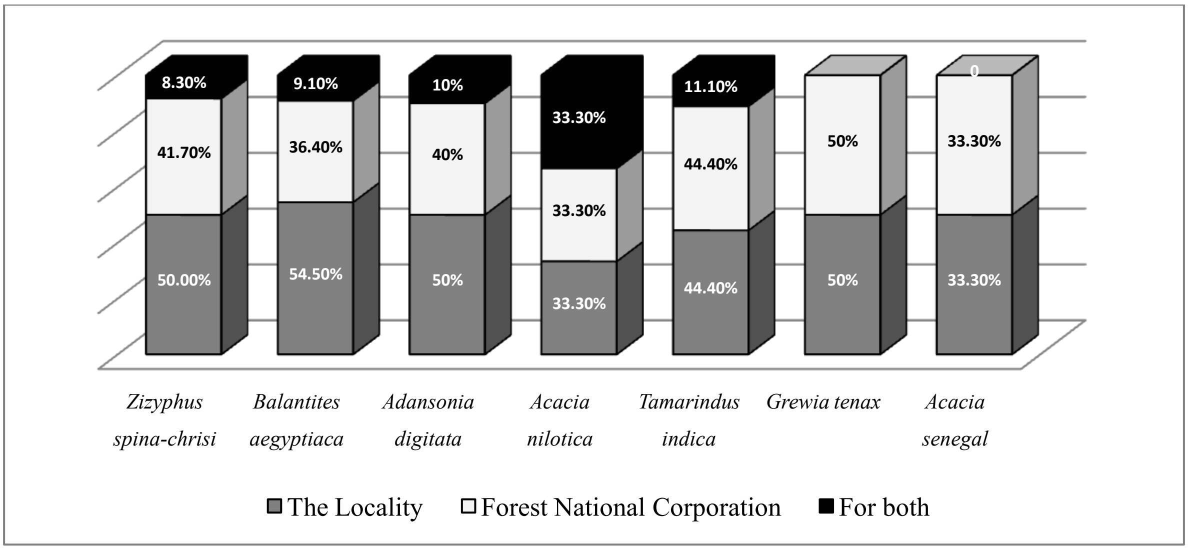
5- Migration

The results found a positive association between migration and the decision of collection of NTFPs. There was a keen and obvious interest by the migrants in collection and commercialization of NTFPs. The exception in this study was related to *Zizyphus spina-chrisi*, *Balantites aegyptiaca* and *Adansonia digitata*, which had a negatively influence in household's decision to collect these products.The current finding is consistent with the migrants status in Palawan, Philippines (Lacuna-Richman, 2006), where the migrants there have been successful in benefiting themselves with the NTFPs from the surrounding forests.

6- Policy influences

The study found that some fees are paid when marketing NTFPs. Fees and taxes are levied for every sack as well as to every Gontar of *Acacia senegal* product.They are paid to the FNC and local authorities (Fig. 4.15). But most of the households don't pay the fees because the quantity of NTFPs sold is small. Fee value for products (SDG. per sack) ranges from 1.18- 6.45€, while for Gontar of gum was about 3.73€. High and uneven fee values, long distance to the main markets and low prices of the small quantity sold beside lack of transportation are the main constraints to marketing of NTFPs in the area.

Figure 4.15: Tax Authorities



7- Increase of inflation

Continuous increase of inflation led to devaluation of the local currency. During the last years, and till now, the Sudanese government faced shortfalls of hard currency to fund imports of essential commodities, due to the impact of conflicts on oil production. Whereas in July, the official inflation rate was 46.8%, in April 2014, the rate decreased to be 23.2 %. As of mid-April, the unofficial black market exchange rate was over SDG 46 per Euro, more than double the official Bank of Sudan exchange rate. Actually, the fall in the official exchange rate was mask the true size of the fall in purchasing power as prices for locally produced, imported food and the non-food items have increased in local currency terms. The high prices of these products are driven by the reduced supply to markets, due to poor production, as well as restricted market access in areas affected by conflict in South Kordofan.

Table 4.5: Product's prices in Khartoum state

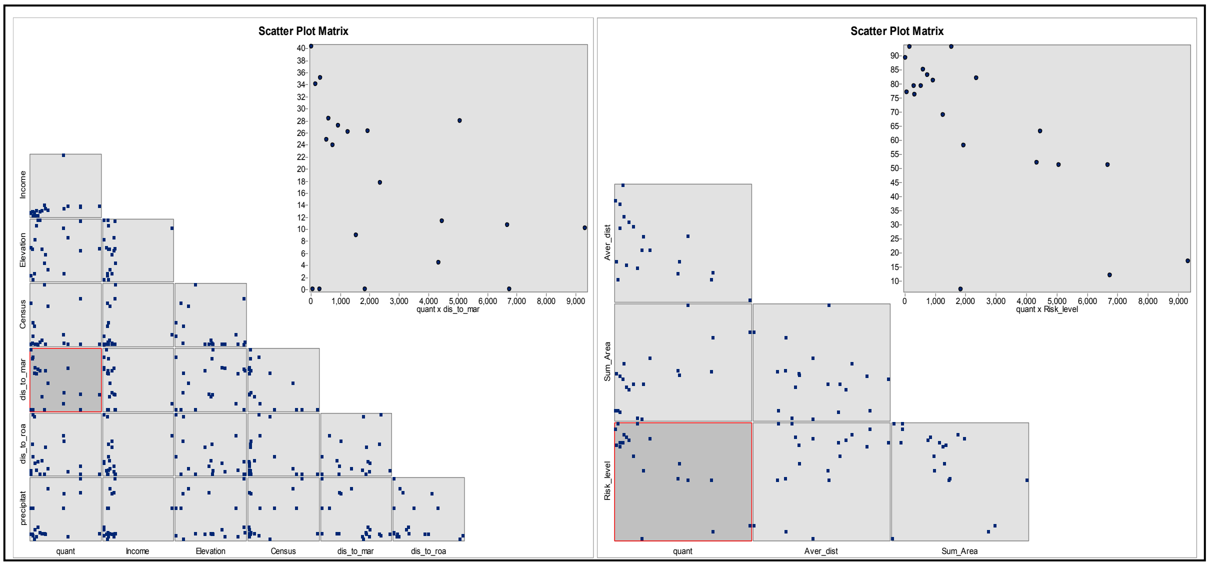
Products	Products price in 2008 (SDG)	Products price in 2014 (SDG)	Products price in 2018 (SDG)
Zizyphus spina-chrisi	3.884	46.615	80
Balantites aegyptiaca	12.430	46.615	83
Adansonia digitata	9.358	93. 229	100
Acacia nilotica	2.344	23.446	45
Tamarindus indica	4.679	70.177	96
Grewia tenax	32.746	56.386	140
Acacia senegal	78.140	96.679	170

Euro in 2008= 1.7 SDG, Euro in 2014 = 11 SDG, Euro in 2018= 55 SDG

4.3.5.2 Impact of the Socio-ecological factors in NTFPs

Both models, global OLS and local GWR, were able to capture and detect prominent factors (variables) that influence NTFPs collection in the study area. However, in the current study, only the useful predictors, those without bias that were entered into the local model, will be discussed. In the exploratory analysis using OLS, many predictors as shown in Figure 4.16, were entered into the models, such as; Income, distance to market, distance to road, average distance, sum area and risk level.

Figure 4.16: Test the different explanatory variables



The OLS model was calibrated to diagnose multicollinearity among the explanatory variables and the result shows that the census, distance to market, distance to road, precipitation and temperature variables, returned Probability and Robust Probability (Robust_Pr [b]) values, were higher than the set redundancy threshold of 10. Therefore, the variables were removed from the model. The final result of the OLS model is presented in Table 4.6. However, Table 4.6 shows that all the predictors returned Large Variance Inflation Factor (VIF) values fairly greater than 1.0, indicating that none of the variables are redundant.

Among these explanatory variables, three are statistically significant, and these are; average of the distance from villages to forest, sum of the area and the risk level (Annex 26). These variables are the most important with respect to the distribution of NTFPs quantities collected. Average of the distance and the risk level returned negative relationships (Table 4.6). The implication of this is that as the risk level and distance to forests increases, the quantities collected of NTFPs decrease. This result coincided with the current situation in Nuba Mountains.

Table 4.6: Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	5328.104017	1377.817630	3.867060	0.001367*	1325.904556	4.018467	0.000994*	--------
Aver_dist	-863.257811	264.127995	-3.268331	0.004831*	241.277104	-3.577869	0.002515*	1.216477
Sum_area	0.928128	0.248665	3.732435	0.001815*	0.211186	4.394827	0.000453*	1.203993
Risk_level	-41.100535	12.873501	-3.192646	0.005664*	13.493969	-3.045845	0.007705*	1.411924

The explanatory variables Aver_dist, Sum_area and Risk_level returned significant t-values of -3.2, 3.7 and -3.1 respectively. Due to the current situation in the study area, this is probably the reason why it fails to return significant t-value of the risk's level and average of the distance to forest. This result, therefore, suggests that security may be an important variable for increasing the quantities collected of NTFPs. The present finding agreed with Deafalla *et al.* (2018), who noted that, the security situation has a direct impact on the local livelihood. The OLS global model revealed that it explained about 78 % (adjusted $R^2 = 0.788$) of the variation in the quantities collected of NTFPs and forest density (Table 4.7).

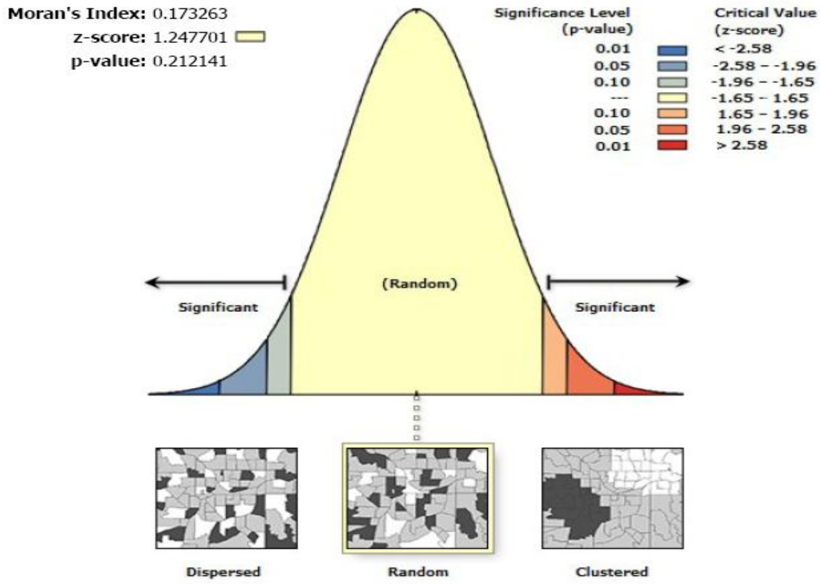
Table 4.7: OLS Diagnostics

Parameters	Values	P-value
Joint F-statistic	24.680578	0.000003*
Joint wald statistic	116.172734	0.000000*
Koenker (BP) statistic	2.913721	0.405120
Jarque-Bera statistic	0.081070	0.960276

$R^2 = 0.822305$; Adjusted $R^2 = 0.788987$; AICc = 351.612035 * Significant parameter at 0.05 level

The ANOVA returned a significant F-value= 24.68 and the Wald statistic has a significant chi-squared value = 116.17. This means that generally, the model proves to be statistically significant. Jarque-Bera statistic returned a non-significant chi-squared value= 0.08 (Table 4.7) indicating that the model's prediction is free from bias (i.e. the residuals are normally distributed). The chi-squared value (2.9) of the Koenker statistic is statistically significant. Importantly, it indicates relationship between some, or perhaps all, of the explanatory variables and the criterion variable are non-stationary or consistent across the region. The explanation for this is that some independent variables may be important, with respect to predicting the outcome of the quantities of NTFPs collected, and forest density in some settlements, but in others they may demonstrate weak predictive capability. It is evident that the model's fitness will likely be improved with GWR, since the Koenker statistic detected non-stationarity in the relationship. This is due to the fact that GWR assumes that relationships across space are non-static. However, the result was further confirmed statistically by applying spatial autocorrelation statistic (global Moran's I). This will automatically detect significant clustering or random patterns in the residuals. The Moran's I report (Fig. 4.17) revealed that the pattern of the residuals is significantly different from random, with a Moran's index value = 0.05 and z-score value = 1.25. That is, the residuals have no statistically significant spatial autocorrelation. In this case, all empirical evidence points to the fact that the OLS residuals fit properly.

Figure 4.17: Spatial autocorrelation regression report



Given the z-score of 1.25, the pattern does not appear to be significantly different than random

Moran's Index	Expected Index	Variance	z-score	p-value
0.173263	-0.052632	0.032779	1.247701	0.212141

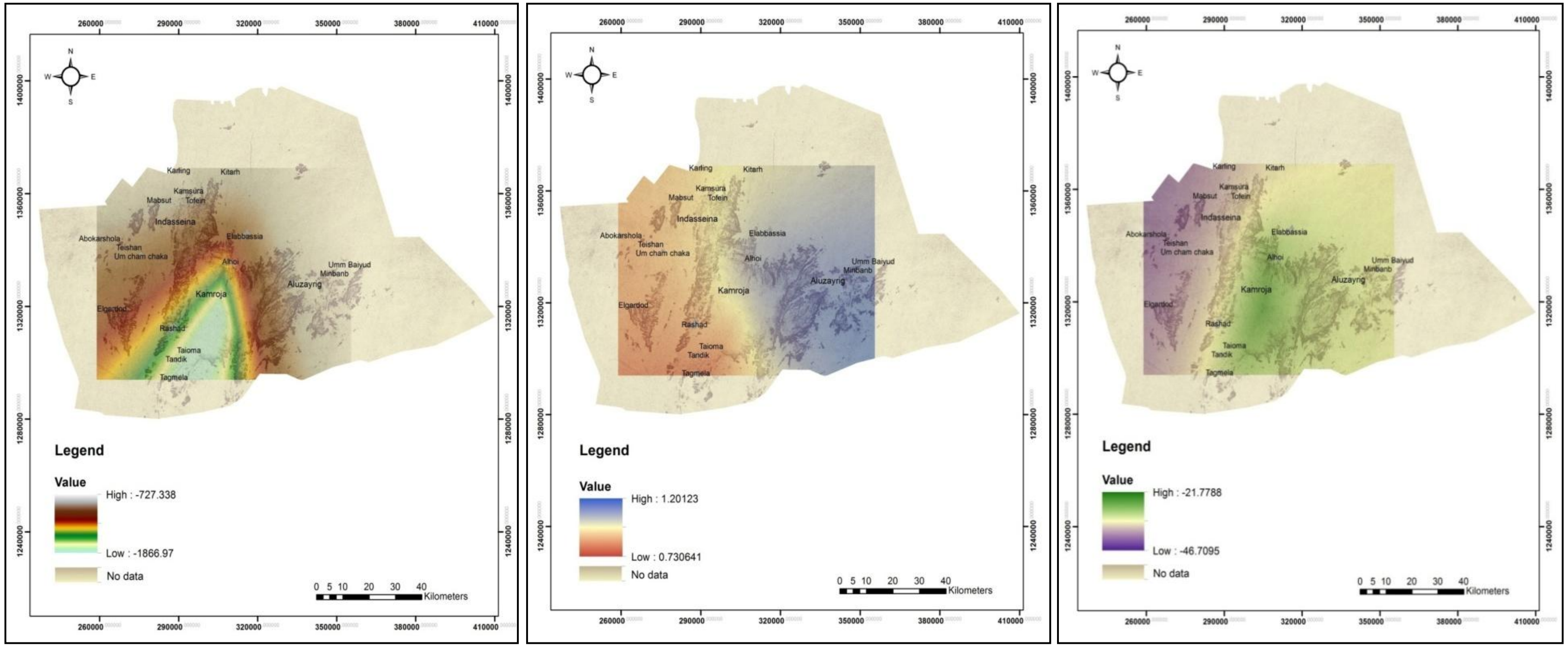
Some predictors exhibited high spatial variability in the resultant parameter estimates of GWR model. These predictors are: sum of forest area, level of risk and the average distance. They are the same that resulted from OLS model; all reflected a combination of negative and positive coefficients across study area. Whereas, the OLS global coefficients for the sum of forest area and the level of risk returned negative values, and this is an evidence that the relationship between the criterion variable and the explanatory variables, captured by OLS, is more complex and, for a reliable result, it needs a local model. The calibrated GWR results suggest that it is a significant improvement on the global model. Comparing both models with the AICc values, show that the value is reduced from 351.612035 * for OLS model to 299.28 for GWR model. The difference is roughly 52.33, based on Nkeki and Osirike (2013) in these cases, (that implying to the local models) fitness is higher when explaining spatial dataset such as the quantities collected of NTFPs and forest density.

Table 4.8: Comparison between OLS and GWR results

Fitness parameter	OLS	GWR
AICc	351.612035*	299.28
R^2	0.8	0.9
R^2 Adjusted	0.78	0.85

As expected, GWR model enhanced the explaining power of the OLS model with about 11% (Table 4.8). Mapping the residuals of GWR indicates that itis randomly distributed (Fig. 4.17). This means the model is properly specified. Verifying with autocorrelation statistic (Moran's I) returned randomly distributed residuals with a z-score= 1.24 and Moran index= 0.17. This means the model is properly specified. Verifying with autocorrelation statistic (Moran's I) returned randomly distributed residuals with a z-score= 1.24 and Moran index= 0.17. Figure 4.17 displays the R^2 value as a spatial smoothing of GWR model showing the area where the model's prediction and strength of relationship is improved. Furthermore, they show that, there is regional variation in the strength of relationship in the study region.

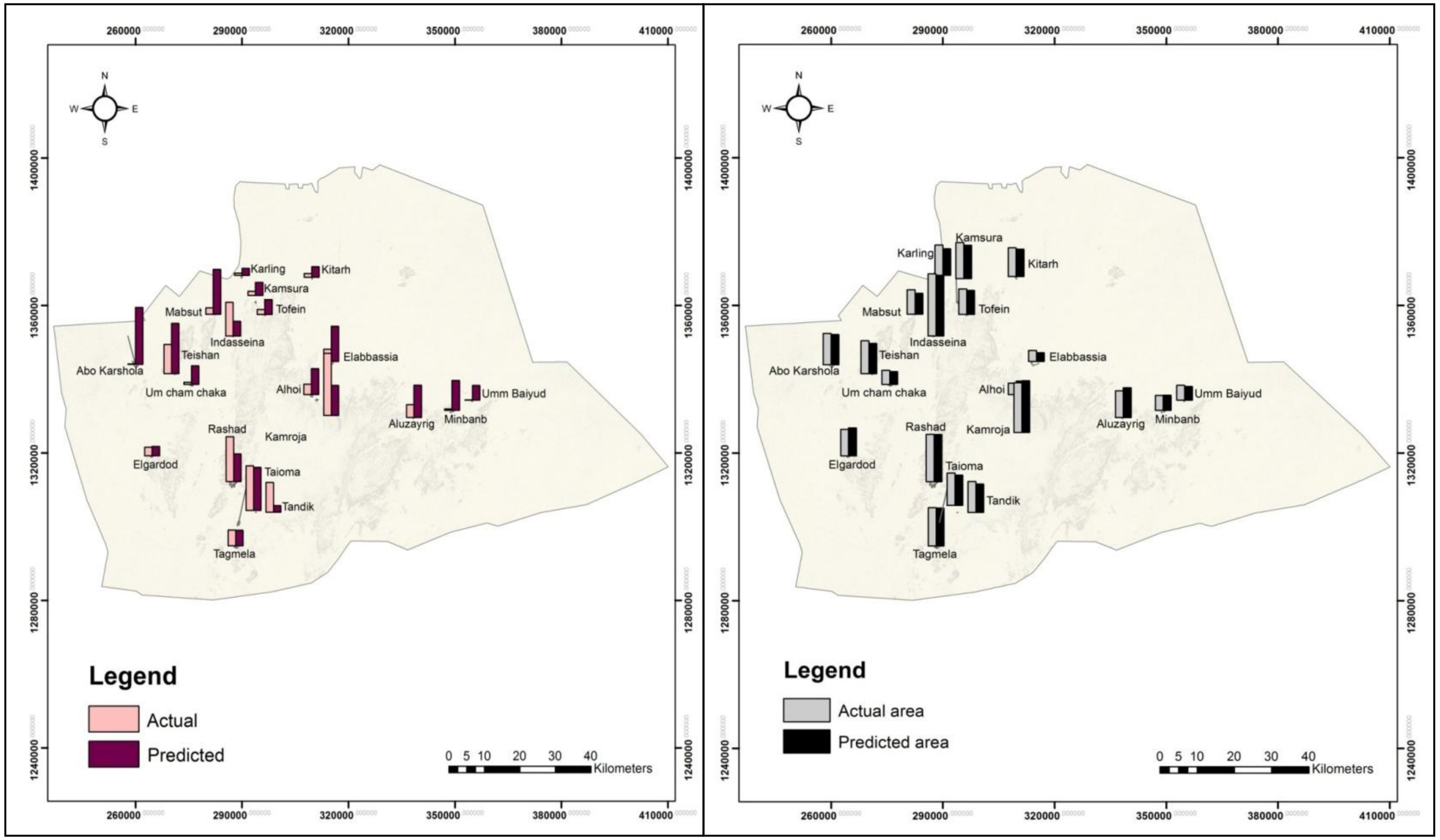
Figure 4.18: Coefficients of: the Average NN distances to forests (A: left), the forest density within the buffer zones (B: middle) and Coefficients of Risk level (C: right)



At the regional level, the resultant spatial variation in the pattern of relationships shows that the strength of relationship decreases from east to west. The only exception was in sum area of forest variable. Thus, this pattern suggests local fluctuation in the relationship (non-stationarity). A fundamental merit of GWR is its ability to display and visualize the parameter estimate of each explanatory variable on a raster surface, which leads to rendering the complex relationship that varies over space easier to comprehend (Nkeki and Osirike, 2013; Shahid and Bertazzon, 2015). As shown by GWR local coefficients, the average of the distance to forests variable is an important factor for estimating the quantities collected of NTFPs. The influence of this predictor is stronger in the north, eastern and western areas of the study site (Figure 4.18A), this is reasonable because the forest cover is low in these regions, while its influence in the central and south margin is weak, due to an increased density of forests in these areas. Indeed that consisted with Harrison and Jackson (1958) as well as with the findings in chapter 3 (section 3.3.2 Trees Location). Another important variable is the sum area of forests; which has high influence in the eastern parts of the study area, as shown in Figure 4.18B, where most of the LU/LC represents Cultivated lands. Unlike the former, its sphere of influence is smaller. This predictor proved to be less relevant in the western and southern parts, even though there is high concentration of households that utilize the lands in cultivation. Risk level, as a very significant predictor as well, exhibits strong negative influence over the dependent variable in the north western part of the region as shown in Figure 4.18C. On the central part of the study area, the influence is very strong and continues to east and down to south. The inverse relationship that risk level seems to reflect on the quantities collected of NTFPs, especially in the central parts, shows that it is a factor that should be looked at,with respect to policy development and, as well, to conducting other management investigations.

The resultant raster surface for the predictors shows that there is spatial variation in relationship between the selected explanatory variables and the quantities collected of NTFPs, as well as with forest density across the study area (Figures 4.19 and 4.20). Positive and negative relationships were manifested in the result of GWR, where the positive relationship means that, as the sum of forest area increase, the quantities of NTFPs collected will equally increase. On the other hand, the negative relationship means that, as the level of risk and the average distance increase, the quantities of NTFPs collected will, and in contrast, decrease. Local coefficient estimates, for each explanatory variable, are presented in Figure 4.19 and 4.20.

Figure 4.19: The current (2014) and predicted (2030) quantities of NTFPs collection (left); Figure 4.20: The current (2014) and predicted (2030) forest density (right)



CHAPTER FIVE

Conclusion and Recommendation

5.1 Conclusion

The spatial heterogeneity and rapid changes observed in the Nuba Mountains region of Sudan motivate the inspection for more efficient, reliable and accurate methods to update the required information for sustainable development. At present, planners and decision makers are not provided with automated data sources of the desired information levels. Over large areas, field surveys are often tedious and time consuming and other innovative methods of gathering the information need to be developed. In this sense, and in accordance with the main goal earlier mentioned, the study reveals that, imagery from mid/higher resolution sensors (i.e. Landsat and Rapideye satellite imagery) linked with GIS data and a socio-economic survey, has great potential in identifying the key of trees species and categorical LU/LC patterns.This method has proven its capability, as an efficient and accurate methodological framework for gaining knowledge about land features, and for identifying areas which are most vulnerable to EC in the study area, in a way that would be relevant to policy makers and other stakeholders. Moreover, the methodological approach of the study exhibits a potential solution to attain precise facts and figures about change dynamics and its driving forces. Since an object is a basic processing unit, among various segmentation criteria tested, the study formed different segmentation results, convenient for each level in the process hierarchy, extraction and rules of optimum features as well as developing models for each particular level. Following the specific objectives, the study can draw the following conclusions:

The pressures imposed resulted in the complex of spatial and temporal interactions within topographical systems at Nuba Mountains, where it has led both to a new rapidity and depth in rural transformation, and a significant impact on urban area as well. These intensive changes may have implications for future ecosystem functions, over a wide array of various spatial and temporal scales. The use of GEOBIA analysis has proven that it has provided offers of unprecedented opportunities, to detect these changes more accurately, over increasingly large areas, with diminishing costs and processing time. GEOBIA are also pertinent and directly interlinked with the post-classification change analysis (that is applied due to area heterogeneity, rapid changes and the variation in data source and season), which generated smooth and accurate classified maps. Meanwhile, the social surveys, of household and focus-group discussions, provide undisputed evidence that there is a need for humanitarian interventions for the surveyed communities. There is a significant increase in insecurity of the surveyed area, as shown by the increased number of displaced people and people reported that they are not feeling safe in their homes. Respondents described the worsening security situation and cited insecurity as the leading barrier to food security, the main reason for displacement. The second point, that has to be noted, many children are not in school. The food security outlook is equally disturbing, as families continue to use drastic coping strategies to fill the food gap. Gathering NTFPs and hunting, for food stocking, were the most widely and frequently used coping strategies. Furthermore, the research highlighted the significant roles of NTFPs and trees in contributing to Nuba Mountains's economic development, food security and environmental health, as well as to indicating what requirements need to be addressed, in order to realize these potentials. The study proved that, drawing on a wide range of forest products for livelihoods, strengthens rural people's ability to deal with, and adapt to both EC and extreme events. It has been established that a significant number of rural, tribal and overall forest dependent communities, derive a significant part of their food, nutrition, healthcare needs and income from NTFPs. This is especially so, at certain times of the year; during droughts or other emergency periods, such war or when cultivated foods are unavailable. NTFPs also contribute to the well-being of rural households, particularly the poor, in terms of food security, nutrition, health and subsistence. The study succeeds to provide updated information about the location of these products to help in strategy formulation and developing appropriate interventions. GEOBIA, with a multi-scale framework, has played a critical role in accurate trees species mapping and helped to define tree species segmentation, the similarity of near objects and in increasing interpretations of vegetation traits.

On the other hand, the research shows, there are some obstacles that restrain collection and marketing of NTFPs, which are related to ecological, social, economical and institutional factors. It also shows the challenges and emerging issues of markets, i.e.; poor transportation facilities, communication systems, financial capital or credit access, as well as limitations in market information and linkages. The study was able to detect, and extract, certain key information concerning stationarity and non-stationarity in spatial data, by using GIS-based local model and global statistics. This was exploited to explore the relationship between NTFPs collection and risk level, forest areas, as well as average distance to forest in Nuba Mountains. Global statistical models often assume homogeneity of relationships between variables across space. However, this exploratory analysis explains the spatial variation in relationship among geographic datasets and across geographic regions. It statistically demonstrated that local models exhibit better fitness than global models, when modeling spatial data. Finally, this study is a contribution to the field of GIS, spatial statistics, forest modeling and simulation.

5.2 Recommendation

Semi-arid land ecosystems are currently in urgent need of strategies and measures to adapt with changes. Kordofan region is struggling with climatic effects and human impacts, land misuse, overgrazing, and ethnic conflicts. Knowledge about the interaction of these variations is still poor, compared to the urgent need of strategies and measures to adapt with these changes. Mitigation strategies can facilitate adaptation to environmental change, by enhancing the resilience through the reduction of anthropogenic pressures and recovering biodiversity. Moreover, new studies that integrate model-based terrestrial and remotely sensed data, to highlight the need of understanding the context of LU/LC, are required to cope with high levels of environmental change. In sum, the successful key, to face the impact of environmental and climate change, is to develop viable policy responses, create dynamic innovative research, strategies, management and policies that focus on local communities, to avoid the hazard of marginalizing those who rely on natural resources for subsistence and income generation.

The wide spread of NTFPs shows great potential in providing multiple needs and income generation, a fact that is clearly supported by the current findings. Adequate innovative research and development are needed to encourage the investments on NTFPs through maintenance and use of indigenes knowledge, industry and gene banks development, particularly for the above mentioned species. Moreover, the development of modeling tools incorporating RS data, could improve forest management systems. It would be interesting to integrate socioeconomic/ecological mechanisms into these models by linking them to environmental data derived from satellite images. This should further improve predictability and usefulness of RS applications in NTFPs management. In addition to that, securing sustainable NTFPs supply by conserving identified species, improving their market value through pre to post processing, expanding their marketing opportunities (ICRAF, 2004), and protecting identified NTFPs uses and users' knowledge, are foundation stones towards improving their environmental benefits in a sustainable manner that leads to ecosystem stability. Furthermore, better access to credit and reliable information on markets and prices, onvalue adding as well as value chains of NTFPs, should be much better understood. Investments in infrastructure, for both roads and IT, should also be increased. Sudan is weak in strategies, policies and legal frameworks that support women rights. Despite that, women play a cornerstone in rural areas, through responsibilities in decision making, extension, motivation and outlook within the milieu of NTFPs. More emphasis should be put on the potential roles and the ability of women to participate in public fora, through capacity building programs. Studies that could contribute to both rural development and objectives of biodiversity conservation are required.

Additionally, more studies regarding the monitoring of NTFPs, by the use of new technique e.g. RS and GIS, are needed. GEOBIA could be used as an efficient solution to extract and update the required information in Nuba Mountains region of Sudan at various abstraction levels of details, utilizing optical multispectral imagery. The study recommends that, the use of GEOBIA to analyze RapidEye imagery for the identification of trees species should be integrated with ancillary data such as DEM and other levels of GIS data to improve the quality of the result.

At the national level, contribution of NTFPs to the Gross Domestic Product, wheather by exporting the products or by cost saving through local exploitation, should motivate the Sudanese government to maintain environmental integrity while managing NTFPs on sustainable basis. Current policies, legislation and regulations need to be revised, modernized and applied effectively, guaranteeing both an enabling environment for investments and engagement in the forest sector by farmers, communities and the private sector, and an effective prevention of destructive and illegal practices. Moreover, realistic plans for the sector at appropriate geographic and commodity levels must be developed and implemented. Strengthening institutions in support of forest development must be given priority. This includes government forest administrations and extension bodies, education/training/research institutions, farmer and community organizations, the private sector, professional associations, and regional organizations with a mandate to handle forest issues. Technical know-how for both the local communities and forest workers must be increased through research, training, partnership, enhanced practical experience.

At the international level, opportunities for partnerships with actors outside Sudan should be explored, for increased investments, access to know-how and expanded markets; for promotional purposes, and for more focus points that explain the significant roles NTFPs. Achieving the UN Sustainable Development Goals (SDGs), must be given highest priority.

Finally, there is a need for Sudan, and other developing nations, to consider legal mechanisms for the standardization and certification of NTFPs utilization, and collection processes, with well defined patent rights. Indeed, the legal protection would protect the rights of local communities and protect their local knowledge from exploitationby commercial interests.

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APPENDIXES

Annex1: Field survey data sheet (LU/LC level)

ID: …………………………..

Date:…………………………   Time:……………………………..

A/ Location:

State :…………………   Locality: …………………   Unit:…. ……………..……………

Forest's name:…………………..

GPS Grid:……….   Coordinates X:…………………….   Y:…………..………..…………

B/ General Description:

Slope Angle:………………………   Slope Aspect:…………………………

Elevation: ………………………...

*Types

F= Forest	**Sc=** Scatter forest	**A=** Agriculture lands	**S=** Shrublands	**G=** Grassland	**B=** Bare land	**D=** Decertified land	**R=** Rocky area/Hill	**W=** Water	**E=** Range	**T=** Settlements	**Other** (specify)

Type	**Observation** **(with specific description)**

C/ Forest Characteristics:

Types of forests (Reserved forest, proposed forest reserves, Social forests, communal land)	Species	Tree species that have appeared (during the past 10 years)	Tree species that maintained (during the past 10 years)	New species (during the past 10 years)	Tree species that naturally regenerated(during the past 10 years)	Forest description	
						Density	Phonological status

<u>Topographic Information:</u>

A. Soil

Texture: 1. Sandy ( ) 2. Silt ( ) 3. Clay ( ) 4. Loam ( ) 5. Stony ( ) 6. Soil absent ( ) 7. Parent material ( )

Soil Moisture: 1. Dry ( ) 2. Moist ( ) 3. Saturated ( ) 4. Signs of seasonally waterlogged soil ( )

Color:……

Comments:

………

B. Water

Impounded water all year? 1. Yes ( ) 2. No ( )

Occasional water? 1. Yes ( ) 2. No ( )

Comments:

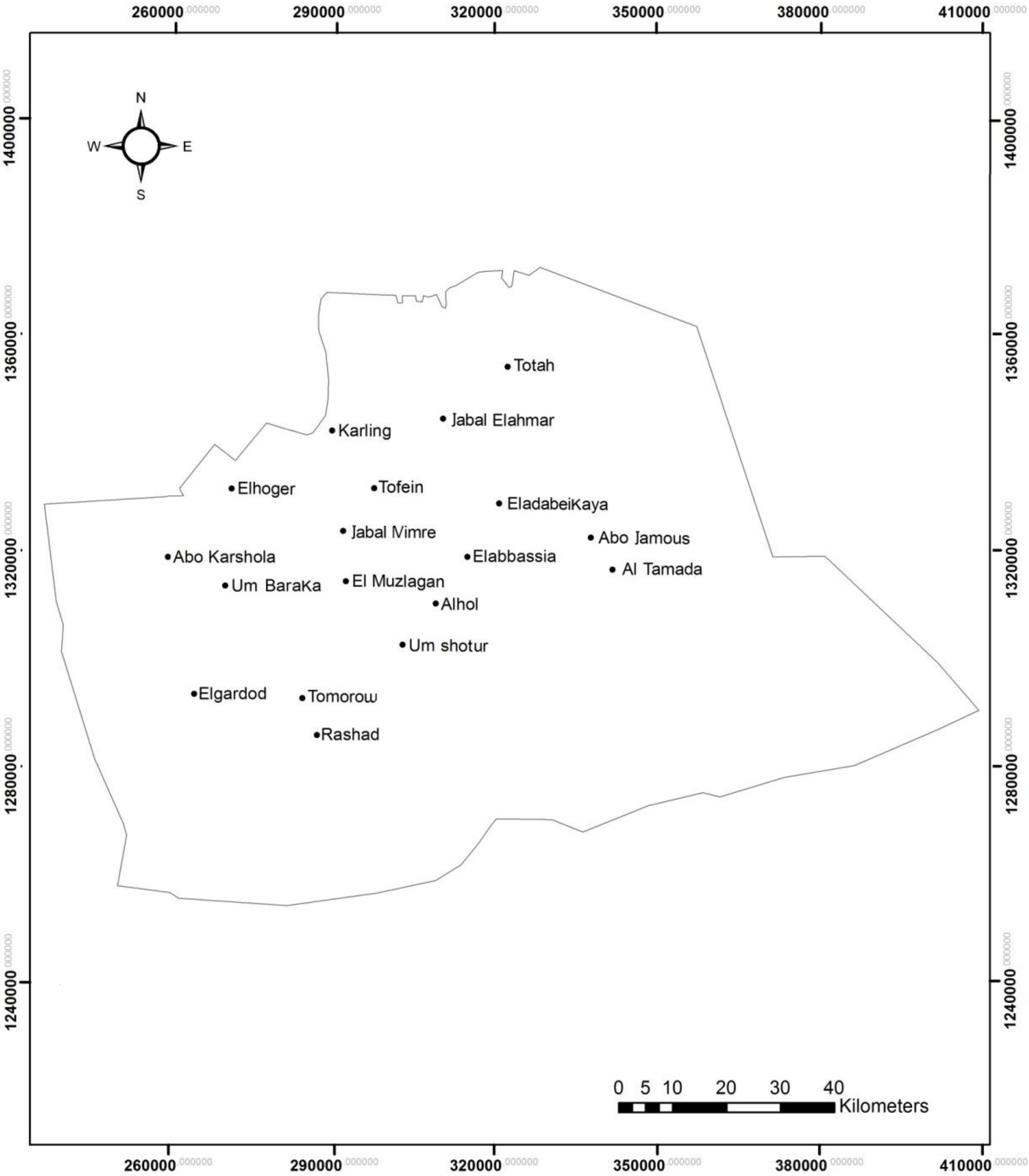
……

C. Vegetation Information

Physiognomic type:………………………………………………………………………………………………

	Dominant Species	**Cover (%)**
Top layer		
Intermediate		
Ground layer		

Annex 2: Villages site map



Annex 3: Questionnaire of Households

ID: ………………..

Date of Interview: ……………………………………

Name of responders: ……………………………….

Responders head of household (√, ×)? …. Not head of household (define)…………………..……..

A/ Location:

Locality: ………………… Unit: …………….… Village/ campus: …………………….………

Coordinate: Lat……………………. Lon…………………….

B/ Personality information

B/1 Characteristics of the family members:

	Relationship with head of household (wife, son, brother, who's living in the same home, other……)	Depend (√) not depend (×) on head of household	Age (by years)	Gender (Male, Female)	Marital status (Single, Married, Widow)	Education level (Illiterate, Khalwa, Basic, Primary , Secondary, Undergraduate, Postgraduate)
Head of household						
Wife 1						
Wife2						
Wife3						
Wife4						
Member 1						
Member 2						
Member 3						
Member 4						
Member 5						
Member 6						
Member 7						
Member 8						

*The family: Defined as a group of people they have same income and eat the same food.

B/2 Property

B/2/1: What are the types of property that you own? And how many do you have?

Property (House, animal, tress……..)	Number of Property	Type of uses (own use, hired out…….)

B/3 Occupation and income generation

B/3/1 Main occupation

B/3/1/1 Please indicate your main occupation according to importance, (For example: the main occupation: farms (1) then NTFP collector (2) ……..…).

Main occupation	The annual income (SDG)
Farms (please specific which type of crop)………………...( ).	
Livestock keeper…………..………………………………..( ).	
Merchant (including NTFPs)…………………………….....( ).	
Officer……………………………………………………....( ).	
NTFPs collector…………………………………………….( ).	
Hired worker………………………………………….….( ).	
Other (define) …………………………………………....( ).	

B/3/2 Secondary occupation

B/3/2/1 Please indicate your secondary occupation according to importance, (For example: the secondary occupation: farms (1) Then NTFPs collector (2) ……..…).

Secondary occupation	The annual income (SDG)
Farms (please specific which type of crop)…………………...( ).	
Livestock keeper……………………………………….....( ).	
Merchant (including NTFPs)……………………………......( ).	
Officer……………………………………………………...….( ).	
NTFPs collector……………………………………….......( ).	
Hired worker…………………………………………………..( ).	
Other (define) …………………………………………..…. .( ).	

B/3/3 Duration of the Main and Secondary occupation:

Activates	**January**	**February**	**March**	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
Main occupation												
Secondary occupation												

For example:

Activates	January	February	March	April	May	June	July	August	September	October	November	December
Agriculture of Maize												
Harvesting Cotton												
Collect NTFPs												

B/3/4 Household expenses

(a) Food purchase ( ) (b) Own production ( ) (c) Fuel ( ) (d) Health ( ) (e) Travel and transport ( ) Housing (f) Farm and livestock inputs ( ).

B/3/5 Household income

(a) Food produced for home ( ) (b) Sale of own surplus produce ( ) (c) Earning- small business ( )

(d) Salary or wages ( ) (e) Sale of assets (livestock) ( ) (f) Sale of NTFPs ( ) (g) Remittances received ( ) (h) Value of charity and relief aid ( ) (k) Loans received ( ).

B/4 War Impacts

B/4/1 Do you have any effects from war?

a. Yes ( ) b. No ( )

2- If yes, what kind ofeffects explain please!

……………………………………………………………………………………………………
……………………………………………………………………………………………………

B/4/2 Economic situation

1- Whatis the current economics' rate in your family after the war?

a. Increase ( ) b. Decrease ( ) c. No change ( )

2- If you have change in your economics' rate could you describe to us?(By percentage)

a. Increase by: a. 20% ( ) b. 50% ( ) c. 70% ( ) d. 90% ( )

b. Decrease by: a. 30% ( ) b. 60% ( ) c. 80% ( ) d. 100% ( )

B/4/3 Migration and Mobility

1- What are the main reasons of migration or mobility in your family?

1)……………………………………………………………………………….……………….……
2)………………………………………………………………………………………………………
3)……………………………………………………………………………………………….……
4)……………………………………………………………………..……………………………

2- To which state or country?

a) State...
b) Country………………………………………………………………………...……………

B/4/3 Gender

a. male ( ) b. female ( ).

B/4/4 Age of members

a. 10- 18 ( ) b. 18-30 ( ) c. 30- 45 ( ) d. 45- 60 ( ) e. up to 60 ( )

B/4/5 What the current rate of outward migration due to war in your family?

a. High ( ) b. moderate ( ) c. low ( ).

B/4/6 Food stock

1- Number of males per day do you have:

- Before the war: a. One ( ) b. Two ( ) c. Three ( ) d. more than four ( ) e. Non ( ).
- After the war: a. One ( ) b. Two ( ) c. Three ( ) d. more than four ( ) e. Non ( ).

2- Accessibility to market:

a. Less than one hour walk ( ) b. One to two hour walk ( ) c. More than a two hours walk ( ).

3- Are the basic commodities available in your local markets?

a. Yes ( ) b. No ( ).

Namely: a. Maize (√ or ×) b. Sorghum (√ or ×) c. Wheat (√ or ×) d. Beans (√ or ×) e. Millet (√ or ×) f. Oil (√ or ×).

4- The households expenses

a. Food purchased ( ) b. Own production ( ) c. Fuel ( ) d. Farm and livestock input ( ) f. Travel/transport Health ( ).

5- What are your coping strategies for food insecurity?

1)…………………………………………………………………………………………………

2)…………………………………………………………………………………………………

3)…………………………………………………………………………………………………

6- Are you depend on NTFPs in your daily males?

- Before the war: a. Yes (   ) b. No (   ).
- After the war: a. Yes (   ) b. No (   ).

C/ Land Use:

1. What are the main uses land in/ and around the village?

…………………………………………………………………………………………………
…………………………………………………………………………………………………

2. What are the main uses of the land after the war in/ and around the village?

…………………………………………………………………………………………………
…………………………………………………………………………………………………

3. General Description of land Use:

a) Cover type:

1. Crop (name/s:…………………………………………………………………………)

2. Pasture: a. Planted (   ) b. Natural (   ) c. Stubble (   ) d. Bare (   ) e. Weeds only (   ) f. Other (   ).

3. Planting technique: a. Row (   ) b. Drilled (   ) c. Broadcast (   ) d. Other (   ).

4. Plant height:……………………..

5. Ground cover: a. 0%-20% (   ) b. 20%-40% (   ) c. 40%-60% (   ) d. 60%-80% (   ) e. 80%-100% (   ).

D/ LU/LC change:

The main reasons in LU/LC change during the last years are:

1)……………………………………………………………………………………………....

2)…………………………………………………………………………………………………

3)…………………………………………………………………………………………………

D/1 Degradation

D1: Agriculture land (for agroforestry system);

1. How do classify the crop of your land?

a. Good ( ) b. medium ( ) c. Poor ( ).

2. Have you experienced any instances of degradation on your farm?

a. Yes ( )   b. No ( ).

3. If yes what are the major indicators?

a. Decrease of crop ( ) b. Increased weed infestation ( ) c. Soil compaction ( ) d. Others (………………..….)

4. If yes, what are the reasons?

a. Rainfall ( ) b. Continuous cultivation ( ) c. war ( ) d. Using inferior seeds ( ) e. Others (……………….……)

5. What are the measures you used to improve and/or mitigate your land?

a. Fertilization ( ) b. Crop rotation ( ) c. Double ploughing ( ) d. Prescriptive fire ( ) e. Abandonment ( ) f. Nothing ( ).

6. What are the grasses and herbs that appeared on your farm when the land degraded?
....
....

D2: Forest:

1. What the reasons of disappearing the tree species during the past 10 years ago?

a. Firewood collection ( ) b. charcoal production ( ) c. climate reasons ( ) d. War ( ) e. Agricultural expansion ( ) f. Other (define ………).

2. The introduced of new species during the past 10 years was by:

a. Reforestation by FNC programs ( ) b. Reforestation by local community ( ) c. Wind ( ) d. Animal ( ) e. Others (define ………).

E/ Non Timber Forest Products:

E/1 Energy

E/1/1Which types of energy used by family and for any purpose?

Types of energy (Gas, charcoal, firewood, etc…..)	**Source of energy (collect, Buy from the village market, etc…..)**	**Preferred energy tree species (*Acacia mellifera, Acacia nilotica, Acacia seyal,* etc…)**	**In case the source collectionof firewood**			**Purpose of energy use (Heating, Cooking, etc ……)**	**If the purpose is cooking, please what the type of cooking stove used**
			Distance of collection (km)	**Frequency of wood collection per month**	**Time spent in wood collection each time (hrs)**		

1								
2								
3								
4								
5								
4								

E/1/2 In case the source was collection to get for energy, who is from family members collect the firewood? Where?

Collector	**Place of fire wood collection**		
	Family land	**Communal land**	**Government land**
Head of the family			
Wife			
Children (sons and daughters)			
Other			

E/1/3 In any month from year do you have energy scarcity? Why?

Types of energy (Gas, charcoal, firewood, etc…..)	**Time of energy scarcity**	**Reason of energy scarcity**

E/2 Types of building materials

E/2/1 which types of building materials used by family and for any purpose? And which types of wood used?

	Types of building materials (bricks, wood, mud, dung, etc ……)	**durability of building materials (by month)**	**Sources of building materials (collect, Buy from the village market, etc…..)**	**The purpose (roof, wall, fence, dividends, etc …..)**	**If the type of building materials was plant, what is the preferred species (*Acacia mellifera*, *Acacia nilotica*, *Acacia seyal*, etc…)**

1					
2					
3					
4					
5					

E/2/2 In case the source was collection to get for building materials, who is the family's members collect the building materials? From where?

Collector	Place of fire wood collection		
	Family land	Communal land	Government land
Head of the family			
Wife			
Children (sons and daughters)			
Other			

E/3 NTFPs safe to eat and /or medicine

E/3/2 Do you depend on NTFPs? a) Yes ( ) b) No ( ).

E/3/2Which from these products **Uses** in your home and collect (or hunting) or buy it? And from where?

Product	Collect	Purchase (and why?)	The place of purchase (Buy from the village market, another market, etc…..)(define)
Ziziphus spina-christi			
Balanites aegyptiaca			
Adansonia digitata			
Acacia nilotica			
Tamarindus indica			
Grewia tenax			
Trees Leaves (define): 1)…………………. 2)…………………. 3)………………….			
Gums (*Acacia senegal*, *Sterculia setigera*, etc....			

define): 1)…………………. 2)…………………. 3)………………….			
Animals hunting (define): 1)…………………. 2)…………………. 3)………………….			
Other products (define): 1)…………………………………… 2)……………………………………			

- Before the war (X) after the war (√)

E/4 <u>Collect</u> of NTFPs safe to eat and /or medicine

E/4/1 from where collect these NTFPs? And who is the family's member collecting it? And how long take that (Time and Distance)?

Products	Place of products collection							
	Family land		Communal land		Government land		Forest	
	Time & Distance	Collector	Time & Distance	Collector	Time & Distance	Collector	Time & Distance	Collector
Ziziphus spina-christi								
Balanites aegyptiaca								
Adansonia digitata								
Acacia nilotica								
Tamarindus indica								
Grewia tenax								
Trees Leaves (define): 1)…………… 2)……………								

3)……………								
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………								
Animals hunting (define): 1)…………… 2)…………… 3)……………								
Other products (define): 1)…………… 2)…………… 3)……………								

*Time: (by hours) from the house until **comeback to it**.

*Distance: (by Km) from the house to place of products collection.

*Collector: (Head of the family, wife, sons, daughters, other, etc…)

E/4/2 When (in any month) do you collect these products? how many time in every month?

Products	**Frequency of collection per month**											
	January	February	March	April	May	June	July	August	September	October	November	December
Ziziphus spina-christi												
Balanites aegyptiaca												
Adansonia digitata												
Acacia nilotica												
Tamarindus indica												
Grewia tenax												
Trees Leaves (define):												

1)…………… 2)…………… 3)……………												
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………												
Animals hunting (define): 1)…………… 2)……………												
Other products (define): 1)…………… 2)……………												

* Frequency of collection: (daily, weekly, monthly, etc…)

E/4/3 What is the part used of the tree and what the quantity collected or consumed or quantity sold by the family?

Products	**Part used**	**Quantity collected in every time**	**Unit of measurement**	**Quantity consumed**	**Quantity Sold**	**price of measurement unit (SDG)**	**Place of sale (name of market) and distance it (by Km) from the village**
Ziziphus spina-christi							
Balanites aegyptiaca							
Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define):							

1)…………… 2)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………							
Animals hunting (define): 1)…………… 2)……………							
Other products (define): 1)…………… 2)…………… 3)……………							

* The parts used: (Fruit, leaves, Seeds, etc…)

* Unit of measurement: (Malwa, Gontar, etc…)

E/4/4 When collecting NTFPs, is it trip just for the purpose of collection?

(1) Yes……………………… No……………………….

(2) If No, what other purpose do you combine with collection?

………
………

E/5 Utilization of NTFPs

E/5/1 If any of NTFPs **uses usually by your family** for specific use (for example: treatment or cosmetic) put (√) in the correct column.

E/5/1/2 If you **know** any of NTFPs uses usually for specific use (for example: treatment or cosmetic) but **not uses** by your family, put (Δ) in the correct column.

Products	**Uses**						
	Food	**Drinks**	**Medicine**	**Feed**	**Cosmetic**	**Row material**	**Other (define)**
Ziziphus spina-christi							
Balanites aegyptiaca							

Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define): 1)…………… 2)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………							
Animals hunting (define): 1)…………… 2)……………							
Other products (define): 1)…………… 2)……………							

- Before the war (X) after the war (√)

E/5/2 For NTFPs uses to treatments: please mention the name of disease do you **<u>think</u>** the product is treat it:

Products	**Name of disease**	**Frequency of uses for this product by your family (always, never, etc….)**	**Alternative methods of treatment if product not used (Visit the doctor or Sheikh, etc…)**
Ziziphus spina-christi			
Balanites aegyptiaca			
Adansonia digitata			
Acacia nilotica			
Tamarindus indica			
Grewia tenax			
Trees Leaves (define): 1)……………			

2)……………			
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………			
Animals hunting (define): 1)…………… 2)……………			
Other products (define): 1)…………… 2)……………			

- Before the war (X) after the war (√)

E/5/3 Methods of collection NTFPS

E/5/3/1 How collect the product and what are the tools used (please write name of tool in the right column).

Products	**Climb the tree**	**Hand picking**	**Dropping fruits**	**Cut the leaves**	**Use the basket**	**Hand picking of the earth**	**Other (define)**
Ziziphus spina-christi							
Balanites aegyptiaca							
Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define): 1)…………… 2)…………… 3)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)……………							

2)…………… 3)……………							
Animals hunting (define): 1)…………… 2)…………… 3)……………							
Other products (define): 1)…………… 2)…………… 3)……………							

E/5/4 Processors and Storage

E/5/4/1 Please indicate the Process /processors /………/ that you apply to the products before consumption or sale and why? (Write the reason in the right column).

Products	**Storage** **(give reason)**	**Product Classification** **(give reason)**	**Cutting** **(give reason)**	**Other processors (define) give reason**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees Leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………				

3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

E/5/4/2 Please indicates the source of expertise in the collection and ways to deal with the product beside methods of storage and utilization for each product.

Products	**Sources of experiences for flowing process**			
	Method of collection	**Method of Storage**	**Method of utilization**	**Other process** **(give reason)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees Leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define):				

1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

Example for sources experiences: (1) Inheritance (2) Practice (3) Receive training (4)……………

E/6 Marketing

If you're marketing to any product:

E/6/1 Who takes the product to the market? why this person specific? (Write the reason)

E/6/2 Who from family members benefit from the generated income?

Products	**The reason**				**Beneficiary of the generated income (Head of the family, Wife, all the family…………….)**
	Head of the family	**Wife**	**Sons**	**Daughter**	
Ziziphus spina-christi					
Balanites aegyptiaca					
Adansonia digitata					
Acacia nilotica					
Tamarindus indica					
Grewia tenax					
Trees Leaves (define): 1)…………… 2)……………					
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………					
Animals hunting (define):					

1)…………… 2)……………					
Other products (define): 1)…………… 2)…………… 3)……………					

E/6/3 How transfers the product to the market? And what is the cost of transport? (Write the cost in right column).

Products	**Cost of transport by (SDG)**			
	Donkey	**Caro**	**Lorry**	**Other (define)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)……………				

2)…………… 3)……………				

E/6/4 Who buys your products?

Products	**Buyer** **(Village merchant, Agent in the market (specific No.), Final consumer…………)**
Ziziphus spina-christi	
Balanites aegyptiaca	
Adansonia digitata	
Acacia nilotica	
Tamarindus indica	
Grewia tenax	
Trees leaves (define): 1)…………… 2)…………… 3)……………	
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………	
Animals hunting (define): 1)…………… 2)…………… 3)……………	
Other products (define): 1)…………… 2)…………… 3)……………	

E/6/5 Do you pay fees or taxes when collecting or marketing NTFPs?

(1) Yes……………………………… (2) No……………………………….

E/6/6 If yes; what is the fees or tax paid it?

Products	**The type of payment or fees (the name)**	**The authority that received payments**	**The unit on which the calculation of payments (for every Gontar, Malwa………)**	**Fees value (SDG per Kg)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

E/6/7 Problems and constraints

E/6/7/1 What are the problems and constraints facing NTFPs collection do you have? (For example: Natural climatic conditions (explain), Long distance from village, etc….) please categorize the problems according to importance.

1/ ……………………………………………..……………………………….…………….

2/……………………………………………………………………………..……………………..

3/………………………………………………………………………………………………….

4/………………………………………………………………………………..………………………

5/………………………………………………………………………………………………….

E/6/7/2 What are the problems and constraints facing of NTFPs marketing do you have? (For example: Natural climaticconditions (explain), low price of NWFPs, Long distance from village, etc….) please categorize the problems according to importance.

1/…………………………………………………………………………………………………

2/………………………………………………………………………………..………………………

3/…………………………………………………………………………………………………

4/………………………………………………………………………………..………………………

5/…………………………………………………………………………………………………

E/6/7/3Do you participate in management or improve of NTFPs?

(1) Yes…………………………..……… (2) No…………..……….…………….

E/6/7/4 If yes; pleas what are these process?

Product or trees	Process used

E/7 Benefits and other uses for forest than NTFPs

What is the other ways you can benefits from forest and trees?

1. Recreation ( ) 2. Children Playgrounds ( ) 3. Shade for animals ( ) 4. Hunting ( ) 5. Windbreaks ( ) 6. Other (define)…………………

E/8 What is your relation with FNC (regarding NTFPs)?

(1) Access to extension services	(2) Licenses
(3) Establishing relationships	(4) The rights and properties
(5) Training	(6) Awareness
(7) ……………………………………	(8) ………………………….

Thank you

Annex 4: Questionnaire of food insecurity

Food item		Number of days eaten during the last 7 days (The code from 0 to 7) 0= Not consumed 4= Four days 1= One day 5= Five days 2= Two days 6= Six days 3= Three days 7= Seven days	Mani food source over the last 7 days (The code from 0 to 7) 0= Not consumed 7= Exchange item for food 1= Own production 8=Gift (food) from family or relevant 2= Hunting, fishing 9=Food aid (NGOs, etc..) 3= Gathering 10= Begging 4= Borrowed 11= Bought on credit 5= Purchase 12= Other 6= Exchange labor for food
1	Wheat		
2	Sorghum		
3	Rice		
4	Millet		
5	Bread and other cereals		
6	Potatoes or other tubers		
8	Beans		
9	Groundnuts		
10	Beef		
11	Goat		
12	Poultry		
13	Eggs		
14	Fish		
15	Milk, yogurt and other diary		
17	Sugar or sugar products		
18	Honey		
19	Oils, fats		
20	Vegetables or		

	leave		
21	Fruits		
22	Tea or coffee		

Annex 5: FCS occurrence questions

	Questions	Response Option	Code
Q1	In the past 4 weeks (30 days), did you worry that your household would not have enough food?	1= Yes 2= No	( )
Q1a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q2	In the past 4 weeks (30 days), were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?	1= Yes 2= No	( )
Q2a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q3	In the past 4 weeks (30 days), did you or any household member have to eat a limited variety of foods due to a lack of resources?	1= Yes 2= No	( )
Q3a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q4	In the past 4 weeks (30 days), did you or any household member have to eat some foods that you really did not want to eat because of a lack of resources to obtain other types of food?	1= Yes 2= No	( )
Q4a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q5	In the past 4 weeks (30 days), did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?	1= Yes 2= No	( )
Q5a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q6	In the past 4 weeks (30 days), did you or any household member have to eat fewer meals in a day because there was not enough food?	1= Yes 2= No	( )
Q6a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q7	In the past 4 weeks (30 days), was there ever no food to eat of any kind in your house because of lack of resources	1= Yes 2= No	( )

	to get food?		
Q7a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q8	In the past 4 weeks (30 days), did you or any household member go to sleep at night hungry because there was not enough food?	1= Yes 2= No	( )
Q8a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )
Q9	In the past 4 weeks (30 days), did you or any household member go a whole day and night without eating anything because there was not enough food?	1= Yes 2= No	( )
Q9a	How often did this happen in the past (4 weeks/30 days)?	1 = Rarely (1–2 times) 2 = Sometimes (3–10 times) 3 = Often (more than 10 times)	( )

Annex 6: Questionnaire of Displaced Nuba people in Khartoum State

ID: ………………..

Date of Interview: ……………………………………

Name of responders: ……………………………….

Responders head of household (√, ×)? ……………… Not head of household (define)……………………..

A/ Location:

Locality: ……………………… Unit: ……………… Village: ……………… Tribe…………………

B/ Personality information

B/1 Characteristics of the family members:

	Relationship with head of household (wife, son, brother, who's living in the same home, other……)	**Depend (√) not depend (×) on head of household**	**Age (by years)**	**Gender (Male, Female)**	**Marital status (Single, Married, Widow)**	**Education level (Illiterate, Khalwa, Basic, Primary , Secondary, Undergraduate, Postgraduate)**
Head of household						
Wife 1						
Wife2						
Wife3						
Wife4						
Member 1						
Member 2						
Member 3						
Member 4						
Member 5						
Member 6						
Member 7						

*The family: Defined as a group of people they have same income and eat the same food.

C/1 Migration and Mobility

C/1/1 What are the main reasons of migration or mobility in your family?

1)………
2)………
3)………
4)………

C/1/2 To which state or country?

c) State...

d) Country…………………………………………………………………………………………

C/1/3 Gender

a. male ( ) b. female ( ).

C/1/4 Age of members

a. 10- 18 ( ) b. 18-30 ( ) c. 30- 45 ( ) d. 45- 60 ( ) e. up to 60 ( )

C/1/5 What the current rate of outward migration due to war in your family?

a. High ( ) b. moderate ( ) c. low ( ).

<u>D/ Non Timber Forest Products</u>

D/1 Energy

D/1/1 Which types of energy used by family and for any purpose?

Types of energy (Gas, charcoal, firewood, etc…..)		**Source of energy (collect, Buy from the village market, etc…..)**	**Preferred energy tree species (*Acacia mellifera, Acacia nilotica, Acacia seyal,* etc…)**	**In case the source collection of firewood**			**Purpose of energy use (Heating, Cooking, etc ……)**	**If the purpose is cooking, please what the type of cooking stove used**
				Distance of collection (km)	**Frequency of wood collection per month**	**Time spent in wood collection each time (hrs)**		
1								
2								
3								
4								
5								
4								

D/1/2 In case the source was collection to get for energy, who is from family members collect the firewood? Where?

Collector	Place of fire wood collection		
	Family land	Communal land	Government land
Head of the family			
Wife			
Children (sons and daughters)			
Other			

D/1/3 In any month from year do you have energy scarcity? Why?

Types of energy (Gas, charcoal, firewood, etc…..)	Time of energy scarcity	Reason of energy scarcity

D/2 Types of building materials

D/2/1 Which types of building materials used by family and for any purpose? And which types of wood used?

	Types of building materials (bricks, wood, mud, dung, etc ……)	Durability of building materials (by month)	Sources of building materials (collect, Buy from the village market, etc…..)	The purpose (roof, wall, fence, dividends, etc …..)	If the type of building materials was plant, what is the preferred species (*Acacia mellifera*, *Acacia nilotica*, *Acacia seyal*, etc…)
1					
2					
3					
4					
5					
6					

D/2/2 In case the source was collection to get for building materials, who is the family's member collects the building materials? From where?

Collector	Place of fire wood collection		
	Family land	**Communal land**	**Government land**
Head of the family			
Wife			
Children (sons and daughters)			
Other			

D/3 Non Timber Forest Products safe to eat and /or medicine

D/3/1 Which from these products **Uses** in your home and collect (or hunting) or buy it? And from where?

Product	Collect	Purchase	The place of purchase (Buy from the village market, anther market, etc…..) (define)
Ziziphus spina-christi			
Balanites aegyptiaca			
Adansonia digitata			
Acacia nilotica			
Tamarindus indica			
Grewia tenax			
Trees Leaves (define): 1)………………… 2)………………… 3)…………………			
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)………………… 2)………………… 3)…………………			
Animals hunting (define): 1)………………… 2)………………… 3)…………………			
Other products (define): 1)…………………………………. 2)………………………………….			

- Before the war (X) after the war (√)

D/4 Sources of gathering of NTFPs safe to eat, income and /or medicine

1)……

2)……

3)……

D/4/1 What is the part used of the tree and what the quantity collected or consumed or quantity sold by the family?

Products	Part used	Quantity collected in every time	Unit of measurement	Quantity consumed	Quantity Sold	price of measurement unit (SDG)	Place of sale (name of market) and distance it(by Km) from the village
Ziziphus spina-christi							
Balanites aegyptiaca							
Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define): 1)…………… 2)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………							
Animals hunting (define): 1)…………… 2)……………							
Other products (define): 1)……………							

2)……………							

* The parts used: (Fruit, leaves, Seeds, etc…)   * Unit of measurement :(Malwa, Gontar, etc…)

D/5 Utilization of non timber forest products

D/5/1 If any of non timber forest products **uses usually by your family** for specific use (for example: treatment or cosmetic) put (√) in the correct column.

D/5/1/2 If you **know** any of non-timber forest products uses usually for specific use (for example: treatment or cosmetic) but **not uses** by your family, put (∆) in the correct column.

Products	**Uses**						
	Food	**Drinks**	**Medicine**	**Feed**	**Cosmetic**	**Row material**	**Other (define)**
Ziziphus spina-christi							
Balanites aegyptiaca							
Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define): 1)…………… 2)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………							
Animals hunting (define): 1)…………… 2)……………							
Other products (define): 1)…………… 2)……………							

•Before the war (X) after the war (√)

D/5/2 For Non timber Forest Products uses to treatments: please mention the name of disease do you **think** the product is treat it:

Products	**Name of disease**	**Frequency of uses for this product by your family (always, never, etc….)**	**Alternative methods of treatment if product not used (Visit the doctor or Sheikh, etc…)**
Ziziphus spina-christi			
Balanites aegyptiaca			
Adansonia digitata			
Acacia nilotica			
Tamarindus indica			
Grewia tenax			
Trees Leaves (define): 1)…………… 2)…………… 3)……………			
Gums (*Acacia senegal*, *Sterculia setigera* , etc.... define): 1)…………… 2)…………… 3)……………			
Animals hunting (define): 1)…………… 2)…………… 3)……………			
Other products (define): 1)…………… 2)…………… 3)……………			

- Before the war (X) after the war (√)

D/5/3 If you collect NTFPs:

D/5/3/1 How collect the product and what are the tools used (please write name of tool in the right column).

Products	**Climb the tree**	**Hand picking**	**Dropping fruits**	**Cut the leaves**	**Use the basket**	**Hand picking of the earth**	**Other (define)**
Ziziphus spina-christi							
Balanites aegyptiaca							
Adansonia digitata							
Acacia nilotica							
Tamarindus indica							
Grewia tenax							
Trees Leaves (define): 1)…………… 2)…………… 3)……………							
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………							
Animals hunting (define): 1)…………… 2)…………… 3)……………							
Other products (define): 1)…………… 2)…………… 3)……………							

D/5/4 Processors and Storage

D/5/4/1 Please indicate the Process /processors /………/ that you apply to the products before consumption or sale and why? (Write the reason in the right column).

Products	**Storage (give reason)**	**Product Classification (give reason)**	**Cutting (give reason)**	**Other processors (define) give reason**
Ziziphus spina-christi				

Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees Leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

D/5/4/2 Please indicates the source of expertise in the collection and ways to deal with the product beside methods of storage and utilization for each product.

Products	**Sources of experiences for flowing process**			
	Method of collection	**Method of Storage**	**Method of utilization**	**Other process (give reason)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				

Tamarindus indica				
Grewia tenax				
Trees Leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

Example for sources experiences: (1) Inheritance (2) Practice (3) Receive training (4)……………

D/6 Marketing

If you're marketing to any product:

D/6/1 Who takes the product to the market? why this person specific? (Write the reason)

D/6/2 Who from family members benefit from the generated income?

Products	**The reason**				**Beneficiary of the generated income (Head of the family, Wife, all the family…………….)**
	Head of the family	**Wife**	**Sons**	**Daughter**	
Ziziphus spina-christi					
Balanites aegyptiaca					
Adansonia digitata					
Acacia nilotica					
Tamarindus indica					
Grewia tenax					

Trees Leaves (define): 1)…………… 2)……………					
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)……………					
Animals hunting (define): 1)…………… 2)……………					
Other products (define): 1)…………… 2)…………… 3)……………					

D/6/3 How transfers the product to the market? And what is the cost of transport? (Write the cost in right column).

Products	**Cost of transport by (SDG)**			
	Donkey	**Caro**	**Lorry**	**Other (define)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)……………				

2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				
Other products (define): 1)…………… 2)…………… 3)……………				

D/6/4 Who buys your products?

Products	**Buyer** **(Village merchant, Agent in the market, Final consumer…………)**
Ziziphus spina-christi	
Balanites aegyptiaca	
Adansonia digitata	
Acacia nilotica	
Tamarindus indica	
Grewia tenax	
Trees leaves (define): 1)…………… 2)…………… 3)……………	
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………	
Animals hunting (define): 1)…………… 2)…………… 3)……………	

Other products (define): 1)…………… 2)…………… 3)……………	

D/6/5 Do you pay fees or taxes when collecting or marketing NTFPs?

(1) Yes……………………………… (2) No……………………………….

D/6/6 If yes; what is the fees or tax paid it?

Products	**The type of payment or fees (the name)**	**The authority that received payments**	**The unit on which the calculation of payments (for every gontar, malwa………)**	**Fees value (SDG per Kg)**
Ziziphus spina-christi				
Balanites aegyptiaca				
Adansonia digitata				
Acacia nilotica				
Tamarindus indica				
Grewia tenax				
Trees leaves (define): 1)…………… 2)…………… 3)……………				
Gums (*Acacia senegal*, *Sterculia setigera*, etc.... define): 1)…………… 2)…………… 3)……………				
Animals hunting (define): 1)…………… 2)…………… 3)……………				

Other products (define): 1)…………… 2)…………… 3)……………				

D/6/7 what are the problems and constraints facing of NTFPs marketing do you have? (For example: Natural climatic conditions (explain), low price of NTFPs, etc….) please categorize the problems according to importance.

1/…………………………………………………………………………………….…………………………

2/……………………………………………………………………………...…..…………..……………

3/…………………………………………………………………………………………………..………

D/6/7/3Do you participate in management or improve of NTFPs?

(1) Yes………………………………….……   (2) No…….……………...………………….…….

D/6/7/4 If yes; pleas what are these process?

Product or trees	Process used

E/7 Benefits and other uses for forest than NTFPs

What is the other ways you can benefits from forest and trees?

1. Recreation ( ) 2. Children Playgrounds ( ) 3. Shade for animals ( ) 4. Hunting ( ) 5. Windbreaks ( ) 6.Other (define)…………………

D/8 What is your relation with FNC (regarding NTFPs)?

(1) Access to extension services	(2) Licenses
(3) Establishing relationships	(4) The rights and properties
(5) Training	(6) Awareness
(7) ……………………………………	(8) ………………………….

Thank you

Annex 7: Questionnaire of Merchants

ID: ………………..

Date of Interview: …………………………………

Name of responders: ………………………………

A/ Location:

Locality: ……………..……….…   Unit: ………………….………   Village/ Town: ….…………..……………

Distance of forest from the Village/ Town :………………..……(Kilometer)

Distance of forest from the Main Market :…………………….…..(kilometer)

B/ Non Timber Forest Products:

B/1 Do you sell the non-timber forest products?

a. Yes ( )   b. No ( )

B/2 What are the most products you sell?

……
……

B/3 The prices of the products by SDG (for each Malwa or Gontar)

……
……

B/4 In which seasons you sells more? Why?

a. Ramadan ( )   b. Winter ( )   c. Summer ( )   d. Autumn ( )

……
……

B/5 Are you collect these products by yourself?

a. Yes ( )   b. No ( )

B/6 Are you preaches these products direct from the collector?

a. Yes ( )   b. No ( )

B/6/1 If no from who you are purchase?

……..
……………………………………...

B/6/2 From which locality or village and how much does it cost?

……
……

B/7 How much the quantities of the most important products you collect or purchase? (Per month)

a)……………………………………………………………………………………………………….
b)……………………………………………………………………………………………………….
c)……………………………………………………………………………………………………….
d)……………………………………………………………………………………………………….
e)……………………………………………………………………………………………………….

B/8 Are you sell these products for direct consumer?

a. Yes ( ) b. No ( )

B/8/1 If No for whom please?
……
……

B/8/2 What is the final price for each Malwa or Gontar?
……
……

B/9 How much the quantities of the most important products you sell? (Per month)
a)………………………………………………………………………………………………………
b)………………………………………………………………………………………………………
c)………………………………………………………………………………………………………
d)………………………………………………………………………………………………………
e)………………………………………………………………………………………………………

B/9 The annual income (SDG) of NTFPs

……
……

B/10 Determine in which markets do you sell of these products?

a)………………………………………………………………………………………………………
b)………………………………………………………………………………………………………
c)………………………………………………………………………………………………………

B/11 Do you pay fees or taxes when collecting or marketing NTFPs?

a. Yes……………………………..… b. No………..……………………….

B/11/1 If yes; what are the types of fees or tax you paid?

Products	The type of payment or fees	The authority that received payments	The unit (for each gontar, malwa………)	Fees value (SDG per Kg)

B/12 Problems and constraints

B/12/1 From your opinion, what are the problems and constraints facing of NTFPs marketing? (For example: Natural climatic conditions (explain), low price of NTFPs, Long distance from village, etc….) please categorize the problems according to importance.

1/………

2/………

3/………

B/13 Did you participated/involved in management or improvement program of NTFPs?

(1) Yes………………………………… (2) No…………..………………….

B/12/1 If yes; pleasespecify the product type and theprocess

Product	Process used

B/14 Recent, do you think the marketing of these products was affected?

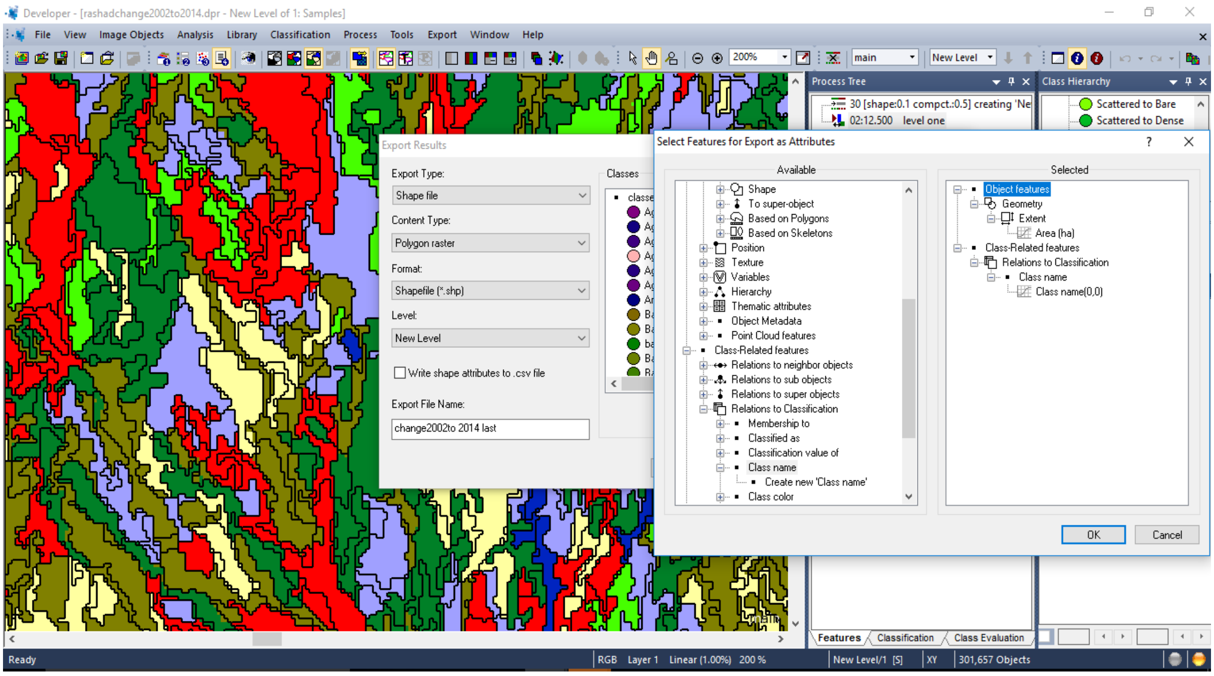
a. Yes ( ) b. No ( )

B/14/1 If yes according to what?

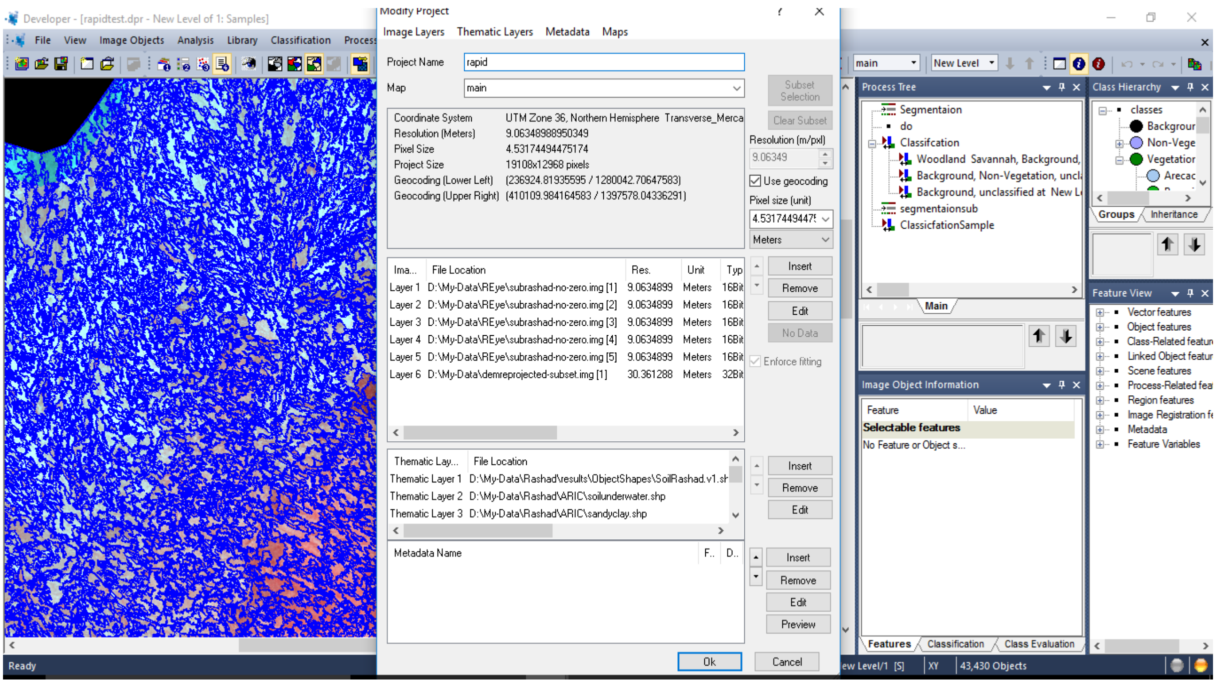
………
………

Thank you

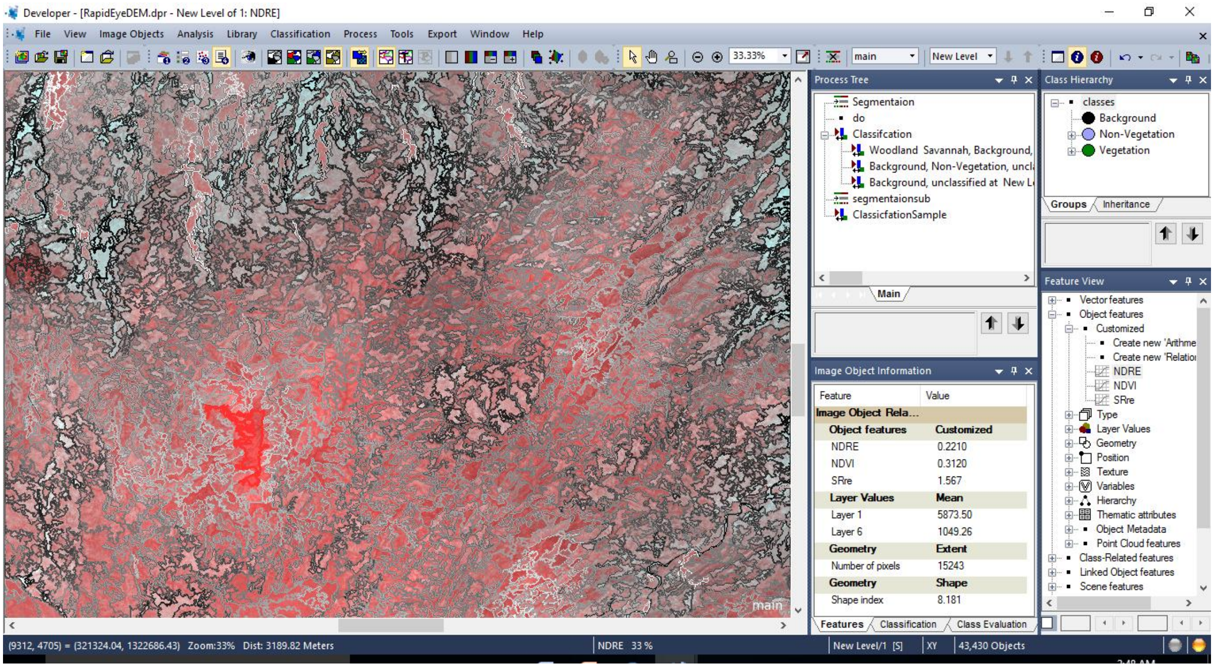
Annex 8: Example of selected features for export as attributes



Annex 9: Example of the integrated thematic layers for classification of the species map

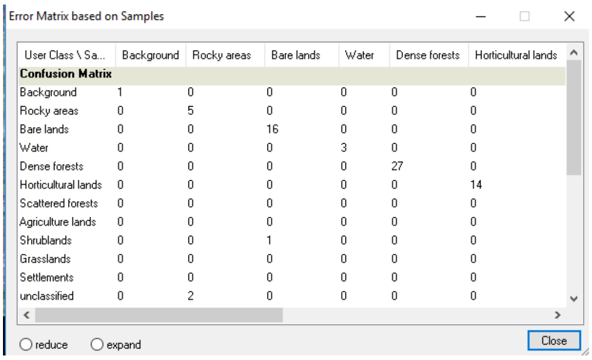


Annex 10: Part of the hierarchical rules developed to extract categorical species map



Annex 11: Example for Classification accuracies for the extracted LU/LC classes by Overall accuracy method- Error Matrix based on Samples

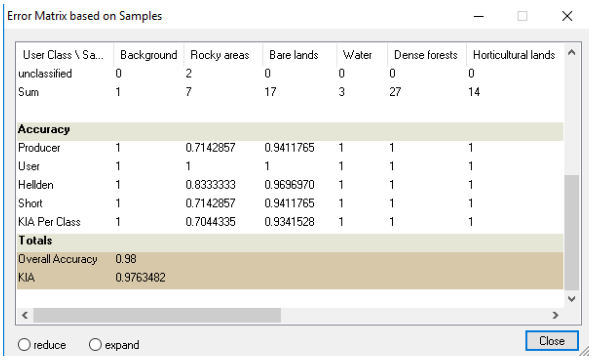
Year 1984



Error Matrix based on Samples

User Class \ Sa...	Background	Rocky areas	Bare lands	Water	Dense forests	Horticultural lands
Confusion Matrix						
Background	1	0	0	0	0	0
Rocky areas	0	5	0	0	0	0
Bare lands	0	0	16	0	0	0
Water	0	0	0	3	0	0
Dense forests	0	0	0	0	27	0
Horticultural lands	0	0	0	0	0	14
Scattered forests	0	0	0	0	0	0
Agriculture lands	0	0	0	0	0	0
Shrublands	0	0	1	0	0	0
Grasslands	0	0	0	0	0	0
Settlements	0	0	0	0	0	0
unclassified	0	2	0	0	0	0

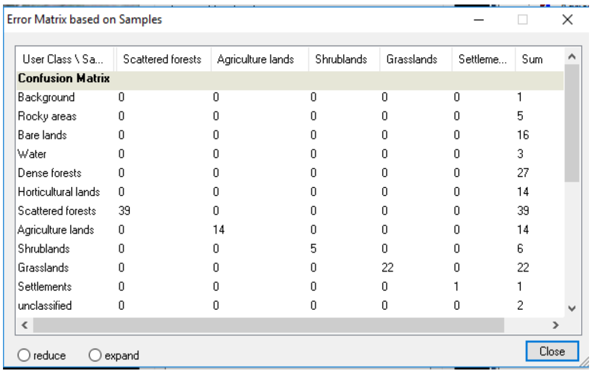
reduce expand Close



Error Matrix based on Samples

User Class \ Sa...	Background	Rocky areas	Bare lands	Water	Dense forests	Horticultural lands
unclassified	0	2	0	0	0	0
Sum	1	7	17	3	27	14
Accuracy						
Producer	1	0.7142857	0.9411765	1	1	1
User	1	1	1	1	1	1
Hellden	1	0.8333333	0.9696970	1	1	1
Short	1	0.7142857	0.9411765	1	1	1
KIA Per Class	1	0.7044335	0.9341528	1	1	1
Totals						
Overall Accuracy	0.98					
KIA	0.9763482					

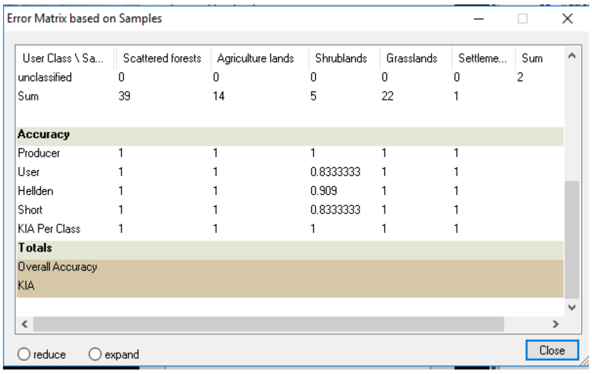
reduce expand Close



Error Matrix based on Samples

User Class \ Sa...	Scattered forests	Agriculture lands	Shrublands	Grasslands	Settleme...	Sum
Confusion Matrix						
Background	0	0	0	0	0	1
Rocky areas	0	0	0	0	0	5
Bare lands	0	0	0	0	0	16
Water	0	0	0	0	0	3
Dense forests	0	0	0	0	0	27
Horticultural lands	0	0	0	0	0	14
Scattered forests	39	0	0	0	0	39
Agriculture lands	0	14	0	0	0	14
Shrublands	0	0	5	0	0	6
Grasslands	0	0	0	22	0	22
Settlements	0	0	0	0	1	1
unclassified	0	0	0	0	0	2

reduce expand Close



Error Matrix based on Samples

User Class \ Sa...	Scattered forests	Agriculture lands	Shrublands	Grasslands	Settleme...	Sum
unclassified	0	0	0	0	0	2
Sum	39	14	5	22	1	
Accuracy						
Producer	1	1	1	1	1	
User	1	1	0.8333333	1	1	
Hellden	1	1	0.909	1	1	
Short	1	1	0.8333333	1	1	
KIA Per Class	1	1	1	1	1	
Totals						
Overall Accuracy						
KIA						

reduce expand Close

Annex 12: Classification accuracies for the extracted Change detection

	Change of period 1984 to 1994	Change of period 1994 to 2002	Change of period 2002 to 2014
Overall accuracy	0.849	0.949	0.877
Kappa statistics	0.846	0.948	0.874

Annex 13: Classification accuracies of the extracted Change detection by Best Classification Result method

1- For period 1984 to 1994

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Bare land to Agri	1947	0.9605662	0.1503339	0.2891064	1
Bare land to Scatt...	1961	0.9875595	0.05763214217	0.534	1
Bare land to Grassl...	5809	0.935	0.1262842	0.3081124	1
Bare land	2755	0.919	0.1862358	0.3061476	1
Bare land to Shrub...	1446	0.9307676	0.1702586	0.2611397	1
Bare and Grasslan...	7220	0.9382596	0.1505714	0.313	1
Arig to Bare land	2607	0.9494576	0.1555510	0.2144931	1
Agri to Dense forest	6104	0.9346645	0.1603067	0.199	1
Agri to Scattered f...	6871	0.5816835	0.09760465549	0.2513358	1
Agri to Grasslands	10136	0.978	0.1138698	0.2264554	1
Agri to Shrublands	2323	0.976	0.1222934	0.2625080	1
Agri	98	0.6472337	0.3173034	0.182	0.9995898
Dense forest to Ba...	270	0.9652977	0.1331668	0.1366005	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Dense forest to Agri	1895	0.9451234	0.1895860	0.204	1
Dense forest	2090	0.9856341	0.07949171181	0.294	1
Dense to Scattere...	2059	0.9911763	0.03815329445	0.6642225	1
Dense to Grasslands	2077	0.9892174	0.04985593944	0.4672917	1
Scattered forest	8473	0.9434620	0.1831021	0.1132487	1
Scattered to Dense	9398	0.9845982	0.09517394363	0.2736359	1
Scattered to Bare	3031	0.9968723	0.02790745718	0.3296418	1
Scattered to Agri	692	0.9325282	0.1002190	0.5441397	1
Dense to Horti	613	0.8951077	0.222	0.155	1
Scattered to Shrub...	162	0.832	0.2224015	0.2684301	0.9998868
Scatterd to Grassl...	12860	0.994	0.03459332275	0.3077571	1
Grasslands	17140	0.9894329	0.04829737871	0.4445363	1
Grasslands to Agri	12807	0.9832570	0.09325091933	0.302	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Grasslands to Bare...	4210	0.6154473	0.1344986	0.208	1
Grasslands to Dense	10733	0.9831789	0.07296079603	0.167	1
Grasslands to Scat...	9483	0.5972311	0.08950206627	0.2017060	1
Grasslands to Shru...	4927	0.9546473	0.1456564	0.3797390	1
Horti	308	0.7902045	0.1963066	0.2683666	1
Horti to Dense forest	136	0.3787895	0.2148247	0.2632908	1
Shrublands	1785	0.9675161	0.1161948	0.402	1
Shrublands to bare...	3230	0.9366479	0.1526925	0.367	1
Shrublands to Agri	3483	0.9756663	0.1103364	0.302	1
Shrublands to Sca...	2897	0.9904319	0.04313092582	0.2861259	1
Shrublands to Gra...	8516	0.8647759	0.2037497	0.1074480	1
Settelements	161	0.7417533	0.3368221	0.2647736	1
Settelments to Bar...	291	0.6454417	0.3097899	0.1671713	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Settelments to Bar...	291	0.6454417	0.3097899	0.1671713	1
Water	381	0.5321536	0.3	0.1402825	1
Rocky areas	402	0.9684374	0.101	0.4013900	1
Scattered to Rock...	3616	0.9318400	0.1596822	0.145	1
Agri to Rocky areas	2876	0.8728863	0.235	0.232	1
Dense to Rocky ar...	899	0.9373286	0.128	0.1906738	1
Grasslands to Roc...	12024	0.7528224	0.1411219	0.1804673	1
Rocky areas to Gr...	452	0.9266780	0.1152371	0.4144766	1
Rocky areas to De...	721	0.9591017	0.09709226934	0.4158235	1
Rocky areas to Sc...	772	0.8447567	0.258	0.2051227	1
Rocky areas to Agri	9009	0.5493109	0.0866113949	0.2764984	1
back	7908	1	0	1	1

reduce expand Close

2- For period 1994 to 2002

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Bare land to Agri	3746	0.9361621	0.1755825	0.1604379	1
Bare land to Scatt...	4169	0.9448835	0.1584173	0.2171193	1
Bare land to Grassl...	8134	0.8156438	0.236	0.2437192	1
Bare land	5806	0.8795710	0.2148280	0.213	1
Bare land to Shrub...	6537	0.9471200	0.143	0.3193775	1
Bare and Grasslan...	571	0.672	0.3036825	0.2033956	1
Agri to Bare land	6712	0.9903990	0.05375468288	0.379	1
Agri to Dense forest	6741	0.961	0.1407232	0.3403587	1
Agri to Scattered f...	12684	0.9567680	0.1382057	0.2383445	1
Agri to Grasslands	791	0.9256761	0.1302759	0.3432230	1
Agri to Shrublands	10901	0.9877432	0.0658070371	0.2865885	1
Agri	19281	0.773	0.2732699	0.1583473	1
Dense forest to Ba...	3547	0.8252818	0.296	0.2508121	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Dense forest to Agri	6480	0.9935502	0.03721196944	0.3882273	1
Dense forest	5369	0.9911086	0.03490794081	0.4856399	1
Dense to Scattere...	201	0.955	0.05644940514	0.6597676	1
Dense to Grasslands	4109	0.983	0.05521317394	0.4681044	1
Scattered forest	10155	0.9717889	0.09911295389	0.303	1
Scattered to Dense	6844	0.993	0.03356441788	0.3697498	1
Scattered to Bare	643	0.8462758	0.2253801	0.3331449	1
Scattered to Agri	8226	0.9921261	0.04682046276	0.4293262	1
Dense to Horti	481	0.8032407	0.2141239	0.3387658	1
Scattered to Shrub...	16687	0.8398383	0.1612686	0.3008002	1
Scatterd to Grassl...	6190	0.9898757	0.03830438363	0.5518919	1
Grasslands	11084	0.9888581	0.04675474758	0.3652054	1
Grasslands to Agri	12197	0.9925575	0.04612009487	0.204	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Grasslands to Bare...	13047	0.9208549	0.1808999	0.2467087	1
Grasslands to Dense	8203	0.9855627	0.04047743111	0.3081339	1
Grasslands to Scat...	14057	0.9923338	0.04086941129	0.4088651	1
Grasslands to Shru...	15471	0.9615196	0.09840686778	0.4136085	1
Horti	633	0.5362159	0.2508444	0.1948679	1
Horti to Scattered f...	599	0.9743646	0.09201371108	0.3374814	1
Shrublands	3931	0.9878421	0.06038317002	0.395	1
Shrublands to bare...	6920	0.9686166	0.1064282	0.2061789	1
Shrublands to Agri	6317	0.7083904	0.2807066	0.2527432	1
Shrublands to Sca...	1905	0.8561524	0.2554026	0.245	1
Shrublands to Gra...	6868	0.7807175	0.2023495	0.288	1
Settelements	193	0.7563679	0.321	0.2332559	1
Settelments to Bar...	643	0.5002546	0.2773071	0.1718186	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Water	150	0.8043750	0.2582331	0.2027555	1
Rocky areas	1117	0.9464393	0.141	0.2593946	1
Dense to Shrublan...	6646	0.9016392	0.2272375	0.265	1
Scattered to Rock...	1914	0.915	0.1744166	0.3482147	1
Agri to Rocky areas	1674	0.7076539	0.1066482	0.2884512	1
Dense to Rocky ar...	1718	0.9797331	0.0611166849	0.537	1
Grasslands to Ro...	1836	0.8567124	0.2261685	0.2882847	1
Rocky areas to Gr...	2153	0.8156361	0.2057002	0.2297338	1
Rocky areas to Sc...	3557	0.8986929	0.1667223	0.3545078	1
Rocky areas to De...	2764	0.849	0.2091745	0.2017862	1
Rocky areas to Agri	3843	0.8861205	0.173	0.2654894	1
back	10065	0.9773719	0.1008772	0.3795469	1

reduce expand Close

3- For period 2002 to 2014

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Bare land to Agri	3453	0.9491432	0.1628591	0.22	1
Bare land to Scatt...	10247	0.941	0.1615703	0.2193119	1
Bare land to Grassl...	10737	0.9185792	0.1736548	0.2475578	1
Bare land	6033	0.9311435	0.1783470	0.3843670	1
Bare land to Shrub...	11319	0.9406583	0.1514773	0.353	1
Bare and Grasslan...	260	0.7811519	0.2501520	0.1591313	1
Arig to Bare land	3940	0.9592595	0.1263269	0.3554967	1
Agri to Dense forest	3730	0.994	0.03469749102	0.4307306	1
Agri to Scattered f...	13847	0.992	0.05365337295	0.3037970	1
Agri to Grasslands	13689	0.9943659	0.03437410195	0.3591218	1
Agri to Shrublands	8434	0.987	0.06132444677	0.3544790	1
Agri	8781	0.9986909	0.01171090385	0.7715399	1
Dense forest to Ba...	3085	0.981	0.09008788726	0.247	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Dense forest to Agri	5198	0.9743369	0.1154263	0.154	1
Dense forest	4024	0.9836409	0.07995735926	0.3845403	1
Dense to Scattere...	10678	0.9862641	0.07463080277	0.2297222	1
Dense to Grasslands	7748	0.9912585	0.03695046797	0.509	1
Scattered forest	15674	0.9893503	0.06585816837	0.318	1
Scattered to Dense	4697	0.9896447	0.04989030615	0.2461904	1
Scattered to Bare	5388	0.962	0.1288261	0.311	1
Scattered to Agri	9201	0.9848005	0.08405179367	0.1862875	1
Dense to Horti	337	0.7507921	0.2502444	0.2075921	1
Scattered to Shrub...	9741	0.9817782	0.09282431796	0.158	1
Scatterd to Grassl...	14336	0.991	0.04197435939	0.2385569	1
Grasslands	10003	0.9852303	0.05342312381	0.4323034	1
Grasslands to Agri	4939	0.9772751	0.101	0.296	1

reduce expand Close

Best Classification Result

Class	Objects	Mean	StdDev	Minimum	Maximum
Grasslands to Bare...	5633	0.9858421	0.06234671755	0.3217161	1
Grasslands to Dense	9316	0.9808615	0.09692238069	0.2048494	1
Grasslands to Scat...	1224	0.9134950	0.1244290	0.3178824	1
Grasslands to Shru...	20100	0.699	0.2671239	0.2841502	1
Horti	172	0.718	0.2503951	0.2754064	1
Horti to Scattered f...	7907	0.9871659	0.06829904028	0.173	1
Shrublands	12876	0.9866972	0.08215395702	0.1662077	1
Shrublands to Bar...	6547	0.9856896	0.06944092123	0.3858134	1
Shrublands to Agri	470	0.6238194	0.2571025	0.3411231	0.9993628
Shrublands to Sca...	556	0.9297275	0.1142361	0.2876339	1
Shrublands to Gra...	16235	0.9117621	0.179	0.404	1
Settelements	267	0.7927708	0.1941125	0.2135653	1
Settelments to bar...	470	0.7256890	0.3567517	0.152	1

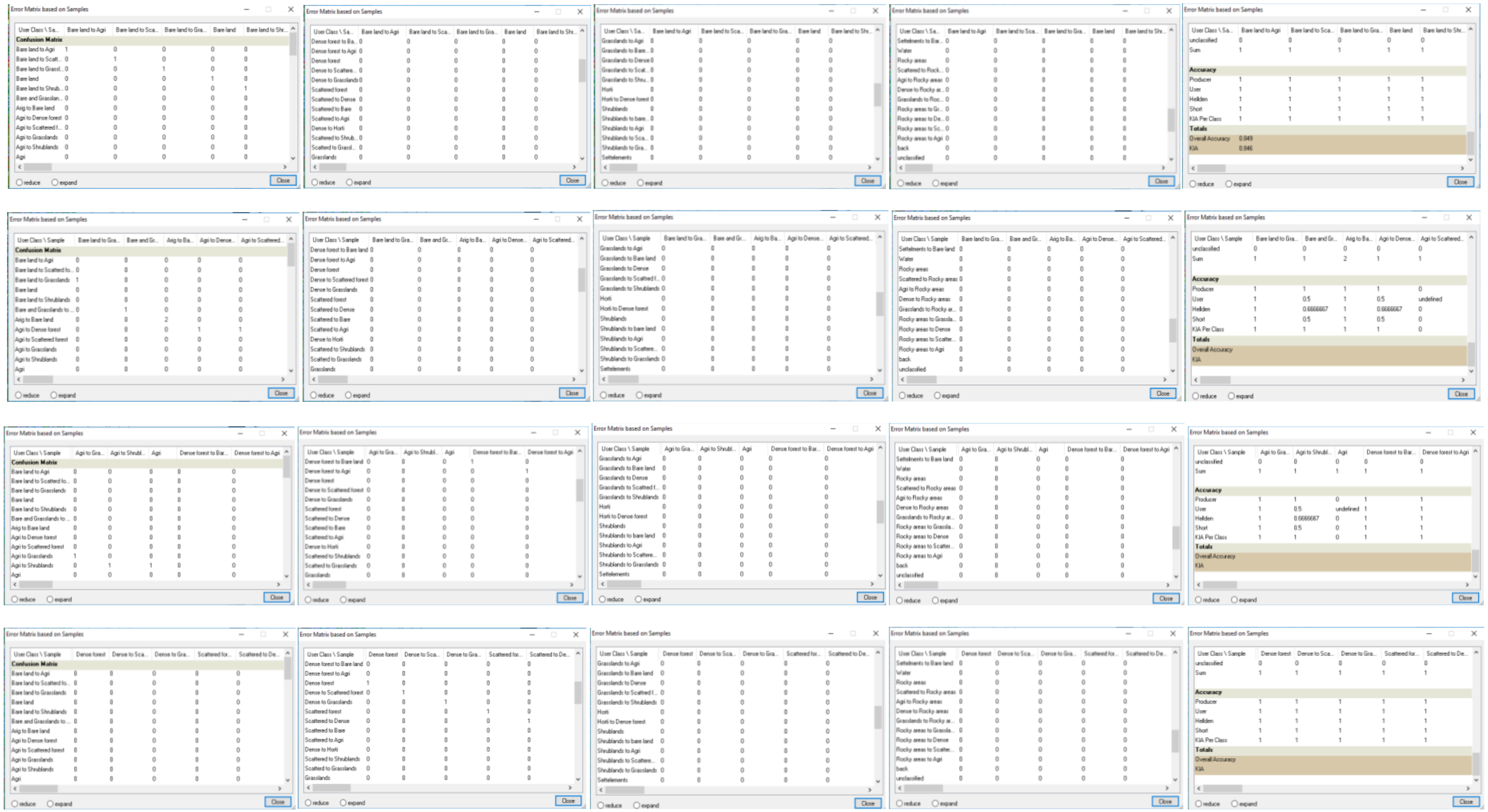
reduce expand Close

Best Classification Result

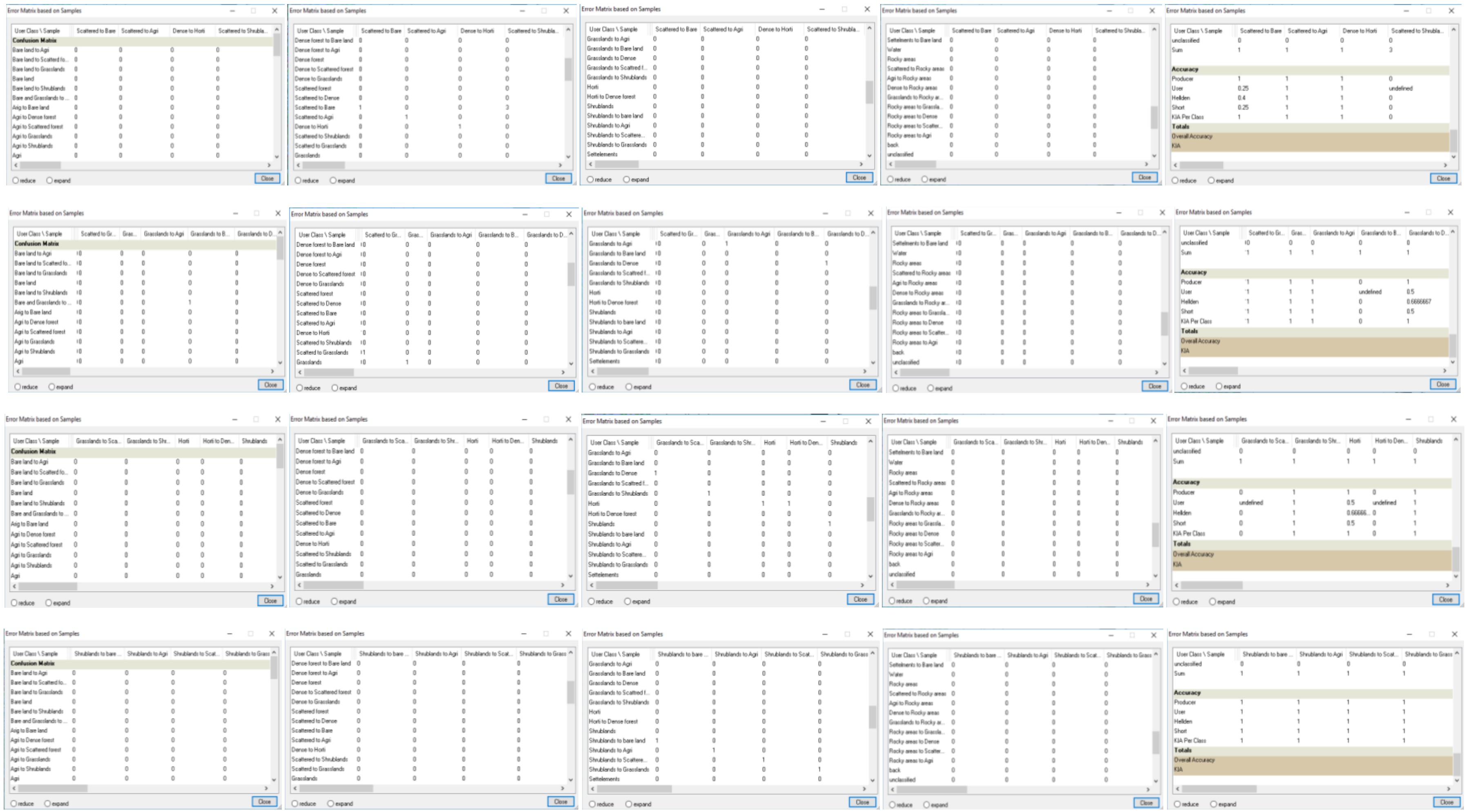
Class	Objects	Mean	StdDev	Minimum	Maximum
Water	572	0.7091472	0.2425191	0.1571147	1
Rocky areas	1438	0.9296232	0.155	0.4486070	1
Dense to Shrublan...	5164	0.9937254	0.03833682983	0.443	1
Scattered to Rock...	758	0.9302565	0.1184717	0.3217279	1
Agri to Rocky areas	909	0.765	0.2198977	0.2888234	1
Dense to Rocky ar...	908	0.9031648	0.153	0.243	1
Grasslands to Roc...	529	0.84	0.1856658	0.2073401	1
Rocky areas to Gr...	1744	0.9395581	0.1171911	0.3334488	1
Rocky areas to Sc...	3416	0.979	0.07062461042	0.3448767	1
Rocky areas to De...	1408	0.663	0.107	0.2462877	1
Rocky areas to Agri	1347	0.9443245	0.124	0.354	1
back	2164	1	0	1	1

reduce expand Close

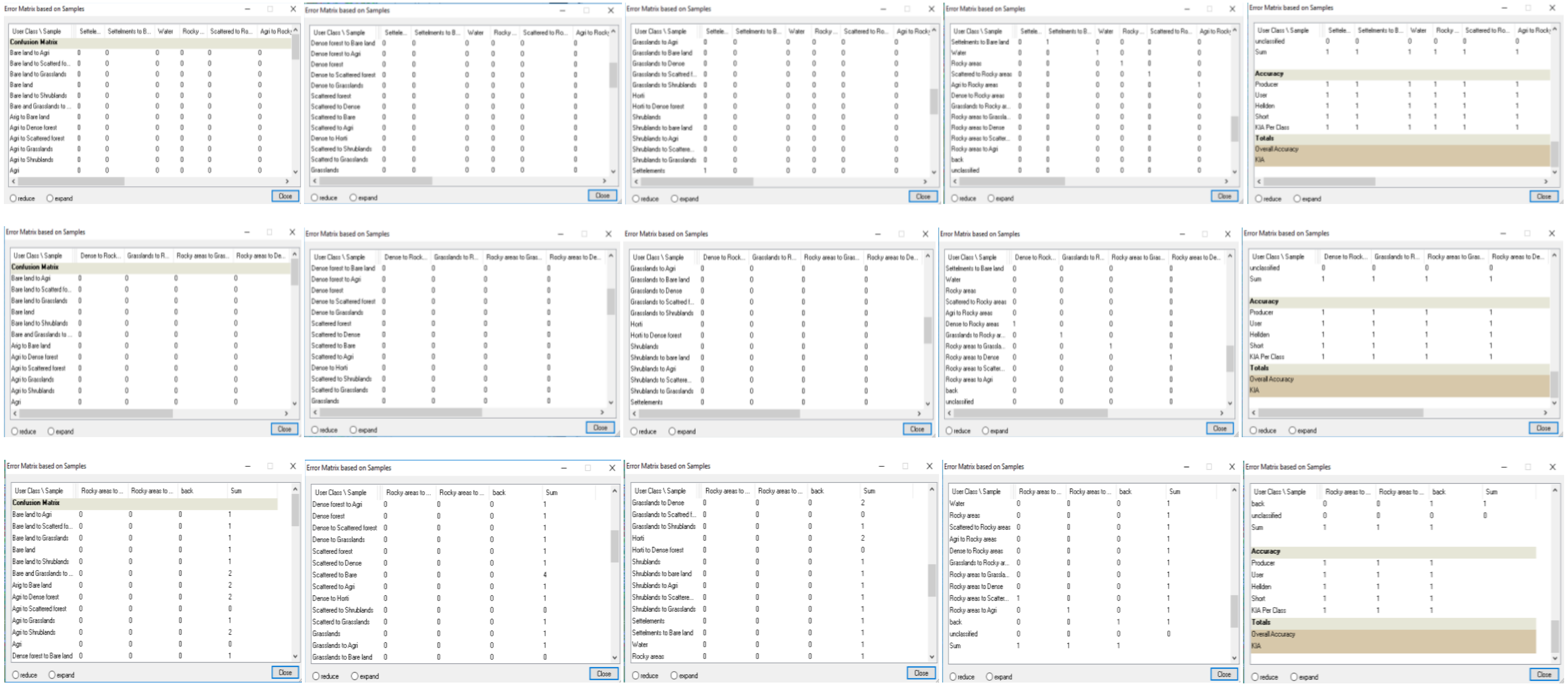
Annex 14: Example for Classification accuracies of the extracted Change detection for period 1984 to 1994 by Overall accuracy method



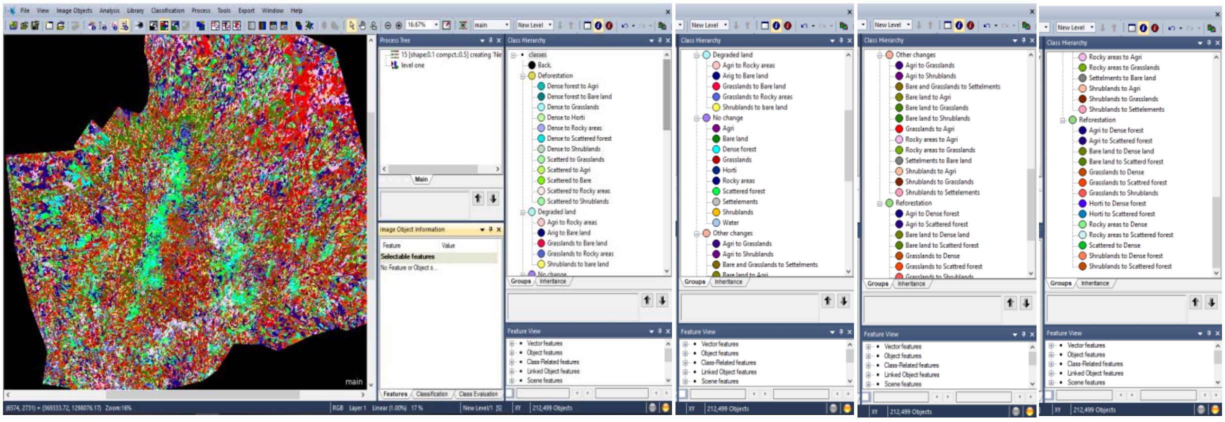
Annex 14: Con.



Annex 14: Con.



Annex 15: Classes of the change detection analysis



Annex 16: Statistical summary of the FCS

1- **For Non-displaced people**

In the past 4 weeks (30 days), did you worry that your household would not have enough food?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	131	65.5	80.4	80.4
	NO	32	16.0	19.6	100.0
	Total	163	81.5	100.0	
Missing	I haven't any problem	37	18.5		
Total		200	100.0		

How often did this happen in the past (4 weeks/30 days)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	18	9.0	62.1	62.1
	Sometimes (3–10 times)	9	4.5	31.0	93.1
	Often (more than 10 times)	2	1.0	6.9	100.0
	Total	29	14.5	100.0	
Missing	I haven't any problem	171	85.5		
Total		200	100.0		

In the past 4 weeks (30 days), were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	103	51.5	75.7	75.7
	No	33	16.5	24.3	100.0
	Total	136	68.0	100.0	
Missing	I haven't any problem	63	31.5		
	System	1	.5		

	Total	64	32.0		
Total		200	100.0		

How often did this happen in the past (4 weeks/30 days)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	20	10.0	62.5	62.5
	Sometimes (3–10 times)	10	5.0	31.3	93.8
	Often (more than 10 times)	2	1.0	6.3	100.0
	Total	32	16.0	100.0	
Missing	I haven't any problem	167	83.5		
	System	1	.5		
	Total	168	84.0		
Total		200	100.0		

In the past 4 weeks (30 days), did you or any household member have to eat a limited variety of foods due to a lack of resources?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	69	34.5	63.9	63.9
	No	39	19.5	36.1	100.0
	Total	108	54.0	100.0	
Missing	I haven't any problem	92	46.0		
Total		200	100.0		

How often did this happen in the past (4 weeks/30 days)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	27	13.5	71.1	71.1
	Sometimes (3–10 times)	10	5.0	26.3	97.4
	Often (more than 10 times)	1	.5	2.6	100.0

	Total	38	19.0	100.0	
Missing	I haven't any problem	161	80.5		
	System	1	.5		
	Total	162	81.0		
Total		200	100.0		

2- For Displaced people

In the past 4 weeks (30 days), did you worry that your household would not have enough food?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	16	66.7	88.9	88.9
	NO	2	8.3	11.1	100.0
	Total	18	75.0	100.0	
Missing	I haven't any problem	6	25.0		
Total		24	100.0		

How often did this happen in the past (4 weeks/30 days)? (Displaced)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	4	16.7	66.7	66.7
	Sometimes (3–10 times)	2	8.3	33.3	100.0
	Total	6	25.0	100.0	
Missing	I haven't any problem	18	75.0		
Total		24	100.0		

In the past 4 weeks (30 days), were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	17	70.8	89.5	89.5
	No	2	8.3	10.5	100.0
	Total	19	79.2	100.0	
Missing	I haven't any	5	20.8		

	problem				
Total		24	100.0		

How often did this happen in the past (4 weeks/30 days)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	11	45.8	84.6	84.6
	Sometimes (3–10 times)	2	8.3	15.4	100.0
	Total	13	54.2	100.0	
Missing	I haven't any problem	11	45.8		
Total		24	100.0		

In the past 4 weeks (30 days), did you or any household member have to eat a limited variety of foods due to a lack of resources?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	13	54.2	86.7	86.7
	No	2	8.3	13.3	100.0
	Total	15	62.5	100.0	
Missing	I haven't any problem	9	37.5		
Total		24	100.0		

How often did this happen in the past (4 weeks/30 days)?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rarely (1–2 times)	6	25.0	75.0	75.0
	Sometimes (3–10 times)	2	8.3	25.0	100.0
	Total	8	33.3	100.0	
Missing	I haven't any problem	16	66.7		
Total		24	100.0		

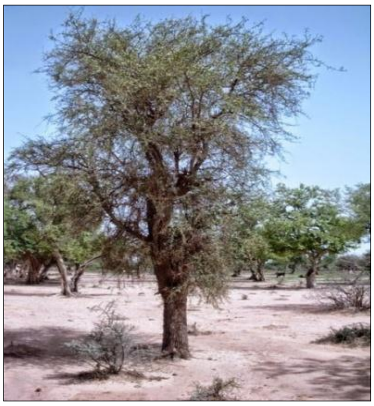
Annex 17: List of the most important of NTFPs in the study area

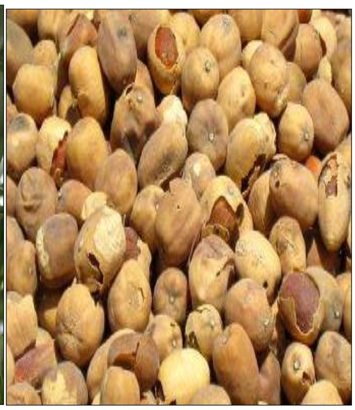
Scientific Name: ***Ziziphus spina-christi***. Local Name: Sider



Taken by author, 2014

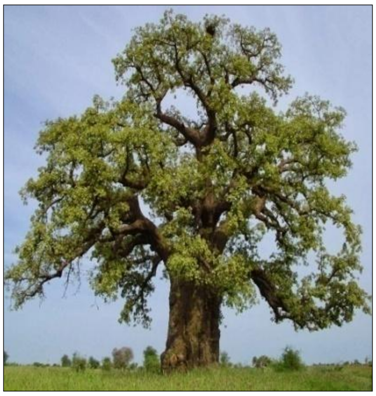
Scientific Name: ***Balanites aegyptiaca***. Local Name: Higlig





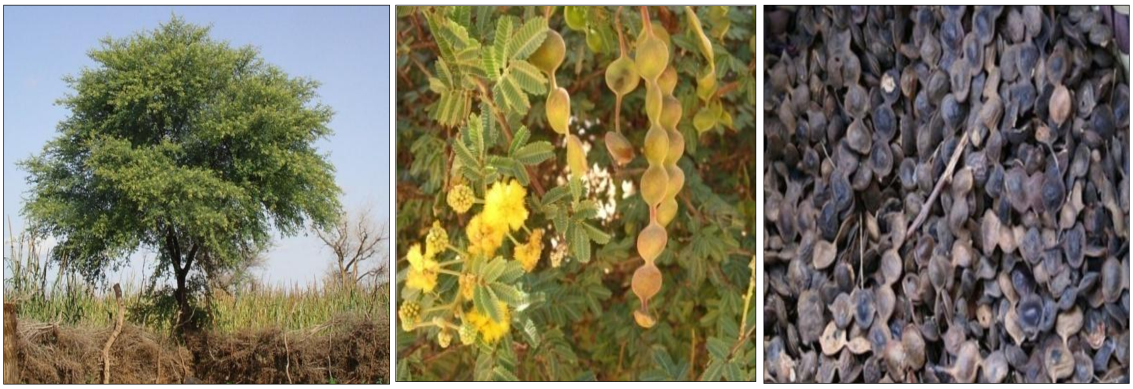
Taken by author, 2014

Scientific Name: ***Adansonia digitata.*** Local Name: Tabaldi



Taken by author, 2014

Scientific Name: ***Acacia nilotica***. Local Name: Sunt



Taken by author, 2014

Scientific Name: ***Tamarindus indica***. Local Name: Aradeib

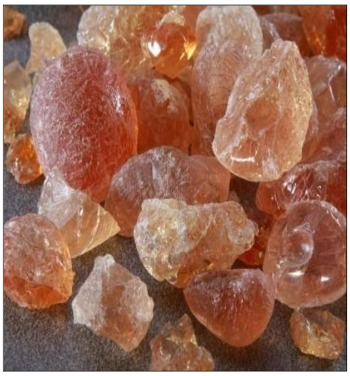
Taken by author, 2014

Scientific Name: ***Grewia tenax***. Local Name: Goudiem

Taken by author, 2014

Scientific Name: ***Acacia senegal***. Local Name: Hashab



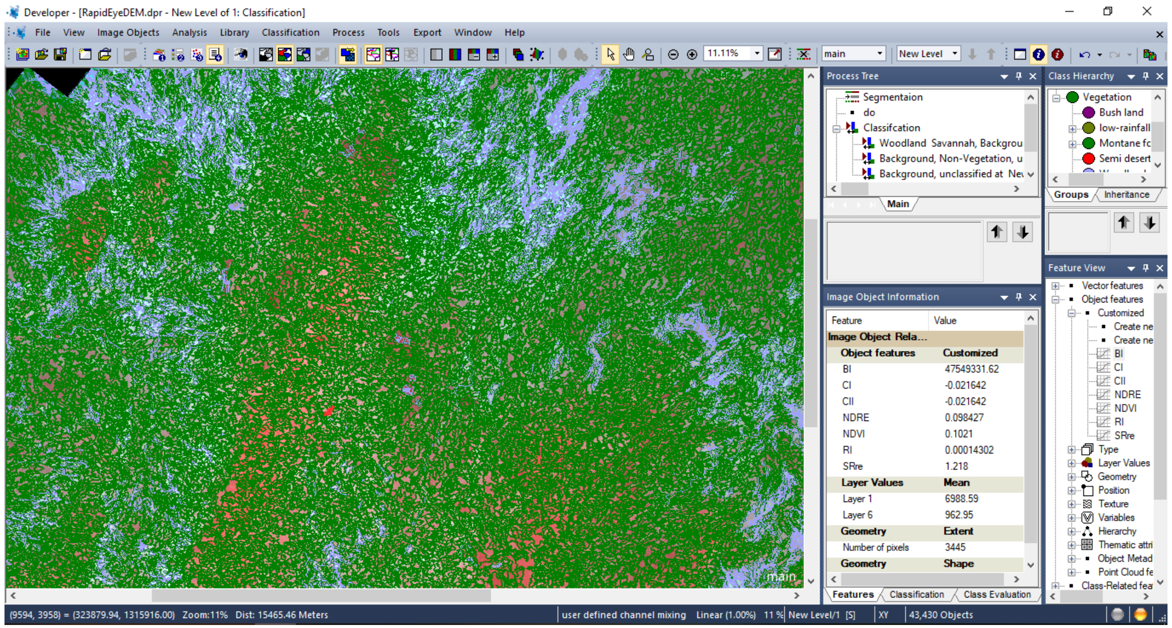


Taken by author, 2014

Annex 18: Some physical and chemical properties of the soil plots

Soil depth (cm)	Sand (%)	Silt (%)	Clay (%)	CaCo3	pH paste	Bulk density g/cm^2	Organic matter (%)	K (mg/100g)	Na (%)
0-20	71.6	12	16.4	34.8	7.2	1.4	0.21	9.8	4
20-40	74	10.2	15.8	2.1	7.4	1.2	0.19	8.9	4
40-60	74.6	7.8	8.2	2.1	7.3	1.4	0.22	12.1	4
60-80	74	8.8	17.2	2.1	7.2	1.3	0.20	8.3	4
80-100	82	4	12	29.7	7.2	1.4	0.20	14.3	4

Annex 19: Part of the classification schemes for the study area based on user experience and spectral indices



Annex 20: The main markets for NTFPs's buyers

Market of *Ziziphus spina-christi* purchase

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Elabbassia	25	11.2	49.0	49.0
	Um Baraka	11	4.9	21.6	70.6
	Tabssa	1	.4	2.0	72.5
	Village's market	4	1.8	7.8	80.4
	Rashad	10	4.5	19.6	100.0
	Total	51	22.8	100.0	
Missing	I don't buy *Ziziphus spina-christi*	173	77.2		
Total		224	100.0		

Market of *Balanites aegyptiaca* purchase

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Elabbassia	23	10.3	44.2	44.2
	Um Baraka	12	5.4	23.1	67.3
	Tabssa	1	.4	1.9	69.2
	Village's market	4	1.8	7.7	76.9
	Rashad	12	5.4	23.1	100.0
	Total	52	23.2	100.0	
Missing	I don't buy *Balanites aegyptiaca*	171	76.3		
	System	1	.4		
	Total	172	76.8		
Total		224	100.0		

Market of *Adansonia digitata* purchase

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Elabbassia	30	13.4	50.8	50.8
	Um Baraka	9	4.0	15.3	66.1
	Tabssa	1	.4	1.7	67.8
	Village's market	4	1.8	6.8	74.6
	Rashad	15	6.7	25.4	100.0
	Total	59	26.3	100.0	
Missing	I don't buy *Adansonia digitata*	164	73.2		
	System	1	.4		
	Total	165	73.7		
Total		224	100.0		

Market of *Acacia nilotica* purchase

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Elabbassia	18	8.0	50.0	50.0
	Um Baraka	5	2.2	13.9	63.9
	Rashad	1	.4	2.8	66.7
	Tabssa	1	.4	2.8	69.4
	Village's market	11	4.9	30.6	100.0
	Total	36	16.1	100.0	
Missing	I don't buy *Acacia nilotica*	188	83.9		
Total		224	100.0		

Market of *Tamarindus indica* purchase

		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Elabbassia	18	8.0	32.1	32.1
	Um Baraka	8	3.6	14.3	46.4
	Elobied	1	.4	1.8	48.2
	Tabssa	1	.4	1.8	50.0
	Village’s market	5	2.2	8.9	58.9
	Rashad	23	10.3	41.1	100.0
	Total	56	25.0	100.0	
Missing	I don't buy *Tamarindus indica*	167	74.6		
	System	1	.4		
	Total	168	75.0		
Total		224	100.0		

Market of *Grewia tenax* purchase

		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Elabbassia market	19	8.5	38.0	38.0
	Um Baraka	9	4.0	18.0	56.0
	Rashad	15	.4	2.0	58.0
	Tabssa	1	.4	2.0	60.0
	Village’s market	5	8.9	40.0	100.0
	Total	50	22.3	100.0	
Missing	I don't buy *Grewia tenax*	174	77.7		
Total		224	100.0		

Market *Acacia senegal* purchase

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Elabbassia market	12	5.4	37.5	37.5
	Um Baraka	4	1.8	12.5	50.0
	Um Rawaba	1	.4	3.1	53.1
	Rashad	15	6.7	46.9	100.0
	Total	32	14.3	100.0	
Missing	I don't buy *Acacia senegal*	192	85.7		
Total		224	100.0		

Annex 21: Time spent in collection of NTFPs (hrs)

Time spent in collection for product (hrs)		*Zizyphus spina-chrisi*	*Balanites aegyptiaca*	*Adansonia digitata*	*Acacia nilotica*	*Tamaraindus indica*	*Grewia tenax*	*Acacia senegal*
N	Valid	149	126	96	56	79	42	46
	Missing	151	174	204	244	221	258	254
Mean		2.76	2.70	3.05	2.55	2.97	2.67	2.48
Std. Deviation		1.877	1.817	2.129	1.868	2.000	1.706	1.656

Annex 22: Distance to place of collection of NTFPs (km)

Distance to place of collection of products (km)		*Zizyphus spina-chrisi*	*Balanites aegyptiaca*	*Adansonia digitata*	*Acacia nilotica*	*Tamarindus indica*	*Grewia tenax*	*Acacia senegal*
N	Valid	99	78	63	34	51	28	26
	Missing	201	222	237	266	249	272	274
Mean		2.32	2.42	2.78	2.74	2.69	2.64	1.92
Std. Deviation		1.640	1.862	2.113	2.365	2.168	2.297	.796

Annex 23: Month's of NTFPs collection

Month of *Zizyphus spina-chrisi* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	47	15.7	27.8	27.8
	March to April	8	2.7	4.7	32.5
	May-June	1	.3	.6	33.1
	July-August	2	.7	1.2	34.3
	September-October	7	2.3	4.1	38.5
	November-December	100	33.3	59.2	97.6
	Throughout the year	4	1.3	2.4	100.0
	Total	169	56.3	100.0	
Missing	I don't collect *Zizyphus spina-chrisi*	99	33.0		
	System	32	10.7		
	Total	131	43.7		
Total		300	100.0		

Month of *Balanites aegyptiaca* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	45	15.0	31.9	31.9
	March to April	11	3.7	7.8	39.7
	May-June	1	.3	.7	40.4
	September-October	8	2.7	5.7	46.1
	November-December	71	23.7	50.4	96.5
	Throughout the year	5	1.7	3.5	100.0
	Total	141	47.0	100.0	
Missing	I don't collect *Balanites aegyptiaca*	127	42.3		
	System	32	10.7		
	Total	159	53.0		
Total		300	100.0		

Month of *Adansonia digitata* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	28	9.3	26.9	26.9
	March to April	9	3.0	8.7	35.6
	September-October	12	4.0	11.5	47.1
	November-December	52	17.3	50.0	97.1
	Throughout the year	3	1.0	2.9	100.0
	Total	104	34.7	100.0	
Missing	I don't collect *Adansonia digitata*	163	54.3		
	System	33	11.0		
	Total	196	65.3		
Total		300	100.0		

Month of *Acacia nilotica* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	7	2.3	15.2	15.2
	March to April	11	3.7	23.9	39.1
	May-June	5	1.7	10.9	50.0
	July-August	1	.3	2.2	52.2
	September-October	3	1.0	6.5	58.7
	November-December	15	5.0	32.6	91.3
	Throughout the year	4	1.3	8.7	100.0
	Total	46	15.3	100.0	
Missing	I don't collect *Acacia nilotica*	210	70.0		
	System	44	14.7		
	Total	254	84.7		
Total		300	100.0		

Month of *Tamaraindus indica* collection

		Frequency	Percent	Valid Percent	Cumulativ e Percent
Valid	January and February	30	10.0	38.0	38.0
	March to April	19	6.3	24.1	62.0
	May-June	3	1.0	3.8	65.8
	September-October	4	1.3	5.1	70.9
	November-December	21	7.0	26.6	97.5
	Throughout the year	2	.7	2.5	100.0
	Total	79	26.3	100.0	
Missing	I don't collect *Tamarindus indica*	182	60.7		
	System	39	13.0		
	Total	221	73.7		
Total		300	100.0		

Month of *Grewia tenax* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	5	1.7	10.4	10.4
	May-June	2	.7	4.2	14.6
	July-August	9	3.0	18.8	33.3
	September-October	18	6.0	37.5	70.8
	November-December	13	4.3	27.1	97.9
	Throughout the year	1	.3	2.1	100.0
	Total	48	16.0	100.0	
Missing	I don't collect *Grewia tenax*	217	72.3		
	System	35	11.7		
	Total	252	84.0		
Total		300	100.0		

Month of *Acacia senegal* collection

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	January and February	14	4.7	29.2	29.2
	March to April	9	3.0	18.8	47.9
	May-June	1	.3	2.1	50.0
	September-October	8	2.7	16.7	66.7
	November-December	13	4.3	27.1	93.8
	Throughout the year	3	1.0	6.3	100.0
	Total	48	16.0	100.0	
Missing	I don't collect *Acacia senegal*	216	72.0		
	System	36	12.0		
	Total	252	84.0		
Total		300	100.0		

Annex 24: Transport Modes

Mode of transport of *Ziziphus spina-christi* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Donkey	7	3.1	5.6	5.6
	Caro	11	4.9	8.8	14.4
	Track	77	34.4	61.6	76.0
	Self transport	7	3.1	5.6	81.6
	Bicycle	22	9.8	17.6	99.2
	Do not use transport	1	.4	.8	100.0
	Total	125	55.8	100.0	
Missing	I don't sell *Ziziphus spina-christi*	69	30.8		
	System	30	13.4		
	Total	99	44.2		
Total		224	100.0		

Mode of transport of *Balanites aegyptiaca* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Donkey	7	3.1	8.9	8.9
	Caro	10	4.5	12.7	21.5
	Track	55	24.6	69.6	91.1
	Self transport	3	1.3	3.8	94.9
	Bicycle	2	.9	2.5	97.5
	Do not use transport	1	.4	1.3	98.7
	Track and Caro	1	.4	1.3	100.0
	Total	79	35.3	100.0	
Missing	I don't sell *Balanites aegyptiaca*	116	51.8		
	System	29	12.9		
	Total	145	64.7		
Total		224	100.0		

Mode of transport of *Adansonia digitata* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Donkey	3	1.3	4.5	4.5
	Caro	6	2.7	9.0	13.4
	Track	47	21.0	70.1	83.6
	Self transport	4	1.8	6.0	89.6
	Bicycle	3	1.3	4.5	94.0
	Do not use transport	2	.9	3.0	97.0
	Track and Caro	2	.9	3.0	100.0
	Total	67	29.9	100.0	
Missing	I don't sell *Adansonia digitata*	127	56.7		
	System	30	13.4		
	Total	157	70.1		
Total		224	100.0		

Mode of transport of *Acacia nilotica* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Caro	5	2.2	20.8	20.8
	Track	14	6.3	58.3	79.2
	Self transport	2	.9	8.3	87.5
	Bicycle	2	.9	8.3	95.8
	Track and Caro	1	.4	4.2	100.0
	Total	24	10.7	100.0	
Missing	I don't sell *Acacia nilotica*	170	75.9		
	System	30	13.4		
	Total	200	89.3		
Total		224	100.0		

Mode of transport of *Tamarindus indica* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Donkey	2	.9	4.4	4.4
	Caro	4	1.8	8.9	13.3
	Track	81	14.3	71.1	84.4
	Self transport	4	1.8	8.9	93.3
	Bicycle	2	.9	4.4	97.8
	Track and Caro	1	.4	2.2	100.0
	Total	94	20.1	100.0	
Missing	I don't sell *Tamarindus indica*	100	66.5		
	System	30	13.4		
	Total	179	79.9		
Total		224	100.0		

Mode of transport of *Grewia tenax* to market

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Caro	3	1.3	12.5	12.5
	Track	19	8.5	79.2	91.7
	Self transport	1	.4	4.2	95.8
	Track and Caro	1	.4	4.2	100.0
	Total	24	10.7	100.0	
Missing	I don't sell *Grewia tenax*	169	75.4		
	System	31	13.8		
	Total	200	89.3		
Total		224	100.0		

Mode of transport of *Acacia senegal* to market

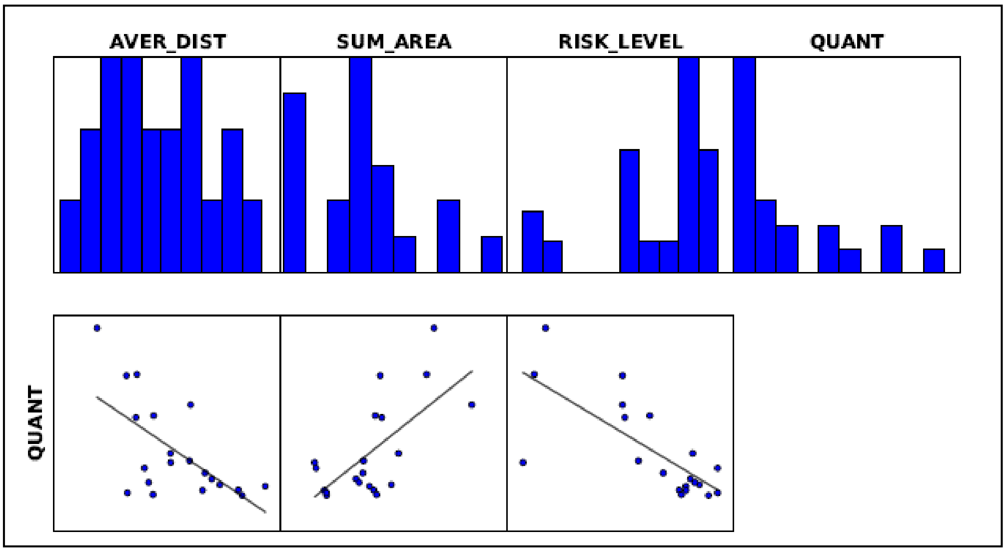
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Donkey	2	.9	8.0	8.0
	Caro	2	.9	8.0	16.0
	Track	117	7.6	68.0	84.0
	Self transport	1	.4	4.0	88.0
	Bicycle	1	.4	4.0	92.0
	Track and Caro	2	.9	8.0	100.0
	Total	125	11.2	100.0	
Missing	I don't sell *Acacia senegal*	68	75.0		
	System	31	13.8		
	Total	199	88.8		
Total		224	100.0		

Annex 25: Socio-economic Factors that affect collection of NTFPs

Products	Age of the responder		Size of household		Marital status of the responder		Tribe		The position in household		Who benefits from NTFPs		Number of wives	
	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)	Correlation Coefficient	Sig. (2-tailed)
Zizyphus spina-chrisi	0.133	0.144	-0.011	0.903	-0.126	0.163	0.099	0.272	0.078	0.386	-0.148	0.131	0.146	0.125
Balantites aegyptiaca	0.065	0.560	0.125	0.258	-0.140	0.206	0.026	.095	-0.060	0.586	-0.055	0.670	-0.162	0.167
Adansonia digitata	0.118	0.367	-0.015	0.905	-0.060	0.638	0.026	0.807	-0.078	0.539	0.185	0.200	-0.288	0.0326
Acacia nilotica	-0.228	0.331	0.039	0.862	-0.237	0.286	-0.116	0.363	-0.395	0.061	-0.088	0.239	-0.029	0.903
Tamarindus indica	0.032	0.840	0.093	0.560	-0.167	0.294	-0.389	0.065	-0.085	0.589	0.231	0.194	-0.273	0.101
Grewia tenax	0.203	0.318	0.182	0.373	-0.081	0.692	-0.275	0.077	-0.024	0.904	-0.071	0.138	-0.045	0.837
Acacia senegal	0.113	0.605	0.438	0.052	-0.114	0.592	0.201	0.344	1	.	-0.179	0.538	0.208	0.378

Annex 26: Model NTFPs collection

Variable Distributions and Relationships



Histogram of Standardized Residuals