MIDLANDS STATE UNIVERSITY

FACULTY OF SCIENCE AND TECHNOLOGY

DEPARTMENT OF SURVEYING AND GEOMATICS

BACHELOR OF SCIENCE HONOURS IN SURVEYING AND GEOMATICS

FINAL YEAR RESEARCH PROJECT

2016

BY LIBERTY MAKACHA (R122068B)

Final Year Research Project submitted to the Faculty of Science and Technology, Department of Surveying and Geomatics, in partial fulfilment of the requirements of the Bachelor of Science Honours Degree in Surveying and Geomatics at the Midlands State University, Zimbabwe

APPROVAL FORM

The undersigned people certify that, they have read and recommend Midlands State University to accept a dissertation entitled

"Location Theory Based Bio-energy Systems planning in site optimisation modelling – Manicaland (Zimbabwe)"

Submitted in partial fulfilment of the requirements of the Bachelor of Science Honours Degree in Surveying and Geomatics. This dissertation meets the regulations governing the award of the degree of Honours in Surveying and Geomatics at Midlands State University, and is approved for its contribution to knowledge and literal presentation.

Supervisor: ……………………………...Signature……………Date…………/……./***2016***

Co-Supervisor: …………………………Signature……………..Date………./……../***2016***

Student: …………………………..……Signature……………..Date………/……../***2016***

Chairperson: …………………...............Signature…………….Date………./……../***2016***

External examiner………………………Signature……………Date………./……./***2016***

RELEASE FORM

Name of Student **:** Makacha Liberty

Registration Number **:** R122068B

Dissertation Title **:** Location Theory Based Bio-energy Systems planning in site optimisation modelling – Manicaland (Zimbabwe).

Degree Title **:** Bachelor of Science Honours in Surveying and Geomatics**.**

Year this degree was granted : 2016

Signed **...**

Date **...**

Permanent Address : **15 Blake Ave**

Yeovil

Mutare

Zimbabwe

Contact Numbers **: 0778 814 336/0717 736 136**

Email Address **: *makachalee@yahoo.com***

DECLARATION

I, Makacha Liberty, hereby declare that:

1) The dissertation is my original work

2) It has not been submitted for degree purposes at any other university,

3) I hereby authorize Midlands State University to lend this dissertation in part or in full to other institutions or individuals for the purposes of scholarly research.

4) The information derived from published and unpublished work of others, was duly acknowledged in the text and bibliography list.

Signature: __________________________ Date: __________________________

ACKNOWLEDGEMENTS

First, I recognise the Almighty God for his providence that saw this work coming to fruition amidst insurmountable challenges. Giving Honour and Glory to God Almighty, in his Mighty name I am blessed.

My final year research project materialised because of the magnanimous support I got from the Midlands State University Surveying Department. Also, the indefatigable academic mentoring given by my academic supervisors***, Ms M Shoko*** and ***Dr C Paradzayi,*** not forgetting ***Mr D Njike*** made this final year research project an insightful quest.

I am very much beholden to ***Mr D Njike*** and his team at the University whose astute mentoring in the five years that I have been part of the Surveying and Geomatics family at the University gave birth to the passion for GIS and Remote Sensing in me.

My sincere Gratitude to my fourth year work supervisors, who gave me invaluable guidance and crystallised my hopes to see light in GIS and Remote Sensing, even in the darkest hours during the work related learning period. Special thanks to ***Engineer P Mundenda***. Thank you for the inspiration, the resources and the constructive criticism. Your criticism cultivated courage, patience and perseverance in me.

Justice would not have been done if mention is not made of the Surveying and Geomatics Class of 2016 students at the Midlands State University for the shared ideas and assistance; you fitted a real definition of a team brothers and sisters.

DEDICATION

To the Aces of my heart,

The pilots of my dreams,

The joys of my life.

And to my lovely daughter ***Sheannah Anenyasha*** and son ***Tinotenda Bradley*** you are the reason why I wake up every day. My wife ***Rosemary*** you have stood the test of time. Everything I do, I do it for you.

ABSTRACT

In as much as decision makers increasingly are turning to Geographical Information Systems to assist them with solving complex spatial problems, these systems on their own do not adequately support decision making because they are lacking in analytical modelling capabilities, do not easily accommodate variations in either the context or the process of spatial decision making. One response to these shortcomings is the development of spatial optimisation modelling techniques which are explicitly designed to address complex spatial problems. The design of such systems, with particular reference to least cost site selection using Analytic Hierarchy Process Modelling in Weighted Overlay Analysis, the decision making processes they support, and a framework for their implementation and subsequent evolution are examined in this research.

The theme of the research can best be summed up in the statement "*Multi-criteria assessment in GIS environments for the location of biomass power plants using Landsat8 imagery, for the estimation of above Ground Biomass (AGB) in Zimbabwe's Eastern Districts*, with a view to spatially identify *least cost sites* for the installation of biomass power plants to support renewable energy generation – improving the current energy mix and countering induced deficits from hydro power plants."

The research managed to identify areas suitable for facility location using the available datasets. However in the availability of more datasets a more informed site location can be achieved.

Table of Contents

List of Figures

List of Tables

List of Acronyms

AGB – Above Ground Biomass

AHP- Analytic Hierarchy Process

CO_2 - Carbon Dioxide

GIS – Geographical Information Systems

GHG –Green House Gas

IEA – International Energy Agency

IPCC - Intergovernmental Panel on Climate Change

IPP - Independent Power Producer

KWh – kilo Watt Hour

LUCE - Levelized Unit Costs of Energy

MW- Mega Watt

PMP - p-Median Problem

P-UFLP - p-Uncapacitated Facility Location Problem

REFIT - Renewable Energy Feed in Tariff

SDSS – Spatial Decision Support Systems

ZESA – Zimbabwe Electricity Supply Authority

ZERA -Zimbabwe Energy Regulatory Authority

ZETDC – Zimbabwe Electricity Transmission and Distribution Company

ZPC- Zimbabwe Power Company

Key terms definition

Biomass is the total amount of live organic matter and inert organic matter (IOM) *aboveground* and *belowground* expressed in tonnes of dry matter per unit area. The total biomass for a region or a country is obtained by up scaling or aggregation of the density of the biomass at the minimum area measured.

Forest Aboveground Biomass (***FAGB***) is a measure of tree or shrub cumulative Net Primary Productivity, NPP (Baral & Katzensteiner, 2015); (Devi, et al., 2014) (Wu & Helldén, 2013).

As an energy source, biomass can either be used directly via combustion to produce heat, or can be used indirectly after converting it into various forms of bio-fuel. Conversion of biomass to bio-fuel is achieved by different methods, which are broadly classified into *thermal*, *chemical*, and *biochemical* methods.

There are five basic categories of ***biomass***:

- ***Virgin wood***, from forestry, arboriculture activities or from wood processing
- ***Energy crops***: high yield crops grown specifically for energy applications
- ***Agricultural residues****:* residues from agriculture harvesting or processing
- ***Food waste***, from food and drink manufacturing, preparation and processing, and post-consumer waste
- ***Industrial waste and co-products*** : From manufacturing and industrial process

The economics of biomass conversion to bio-energy means that some sources of biomass are excluded for energy applications for example high value material for which there is an alternative market. Therefore cost-benefit analysis is a key component of the analysis for biomass conversion systems. There are huge resources of residues, co-products and waste that exist, which could potentially become available, in quantity, at relatively low cost or even negative cost where there is currently a requirement to pay for its disposal.

Chapter 1

Introduction

The core theme of this research is bio-energy systems planning and optimization modelling, with a view to spatially identify *least cost sites* for the installation of biomass power plants to support renewable energy generation and reduce dependencies on electricity importation. The highly dispersed geographical distribution of biomass presents a spatial complexity for countrywide bio-energy systems planning (Jingyuan, 2008) and warrants scientific tools for sustainable exploitation of biomass resources for energy production. Faced with such spatial complexities this research seeks to harmonize and regulate the decision making process in locating *optimum sites* for biomass power plant installation in Zimbabwe. The most promising and targeted source of biomass for the power plant in question is biomass waste from sawmills currently operational in the Eastern districts of the country.

Decision makers, when faced with a complex spatial problem often have multiple, conflicting objectives for its solution. An acceptable solution therefore must reconcile these conflicting goals. In as much as decision makers increasingly are turning to Geographical Information Systems to assist them with solving complex spatial problems, these systems do not adequately support decision making because they are lacking in analytical modelling capabilities, do not easily accommodate variations in either the context or the process of spatial decision making. One response to these shortcomings is the use of analytical modelling techniques - Analytical Hierarchy Process Model (AHP) in weighted overlay analysis to make objective judgements from subjective expert knowledge factors in the decision model, which are explicitly designed to address complex spatial problems.

The research proposes a weighted factor analysis employing AHP model for locating biomass power plants using Landsat (L8 OLI/TIRS) data for biomass distribution mapping. An integrated methodology combining Remote Sensing for biomass availability, biomass supplies and quantification assessment, and discrete location theory for biomass power plant candidate site selection, and location-allocation of power plant is employed.

To find the most suitable sites for constructing biomass power plants, the Analytic Hierarchy Process (AHP) and GIS based suitability analysis are employed subject to *economical*, *societal*, *public health*, and *environmental* constraints and factors. Land use planning constraints, regulatory requirements imposed by Acts such as the *Environmental Management Act* [*Chapter 20:27*], *Regional Town and Country Planning Act* [*Chapter 29:12*] and other related Acts and statutes are some of the major model parameters of the decision rules.

Therefore, taking into consideration the complex nature of datasets under consideration in the site selection problem, Spatial Optimisation Modelling and decision Analysis poses as a lucrative way forward. However, the domesticity of such complicated spatial planning in a developing nation like Zimbabwe would be to all intents and purposes impracticable, and such planning ought to be heavily aligned to the success stories of the developed community to avert disastrous incidences.

Many researchers have proposed various approaches to obtain competitive power generation prices from biomass in many different ways dictated by location dynamics and technologies, but still communities are still caught in the dilemma of conserving biomass resources against meeting ballooning energy requirements.

1.0 Background to the study

1.0.1 Current Energy mix and Generation Capacities in Zimbabwe

The country's energy mix is primarily dominated by fossil fuels with the only major non-fossil source being hydroelectricity that is produced at Kariba.

Table 1: Zimbabwe Power Generation Statistics – (Extracted from ZETDC website on 29 February 2016)

Power Station	Installed Capacity	Actual	% of Installed Capacity
Kariba South Hydro	750	,440	58,67
Hwange Thermal	920	268	29,13
Harare Thermal	80	30	37,50
Munyati Thermal	80	30	37,50
Bulawayo Thermal	90	15	16,67
Total	1920	783	40,78

Table 2: Installed Capacity vs. Dependable Capacity by Type of Station (Adopted from a Presentation by O Nyatanga – ZETDC General Manager (Corporate Affairs) Harare

ELECTRICITY GENERATION INFORMATION

CURRENT POWER STATIONS

POWER STATION	TYPE OF STATION	INSTALLED CAPACITY	DEPENDABLE CAPACITY
Hwange Power Station	Thermal	920 MW	780 MW
Kariba Power Station	Hydro	750 MW	750 MW
3 x Small Thermals	Thermal	270 MW	170 MW
TOTALS		1 940 MW	1 700 MW

Zimbabwe has been experiencing acute power outages due to the low water levels at Kariba Dam with some residents going for 18 hours a day without electricity. Climate change and global warming has led to reduced water levels in the Kariba Dam, a situation which has resulted in reduced generation capacities of hydro power by the Zimbabwe Power Company. The Kariba dam, which provides about 60 percent of peak electricity demand, is operating at around 50 percent of its capacity and risks a complete shutdown, if water levels decrease further (IMF, 2016). [1]

ZPC is generating under half of the required 2 200MW. Government has lately enlisted three foreign companies for the installation of an emergency diesel power plant at Dema substation in Seke as it moves in to ameliorate power shortages bedevilling the country. The emergency power

[1]Under Article IV of the IMF's Articles of Agreement, the IMF holds bilateral discussions with members, usually every year. A staff team visits the country, collects economic and financial information, and discusses with officials the country's economic developments and policies. On return to headquarters, the staff prepares a report, which forms the basis for discussion by the Executive Board.

plant, being introduced as a stop-gap measure while big power generating projects materialize, is expected to provide 200 megawatts to the national grid. The emergency plants are expensive to run and the Ministry of Energy and Power Development has already warned that beginning February 2016, Zimbabweans have to embrace significant power tariff increases to reduce the load-shedding hours. Consumers are currently being levied about ***9,86c/kWh*** and the use of diesel generators is likely to see cost moving to ***14c/kWh.***

With the current status quo, there has been a growing concern from residents, industry and commerce to come up with alternative sources of energy, mainly Renewable Energy sources to feed into the national grid, one of which is above ground BIOMASS Energy. However to tap into this source of Renewable Energy there is need for spatially intelligent decision making in plant location for cost reduction, effectiveness and efficiency in tapping into this alternative Energy source.

It is the duty of ZESA as an enterprise to come up with the best locations for the establishment of BIOMASS Energy plants to feed into the national grid. Location of BIOMASS Energy Plant sites by ZESA Holdings is determined by spatial distribution and quantity allocation of above ground BIOMASS, also taking into consideration the current network infrastructure with a strong emphasis on cost reduction and spatial load demand forecasting.

Currently energy demand is higher among Zimbabwe's urban populace. Given the current energy situation in the country, Estimation of above ground BIOMASS with a spatial reference is a problem that requires determining least-cost sites for BIOMASS plant installation among other alternatives.

Because resources are scarce there is need to optimize the solution of site selection for the establishment of power plant sites in a bid to cushion the country from its current power shortages, more so with a view to revitalize the country's economy through industry.

1.0.2 Sustainability in resource utilisation and environment conservation a global concern

The main objectives of the Kyoto Protocol and the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) project, housed under the United Nations Framework

Convention on Climate Change (**UNFCCC**), particularly for the developing world, is improving the conservation of forests in the face of a changing climate. The global movement, which began with the 1972 Stockholm conference on the Human Environment, pushed the ideas of sustainable development. The World Commission on Environment and Development (**WCED**), chaired by the Norwegian Prime Minister, Dr Gro Harlem Brundtland explicitly defined sustainable development in their report, Our Common Future, published in 1987. This report is often credited for successfully making the environmental issues a world concern.

African states henceforth have been prepared to have an input into resource sustainability by the Earth Summit which was held in Brazil in June 1992. The Earth Summit identified major environmental strategies and challenges in the 1990s and into the new millennium among its main objectives being Environmental monitoring as emphasized by the Rio Declaration establishing the fundamental responsibilities and actions of governments, organizations and individuals on the environment, a comprehensive action plan setting out steps governments, international organisations and others should take to protect the environment and promote sustainable development under Agenda 21, Conventions to address two vital global problems, climatic change and threat to bio-diversity; and a statement of principles for the conservation of the world's forests. Governments therefore have a mandate to conserve the environment at the same time meeting the demands imposed by population explosions. Energy supply is one such demand.

From the environmental and energy security perspective, it is a time-honoured fact that the dependence on conventional energy resources in Zimbabwe has to be reduced and renewable energy resources are one of the promising options available to counter effects of climate change, which has posed a major challenge to the current energy mix and specifically to hydropower generation in the country. One such renewable energy source that can be harnessed for electrical energy supply in the country is aboveground Biomass energy.

1.0.3 The Biomass Mapping and quantification debate

To tap into the biomass resource as an alternative energy source and to come up with optimal sites for the establishment of Above Ground biomass power plants, the quantification, mapping and monitoring of biomass are central issues of consideration within the confines of sustainability. The quantification of biomass is a challenging task, especially in areas with complex stands and varying environmental conditions, and requires accurate and consistent measurement methods. To use biomass efficiently and effectively as a renewable energy source, it is important to have detailed knowledge of its distribution, abundance, and quality. (Kumar, et al., June 16, 2015) argued that remote sensing offers the technology to enable rapid assessment of biomass over large areas relatively quickly and at a low cost. However, other researchers are still of the opinion that the best results can be found through the empirical method involving allometric equations and the measurement of biometric parameters (Gibbs, et al., 2007).

Biomass is one source of energy which can be used for direct heating in industrial or domestic applications, in the production of steam for electricity generation or in the production of gaseous or liquid fuels. Direct heating is the most widespread application of biomass but electricity production and bio-fuels are currently gaining considerable interest among energy policy makers. However policy-makers in most developing economies lack a fully informed savoir faire on optimum site selection, the factors that determine energy choices for sustainable development and the technologies at their disposal in such national projects (Von Maltitz & Scholes, 1995) and (Banks, et al., 1996). Data on standing woodland biomass volumes, spatial distribution and quality, and rate of extraction is often lacking. Quantitative data on convertible biomass resources provides useful input for strategic energy planning and modelling purposes. Macro-level strategic energy planning is currently being compromised by the use of generalized biomass estimates (Grabitzki, 2004) in (Paradzayi & Annegarn, 2012). Knowledge of existing aboveground biomass stocks encourages the adoption of mechanisms for sustainable utilization of forest and woodland resources.

1.0.4 Manicaland's Bio-Energy Potential

Compared to other regions in Zimbabwe, Manicaland is generally a rich province in terms of energy resources. Zimbabwe has a large timber industry, 90% of which is concentrated in Manicaland province. Manicaland is characterized by a heterogeneous physiography and all the five agro-ecological regions are found in this region. Areas with highest rainfall support high biomass growth and perennial river systems where small hydro potential remains the highest in the country. Forestry activities produce huge amounts of forest residues including off cuts and bark. There is considerable potential for productive utilization of this biomass residue from both sawmills and forestry operations for electricity and heat generation. Large amounts of this residue are either burnt in inefficient incinerators at sawmills, burnt directly infield or dumped in municipal landfills.

The residue from forestry operations is mainly sawdust, chips and slabs. In addition, a lot of bark is generated at the rate of 7% of sawmill log input. For instance, one of the largest sawmills in the Chimanimani area has a saw log input of about 200,000m^3 per year. The amount of residue left is considerable, 13,000m^3 of bark, 80,000m^3 of wet chips and sawdust and 2,000m^3 of dry chips. The thermal energetic value of the residue from this sawmill alone would be around 185GWh per year, enough to supply a 3 to 4 MW power plant generating 25GWh of electricity annually. Cogeneration in the timber industry could benefit the industries and local community. The use of the biomass waste would reduce the open-air incineration and dumping of waste which has contributed to local air pollution and global carbon emissions.

1.0.4.1 Current sources of Forestry Plantation Biomass Waste

The timber industry in Zimbabwe is almost entirely based on plantation timber, whose production is dominated by three large organizations, Border Timbers, Allied Timbers and Wattle Company, producing about 87% of the national output. Plantation forests occupy about 0.02% of the total land area of Zimbabwe, comprising 81,000 ha of pine, 24,000 ha of eucalyptus and 13,000 ha of wattle, a total of about 120 000hectares of timber plantations, the majority of which are in the Eastern Highlands. Sawmilling is the largest sector of the industry. The large volume of timber waste from sawmilling has given rise to open-air incineration and dumping in municipal landfills, contributing to local air pollution and global carbon emissions. While some sawmills have been designed to use a portion of the waste in their boilers to produce steam for drying kilns, waste disposal remains one of the biggest challenges facing the industry and local municipalities. Thus, utilizing the wood wastes for direct electricity generation either on site or at a more centrally located independent biomass power plant has become an attractive option.

Allied Timbers generate around 60tonnes of Timber waste at its Chisengu facility per day, of which 10% is used for kiln drying and the balance burnt. Other sawmills currently in operation are Martin Sawmill, Border Timbers Tilbury Sawmill, Border Timbers Charter Sawmill, Zimpala Sawmill, Rathmore Sawmill, Chimanimani Sawmill, Chinhokwe Sawmill which produces about 2 000 cubic meters of timber per day with smaller bush mills scattered around the region. On average, 47% of log input into sawmills is turned into sawn timber. In 2013 over 70 000tonnes of biomass waste were being produced annually with long term projections that the amount would have more than doubled by 2015 if production levels increase with demand for timber especially for the South African and Botswana market. At the largest mills the amount of biomass waste generated on-site could alone yield as much as 4 MW of usable power. While at the largest mills a small fraction (~10%) of the wood waste generated is currently consumed in process steam boilers for lumber drying kilns, the vast majority is burned in the open air or dumped.

1.0.5 Earlier attempts at Biomass Power Generation - Zimbabwe

1.0.5.1 Allied Timbers' Chimanimani Biomass Power plant – The details

In 2013, ALLIED Timber Holdings entered into a partnership agreement with Indian Lurosa Investments (Pvt) Ltd to establish a biomass gasification power plant. The venture known as Zimbabwe Green Energy plant had plans to build a two-megawatt biomass gasification power plant in Chimanimani. In March 2013, the Environmental Management Agency (EMA) approved the project to take off. A temporary license was then issued by the Zimbabwe Energy Regulatory Authority in April of the same year. Application for the construction of the power plant was done in terms of *Section 42* of the *Electricity Act* (*Chapter 13:19*) of *2002*. The plant would use abundant wood waste from local sawmills and had a planned capacity of about 40 megawatts, 20MW short of Mutare's current energy requirement of 60MW.

When completed, the project was going to be the biggest biomass power plant under one company in Africa. If the initiative could have helped Chimanimani ease its power problems, a more centralized and well planned endeavour could be applied to serve a national interest in terms of energy supply in Zimbabwe and reduce the burden on the national utility. This might also reduce severe power cuts. In line with the licensing provisions, only the pilot project was rolled out.

1.2 Problem Definition

A great deal of information about the forested public lands of Zimbabwe is known, but most of the information is derived in a very coarse manner and lacks the needed precision, accuracy, and resolution to help determine where and when management activities should occur (Oswalt, et al., 2014). Due to the lack of fine grained, timely, accurate, and precise information, managers especially in public utilities like ZESA holdings often follow a less than optimal approach to identifying potential problems and recognizing alternative courses of action to keep public utilities afloat. Such institutions are therefore lacking in the manner of decision implementation and systematic approaches of redress are recommended. One such approach in the case of Zimbabwe is bio-energy systems planning and site optimisation modelling employing an integrated approaches combining remote sensing and location theory in renewable energy systems design and sustainability management.

It has been established that power is critical to economic development and that there is a positive correlation between reliable power supply and growth in gross domestic product (GDP). With industry operating at between 25 percent and 30 percent capacity, Zimbabwe's requirement for energy is estimated at 2 200MW. The country currently has an energy deficit averaging 600 megawatts (MW) due to obsolete machinery and limited investment in the energy sector.

Assuming that industry grows its capacity to 70 percent in the next five years and that mining and agriculture continue to grow at the current pace, the demand for energy in Zimbabwe could double to 4 400MW. Incapacity to meet current and anticipated future national power requirements will cripple the country's economic recovery efforts unless massive power investments are made.

Zimbabwe is currently facing a huge power deficit, a situation that has adversely affected all facets of the economy. Energy and environmental issues are two common concerns of modern society. The rather dispersed geographical distribution of biomass potential, its strong dependency on climatic conditions, terrain models and soil types poses a great challenge in the quantification and mapping of biomass. Least cost site selection on the other hand for the establishment of aboveground biomass power plants is another source of dilemma and so has raised the interest of researchers in using analytical modelling and location theory for the evaluation of the biomass supply characterisation, as well as the site selection for energy power plant development.

In order to address the country's current energy problems, renewable energy generation is an alternative which must be looked into, in line with global energy policies. However an intelligent spatial location of energy sites is of paramount importance to receive considerable benefit out of the economics involved.

In order to spatially locate possible sites for aboveground biomass power plants in Zimbabwe to address power deficits in the country, a problem statement was formulated as follows:

There is therefore a serious problem in the current energy mix in the country. Zimbabwe is currently facing huge power deficits. The disruption in power supply has caused serious inconveniences to domestic, commercial, industrial and farming consumers. Power cuts have drastically affected the conduct of business nationwide to an extent that some operations that require uninterrupted power supplies had to shut down or limit the scale of operations, while others resorted to expensive and unsustainable alternative power sources such as diesel power generation. Power deficits would persist for the foreseeable future - notwithstanding the on-going rehabilitation programs at the main power stations. Despite efforts by the Zimbabwe Electricity Supply Authority to avert the effects imposed by such imbalances in the current energy mix through power imports and improvements in power generation capacities locally. This problem continues to cripple Zimbabwe's economy as the country's debt-laden power utility fails to adequately supply electricity to industry, commerce, agriculture and the public at large. A possible cause of this problem is the skewed mix of energy supply which relies heavily on hydro power, thermal power and imports. Perhaps a study which investigates alternative renewable sources to feed into the national grid will go a long way to bring back the lost glory. The location of biomass power plants using Remote Sensing technologies, Location theory and site optimisation strategies could remedy the situation.

This research therefore seeks to answer the question, "What are the spatial dynamics involved in the least cost site selection of aboveground biomass power plants in Zimbabwe in an optimization procedure so as to efficiently and effectively tap into the country's natural endowments sustainably?"

1.3 Research Question

The research aims to answer the following research question:

- How can an accurate estimate of biomass reserves be incorporated into a multi-factor weighted analysis for biomass power plant site optimization with a desirable level of economic sustainability?

1.4 Objectives

1.4.1 Main Objective

The research seeks to tackle the problem of identification and estimation of economically exploitable biomass potential sites in Zimbabwe's Manicaland province as well as identifying least cost sites for the development of biomass power plants in the Eastern Districts of Zimbabwe using Remote Sensing, location theory and site optimisation techniques. The major variables of concern are quantity of biomass, its geographical distribution across the natural region of choice, as well as the geographies of candidate sites.

1.4.2 Specific Objectives

The specific objectives of this research can thus be summarised as to:

- Develop a spatially explicit biomass potential availability assessment model to evaluate Biomass Supply from Forest Plantation Residues in Zimbabwe's Manicaland Province;
- Develop a GIS and Analytic Hierarchy Process (AHP) factor weighting model for potential biomass power plant candidates selection to be used for power plants location by considering multiple constraints and factors;
- Develop a spatial optimisation model for power plant sitting employing location theories for spatially optimal bio-energy systems design;
- Employ a multi-factor suitability analysis approach of solving the location allocation problem in the site location and present the results using GIS map presentations.

1.5 Research Motivation/ Justification

The research puts into perspective the case that energy transitions are not merely shifts in energy supply but are also simultaneously fundamental shifts in prevailing spatial relations, so that energy transition management is best conceived as a spatial strategy with emphasis on regional level land-energy planning and optimisation modelling. The research therefore seeks to emphasise the new and ballooning underpinnings of *Bio-geosciences*, a field of study which has not received considerable airplay in Zimbabwe. Bio-energy planning deals with a production chain with many links and bio-energy activities across several traditional professional boundaries. Consequently, planning structures for bio-energy are often more complex than for other industries. This complexity calls for stringency and transparency of the planning methods.

The research findings aim to provide decision support in favour of this spatial strategy. This begins with a comprehensive critical review of how GIScience and Remote Sensing have been applied in Renewable Energy assessments and spatial planning. The literatures cited in this study engage key gaps in the literature and are the analytical contributions of the thesis. The focus of the research is on biomass quantification assessment in the Eastern districts of Zimbabwe. Land-energy trade-offs are modelled and their implications in the context of incentivising Renewable Energy development are discussed.

1.5.1 World Renewable energy Trends

There are two driving forces behind renewable energy development: the threat of climate change and the need for countries to secure their own energy production and hence reduce reliance on electricity importation (Warren, et al., 2005). A significant part of most countries' energy production comes from burning fossil fuels, with Zimbabwe no exception. This process releases carbon dioxide (CO_2), contributing to the greenhouse effect and global warming. Thus, governments are under pressure to promote and encourage new forms of energy production with zero CO_2 emissions.

Energy is at the forefront of the global agenda. It is central to the issues of development, global security and environmental protection and achieving the MDGs. Somehow, people across the entire environ-political spectrum seem to have reached a tacit, near-unanimous agreement about what renewable means: It is an energy category that includes solar, wind, water, biomass, and geothermal power (Stover, 2011). Renewable energy is gradually replacing conventional fuels in four distinct areas: electricity generation, hot water/space heating, motor fuels, and rural (off-grid) energy services (Sawin & Martinot, 2010).

Based on REN21's 2014 report, renewable energy sources contributed 19 percent to our energy consumption and 22 percent to our electricity generation in 2012 and 2013, respectively. This energy consumption is divided as 9% coming from traditional biomass, 4.2% as heat energy (non-biomass), 3.8% hydroelectricity and 2% electricity from wind, solar, geothermal, and biomass. Worldwide investments in renewable technologies amounted to more than US$214 billion in 2013, with countries like China and the United States heavily investing in wind, hydro, solar and bio-fuels (Sawin & Sverrisson, 2014). Renewable energy resources exist over wide geographical areas, in contrast to other energy sources, which are concentrated in a limited number of countries. Rapid deployment of renewable energy and energy efficiency is resulting in significant energy security, mitigation of climate change, and economic benefits (International Energy Agency, 2012). In international public opinion surveys there is strong support for promoting renewable energy sources. At the national level, at least 30 nations around the world already have renewable energy contributing more than 20 percent of energy supply. National renewable energy markets are projected to continue to grow strongly in the coming decade and beyond (Sawin & Sverrisson, 2014).

Biomass is envisioned as a win-win way to produce energy in light of the availability of biomass across most regions of the world. In many parts of the world where biomass is extensively used to heat homes and cook meals, this *renewable* energy is responsible for severe deforestation and air pollution. The following table shows increasing nameplate capacity[2], and has capacity factors that range from 11% for solar, to 40% for hydropower.

[2]**Nameplate capacity** is the number registered with authorities for classifying the power output of a power station usually expressed in megawatts (MW). Power plants with an output consistently near their **nameplate capacity** have a high **capacity** factor

Table 3: Selected renewable energy global indicators

Selected renewable energy global indicators	2008	2009	2010	2011	2012	2013	2014	2015
Investment in new renewable capacity (annual) (10^9 USD)	182	178	237	279	256	232	270	285
Renewables power capacity (existing) (GWe)	1,140	1,230	1,320	1,360	1,470	1,578	1,712	1,849
Hydropower capacity (existing) (GWe)	885	915	945	970	990	1,018	1,055	1,064
Wind power capacity (existing) (GWe)	121	159	198	238	283	319	370	433
Solar PV capacity (grid-connected) (GWe)	16	23	40	70	100	138	177	227
Solar hot water capacity (existing) (GWth)	130	160	185	232	255	373	406	435
Ethanol production (annual) (10^9 litres)	67	76	86	86	83	87	94	98
Biodiesel production (annual) (10^9 litres)	12	17.8	18.5	21.4	22.5	26	29.7	30
Countries with policy targets for renewable energy use	79	89	98	118	138	144	164	173

Source: The Renewable Energy Policy Network for the 21st Century (REN21)–Global Status Report

World energy consumption has been increasing at a very rapid rate. There has been a noted direct correlation between energy consumption and a marked improvement in the quality of life of populations. Today, fossil fuels based energy resources, such as coal, gas, and oil, supply the majority of the total world energy requirement.

In 2014, world Total Primary Energy Supply (TPES)[3] was 13,700 Mtoe, of which 13.8%, or 1,894 Mtoe (up 2.6% on 2013), was produced from renewable energy sources.

[3]***Total primary energy supply (TPES)*** - Total primary energy supply (**TPES**) is made up of production + imports – exports – international marine bunkers – international aviation bunkers ± stock changes. For the world total, international marine bunkers and international aviation bunkers are not subtracted from TPES.

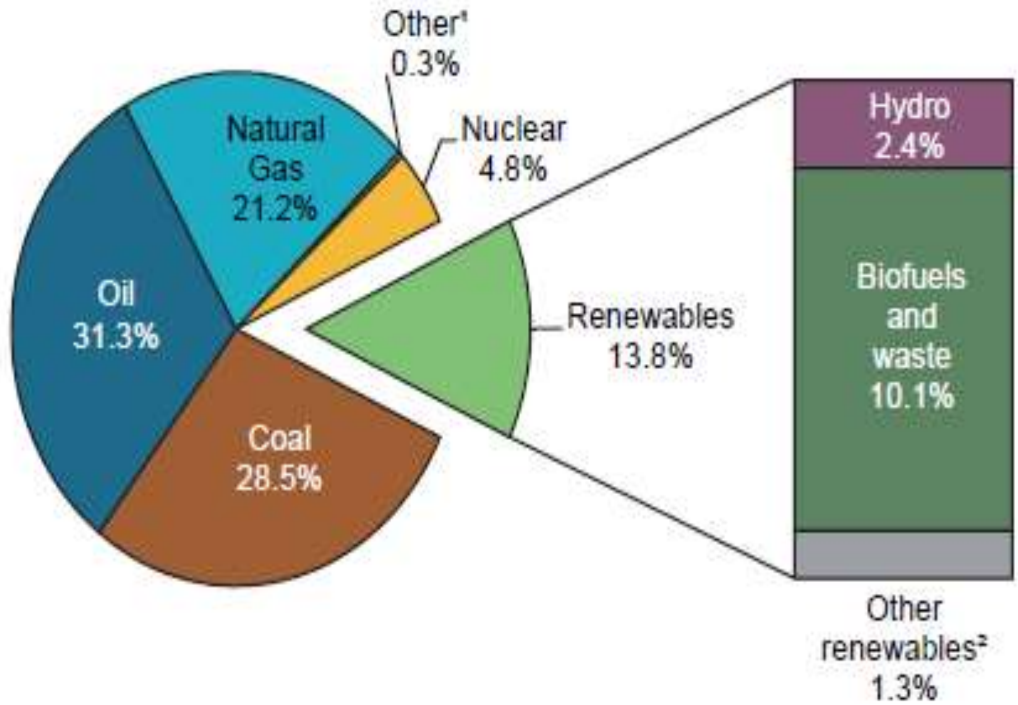

Figure 1: 2014 Fuel shares in world total primary energy supply ((International Energy Agency, 2016)

Electricity generation from solid bio-fuels grew from 95.2 TWh to 179.8 TWh between 1990 and 2015, yielding a 2.6% average annual growth. As the third largest renewable electricity source after hydropower and wind, solid bio-fuels accounted for 7.3% of renewable electricity generation in 2015. The United States (47.6 TWh) accounted for 26.5% of electricity generated from solid bio-fuels within the OECD, where it makes up 8.5% of the country's renewable electricity production. The second largest producer of electricity from solid bio-fuels is Japan (32.6 TWh), where it represents 19.8% of the country's renewable electricity supply. Other large producers of electricity from solid bio-fuels in the OECD in 2015 are UK, Germany, and Finland, producing 19.6 TWh, 12.3 TWh and 10.0 TWh respectively (International Energy Agency, 2016).

1.5.2 Zimbabwe Policy Reflections and emphasis on Renewable Energy and diversified energy mixes.

1.5.2.1National Climate Policy Reflections in Zimbabwe – The Legal and Policy Framework

There are a number of laws and policies with implications on the administration of the energy sector in Zimbabwe. Some are specific to the energy sector while others are general natural resources management laws that have some relevance to the management of the energy sector. The Environmental Management Act [EMA] of 2002 is the main act governing environmental management in Zimbabwe. Among its most progressive provisions are the recognition of environmental rights as human rights and principles of environmental management. Section 4(c)(ii) states that it is everyone's right to participate in sustainable use of natural resources while promoting justifiable economic development and this includes the energy sector.

Zimbabwe is among the countries that seriously consider the reality and impacts of climate change. Its attention to the global problematique can be traced back as early as 1992 when it joined the international community in participating in various climate policy regimes. The Government of Zimbabwe (GoZ) is a signatory to the two major environmental laws governing climate change; namely, the UNFCCC, which it signed and ratified in 1992 and the Kyoto Protocol ratified in 2009. Since then, the country has vigorously pursued national climate policies. As part of its willingness to contribute towards GHG stabilisation, climate change issues have broadly been included in the 2009 National Environmental Policy (NEP). The NEP, however, does not address climate change as a standalone issue but is implied in strategies and activities that result in GHG emissions. Alongside the NEP are various environmental policies that also address climate change issues. These policies include; the Environmental Impact Assessment Policy (1997), the National Environmental Education Policy and Strategies (2003) and the National Fire Strategy and Implementation Plan (2006). Other policies related to GHG stabilisation include; the National Energy Policy (2009), the Zimbabwe Agricultural Policy Framework (ZAPF), which gives a 25 year horizon (1995-2020), the Water Policy and the Science and Technology Policy. It should be noted here that these policies, although lacking specificity to climate change, collectively infer to mitigation and adaptation measures to climate change ((Government of Zimbabwe, 2012a); (Government of Zimbabwe, 2012b); (Government of Zimbabwe, 2014)).

1.5.2.2 Emphasis of ZimAsset on renewable energy supplies

In pursuit of a new trajectory of accelerated economic growth and wealth creation, the Zimbabwean Government formulated a new plan known as the Zimbabwe Agenda for Sustainable Socio-Economic Transformation (ZimAsset): October 2013 - December 2018. ZimAsset was crafted to achieve sustainable development and social equity anchored on indigenization, empowerment and employment creation which will largely be propelled by the judicious exploitation of the country's abundant human and natural resources.

This Results Based Agenda is built around four strategic clusters that will enable Zimbabwe to achieve economic growth and reposition the country as one of the strongest economies in the region and Africa. Energy reforms and transformation falls under the *Infrastructure and Utilities* cluster[4]. ***Section 2.19*** of the document emphasizes that Energy is a key enabler to productivity and socio-economic development. However, the sector has experienced challenges largely due to dilapidated and obsolete generation equipment and infrastructure as well as inadequate financing and capitalization among other structural bottlenecks.***Section*****2.22** also stresses the importance of energy and power development in its coined statement, "More immediately the key infrastructural areas of energy and power development, roads, rail, telecommunications, water, and sanitation will require urgent attention. ***Section*** **3.4.1(**iv.) emphasizes increased investment in infrastructure such as *energy and power development, through acceleration in the implementation of Public Private Partnerships (PPPs) and other private sector driven initiatives.* ***Section*** **3.5.1(**iii) highlights that the key drivers for this growth and employment creation will be accelerated development through value addition processes in the Infrastructural sectors primarily focusing on *power generation strategies.* To this end, Government will rehabilitate, upgrade and develop the national power grid.

In ***Section 3.15*** of the ZimAsset document the government of Zimbabwe highlights its plans for the Energy Sector, in addition to prioritising attainment of optimal generation of power, the production and use of bio-fuels as enablers for economic productivity and growth.

[4]The other clusters are Food Security and Nutrition, Social Services and Poverty Eradication and Value Addition and Beneficiation

To this end the Ministry of Finance and Economic Development came up with growth targets for the Zimbabwean economy, as depicted in the table below, with the Electricity and water sector projecting a 16% growth target by 2018 (ZimAsset BluePrint Document, October 2013-December 2018).

Table 4: Growth targets for ZimAsset

Sector	2013 Proj. %	2014 Proj. %	2015 Proj. %	2016 Proj. %	2017 Proj. %	2018 Proj. %
Agriculture, hunting and fishing	-1.3	9.0	5.1	7.0	8.0	12.5
Mining and quarrying	6.5	11.4	9.2	6.5	12.0	12.6
Manufacturing	1.5	3.2	6.5	7.5	8.4	9.5
Electricity and water	4.2	4.5	7.0	9.8	11.0	16.0
Construction	10.0	11.0	13.5	12.0	13.0	15.0
Finance and insurance	2.6	6.4	6.2	6.2	8.1	10.3
Real estate	10.0	11.0	13.5	12.0	13.0	15.0
Distribution, hotels and restaurants	3.4	5.2	5.0	5.0	7.1	9.3
Transport and communication	3.4	4.4	5.5	5.3	5.4	8.0
Public administration	5.2	4.2	4.5	3.5	2.4	2.5
Education	5.5	4.0	4.5	5.0	4.5	4.4
Health	4.3	3.4	4.3	6.2	2.0	4.0
Domestic services	1.5	1.5	3.0	1.8	2.1	2.2
Other services	2.5	2.5	3.0	2.5	2.8	2.8
GDP at market prices	3.4	6.1	6.4	6.5	7.9	9.9

Source: Ministry of Finance and Economic Development

1.5.2.3 Current Energy policies- Zimbabwe's Renewable Energy Feed in Tariffs

As a measure to promote use of renewable energy as an alternative source of energy in Zimbabwe, the government, through the Zimbabwe Energy Regulatory Authority **(***ZERA***)** recently drafted an independent power producer (IPP) framework, a regulatory policy framework on Renewable Energy**,** which is meant to incentivise and stimulate investment in the renewable energy sector. This scheme is expected to charm huge investment in the sector and ensure increased access to clean and sustainable energy for economic growth. The Zimbabwe energy Regulatory Authority (**ZERA**) is a statutory body established in terms of the Energy Regulatory Act 2011 (*Chapter 13:23*) read in conjunction with the Electricity Act (*Chapter 13:19*) (*No. 4 of 2002*) and the Petroleum Act (*Chapter 13:22*) (*No. 11 of 2006*).

The authority also came up with a Renewable Energy Feed in Tariff (*REFIT*) programme, which is now awaiting government approval. *REFIT* is a policy instrument that makes it mandatory for energy companies or utilities responsible for operating the national grid to purchase electricity from renewable energy sources at a pre-determined price that is sufficiently attractive to stimulate new investment in the sector. It is further reported that ZERA has engaged clean energy consultants, CAMCO, to develop Refit for the county's electricity supply.

The move is primarily aimed at enhancing the country's power supply situation as the instrument was developed for renewable energy technologies such as solar PV, solar hydro, biomass, bagasse and wind.

1.5.4 Zimbabwe Energy Situation - Power deficit statistics and Current Energy Mix

ZESA's generation capacity, as at February 17, 2016, was only 845 MW: Against a projected demand of 2 200 MW, this result in a deficit of 1 355 MW or 62 percent deficit. Although the installed capacity of Zimbabwe power stations is 1 940 MW, we are producing 845 MW which is only 44 percent of installed capacity. According to ZESA statistics as at February 17, 2016, Hwange has an installed capacity of 900MW, but was producing 476MW, which is 56,33 percent of national power output. At times, Hwange produces much lower power due to frequent equipment breakdowns.

Kariba with an installed capacity of 750 MW is producing 285 MW, which is 33, 73 percent of national power output. This is due to the current lower water levels on Lake Kariba and other technical challenges. Combined Hwange and Kariba are producing 761 MW, which is 56, 33 percent and 33, 73 percent, respectively or 90, 06 percent of total power output of 845 MW.

At our current national power production levels, it goes without saying that unless there is strong political will and significant investments in rehabilitation of existing power plants and in new power generation, our economic turnaround endeavours will remain like "a pie in the sky". They will not be realised. Currently, our power deficit is being met by expensive power imports from ESCOM, South Africa, Cabora Bassa, Mozambique, and Sinai, the Democratic Republic of Congo at an average cost of ***US$0,155/kWh***. This is economically unsustainable as ZESA sells the same power to consumers at a subsidized rate of ***US$0,986/kWh***.

1.5.4.1 Thermal power

As at February 17, 2016 ZESA national grid statistics, actual thermal power generated in Zimbabwe was 66,27 percent of the total power output of 845MW, split as Hwange (56,33 percent) and the smaller thermal power stations: Harare (3,55 percent), Bulawayo (2,84 percent) and Munyati (3,55 percent). The installed capacity generation of thermal power stations in Zimbabwe is 1 190 MW, which is 61 percent of the country's installed capacity of 1 940MW.

Zimbabwe is endowed with enormous coal resources. According to geological experts, Zimbabwe has coal reserves amounting to 30 billion tones and at current levels of exploitation; it will take more than 100 years to exploit all coal reserves. Zimbabwe can use these coal reserves strategically to generate its power requirements and to create excess power for export. What Zimbabwe needs to do is to invest in environmentally sustainable technologies that reduce carbon emissions. Advanced technologies that capture carbon emissions and use the gas for other commercial activities have been developed in some countries that rely on thermal power.

Seventy-four percent of power generated in the Southern African Development Community region is from coal (thermal power). Eighty-one percent of coal produced in South Africa is for power generation. South Africa's ESCOM generates about 77 percent of South Africa power requirements from coal.

1.5.4.2 Hydro electricity

At generation levels as at February 17, 2016, Zimbabwe was generating 33, 73 percent of its main grid power from water. Kariba is the flagship hydro power station followed by smaller hydro plants at Chisumbanje, Triangle, Duru, Pungwe, Honde Valley to mention a few. Most of the smaller hydro plants do not, however, feed into the main grid.

Hydro generation capacity in Zimbabwe can be doubled from the current capacity of about 850MW through rehabilitation and expansion of generation capacity at Kariba South (a project underway and expected to generate an additional 300MW) and the development of new projects such as the Batoka Gorge Project (expected to generate 1 600MW). Smaller hydro power stations in Manicaland (i.e. Duru: 2,2MW, Pungwe A: 2,75MW, Nyamingwa: 1.1MW, Triangle: 45MW, Hippo: 33 MW, Pungwe B: 15MW) can be developed to produce an additional 100MW into the national grid**.**

1.5.4.3 Renewable energy

In order to address the current power challenges in Zimbabwe, the calling is on the Zimbabwe government to focus not only on fossil fuels such as coal, but on alternative and sustainable renewable power resources such as water, wind, and solar. Lately bio-energy systems have been tabled for consideration as another alternative.

Zimbabwe is endowed with sun, water and wind and needs to develop or adopt technology that makes harvesting of power from renewable resources cheaper. The country has the potential to meet most of its energy requirements from these sustainable renewable resources. Renewable energy resources are sustainable since they can be used over and over again without them running out (depleting). Renewable power will be produced sustainably at zero carbon emission, thus protecting our environment and reducing global warming.

If water sources at Kariba and in Manicaland are fully developed, Zimbabwe has the potential of producing 1 150MW, which is 52 percent of current national requirement of 2 200MW. (Example: Kariba Main 750MW, Kariba South 300MW, Manicaland hydro-stations 100MW). If the Kariba South and Batoka Gorge projects were to be completed, Zimbabwe could produce 2 750MW and be able to meet all its current power requirements from water at zero carbon emission!

1.5.5 The negativities of energy from fossil fuels.

In as much as fossil fuels consumption has improved our way of life by providing us energy, it's burning has also created grave environmental threats which the current environmental policies seek to curtail. As Henry Ford II said, "The economic and technological triumphs of the past few years have not solved as many problems as we thought they would, and, in fact, have brought us new problems we did not foresee". Initially fossil fuels were believed to be a perfect energy source as evidenced by their increased usage with the 20th century described as the golden era of fossil fuels. For example, the electricity generated by fossil fuels increased from less than 2% in 1900 to more than 30% by 2000 (Smil, 2000). Environmental implications began to emerge due to the exponentially increased applications of fossil fuels in the middle part of the 20th century (Venema, 2004). Fossil fuels consumption is believed to be the primary factor contributing to serious environmental problems, such as global warming, climate change and acid rain, which are a serious threat to the world's ecosystems and the prosperity of human civilizations.

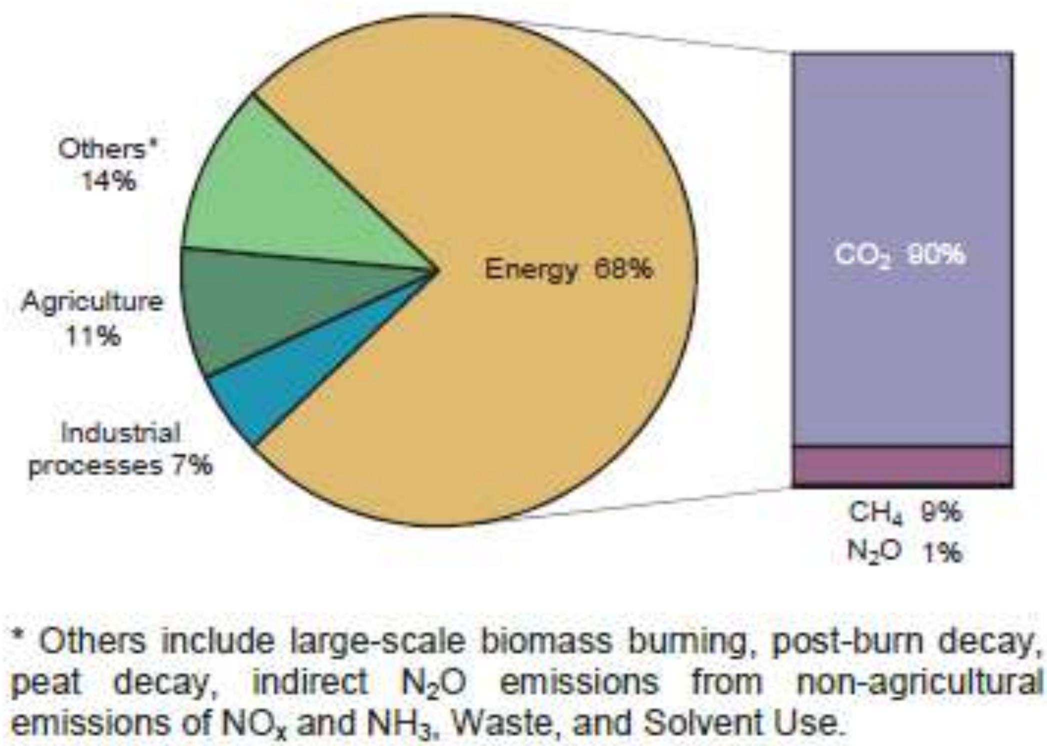

Figure 2: Shares of global anthropogenic GHG, 2010 Source: IEA estimates for CO_2 from fuel combustion

Energy is at the core of the greenhouse gas estimation. It is estimated that for Annex I Parties[5] energy accounts for 82% of total GHG emissions, while for the world the share is about 60%, although shares vary greatly by country. Within energy, CO_2 from fuel combustion accounts for the largest fraction, 92% for Annex I countries, once again varying depending on the economic structure of the country.

[5] The Annex I Parties-Parties subscribed to the 1992 UN Framework Convention on Climate Change (UNFCCC)

Table 5: Zimbabwe Carbon Dioxide emissions and Energy intensities 1971- 2013

	1971	1975	1980	1985	1990	1995	2000	2005	2010	2012	2013	avg. ch. ref-13 [3]
Zimbabwe												
CO_2 emissions	45	44	49	60	100	93	82	63	56	78	83	-0.8%
Population	51	59	70	85	100	111	120	121	125	131	135	1.3%
GDP per population (GDP per capita)	101	102	93	94	100	95	100	67	58	63	65	-1.8%
Energy intensity (TPES/GDP)	113	105	107	100	100	100	90	128	141	140	138	1.4%
Carbon intensity: ESCII (CO_2/TPES)	76	69	70	75	100	88	76	61	55	67	68	-1.6%

Therefore, climate scientists argue that in order to stabilize the earth's climate and prevent further global warming, the earth requires a 70% cut in present carbon dioxide emissions by 2050 (Flannergy, 2005)

Besides the environmental fatigue or failure caused by the dominance of the current fossil fuel-dominated-energy systems, (Li, 2005) claimed that energy diversification and localization can provide security for energy supply and distribution as well for the energy consumers. (Li, 2005), recommended that energy diversity should be promoted as the only sensible and feasible solution for sustainable development. Therefore this research seeks to emphasize the proposed energy mix in a Zimbabwean situation. In order to mitigate climate change and global warming, carbon dioxide emission must be reduced significantly. The applications of renewable energy resources, such as biomass energy, hydropower, geothermal, wind power, and solar, should be encouraged. In the executive summary of (IEA, 2006), it claims "Beyond 2020, the role of renewable energy in global energy supply is likely to become much more important".

1.5.6 Why bio-energy has stood up as a lucrative alternative among renewable energy sources in Zimbabwe

Bio-energy is a carbon-neutral and renewable energy source that is attracting research and development worldwide. The interest is driven by its ability to provide an alternative option to other, less sustainable, fuels. Biomass energy is a traditional source of sustainable energy, which has been widely used in developing countries. As well, bio-energy will continue to be the major energy source in developing countries over the next two decades (IEA, 2006). First of all, the collected biomass from forestry residues is transported from the field to a conversion facility (i.e. biomass power plant). The energy stored in the chemical bonds of the biomass are extracted and converted into electricity by initially combusting with oxygen (O_2). Fossil fuels which take millions of years to be converted from biomass are not deemed as renewable within a time-scale mankind can use.

As (McKendry, 2002) has pointed out "burning fossil fuels uses 'old' biomass and converts it into 'new' CO_2 which contributes to the greenhouse effect and depletes a non-renewable resource". Besides the environmental benefits from biomass energy application, (McKendry, 2002) summarized two other factors that drive the usage of biomass energy as: firstly, technological developments relating to the conversion promise the application of biomass at lower cost and with higher conversion efficiency than was possible previously. For example, when low cost biomass residues are used for fuel, the cost of electricity is already now often competitive with fossil fuel-based power generation. More advanced options to produce electricity are looking promising and allow a cost effective use of energy crops.

The second main stimulus is the abundance of timber plantations and dense vegetation in the Eastern highlands districts, which is a promising source of biomass. This situation has led to a policy in which land is set aside in order to reduce excessive deforestation. The tenure regimes in the Eastern districts have promoted densification of such biomass sources. The gradual depopulation of rural areas as a result of rural urban migration has also contributed in the preservation of such biomass densities. Demand for energy will provide an almost infinite market for energy crops grown on such potentially surplus land. (Venema, 2004), presents a comprehensive discussion about the role of rural renewable energy design. He concluded: "alleviating rural energy poverty begins with improved management and use of local bio-energy resources". By adopting modern conversion technologies, existing biomass resources could be more efficiently converted into electricity, thereby addressing chronic energy shortages in the rural areas of Zimbabwe. In Zimbabwe, access to modern energy is very low, casting doubts on the country's efforts at sustainable development, which energy experts say is not possible without sustainable energy. According to (Venema & Calamai, 2003) Biomass based decentralized renewable generation (DRG) may become the most plausible way to achieve rural electrification.

The benefits of using biomass fuel for electricity generation are clear.

- Biomass power has a high load factor (Base Load) in the region of 200 000MwH per annum (90 % in comparison to other technologies which have 30 - 40% availability factors);
- The value chain creates higher employment in operations;
- This is technology proven over many years;
- The forestry industry is not as affected by seasonality and climatic conditions in contrast with annual crop supply chains; and
- Unlike coal the forestry industry can reinvest in raw material supply by replanting trees for future use as an energy source.

Despite the potential benefits from the applications of bio-energy, the large scale use of biomass is still controversial. Negative impacts of large scale uses of bio-energy may be imposed on land use, soil, biodiversity, hydrology energy and carbon balance, and natural scene when applying dedicated second generation biomass crops for power generation and liquid transportation (Rowe & Street, 2007) Therefore, a local or regional scale of bio-energy application for power generation is more attractive. By only considering the agricultural and horticultural residues as the biomass feedstock to feed small scale of decentralized renewable generators, the impacts on the local environment and economics will be much reduced.

However, the highly dispersed geographical distribution of biomass makes it difficult to estimate the potential biomass production, locate the best sites to construct decentralized bio-power plants and allocate available biomass to these selected plants optimally. The research presented in this thesis focuses on regional bio-energy systems planning for power generation, and introduces a set of optimization models which utilise GIS screening techniques and discrete location theory to assess biomass availability, and select optimised bio-power plant locations and biomass allocation scenarios. The results from this research are important in aiding spatial biomass energy system design practices.

1.6 Sustainability Assessment for a bio-energy project for Zimbabwe

The European Commission, and many other public and private organizations, believe that biomass for power and heat production can play an important role in meeting Europe's "202020" targets: by the year 2020, greenhouse gas emissions should be reduced by 20 percent, renewable energy sources should represent 20 percent of Europe's final energy consumption and energy efficiency should increase by 20 percent. This belief has been lately extended to all other continents on earth. However, there are also a number of major uncertainties and misperceptions in the debate regarding biomass energy, for instance regarding its sustainability, cost competitiveness, logistical viability, availability, and its potential impact on food and feed production. The feasibility of a system that utilizes solid biomass to generate heat, power, or CHP largely depends on the availability of feed stocks.

Table 6 provides a list of potential solid biomass feed stocks.

Wood Residues	Agriculture Residues	Energy Crops
Mill residues (sawdust, etc.) Urban wood waste Forest thinnings	Corn stover Wheat straw Rice hulls Sugarcane bagasse Animal waste	Switchgrass Hybrid willow Hybrid poplar

Table 6: Examples of Solid Biomass Resources

Although all of these resources are possible feed stocks, in most countries non-food crops, such as switchgrass (*Panicum virgatum*), are the main focus, as well as agricultural and forestry residues and waste materials and gases. By 2050, the world will also need to produce 50–70% more food, increasingly under drought conditions and on poor soils.

1.6.1 Sustainability metric

As yet there is no consensus on what criteria should be used as a metric for evaluating biomass sustainability. Social as well as environmental and economic factors must be included. For example, international stakeholders (non-governmental organizations, policy-makers, research and development, bio-energy producers, end-users and traders) from 25 European and 9 non-European countries surveyed in 2011 agreed unanimously on only one criterion — minimization of greenhouse-gas emissions. But whether this constitutes sustainability measure is a question of debate.

1.6.2 Bio-energy, Energy and the Environment

Energy and environmental issues are both very important in modern society. Energy consumption is related to the quality of life. As the energy consumption per capita increases, an indicator of quality of life, the Human Development Index (HDI) which is calculated using the United Nations standard, also increases accordingly (Arto, et al., May 2016). In the literature (Arto, et al., May 2016) go on to say that energy is considered a prime agent in the generation of wealth and also a significant factor in economic development. With the increasingly development of some countries, the world energy demand will be increased by 57% between 1997 and 2020 and electricity demand will grow more rapidly than any other end-use fuel (International Energy Agency, 2001). However, with the transition from woody fuels to fossil fuels, environmental issues begin to emerge such as climate change, global warming, rising sea level, ozone depletion, and increased pollution, which are associated with elevated consumption of fossil fuels. During the past two decades, the risk and reality of environmental degradation have become more apparent. With the relative advantages of bio-energy applications with respect to the environment and the progress in conversion technologies, bio-energy is becoming the most promising alternative to fossil fuels.

1.6.3 Bio-energy Application and Energy Supply

Energy application plays an important role in the world's future and affects all aspects of modern life. The demand for energy is increasing at an exponential rate due to the exponential growth of the world population. The (International Energy Agency, 2001) study indicates that the world primary energy demand is expected to continue to grow steadily, as it has over the last two decades. Energy resources have been divided into three categories: fossil fuels, renewable resources, and nuclear resources. Biomass is a renewable resource that has the ability to be converted into almost all kinds of energy. This ability allows bio-energy to meet most energy demands, from traditional biomass combustion to electricity generation. However, due to the relatively high costs of generating bio-energy and the public opposition to biomass energy development (Buchholz, et al., 2007), its share in total primary energy supply is much lower than fossil fuels. (International Energy Agency, 2001) summarized the current and future worldwide application of bio-energy as follows:

- The use of bio-energy in combined heat and power (CHP) applications, where markets for heat exist, can be cost-effective in some cases. Co-firing may be a low-cost option for existing coal power plants, especially for low-cost sources of bio-energy such as waste derived fuels. Bio-energy for heat applications may be cost effective in some OECD countries, especially where wood resources are available. On average, however, the development of bio-energy projects for electricity production will remain fairly costly.
- Bio-fuels currently account for only a small portion of global transport fuels. In most countries, they are only competitive if they enjoy government subsidies. Technological advances in the production of bio-fuels, for example the use of woody bio-energy instead of agricultural crops, could reduce costs and increase renewables' market share in the longer term. Bio-energy will continue to be a major energy source in developing countries over the next two decades. The level of demand for bio-energy will increase by nearly 25% in these countries, but its share in total primary consumption will fall.
- The share of bio-energy in residential energy demand in some developing countries is greater than 90%. Improving the efficiency of its use can lead to important savings in fuel-wood consumption and can prevent the rapid decline in forested areas.
- Availability and cost will remain key factors in bio-energy development. Competition from agricultural uses, the seasonality in bio-energy crop production and the distances from bio-energy sources and energy use are major factors influencing cost.
- The use of bio-energy can have many environmental benefits over fossil fuels if the resource is produced and used in a sustainable way. Environmental issues, resulting from airborne emission from solid bio-energy combustion will, however, increase in importance along with the use of this fuel. This is particularly important for waste incineration, which faces public opposition, and sitting new facilities may be difficult.

Bio-energy can help to diversify the world energy supply and to increase energy security (Li, 2005). However, the costs of bio-energy generation limit its wide usage. Although the costs have largely fallen, further reductions are needed for them to compete with fossil fuels. The production costs will be more important to the long term energy supply outlook than the resource base (International Energy Agency, 2001). Therefore, in order to increase bio-energy application toward total energy supply, all aspects of reducing bio-energy generation cost are essential. This research proposes an integrated methodology to reduce transportation costs of delivering biomass feedstock from fields to the biomass power plant facilities. Furthermore, the use of biomass as a source for power generation is investigated through the minimization of the Levelized Unit Costs of Energy (LUCE) (Venema, 2004).

1.6.4 Bio-energy Application and Environmental Issues

As a very important renewable energy source, the most significant contribution of bio-energy applications is to protect the environment via climate change mitigation, Green House Gas (GHG) emission reduction, as well as the reduction of acid rain and local or regional air pollution. The Kyoto Protocol to the United Nations Framework Convention on Climate Change (UNFCCC), agreed to in December 1997, and marks an important turning point in efforts to promote the use of renewable energy worldwide. Since the original Framework Convention was signed at the Earth Summit in Rio de Janeiro in 1992; climate change has spurred many countries to increase their support of renewable energy. Even more ambitious efforts to promote renewable energies can be expected as a result of the Kyoto pact, which includes legally binding emissions limits for industrial countries, and for the first time, specially identifies promotion of renewable energy as a key strategy for reducing greenhouse gas (GHG) emissions. The risk of climate change due to emissions of carbon dioxide (CO2) from fossil fuel is considered to be the main environmental threat from the existing energy system.

1.7 Significance of the study

The significance of this dissertation is that a fully comprehensive approach mixed with the applications of GIS, spatial analysis techniques, an AHP method and location theories has been developed to address region-wide bio-energy systems planning, involving biomass potential estimation, power plants sitting, and facility locations and supplies allocation scenarios. With the availability of the spatial and statistical data, these models are capable of evaluating and identifying electric power generation from renewable bio-energy on the country scale optimally. It thus provides the essential information to decision makers in bio-energy planning and renewable bio-energy management.

The characteristics of many Renewable Energy resources that distinguish them from fossil fuels and nuclear systems include their natural unpredictability and variability over time scales ranging from seconds to years. These can constrain the ease of integration and result in additional system costs, particularly when reaching higher Renewable Energy shares of electricity, heat or gaseous and liquid fuels. Existing energy infrastructure, markets and other institutional arrangements may need adapting, but there are few, if any, technical limits to the planned system integration of Renewable Energy technologies across the very broad range of present energy supply systems worldwide, though other barriers (e.g., economic barriers) may exist. Improved overall system efficiency and higher Renewable Energy shares can be achieved by the increased integration of a portfolio of Renewable Energy resources and technologies.

The research will enhance the optimal identification of least cost sites for the establishment of Biomass plants in a bid to increase electricity supply in Zimbabwe thereby reducing dependency on hydro-power and improving the current energy mix. There has been a reported decrease in the levels of water in the Kariba Dam as a result of climate change and increased global warming. Therefore there is need for alternative sources of energy in Zimbabwe and ZPC, a subsidiary of ZESA holdings has the mandate to look into such alternative means of electrical power generation.

Optimum, least cost site selection using spatial logistic regression and spatial temporal modelling should be embraced in this endeavour, and this research sought to identify possible least cost sites for such purposes taking land tenure regimes, socio-economic dynamics into consideration. Accurate Biomass quantification for sustainable exploitation for electrical power generation is the theme behind this research.

1.8 Study area and research delimitations

A number of delimitations are necessary to provide focus and define the boundaries of manageability of the research (Ritchie & Lewis, 2003). The country has five (5) Agricultural regions and of these the Eastern Region seems a natural candidate for plant installation because of its natural endowment with dense vegetation and plant species. Zimbabwe lies entirely within the tropics but much of the Highveld and Eastern Highlands have a subtropical to temperate climate due to the modifying effect of altitude.

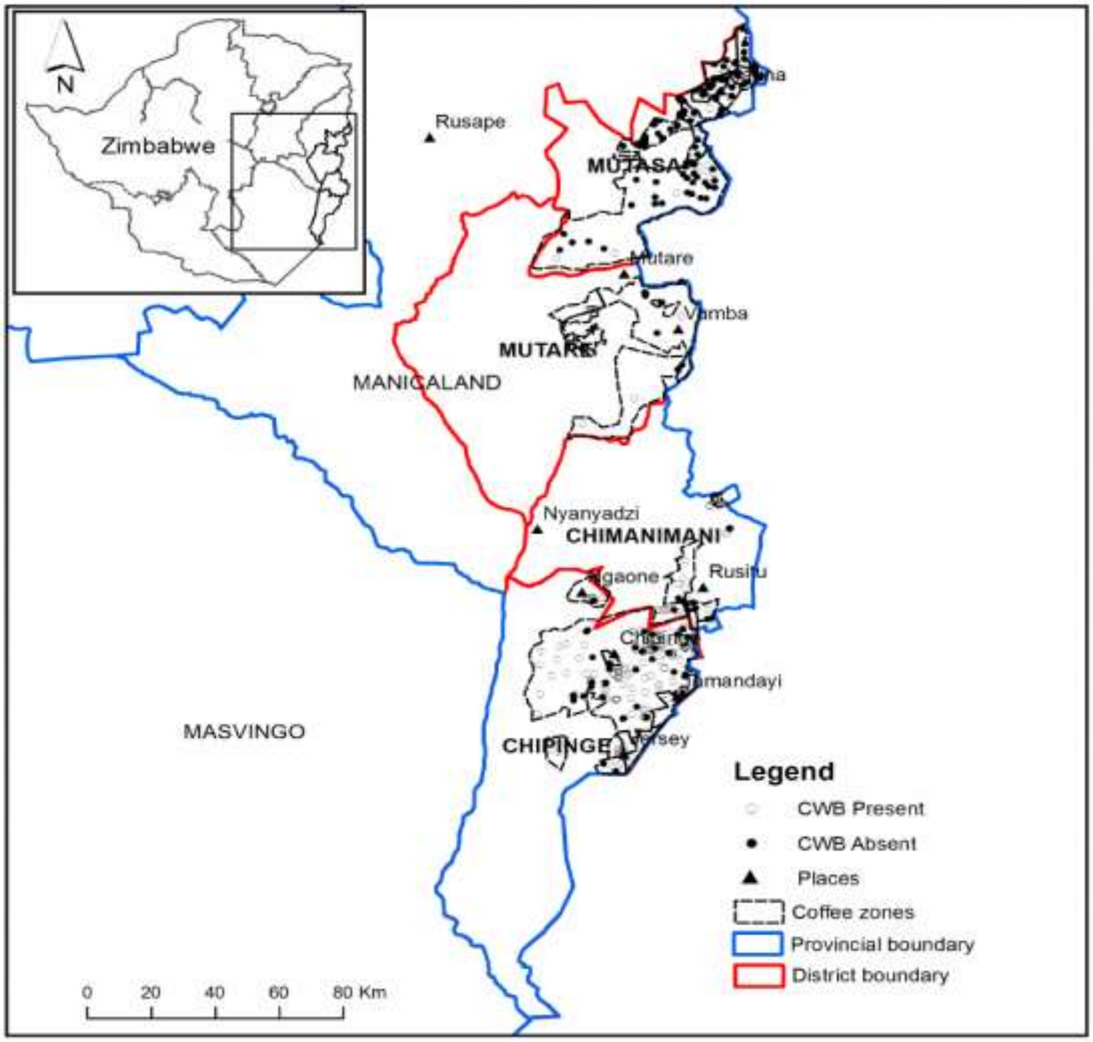

Figure 3: Map showing Manicaland Province under consideration for establishment of biomass power plants (extracted from ZETDC Database)

The research is limited to Manicaland Province's Eastern Districts, a region highly endowed with plantation forests whose forest plantation biomass waste products have not been used for any meaningful benefit to the economy of Zimbabwe. The study area is covered by Landsat-8 OLI image scenes (path/row: 168/72, 168/73, 169/73, 169/74 and 168/75).

1.8.1 Agro-ecological zones of Zimbabwe

(Vincent & Thomas, 2013), divided Zimbabwe into five main natural regions according to differences in effective rainfall (Figure 4; Table 7). Annual rainfall is highest in Natural region I which covers approximately 2% of the land area. It is a specialised and diversified farming region with plantation forestry, fruit and intensive livestock production. An exciting aspect is that the Eastern Highlands of Zimbabwe presents a unique technical, political, economic, and environmental region for the study of sustainable biomass energy schemes. The Eastern Highlands and western Mozambique encompass a steep altitude and environmental gradient where a diverse set of tree species thrive, as well as a wide range of non-timber products (mushrooms, rattans, tubers, maize, ranch and free-range cattle and goats, and so forth). These crops can all be raised and evaluated in conjunction with wood to expand the economic and sustainability value of the biomass energy scheme. This diversity is particularly important to household and community groups that have limited access to land holdings, and require payback times shorter than large industries such as sawmills.

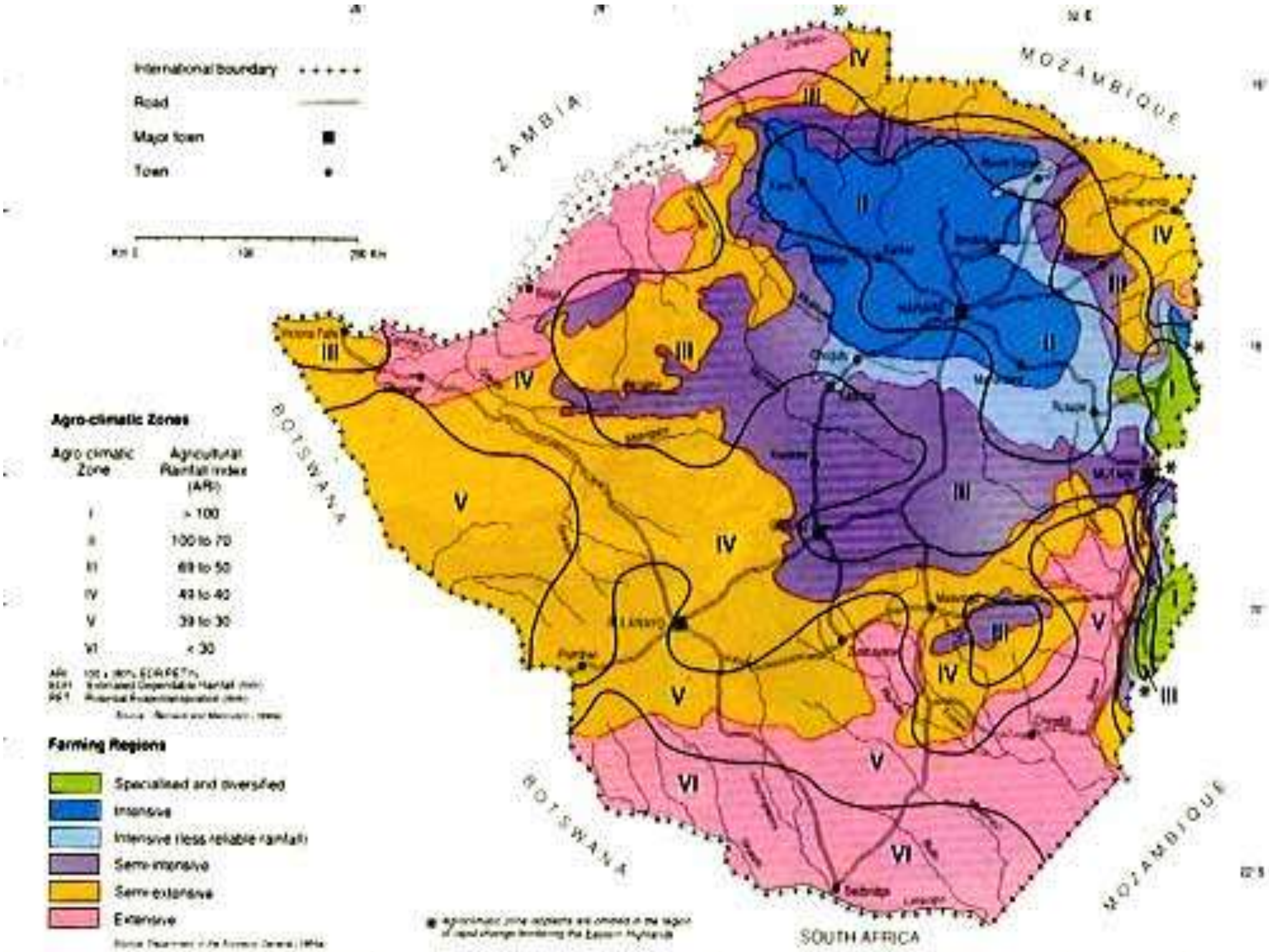

Figure 4: Map of agro-climatic zones and farming regions (Vincent and Thomas 2013)

Natural Region	Area (km^2)	Rainfall (mm yr^{-1})	Farming system
I	7 000	>1 000	Specialised and diversified farming
II	58 600	750 – 1 000	Intensive farming
III	72 900	650 - 800	Semi-intensive farming
IV	147 800	450 - 650	Semi-extensive farming
V	104 400	<450	Extensive farming

Table 7: Agro-ecological zones of Zimbabwe and recommended farming systems in each zone (Vincent & Thomas, 2013).

1.9 Requirements Analysis (Data sets)

The major datasets required to successfully tackle this research are

1) Biomass distribution information. This dataset will be downloaded from USGS – Earth Explorer. The required dataset will be L8 OLI/TIRS
2) Land Use Regulations information
3) National Heritage Items datasets
4) Roads Network dataset for the study area
5) Hydrographical Network of the study area
6) Current power network Infrastructure

1.10 Hypothesis

- There is a high positive correlation between NDVI index and forest plantation above ground, AGB biomass.

- Medium-resolution multispectral Landsat 8 derived vegetation indices can be applied for mapping aboveground forest plantation biomass of Pine Forests in Manicaland Zimbabwe.

1.11 Assumptions

There is a direct positive correlation between forest plantation biomass and calorific content in Manicaland Region, Zimbabwe

1.12 Organization of the Study

The research document is divided into five Chapters. Chapter one is an introductory Chapter emphasising the objectives, background information and research motivation to undertake the research. Chapter two reviews related literature on biomass estimation from remote sensing Imagery as well as available literature on site optimisation modelling. Its main purpose is to herald the best methods and procedures to employ in the delivery of expected results. Chapter 3 picks on from the best recommendations of Chapter two and describe how the research was undertaken. Chapter 4 discusses the results of the study, with chapter 5 included to discuss research best practices recommendations and highlight the grey areas for further study. Therefore all the chapters are interdependent and provide a holistic framework for the identification of least cost sites from a multi-factor and variable input. The most important input for the weighted overlay analysis was the biomass distribution dataset, hence its inclusion as a core requirement, justifying why biomass distribution assessment modelling was included in this research.

Chapter 2– Background and Literature Review

2.0 Introduction

The purpose of this section of the research work, Background and Literature Review, is to prove that no one has studied the gap in the knowledge **as** outlined in Chapter 1. The purpose of this chapter is to cite major conclusions, findings, and methodological issues related to the gap in the knowledge from the previous section. The Review of Literature section of this study ends with a Conclusion that clearly states that, based on the review of the literature, the gap in the knowledge that is the subject of this study has not been studied and deserve attention to address the problem context of site optimization modelling for biomass power plants in Zimbabwe. The main objective of this section is to review literature on the integration of methods and techniques which can be used in bio-energy systems planning incorporating aboveground biomass quantification in plantation forests and mapping as well as spatial optimisation techniques in bio-energy power plants site location.

2.1 Bio-energy in the renewable energy debate

Bio-energy poses a lucrative alternative in the renewable energy debate, with overtly significant benefits to climate change and global warming, through carbon sequestration, and alternative energy supplies. Compared with inveterate sources such as fossil fuels, modern bio-energy applications in power production have the ability to generate cleaner electricity and moderate Green House Gas emissions.

In most developing economies, quantitative information on available woody biomass resources at scales appropriate for energy planning is often lacking (Paradzayi & Annegarn, 2012). New remote sensing methods, including sensors, image processing, statistical methods, and uncertainty evaluations, are constantly being developed to estimate biophysical forest changes. Remotely sensed AGB is broadly used in forest management studies, conservation status evaluations, carbon source and sink investigations, and for studies of the relationships between environmental conditions and forest structure. Uncertainties in AGB estimations were found to be heterogeneous with biases related to sensor type, processing methodology, ground truthing availability, and forest characteristics. (Moghaddam, et al., 2002) found that the estimation accuracy of forest variables (e.g. biomass) is significantly improved when the radar and optical data are used in combination, compared to estimates using a single data type alone.

However, in as much as (Moghaddam, et al., 2002) have recommended the combined use of radar and optical data in AGB estimation, a couple of studies in the literature on AGB estimation still use a single type of sensing technology. The factors which are led to this are both scientific and economic, each case with its own justifications.

In the quantification and mapping of aboveground biomass for purposes of establishment of AGB power plants, of prime importance is the velocity and direction of spatial and temporal changes in aboveground biomass (AGB). In order to tap into the potential of these energy sources, there is a need to assess the availability of resources spatially as well as temporally. The question still remains therefore, whether biomass is really a lucrative alternative for renewable power generation. However, this question has a location bias as the value of biomass in renewable energy supply is dictated by location dynamics, also bounded by the legal and constitutional frameworks in the specified regions. In this respect this section looks at countries that have successfully implemented AGB conversion systems for powering national grids.

2.2 Countries that have successful Aboveground biomass conversion plants for powering the national grid.

2.2.1 Sweden's Bio-energy Success Story

Sweden's Bio-energy Pyrogrot uses forest residues as feedstock, and produces about 160,000 tons per year of pyrolysis oil with the energy content estimated at about 750 GWh. The plant operates at an input processing capacity of 720 tons a day of dry biomass waste. Forest residue is the leading bio-energy source in Sweden, and bio-energy is the nation's leading energy source. Since the 1970s when 70-80 percent of Sweden's energy mix came from imported oil, the country has transformed its energy system to the point where oil is almost entirely a transport fuel, while bio-energy is used in district heating, industry and electricity production. For nations whose bio-energy industry is emerging or struggling with policy issues, Sweden is an example of how to get it right.

Swedish bio-energy use has grown from 40 TWh/year in the 1970s to around 140 TWh in 2012. Bio-energy steamed past oil in 2009 to become the leading energy source for the nation. And since 2009 bio-energy has made up more of Sweden's energy mix than hydropower and nuclear power combined. Bio-energy was the leading factor in Sweden's 9 percent decrease in greenhouse gases between 1990 and 2010, while GNP increased by 50 percent.

The main reasons for the Swedish bio-energy sector's phenomenal growth are broad political support and strong incentives such as the CO_2 tax introduced in 1991, the green electricity certificates introduced in 2003, and tax exemptions for transport bio-fuels. Bio-energy success in Sweden is also due to Sweden's long-standing tradition of using its natural forest resources – the nation has more forests than any other EU member state.

2.2.2 United States of America

Renewable energy resources account for 6.7% of the total energy consumed in the United States, with an approximate 2,500MW of MSW used for electric power generation. If liquid bio-fuels are included, then biomass energy constitutes the greatest source of renewable energy in the United States. Figure 4 shows that biomass energy (consisting of wood energy, bio-fuels, and waste energy) currently provides more than half of the renewable energy consumed in the United States, with approximately two-thirds of the total biomass energy being used to generate heat, power, or CHP through wood energy.

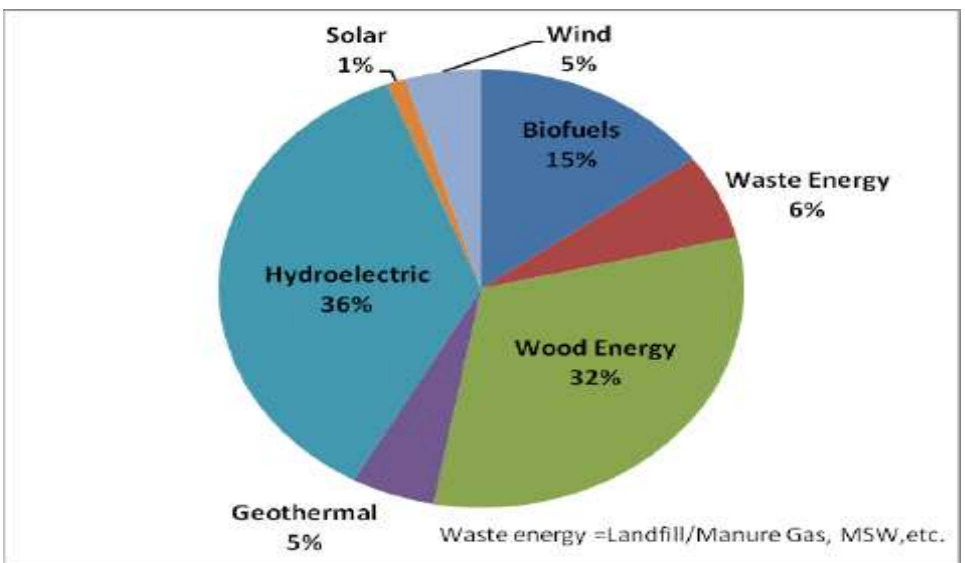

Figure 5: Total U.S. renewable energy consumption, 2007

2.2.3 National Biomass Action Plan for Germany

The point of the National Biomass Action Plan for Germany is to give a comprehensive idea to fundamentally expand the bio-vitality offer in Germany's energy supply while holding fast to manageability criteria. Bio-energy is a perfect decision in endeavours to moderate the impacts of environmental change, secure supply and advance financial improvement. It likewise serves in boosting household esteem creation – particularly in rustic territories.

In 2007 bio-energy (with respect to general energy utilization) gave 3.9 percent of the power utilized as a part of Germany, 6.1 percent of aggregate warmth and 7.3 percent of aggregate fuel utilization. Bio-energy accordingly made up 4.9 percent of general essential energy utilization.

Table 8: 2007 - 2020 Bio-energy against Total Renewable Energy Trends (Germany)

	2007		2020	
	Total Renewable Energy	Of which Bioenergy[2]	Total Renewable Energy Meseberg[3] (EEG or EE-RL)[4]	Of which Bioenergy[4] as per Pilot Study 2008
Share of REN in overall primary energy consumption	6.7 %	4.9 %	16 %	11 %
Share of REN in overall end energy use[5]	8.6 %	6.2 %	18 %	10.9 %
Share of REN in overall electricity consumption/ electricity supply[6]	14.2 %	3.9 %	minimum 30 %	8 %
Share of REN in overall renewables use of heat	6.6 %	6.1 %	14 %	9.7 %

2.2.4 Status of Africa's Energy Sector

Africa's vitality area can best be comprehended as three particular districts. North Africa, which is intensely depended on oil and gas, South Africa, which relies upon coal and Sub-Saharan Africa, which is to a great extent dependent on biomass (Karekezi & Kithyoma, 2- 4 June, 2003). Figures for Eastern and Southern African nations show that a high extent of aggregate national energy supply is gotten from biomass resources. Biomass energy is frequently utilized as a part of its customary and natural structure. Indeed, even oil-rich sub-Saharan African nations keep on relying on biomass resources to meet the heft of their household level energy requirements: in Nigeria, it is estimated that 97% of the family energy needs are met by biomass (International Energy Agency, 2001).

2.3 Legal and Constitutional Frameworks on Biomass Management and Bio-energy power plant sitting in Zimbabwe

As well as giving a monetary asset to neighbourhood populaces, forests assume a shockingly huge part in worldwide carbon sequestration forms, which require measurement under universal understandings, for example, the United Nations initiative on Reducing Emissions from Deforestation and forest Degradation (UN-REDD) while likewise as biodiversity stores under the United Nations convention on Biological Diversity (UNCBD). Consequently, land managers are turning to remote sensing as a cheaper, more rapid and conservative alternative to traditional forest inventory methods to enable viable biomass measurement (Hall, et al., Nov. 2011).

2.3.1 Zoning policy in Zimbabwe, considerations and best practices

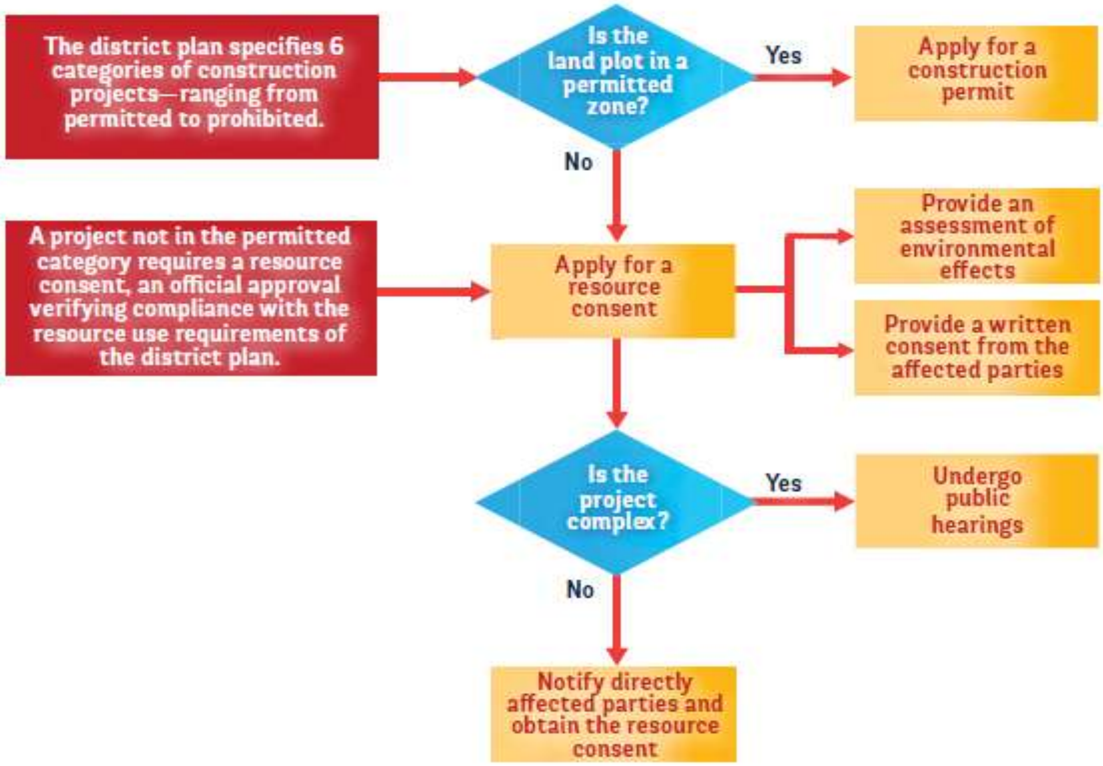

Figure 6: Zoning Flow Diagram

In Zimbabwe physical and spatial planning administrations are coordinated by the Department of Physical Planning (DPP), a specialized arm of the legislature that is responsible for dealing with the spatial planning framework and providing technical advice for the implementation of the development planning systems ((IBRD/WB, 2012); (Toriro, 2007)). Among its significant wards, the office has oversight on the nation's local authorities, who must hold fast to the arrangements of the Regional, Town and Country Planning Act (RTCPA) (Chapter 29:12) and related enactment. There are three bits of enactment which govern the use of land in Zimbabwe: the Regional, Town and Country Planning Act, the Urban Councils Act and the Rural District Councils Act.

As per the RTCPA, the DPP additionally educate the Minister of Local Government on the interpretation of planning provisions and the execution of planning functions under the reserved powers of the Minister. DPP is also involved in facilitating sites for the development of government, state enterprises, as well as parastatal activities on state land in whose domain the research requirements of this document are embedded. It also carries out technical evaluation of plans (master plans, local plans and layout plans) originating from local planning authorities to aid the Minister in making decisions on the plans. Physical planning embraces aspects of environmental planning, building codes (Cote & Grant, 2008), and mediating between land-uses among stakeholders to avoid incompatibility and conflict in land-use and land conflicts arising from spatial planning decisions that interfere with other people's land rights

Land-use planning is a critical determinant in the sitting of any facility. Such provisions are specified in the master, local, structure, and subject plans of a given local authority. It is important to ensure that there are no conflicts between the master plans and the local plans. The RTCPA is an instrument to ensure coordinated and harmonious development and re-development of land use in a given area. Sometimes the development proposed is incompatible with existing and proposed uses of land. Existing local development plans assist in showing the current and future pattern of development.

2.4 Methods to Estimate Above-Ground Biomass - A Review

This section of the research reviews and summarises the various methods and studies that have been carried out to estimate above-ground forest biomass especially in artificial forests, with their corresponding strengths and limitations, as per one of the objectives of the research. Many researchers converge on the idea that field data observation is the most conventional and relatively accurate method of estimating forest biomass within limits of experimental error. Although, this method of forest biomass estimation is the most accurate for its purposes, it is strenuous, expensive, time consuming and destructive (which may not be very practical for those forest ecosystems with threatened or rare or protected plant species). The method is also most applicable to small sample biomass surveys and small-scale analysis.

The accurate assessment of biomass estimates is important for many applications like timber extraction, bio-energy systems planning, tracking changes in the carbon stocks of forest and global carbon cycle. Forest biomass can be estimated through field measurements and remote sensing and GIS methods (Ravindranath & Ostwald, 2008); (Lu, 2006)

The IPCC Guideline for National Green House Gas Inventories (IPCC., 2006) mentioned two ways, direct and indirect to derive aboveground biomass. In another research (Lu, 2006) mentioned approaches to estimate biomass based on field measurements, remote sensing and GIS. Although providing the best accuracy, the traditional techniques based on field measurements are also very costly and time consuming (de Gier, 2003). Satellite Imagery based techniques provide an alternative to traditional methods by providing spatially explicit information and enable repeated monitoring, even in remote locations, in a cost effective way (Patenaude, et al., 2005) with the advantage of capability to provide spatial, temporal, and spectral information (Brown, 2002). Remote Sensing can be used as a tool to estimate biomass and carbon, to meet the requirements of the Kyoto Protocol, but no such instrument can measure aboveground biomass directly; therefore in situ data collection is always necessary. (Rosenqvist, et al., 2003). Traditionally, two methods of field measurement are available for the determination of biomass (Murali, et al., 2005).

Table 9: Summary of techniques for above-ground biomass estimation

Category	Methods	Data used	Characteristics	References
Field measurement-based methods	Destructive sampling	Sample trees	Individual trees	Klinge *et al.* (1975)
	Allometric equations	Sample trees	Individual trees	Overman *et al.* (1994), Honzák *et al.* (1996), Nelson *et al.* (1999)
	Conversion from volume to biomass	Volume from sample trees or stands	Individual trees or vegetation stands	Brown and Lugo (1984), Brown *et al.* (1989), Brown and Lugo (1992), Gillespie *et al.* (1992), Segura and Kanninen (2005)
Remote sensing-based methods	Methods based on fine spatial-resolution data	Aerial photographs, IKONOS	Per-pixel level	Tiwari and Singh (1984), Thenkabail *et al.* (2004)
	Methods based on medium spatial-resolution data	Landsat TM/ETM+, SPOT	Per-pixel level	Roy and Ravan (1996), Nelson *et al.* (2000a), Steininger (2000), Foody *et al.* (2003), Zheng *et al.* (2004), Lu (2005)
	Methods based on coarse spatial-resolution data	IRS-1C WiFS, AVHRR	Per-pixel level	Barbosa *et al.* (1999), Wylie *et al.* (2002), Dong *et al.* (2003)
	Methods based on radar data	Radar, lidar	Per-pixel level	Harrell *et al.* (1997), Lefsky *et al.* (1999b), Santos *et al.* (2002, 2003)
GIS-based methods	Methods based on ancillary data	Elevation, slope, soil, precipitation, etc.	Per-pixel level or per-field level	Brown *et al.* (1994), Iverson *et al.* (1994), Brown and Gaston (1995)

This method involves the complete harvesting of plots followed by extrapolation to a unit area of land (Klinge & Herrera, 1983).The destructive method, also known as the harvest method has been proved to be the most direct method of forest biomass estimation in forest ecosystems. (Gibbs, et al., 2007). This method involves harvesting of all the trees in the known area and measuring the weight of the different components of the harvested tree, like the tree trunk, leaves and branches [(Ravindranath & Ostwald, 2008), (Devi & Yadava, 2009)] and measuring the weight of these components after they are oven dried. This method of biomass estimation is limited to a small area or small tree sample sizes. Although this method determines the biomass accurately for a particular area, it is time and resource consuming, strenuous, destructive and expensive, and it is not feasible for a large-scale analysis. This method is also not applicable for degraded forests containing threatened species (Montès, et al., 2000). Usually, this method is used for developing biomass equations to be applied for assessing biomass on a larger-scale [(Navár, 2009); (Segura & Kanninen, 2005)].

2.4.2 Allometric Equations for Biomass Estimation

A more widely used traditional method for estimating forestry biomass is based on allometry where allometric equations are used to extrapolate both in situ and remotely sampled data to a larger area to derive biomass and canopy volume from biometric characteristics such as diameter at breast height (**DBH**), tree height, etc. Allometric relationships are used for estimating tree allometry which establishes quantitative relationships between key biometric characteristics such as dimensions of trees (easy to measure) and other properties (which are difficult to assess).

(Brown, et al., 1989) developed allometric regression equations to estimate the above-ground biomass of individual trees for tropical forests as a function of diameter at breast height, total height and wood density. (Nelson, et al., 1999) conducted a study to develop species-specific and mixed-species allometric relationships for estimating total above-ground dry weight using eight abundant secondary forest tree species in the Amazon.

2.4.3 Merits and demerits of traditional methods

The two traditional methods discussed above are accurate but are extremely time-consuming, costly, and generally limited to small areas and small tree sample sizes (Hyde, et al., 2006), (Ketterings, et al., 2001), (Hyde, et al., 2007). Moreover, extending this method to map forest biomass across a large area is extremely challenging when factors such as ecological differences, variations in inventory systems, and scattered sources of biomass data are considered. In addition, since the allometric coefficients are site and species specific and are based on a certain range of tree diameters, the use of standard allometric equations can lead to significant errors in vegetation biomass estimations if used outside the area where they were originally produced (Chave, et al., 2005). However, reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests is possible as pointed out by (Ketterings, et al., 2001).

There have been efforts in developing generalized regional and national tree biomass equations that could be applied to a larger geographic footprint than most existing allometric equations (Lambert, et al., 2005); (Case & Hall, 2008)].Another vegetation type of great interest is the tropical savannah, not only for the large regions it covers but also for the high inter-annual biomass dynamics.

Therefore, to use these methods as a source of biomass information should be carefully considered, especially depending on the accuracies sought in the project and the allowed timeframe for the delivery of results. In certain instances a compromise can be taken and such methods can still supply the required information.

2.4.4 Use of Remote Sensing and GIS for Biomass Estimation

The advent of remote sensing technology sought to provide a solution to the challenges inherent in the traditional methods of biomass quantification and assessment. Forest biomass assessment, mapping and monitoring vegetation, land cover and land-use change can be evaluated using remote sensing technology. Several studies have been conducted to estimate forest biomass using remotely sensed data [(Nelson, et al., 1988); (Häme, et al., 1997); (Drake, et al., 2003)]. Remote sensing technology provides a synoptic view of the surface area of interest, thereby capturing the spatial variability in the attributes of interest. A major advantage of remote sensing technology is that it can obtain information about an area of interest that is difficult to access or inaccessible. Remote sensing enables us to monitor natural resources on a continental, even on a global scale. It is also the only realistic and cost-effective way of acquiring data over a large area. The major landslide developments in sensing technologies have also improved the accuracies involved.

(Nelson, et al., 1999) conducted a study to determine the utility of laser profiling data for the estimation of forest biomass and volume. In this study, they co-related the data of forest biomass and volume, obtained from field measurements taken from specific plots of the laser flight lines, with the corresponding estimates of forest canopy height obtained from the laser profiling. (Steininger, 2000) conducted a study to examine the potential of Landsat TM images in estimating the aboveground biomass of tropical secondary forests. (Lu, 2005) also conducted another study to estimate the above-ground biomass in the Brazilian Amazon using Landsat TM data. The study showed that the use of Landsat TM imagery for estimating forest above-ground biomass is more successful for successional forest rather than mature forests.

(Lefsky, et al., 2001) estimated the above-ground biomass in three biomes-temperate deciduous, temperate coniferous and boreal coniferous, using LiDAR remote sensing. LiDAR remote sensing is designed to allow the signal to penetrate the canopy. LiDAR systems send out pulses of laser light and measure the signal return time to directly measure the height and vertical structures of forests. They compared the LiDAR-measured canopy structure with the field measurements of above-ground biomass and found that a single equation can be used to relate the remotely sensed canopy structure to the above-ground biomass for all the three biomes with distinctly different forest communities. (Popescu, 2007) found that LiDAR data can be used to measure precisely the biophysical parameters of individual trees such as the diameter at breast height (dbh) which is one of the commonly used variables for biomass estimation of forest. (Hudak, et al., 2012) evaluated and found that repeated LiDAR surveys along with field sampling and statistical modelling can successfully be used for accurately estimating high resolution and spatially explicit biomass and carbon dynamics in conifer forests. (Ene, et al., 2012) conducted a study to assess the accuracy of LiDAR-based biomass estimation where they used the airborne laser scanning (ALS) sampling approach. Their finding suggested the systematic ALS assisted survey was more efficient than the ground-based inventory.

Image texture is an important property which gives information about an object or a selected region in an image. Studies have been carried out using texture measurements with optical data and SAR data for biomass estimation. (Sarker & Nicho, 2011) explored the potential of optical imagery using ALOS AVNIR-2 texture indices for biomass estimation and obtained a significant improvement while using the ratio of texture parameters. (Eckert, 2012) also obtained similar results in the estimation of forest biomass while using the texture measurement from WorldView-2 satellite data. In another study by (Cutler, et al., 2012), a combination of SAR image texture and LANDSAT TM data were used for the estimation of tropical forest biomass. The result of their study suggested that inclusion of SAR texture with multispectral data can be successfully applied to a predictive relation at times and space other than for which it was developed. Although, texture measurements demonstrate a promising result for biomass estimation, it requires further investigation.

(Baccini, et al., 2004) estimated the forest biomass for eighteen National Forests in California. For the estimation of forest biomass, they used a combination of data sources like remotely sensed data, topographic information and climatic variables, to map the above-ground biomass. They found that the estimate of forest biomass at the regional scale with this method gives pretty much accurate estimates of the aboveground biomass.

Biomass estimation using remotely sensed data is an emerging technology and it is being increasingly used to inventory forest biomass. Satellite-based estimates of biomass are likely to become more accessible over the next few years (Gibbs, et al., 2007). However, remote sensing data does not directly estimate the amount of biomass that is present in the forest. It only measures the parameters which are correlated to biomass like the tree height, crown size, forest density, forest type, forest volume, leaf area index, etc. Remote sensing data coupled with the field-based measurement of the forest is used to estimate the above-ground biomass. The field measurements are commonly used to develop predictive models or allometric equations for biomass and to validate the results obtained from the remotely sensed data. Once it is validated the remotely sensed data can be used to estimate the forest biomass for wider area where there is very little or no field measurement data available.

2.4.5 Best practice approach for the modelling of aboveground forest biomass using Remote Sensing

Landsat Thematic mapper (TM) image has long been the dominate data source, and recently LiDAR has offered an important new structural data stream for forest biomass estimations. On the other hand, forest biomass uncertainty analysis research has only recently obtained sufficient attention due to the difficulty in collecting reference data. This section of the research provides a brief overview of current forest biomass estimation methods using both TM and LiDAR data. Results indicate that Landsat TM data can provide adequate biomass estimates for secondary succession but are not suitable for mature forest biomass estimates due to data saturation problems. LiDAR can overcome TM's shortcoming providing better biomass estimation performance but has not been extensively applied in practice due to data availability constraints. The uncertainty analysis indicates that various sources affect the performance of forest biomass/carbon estimation. With that said, the clear dominate sources of uncertainty are the variation of input sample plot data and data saturation problem related to optical sensors. A possible solution to increasing the confidence in forest biomass estimates is to integrate the strengths of multi-sensor data.

2.4.5.1 Review of the use of Lidar remote sensing for biomass estimation to support renewable energy generation.

The two-dimensional (2-D) nature of optical remote sensing data limits its use in direct quantification of some vegetation characteristics like tree height, canopy height, volume, etc. Overall, optical sensor data are found suitable for extracting horizontal vegetation structures such as vegetation types and canopy cover; however, the 2-D data have limitations in estimating vertical vegetation structures such as canopy height, which is one of the critical parameters for biomass estimation. (Wallerman, 2010) investigated 3-D information derived from SPOT 5 stereo imagery to map forest variables such as tree height, stem diameter and volume. These studies show that high-resolution stereo data can be used as a valuable alternative to derive vegetation height information; however, more studies are needed to support this.

2.4.5.2 Biomass Estimation from Lidar metrics

LiDAR is a relatively new and sophisticated technology that helps to overcome the limitations of Optical remote sensing due to its ability to extend the spatial analysis to a third dimension. The 3-D LiDAR points represent latitude, longitude, and ellipsoidal height based on the WGS84 reference ellipsoid. Ellipsoidal heights are converted to elevations. LiDAR instruments have the ability to sample the vertical distribution of canopy and ground surfaces, (Dubayah & Drake, 2000), (Harding, et al., 2001) and several studies have established a strong correlation between LiDAR metrics and aboveground biomass, thus allowing estimation of biomass in forested environments. LiDAR technology has seen considerable advancement with the advent of full waveform digitizing sensors, (McGlinchy, 2014) which has allowed this tool to be increasingly used in the study of forest structures in a variety of forest environments.

(Lefsky, et al., 2001) has it to say that it has become the most efficient technology for structural assessment since it captures landscape structural data that are suitable for volume and biomass estimation (Zhao, et al., 2009). Biomass can be estimated at the individual tree level with allometric equations using LiDAR data of sufficient post spacing (e.g., >1 return/m^2) (Lucas, 2010). (Lim, 2003) gives a detailed review of LiDAR data applications in forestry inventory management.

Discrete return airborne LiDAR systems are more suitable for fine-scale biomass mapping, while waveform space-borne LiDAR, e.g., The Geoscience Laser Altimeter System (GLAS) on board Ice, Cloud, and Land Elevation Satellite (ICESat) has the potential for broad-scale biomass mapping according to (Chen, 2013), (Saatchi, 2011).

Although LiDAR data have some advantages over optical data, there are a few issues that restrict its use for field applications. For example, LiDAR data analyses are not simple and require more image processing knowledge and skill and specific software. The LiDAR data acquisition process is expensive and covers smaller areas; hence study areas are still limited to specific areas and have not been applied extensively to larger areas for biomass estimation.

The structural forest measurements from LiDAR data permit the accurate estimation of height, crown size, basal area, stem volume, LAI, NPP, and aboveground biomass, even in high biomass forests, a difficult task with passive sensors (Lefsky, 2002). Biomass mapping from airborne discrete return LiDAR is based on two approaches:

(1) Area-based and

(2) Individual tree-based methods (Chen, 2013).

Area-based methods develop statistical models to relate biomass with metrics derived from a LiDAR point cloud at the plot or stand level and apply the models over the whole study area (Thomas, 2006). The development of statistical models requires field data for calibration and validation.

The most widely used area-based LiDAR metrics for biomass prediction are various height metrics. (Patenaude, 2004) calculated based on first, last, or all returns. Height metrics can also be calculated from grids of the canopy height model (Patenaude, 2004). Individual tree-based methods identify individual tree crowns and extract individual tree information from LiDAR point cloud, such as tree height and crown size, which can be related to biomass and other canopy structure variables through allometric equations (Saremi, 2014). In this case, the amount of fieldwork required is much smaller than that for area-based methods because field data are needed only for a sample tree and not for sample plots or stands. Discrete return systems have been used to estimate biomass at the individual tree level up to the stand level (Saremi, 2014). The DEMs generated from airborne LiDAR data are very accurate and widely used in forest mapping and tree parameter estimations. It captures elevation information from the forest canopy as well as the ground beneath and can be used to assess the complex 3-D patterns of canopy and forest stand structure such as tree density, stand height, basal area, LAI, and forest biomass and volume (Lefsky, et al., 2001). In densely vegetated areas when passive sensors saturate at high biomass levels (higher than 100 mg ha−1) (Cohen & Spies, 1992), LiDAR has been found to accurately estimate LAI and biomass in such high biomass ecosystems (Lefsky, et al., 2001).

2.4.5.3 Use of Radar in Biomass Estimation

Satellite radar can play an important role in the remote measurement of forest bio-physical parameters which have been shown to closely relate to biomass accumulation and biodiversity (Houghton, et al., Jun. 2009). Synthetic aperture radar (SAR) data collected by satellites using lower microwave frequencies such as L-band (1–2 GHz) are one of the most widely used datasets especially in tropical areas, particularly during the last 5 years. This is due mainly to five reasons:

1) L-band frequencies have the ability to penetrate clouds and dense vegetation canopies since the elements of both are relatively small in comparison to the L-band wavelength;

2) There is an established proportionality of the L-band backscattered intensity to biomass;

3) The significant archive of radar data collected by the satellite L-band SAR sensor ALOS PALSAR;

4) The wide range of methods that can be used with ALOS PALSAR data to derive biomass predictions;

5) The expectation of renewed global capability for, monitoring the same forest parameters using ALOS PALSAR 2 sensor and the NASA airborne UAVSAR system.

However, cost limitations in this research have resulted in the research being restricted to other sensing techniques.

2.4.5.4 Use of Radar and LiDAR

Despite the popularity of radar and LiDAR data in forest biomass analyses, very few studies have utilized such data in the estimation of forest biomass. (Dusseux, 2014) compared the performance of variables extracted from four optical and five SAR satellite images to monitor grassland biomass. They concluded that the classification accuracy of SAR variables was higher than those using optical data. (Buckley & Smith, 2010) used radar, LiDAR, and hyper spectral data to monitor grassland biomass and they argued that radar and LiDAR data were not affected by weather conditions as optical remote sensing data is.

2.4.5.5 Correlation analysis between biomass and spectral vegetation indices of forest ecosystem

Satellite based vegetation indices (VIs) models, including SAVI, the modified soil adjusted vegetation index (MSAVI), NDVI, and normalized difference water index, are the most commonly used models for estimation of biomass in many studies (Hurcom & Harrison, 1998); (Foody, 2001); (Zheng, et al., 2004); (Schlerf, et al., 2005). Vegetation indices have been recommended to remove variability caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties Many previous studies have shown significantly positive relationship between biomass and vegetation indices (Hurcom & Harrison, 1998); (Boyd, et al., 1999); (Steininger, 2000); (Zheng, et al., 2004); (Maynard, et al., 2007) however, some results have shown poor relationship (Foody et al., 2003; Schlerf et al., 2005).

The spectral reflectance are used for understanding the nature of vegetation characteristics, however it is affected by various factors like vegetation composition, soil characteristics, atmospheric conditions, topography and moisture content (Chen & Wang, 2008).

2.4.5.6 Other techniques of biomass quantification

Image classification, such as support vector machine classifier (Mirik, 2013), object-based classification (Mirik & Ansley, 2012), and ANN (Xie, 2009), are other techniques frequently used for biomass quantification. In addition, multiple regression analysis models were the most commonly used statistical approaches (Friedl, 1994). However; the performance of these techniques varies and depends on the structure of the study area and the nature of the remotely sensed data used to estimate biomass.

(McGlinchy, 2014) used LiDAR for biomass estimation in savannah ecosystems with some success in a South African savannah landscape. Others have utilized new approaches involving the fusion of high-fidelity VIS/NIR imaging spectrometer data with scanning, waveform light detection and ranging (wLiDAR) data to assess biomass in African savannas (Kelbe, 2010). The findings established the potential of fused hyper spectral and wLiDAR data for herbaceous biomass modelling in savannas.

2.4.5.7 Estimates of Aboveground Biomass from Texture Analysis of Landsat Imagery

The direct mapping techniques employing spectral band ratios, such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), tend to under-predict forest biomass in regions where there is high biomass content per unit area and multi-storied forest canopies where NDVI in particular is affected by saturation. Biomass quantification and mapping using Synthetic Aperture Radar has tended to be a promising technique for biomass quantification, especially when used in conjunction with methods that model forest biomass by empirically relating backscatter to ground-based biomass measurements, and Interferometric SAR (InSAR) techniques that can estimate forest height. SAR biomass estimation techniques however, also have been shown to saturate in regions of dense forest canopy, and SAR data is only available on a limited basis and where it is available, the costs of data acquisition tend to be exorbitantly too high. On another dimension, LiDAR provides a direct measure of forest canopy height relating to DBH, but its wide scale use is currently limited by the expense of acquiring LiDAR data at fine spatial scales. Only until these data access limitations are resolved, other publicly available remote sensing products need be embraced to create regional biomass maps.

Texture analysis is an image processing technique that addresses some of the existing problems with vegetation index saturation and data acquisition constrains related to mapping forest biomass at regional scales. Texture is a measure of variability in pixel values among neighbouring pixels for a defined analysis window. A primary advantage of texture is that it can be calculated from optical data, among other types of raster data. The use of optical imagery in calculating texture is advantageous because there are several sources of openly available optical imagery, including Landsat, and, therefore, mapping biomass with image texture analysis is not subject to the constraints in obtaining data that are present for SAR or LiDAR. Furthermore, image texture has been used to aid in mapping forest biomass in dense tropical forests, and in some regions texture is a better predictor of biomass than spectral vegetation indices.

Models including image texture variables are more strongly correlated with biomass than models using only physical and spectral variables. Additionally, (Katharine & Jason, 2014) suggest that the use of texture appears to better capture the magnitude and direction of biomass change following disturbances compared to spectral approaches. Since texture has been shown to be a powerful strategy for mapping biomass in thick shades, and can be computed on generally accessible optical imagery, texture might be a helpful alternative for enhancing biomass maps at local and territorial scales.

2.4.6 Image Processing and Analysis Techniques for Remotely Sensed Imagery – A review

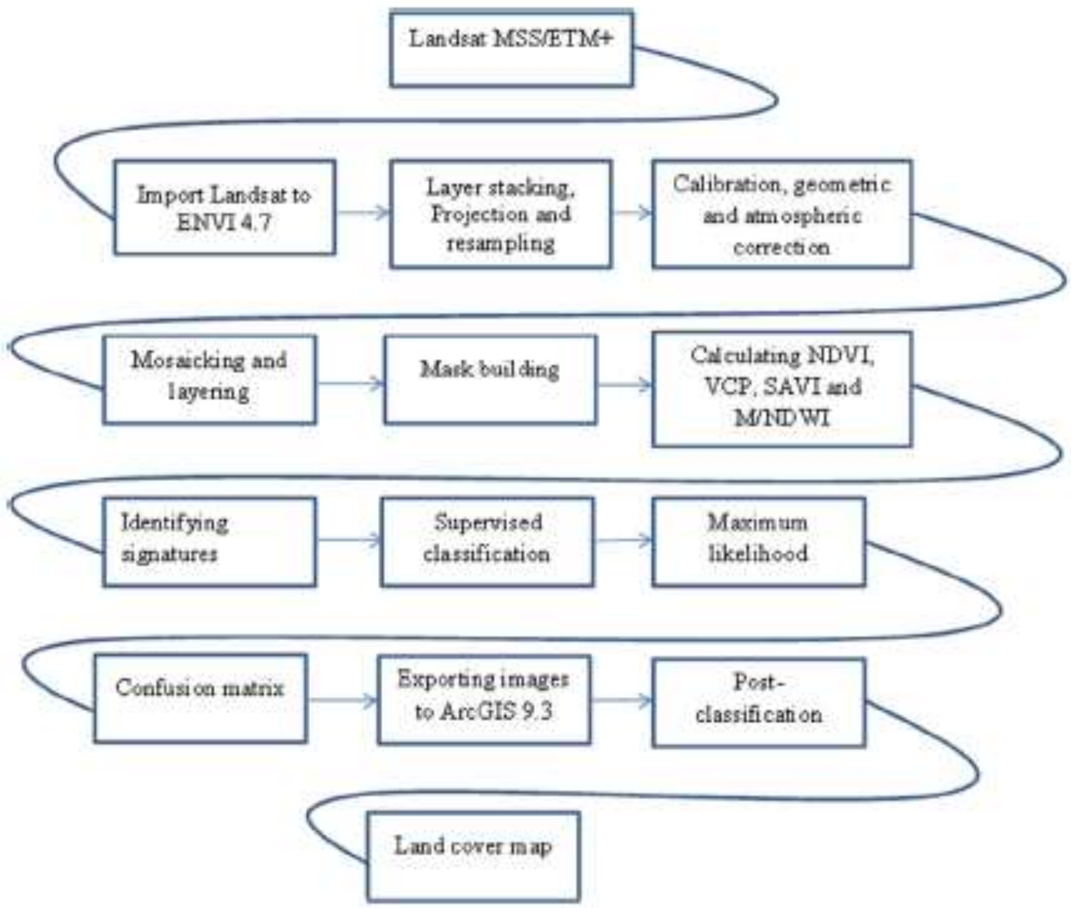

Figure 7: Generalized Landsat Image Processing in ENVI4.7 and ArcGIS 9.3

Many image processing and analysis techniques have been developed to aid the interpretation of remote sensing images and to extract as much information as possible from the images. The choice of specific techniques or algorithms to use depends on the goals of each individual project. Prior to data analysis, initial processing on the raw data is usually carried out to correct for any distortion due to the characteristics of the imaging system and imaging conditions. Depending on the user's requirement, some standard correction procedures may be carried out by the ground station operators before the data is delivered to the end-user. These procedures include radiometric correction to correct for uneven sensor response over the whole image and geometric correction to correct for geometric distortion due to Earth's rotation and other imaging conditions (such as oblique viewing). The image may also be transformed to conform to a specific map projection system. Furthermore, if accurate geographical location of an area on the image needs to be known, ground control points (GCP's) are used to register the image to a precise map (geo-referencing).

2.4.6.1 The challenges of remote sensing-based biomass estimation –Discrimination of plant species

Biomass estimation remains a challenging task, especially in those study areas with complex forest stand structures and environmental conditions. Either optical sensor data or radar data are more suitable for forest sites with relatively simple forest stand structure than the sites with complex biophysical environments. A combination of spectral responses and image textures improves biomass estimation performance. (Asner, et al., 2003) summarized per-pixel analysis of forest structure using vegetation indices, spectral mixture analysis, and canopy-reflectance modeling. (Culvenor, 2003) summarized the techniques for extraction of individual tree information using fine spatial-resolution images. For fine spatial-resolution data using optical sensors, the approaches which have been used to extract biophysical parameters include a bottom-up algorithm (valley-following and directional texture), a top-down algorithm (multi-scale edge segments, threshold-based spatial clustering, a double-aspect method, and vision expert system), and template matching. The fine spatial resolution and associated multispectral characteristics may become an important data source for AGB estimation. One important application may be its use as reference data for validation or accuracy assessment for medium and coarse spatial-resolution data applications.

(Nelson, et al., 2000) analysed secondary forest age and AGB estimation using Landsat TM data and found that AGB cannot be reliably estimated without the inclusion of secondary forest age. (Steininger, 2000) explored the ability to estimate AGB of tropical secondary forests using Landsat TM data and found that data saturation was a problem for AGB estimation in advanced successional forests. The table below summarises selected examples of biomass estimation using Landsat TM.

Table 10: Selected examples of biomass estimation using Landsat data.

Datasets	Study area	Techniques	References
Landsat 5	Mauaus, Brazil	Liner and exponential regressions	Steininger (2000)
Landsat 5	Pará state (Altamira, Bragantina, and Ponta de Pedras) and Rondônia state (Machadinho d'Oeste)	Multiple regression analysis	Lu (2005)
Landsat 5	Sabah, Malaysia	Estimated crown diameter using an exponent model, then calculated biomass using crown diameter	Phua and Saito (2003)
Landsat 4 and 5	Manaus, Brazil; Danum Valley, Malaysia; Khun Kong, Thailand	Multiple regression model, neural network	Foody *et al.* (2003)
Landsat 5	Central Sweden	*K* nearest-neighbour method	Fazakas *et al.* (1999)
Landsat 5	Madhav National Park, India	Multiple regression analysis	Roy and Ravan (1996)
Landsat 7	Northern Wisconsin, USA	Multiple regression analysis	Zheng *et al.* (2004)
Landsat TM derived land cover data, forest inventory data, climate and soil data	South-eastern USA	A productivity model (PnET)	Mickler *et al.* (2002)

2.4.7 Principles of biophysical parameter retrieval methods

2.4.7.1 Information Extraction from Remote Sensing Imagery: The Geo-/Bio-Physical Variables Retrieval Problem

The analysis of remote sensing imagery is divided into *image*-centred and *data*-centred approaches. The former approach refers to the interpretation of the scene on the basis of the spatial relationships among features on the ground. The information can be extracted from the scene either by an experienced user through photo interpretation or by a computer aided system in a quantitative and objective manner. Typical examples are the identification of land-cover/land use classes on the ground and the recognition of changes among them. Data-centred approaches perform the analysis of the acquired scene driven by the data, i.e., the physical measurements of emitted and/or scattered/reflected electromagnetic energy. To this type of analysis usually belong intrinsically quantitative tasks, such as the measure of spectral absorption of a target, the estimation of fractional abundances of surface materials and the retrieval of geo-/bio-physical variables. In this dissertation we focus the attention on the last issue.

Geo-/bio-physical variables are continuous attributes that quantify physical and/or structural properties of natural targets. Typical examples are the temperature and the moisture percentage of soil superficial layers, the depth and density of snow packs (which product gives rise to the so called snow water equivalent (SWE)), the concentration of biological particles and chemical pollution in costal sea waters, the amount of leaf covered area per ground unit (the so called leaf area index (LAI)), biomass and leaf bio-chemical constituents of a vegetated target, and many others. Geo-/bio-physical variables are of fundamental importance in several application and research domains.

All the aforementioned applications and research domains require spatially and temporally distributed measurements of the variables of interest. Satellite remote sensing, through its synoptic and regular imaging characteristics of the Earth surface, implicitly fulfils these requirements. From a physical viewpoint, changes in the chemical, physical and structural characteristics of a target (either natural or man-made) determine variations of its electromagnetic response in terms of absorption, emission, transmission and reflection. The possibility to quantitatively infer into the geo-/bio-physical variable of interest from the measurements performed by a remotely sensing sensor is based on this behaviour. However, this task is not straightforward for many reasons. These can be summarised as under:

· *The complexity and non-linearity that usually characterize the relationship between remote sensing measurements and target variables;*

· *The ill-posed nature of the retrieval problem*-variable equifinality issue, i.e., the phenomenon whereby similar electromagnetic responses can be associated with different geo-/biophysical variable configurations.

· *The image formation process at sensor level*-The electromagnetic energy measured within an elementary resolution cell is the result of the presence of multiple objects on the ground with slightly (or sometimes strongly) different characteristics. The response corresponding to a pixel can also be affected by radiation components coming from the surrounding of the area investigated.

· *The influence of external disturbing factors*-noise and non-linearity at sensor level and the presence of the atmosphere.

This list, points out the general complexity of the retrieval process. These considerations call for the definition and use of proper methods for processing satellite remote sensing data and retrieve the desired geo-/bio-physical variable.

2.4.7.2 The Retrieval Process: a Pattern Recognition Perspective

The retrieval of geo-/bio-physical variables from remote sensing data has been mainly treated as a more general pattern recognition problem.

From a conceptual viewpoint, the steps involved can be grouped into data pre-processing and data analysis. The former consists of all the steps required for reducing possible errors, noise and other disturbing factors in the data associated with the acquisition phase and for extracting the most relevant information (i.e., the features) for the addressed problem. The latter deals with the recognition of patterns and processes in the study sample. Both data pre-processing and data analysis might rely on the availability of prior knowledge on the addressed problem. In the geo-/bio-physical variable retrieval process this task has been addressed mainly following two approaches which are the derivation of empirical data-driven relationships and the inversion of physical based analytical models.

The first approach relies on the availability of a set of reference samples, i.e., couples of *in-situ* measurements of the desired target variable associated with the corresponding measurements of the remote sensor. These samples are exploited for deriving an empirical mapping, e.g., by means of statistical regression techniques in combination with parametric (linear, logarithmic or polynomial) functions. Then the identified relationship is extended to the problem context.

2.5 Review of Bio-energy Systems Design and Modelling

In order to meet rapidly increased energy demands and alleviate the pressure from environmental problems, much research has been conducted in almost every aspect of bio-energy application. These include improving the yields of agricultural products for food to leave more land for energy crops cultivation, increasing the yields of energy crops and shortening the harvest periods, researching bio-energy conversion technologies to make progress on conversion efficiency, and transportation modelling approaches for reducing the delivery costs of biomass.

The development and application of personal computers have enabled the use of Geographic Information Systems (GIS) to manipulate spatial data and construct complicated numerical models and various scenario analyses to better understand bio-energy systems design problems. Despite the generally high spatial heterogeneity of biomass resources, applications of location theory to bio-energy systems design are seldom found in the relevant literature. Although almost all aspects of bio-energy applications have been investigated separately, very few references address an integrated methodology for bio-energy systems planning taking account of potential biomass assessment, power plant sites selection and biomass allocation –notable exceptions are (Venema & Calamai, 2003),which have appeared in the operations research and rural development literature, not in bio-energy systems design literature. The section that follows provides a comprehensive review of existing research on biomass availability assessment, power plant sitting, and discrete location theory based modelling approaches on spatial optimization. GIS based biomass assessment, biomass power plant sitting, and location theory models are all a key component of the literature sighted in this study.

2.5.1 Biomass Availability Assessment

Biomass availability assessment is very important in the bio-energy systems planning process. Many previous studies have been conducted in this area. In 1998, an optimization model for energy generation from agriculture residues was developed by (Kanniappan & Ramachandran, 1998). By suitably allocating the land area for cultivation of various crops, their optimization model used linear programming to determine the maximum output of surplus biomass (agricultural residues) excluding the biomass assigned for fuel and fodder for animals. The optimal land use scenarios greatly increased power generation from agricultural residues. (Graham & English, 2000) employed a GIS based modelling system for estimating potential biomass supplies from energy crops. They focus on the influence of geographic variation on the cost of biomass costs and supplies. They developed raster map products showing biomass feedstock delivery costs in selected states in the United States. (Voivontas, et al., 2001) have introduced a GIS based method to estimate the biomass potential for power production from agriculture residues. Their proposed Decision Support System (DSS), evaluates the theoretical potential, available potential, technological potential, and economical potential of biomass for electric power production. This DSS considers all possible restrictions and identifies candidate power plants.

GIS is used in spatial and temporal analysis of the resources and demand and also aids the Decision Support System (DSS) for implementing location specific renewable energy technologies. Some of the related literature on biomass availability assessment can be found in (Grassi & Bridgwater, 1993), (Liang & Khan, 1996), and (Lewandowski & Weger, 2006). Researches aiming at finding ways to decrease the biomass energy production costs were also carried out. (Noon & Graham, 1996) fully discussed Regional Integrated Biomass Assessment (RIBA) by analyzing transportation and site location in the United States. A series of costs related to biomass production and transportation are discussed in detail such as the hauling distance cost, the hauling time cost, the loading and unloading cost, and the marginal price for delivered energy crops. GIS-based continuous raster maps were derived from the costs model, representing costs of supplying energy crops feedstock upon the spatial variation. The RIBA systems also can select the sites of proposed conversion facilities and proximal Bio-energy supply sites (pixels in the raster map). (Graham & English, 2000) investigated the effect of location and facility demand on the marginal cost of delivered wood chips from energy crops.

Using GIS-based spatial Decision Support Systems cost-supply curves can be developed which assists spatial planners with guidance on making land use decisions. (Swezey & Porter, 1995) summarizes the work undertaken to assess the status of externalities considerations in states and utility electricity resource planning processes and to determine how externalities considerations might help or hinder future development of biomass power plants. They suggested the bio-energy industries should emphasise the environmental and non-environmental benefits of applying biomass energy to the states and the public in order to get more government subsidies. (Moller & Nielsen, 2007) analyzed transportation costs of forest wood chips in Denmark. GIS raster data based techniques are employed to screen the transportation costs surface map between the highly distributed forest wood biomass and selected bio-energy plants.

2.5.2 Biomass Power Plant Sitting

In order to develop decentralized power generation from biomass feedstock, appropriate sites of power plants should be identified by taking into account a variety of criteria. Common power plant sitting criteria involve community impacts, public health and safety concerns, environmental impacts, land use impacts, and economic impacts. Sitting analysis with GIS began in the1970s and provided a variety of analytical tools for the integration of different spatial data, related to the parameters affecting the suitability of a location. GIS has been commonly used in many facility sitting applications, such as power-plant locations, recreational and public facility location sitting, ski resort sites, public school facility, and landfill sites identification.

The best early examples of sitting analysis with GIS involved identifying a power plant site in the state of Maryland in which a variety of parameters were considered in a raster map presentation. A GIS approach was utilized in order to apply the location criteria using three methods of overlay analysis, *the process of combining spatial information from two or more maps from the same geographic area to derive a map consisting of new spatial boundaries and entities or themes*, for finding the most suitable locations for the sitting of a coal power plant while considering all identified criteria, i.e. socio-economic and environmental. The results of their study outlined the real extent of suitable versus non-suitable sites in Franklin County, Illinois and can be further used as a tool to assist planners and managers in the decision making process. The research considers many factors that may influence the power plant sites selection such as transportation accessibility, gas pipe network, earthquake and geological faults, topographic consideration, water resources, power demand centres and so on. Suitable locations for constructing new power plants areas were selected and presented using GIS maps.

The Analytic Hierarchy Process (AHP) is a structured technique for helping people deal with complex decisions and has been extensively studied and successfully used in helping decision makers to structure and analyse a wide range of problems. However, it is rarely seen in the bio-energy systems planning literature. *Expert Choice*[6], an AHP based tool for decision making was used in a particular biogas-fuelled combined heat and power (CHP) system to evaluate the impacts of a variety of factors considered, such as air pollutants, GHG emissions, land use, economics, on the CHP system (Madlener, 2001). After applying AHP in the aquaculture/farming agent decision process, The AHP method is an easy way to help multi-criteria decision making adapt to each decision maker. In this research, the AHP method is used for determining the weights of the factors in the suitability analysis. Each factor is assigned a weight indicating the relative importance of the factors in the sitting of power plants.

[6]Developed mainly by Saaty

2.5.3 Spatial Optimization

Discrete location models are often classified in the literature based upon the number of facilities being located. Location models are widely employed in school planning and health care services planning (Rahman & Smith, 2000). But there is very little formal spatial optimization research in the field of bio-energy systems design, especially location-allocation models for minimizing the levelized unit cost of energy resulting from the application of different bio-energy conversion technologies. (Venema & Calamai, 2003) developed an approach for bio-energy systems planning using location-allocation and landscape ecology design principles to derive a two-stage p-median problem (PMP) model formulated to minimize domestic and commercial feedstock delivery costs. In a case study in India, the first stage of the model is to acquire domestic energy from proximal supply locations to feed the villages demand according to PMP location-allocation principles. A simultaneous PMP is also formulated between village demand locations and conversion facility locations to establish the commercial energy handling requirements at each active conversion location.

The model is modified by adding a term that accounts for the cost of transporting biomass feedstock from the production zone to the centroid (biomass collection locations) to fully account for the weighted biomass flow-path distance in the designed systems. Their research focuses on developing bio-energy systems that address the rural socio-ecological problem rather than toward a tool for general bio-energy systems planning, i.e. biomass availability and location-allocation power plant and biomass resources.

Spatial optimization models are often combined with GIS screening techniques with the advantages of data acquisitions and manipulations. (Venema & Calamai, 2000) addressed multi-objective spatial design principles for rural biomass energy planning. Their paper aimed at improving accessibility and ecological sustainability of biomass resources by applying remotely sensed landscape information, GIS analysis, spatial optimization, and landscape ecology design principles for decentralized landscape-based biomass energy systems planning. Many research papers employing location allocation models in health service development planning in developing nations are fully reviewed by (Rahman & Smith, 2000). Location models applied in the field of bio-energy systems planning are rarely found in the literature. (Li & Yeh, 2005) introduced a method integrating genetic algorithms (GAs) and GIS for optimal location search. This research involves finding optimal sites for building one or more facilities based on various constraints and multiple-objectives. GIS tools are employed to get the detailed population and transportation data in the study area, and then use the derived information to facilitate the calculation of fitness functions. Finally, genetic algorithms are used to solve the non-constrained multiple-objectives optimization problems.

The results indicate the proposed method has much better performance than either a standalone GIS approach or a simulated annealing search method. A more comprehensive research in bio-energy systems planning in rural areas in the developing countries is found in Venema's PhD thesis (Venema, 2004). A rural renewable energy design approach that employs spatial optimization techniques for rural bio-energy planning and bio-energy constrained hybrid rural renewable energy system design is fully discussed.

In addition, the research on individual aspects of bio-energy application are usually studied by researchers from different disciplines and integrating each aspects associated with bio-energy applications into an optimal bio-energy system has not received much attention. Therefore, continued research on an integrated methodology for bio-energy systems planning is necessary. The research in this thesis focuses not only on decreasing the bio-energy production costs, but also on making significant contribution to the environment. Methodologies, principles, and results are integrated in designing an optimal bio-energy system.

2.6 Multi-criteria assessment in GIS environments for site optimization – A review.

2.6.1 Earlier attempts at site optimization in related Literature

GIS-MCA techniques have been applied within a large number of disciplines, using the appropriate criteria and factors, such as town and rural planning, choosing a site for different types of installation, ground-use maps, reducing natural risks and environmental impact, distribution of limited resources, etc. ((Bórdas, 2006); (Mena, et al., 2006); (Sumathi, et al., 2008); (Malczeweski & Jackson, 2000)). One of the first multi-criteria assessment studies in the context of renewable energies, dealing with wind-generated electricity, was carried out by (Voivontas, 1998), who developed a DSS to estimate the maximum obtainable generating potential in Crete (Greece). Another study by (Grabaum & Meyer, 1998) used GIS-MCA for regional planning and development in Germany and focused on functional evaluation methods to minimize the conflict between ground use and environmental impact. (Chen, et al., 2001) followed the same line, combining MCE and GIS to evaluate natural risks and presented three different evaluation methods for the same analysis, using a comparison of the results as an aid to subsequent decision making. The three methods he used were: Weighted Linear Summation (WLS), techniques for order preference by similarity to an ideal solution (TOPSIS) and compromise programming (CP). Studies using MCA-GIS techniques in the context of renewable energies include (Cheng-Dar & Grant Gwo-Liang, 2007) in Taiwan and (Butchholz, et al., 2009) in Uganda. The former was carried out in a GIS environment to assess the viability of local renewable energy sources as a source of investment. The latter focused on determining criteria and assigning weights in the renewable energies field to facilitate the design and implementation of sustainable bio-energy projects by applying and comparing four decision tools: Super Decisions, DecideIT, Decision Lab and NAIADE. In forestry, (Mitchell, 2000) proposed a decision support system (DSS) for bio-energy applications in the form of a model that combines biomass production, conversion and electricity generation.

Multi-criteria evaluation must always finish off with a sensitivity analysis as the last step in all decision problems, as in the case of (Crosetto & Tarantola, 2001), who establishes a clear distinction between an uncertainty analysis (Morris method) and a sensitivity analysis in the true sense of the term using the Sobol' and extended-FAST methods. Both these analyses can be used in the planning stage with GIS tools to optimize the assignment of resources when acquiring spatial data. Also following the general line of the above cited authors but in the field of hydrology, (Dˇ ıOvidio & Pagano, 2009) proposes a stochastic approach (as opposed to the traditional determinist model) for the optimal design of biomass plants by comparing different technological solutions (steam generation, gas cycle and combined cycle).

This research focuses on identifying suitable sites for locating biomass plants in response to the joint European and Organisation of African Unity (OAU) strategy for bringing the potential of renewable energies (RE) to the attention of African governments and to develop strategies for large scale Renewable Energies introduction in African countries. Using biomass to generate energy has many advantages and provides important benefits (Hermann, et al., 2000). The MCA-GIS method was used to help in taking decisions on land-use issues, in this case as an Energy Spatial Decision Support System (ESDSS).

2.6.2 Three stage site optimisation framework – New York

In a three stage framework study conducted in New York State using ArcGIS 9.3.1 for site optimisation it was recommended that the stages in the site optimisation criteria be undertaken as outlined: Stage 1 entailed the exclusion of non-feasible sites, Stage 2 consisted of an economic evaluation, and Stage 3 was a bird impact evaluation. This study can be regarded as more involving in terms of evaluating the economic arguments and constraints, and is atypical among wind farm site suitability studies because it looks at an entire (relatively large) state rather than a small geographic study area. The authors used the term spatial multi-criteria assessment (SMCA) to describe their approach. In addition to the expanded dataset and economic evaluation, other unique facets of this study are the inclusion of geologically unstable areas, the exclusion of important bird areas, land clearance costs, and a measure of cost optimization between building new substations and upgrading/expanding existing facilities. After the exclusion of non-feasible sites in the first stage, the authors ranked the remaining areas by net present value (NPV) based on the cost for adding feeder lines, the cost for building new roads, and the cost of land clearing.

2.8 AHP Model in Site Location

The AHP is a heuristic algorithm that follows a hierarchical structure for multi-criteria decision making and it provides mathematical measures of consistency. For site suitability analysis it is critical that the assigned weights are logically consistent and mathematically defensible, so the AHP is used to derive the input criteria weights that will be applied to the weighted overlay technique. The Analytic Hierarchy Process (AHP) is a systematic procedure for representing the elements of any problem, hierarchically (Saaty & Kearns, 1985). It breaks a problem down into smaller and smaller parts and guides the decision making process through a series of pair-wise comparison between objectives or alternatives. The AHP enables the decision makers to express their qualitative judgments in a quantitative format, instead of assigning arbitrary weights to the qualitative factors. The first task of the AHP process is to structure the decision problem hierarchically

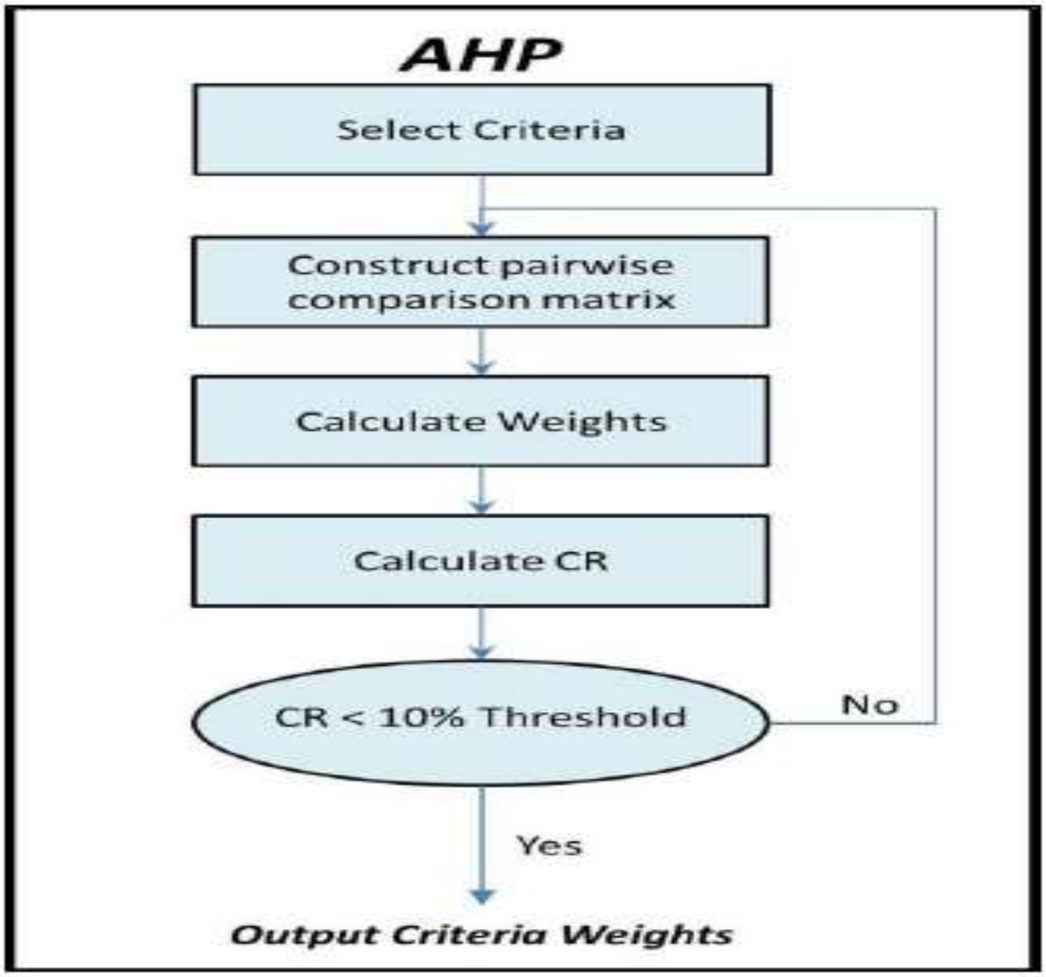

Figure 8: Schematic of the criteria weight selection process using AHP, adapted from Chen, Yu, & Khan (2010).

Table 11: Expert Opinion Index Evaluation table

Definition	Index	Definition	Index
Equally important	1	Equally important	1/1
Equally or slightly more important	2	Equally or slightly less important	1/2
Slightly more important	3	Slightly less important	1/3
Slightly to much more important	4	Slightly to way less important	1/4
Much more important	5	Way less important	1/5
Much to far more important	6	Way to far less important	1/6
Far more important	7	Far less important	1/7
Far more important to extremely more important	8	Far less important to extremely less important	1/8
Extremely more important	9	Extremely less important	1/9

2.8.1 Valuation of factors

Pairwise comparison matrices can be developed within a database framework or imported from standalone processing and computing platforms and then used to value the selected factors and their classes. Each criterion/factor is assigned an established $Value_{ij}$from each class in order to determine numerical values calculated from the pairwise comparison matrices. The aim was to determine the final values of each factor ($Value_{ij}$) in each of the hierarchies and to obtain the matrix consistency ratios (CR), which indicate the arithmetic consistency of the values assigned in each matrix, according to Eq. (1):

$$C.R = \frac{C.I}{R.I} \quad \text{Eq. (1)}$$

where $\mathrm{CI} = (\lambda\max - n)/(n-1)$, λ being a value obtained from the product of the normalised principal eigenvector multiplied by the comparison matrix, and n is the number of factors (or classes) in the comparison matrix. The random index (RI) is the reciprocal diagonal matrix between the values 1.59 >RI >0, RI being = 0 for n = 1 and RI = 1.59 for n = 15) (Malczewski, 1999).

After obtaining the values of the set of factors, they are then weighted by Saaty's Analytic Hierarchy method so as to be able to establish hierarchies of relative importance. This involves using pairwise comparisons with a scale of values between 1 and 9 using value judgements to compare sub-categories two by two. In this process 1 indicates equally preferred and 9 is extremely preferred and, in practice, consists of completing all matrix cells (a_{ij}) by these values and their reciprocals ((Gómez & Barredo, 2005); (Malczewski, 1999)).

The use of the AHP model outdoes the requirement for subjective decision making and is found fit for purposes where the decision has a bearing on a varied spectrum of stakeholders.

2.8.2 Applying the decision rules

After superimposing the spatial layers, the decision rule is applied to the simple objective and multiple criteria problem in order to obtain the alternatives map according to suitability. The linear summation and ideal point analysis, based on different procedures ((Gómez & Barredo, 2005); (Malczewski, 1999)), were chosen as decision rules to compare results and observe the behaviour of the data during the application of both methods.

The results of the weighted linear summation are obtained by directly applying Eq. (2) to the layer obtained after spatial imposition in the GIS-associated database. In this way we can calculate the global value of each alternative by multiplying the value of each criterion by its weight:

$$r_i = \sum_{j=1}^{n} W_j V_j \qquad \text{Eq. (2)}$$

Where r_i is the suitability level of alternative i, W_j is the weight of criterion j, in which $\sum_{j=1}^{n} W_j = 1$ and V_j is the value of alternative *i* in criterion *j*.

The results of applying the ideal point method are calculated by Eq. (3):

$$D_p = \left[\sum_{j=1}^{n} w_j |v_{ij} - v_j^*|^p \right]^{1/p} \qquad \text{Eq. (3)}$$

Where D_p is the distance between each alternative and the ideal point, W_j is the weight assigned to criterion j.$\sum_{j=1}^{n} W_j$ must be equal to 1, v_{ij} is the value of alternative $i$in normalised criterion j, $v_j^*$is the ideal point value for criterion j, whose value is 1, and p is the distance metric, p = 2 being the Euclidean distance.

2.9 Spatial Decision-Making Problems

Spatial decision making is often complex and requires information produced from many sources and interpreted by a variety of decision makers in relation to different goals and objectives. (Simon, 1960), characterized decisions as being structured (programmable), semi structured, or unstructured (nonprogrammable), with the latter representing those that suffer from a lack of knowledge, large search space, need for data that cannot be quantified, and so on (Carlson, 1978). Spatial decisions are often described as semi structured, meaning that they fall between structured and unstructured. These semi structured problems are often multidimensional, have goals and objectives that are not completely defined, and have a large number of alternative solutions (Gao, et al., 2004). Spatial decision problems are also often characterized by uncertainty and conflicts between the various stakeholders interested in the process (Wang & Cheng, 2006). Important aspects of the decision alternatives and the potential outcomes also can vary spatially, adding to the complexity. The great complexity involved in spatial decision making suggests the use of automated or computer-based techniques. However, there is usually not a single solution that meets all objectives for all stakeholders (Xiao, 2007).

(Panichelli & Gnansounou, 2008), presents a GIS-based decision support system for selecting least-cost bio-energy locations when there is a significant variability in biomass farm-gate price and when more than one bio-energy plant with a fixed capacity has to be placed in the region. The methodology tackles the resources competition problem between energy facilities through a location-allocation model based on least-cost biomass quantities. A GIS-based approach combined with a biomass allocation algorithm is effective for selecting suitable energy facilities location. The procedure used was as follows:

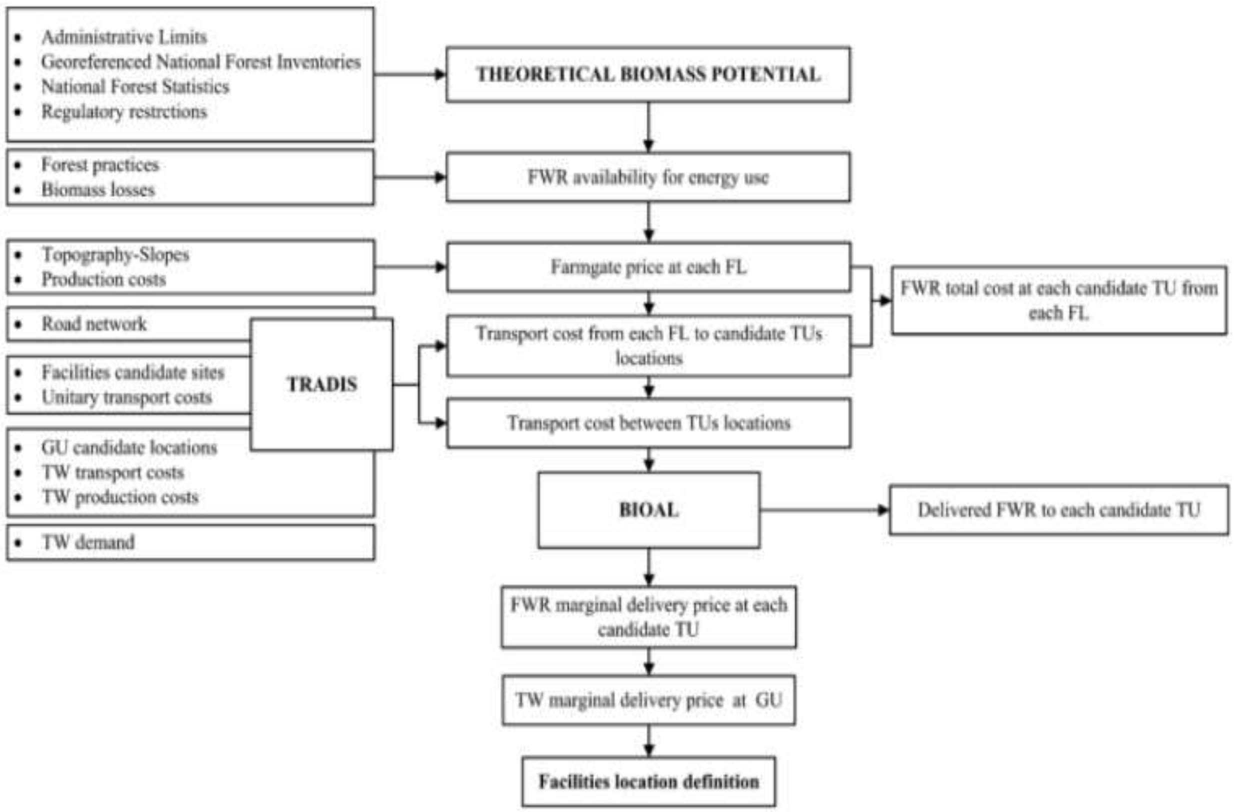

Figure 9: A GIS-based approach combined with a biomass allocation algorithm for selecting suitable energy facilities location Extracted from (Panichelli & Gnansounou, 2008).

(Voivontas, et al., 2001), also proposed a GIS decision support system to identify the geographic distribution of the economically exploited biomass potential based in four level analysis to determine the theoretical, available, technological and economically exploitable potential.

2.10 Chapter Summary

This chapter reviewed related literature on site optimisation modelling using multiple factors, the location allocation problem as well as methods for biomass modelling as an input into the site optimisation procedure in biomass power plants location. Previous research related to bio-energy systems planning are also reviewed such as biomass feedstock availability assessment, bio-energy conversion facility locations identification, and spatial optimization design. Methods and techniques for optimum results were reviewed in a bid to recommend improve or continue earlier studies on the topic, though with a specific reference to Zimbabwe as a study area. However it remains pertinent to highlight that factor weighting and site optimisation is region and jurisdiction specific. In as much as concepts can be borrowed, the domestication of such approaches is a pre-requisite in site optimisation modelling.

A review of how other countries have solved energy crisis by adopting renewable energy generation is also part of the literature review, to guide the implementation of system development in Zimbabwe.

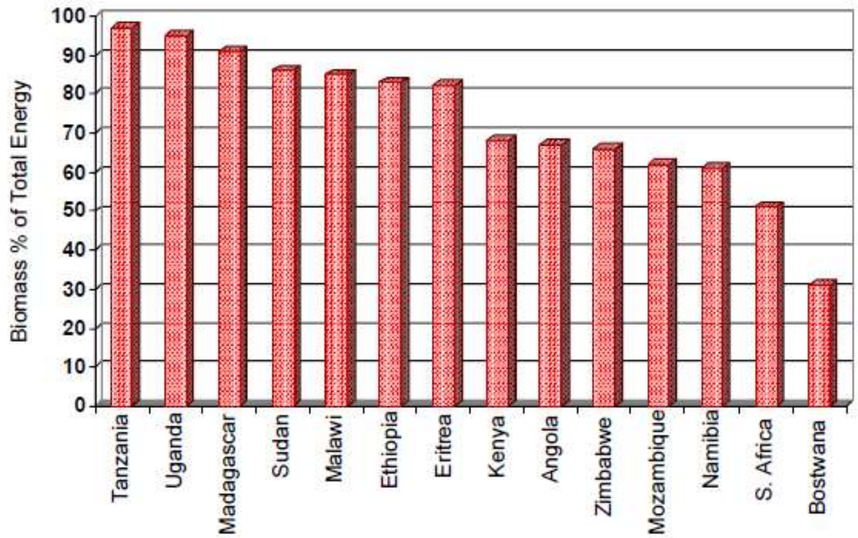

Figure 10: Biomass Energy as a percentage of total energy for selected Eastern and Southern African countries (International Energy Agency, 2012)

The figure above summarizes trends and possibilities in the implantation of bio-energy systems in Africa.

The impacts of biomass energy applications on world energy supply and environmental issues are also briefly discussed. The new methodology proposed in this thesis is intended to integrate the method and theories associated with bio-energy systems design and improve the performance of the systems by applying GIS screening techniques, Analytic Hierarchy Process (AHP), and location models. Chapter three (3) therefore borrows from success trends and methods emphasised in the Literature review section and therefore introduce the adopted methods, procedure and tools utilized in this research.

Locating and quantifying potential sources of available feedstock is vital to the success of a biomass project. A number of other factors also dictate whether a local feedstock can be used, including costs associated with the collection, preparation, storage, and transportation of the biomass resource; sustainability of the resource; quality and composition of biomass as well as ease of converting the biomass resource to energy.

Biomass resource availability is the most important issue in terms of the economics and long term project sustainability, therefore projects that can utilize a reliable, onsite supply of fuel-such as sawdust at a wood products plant or wastes from agriculture processing operations-have a distinct advantage. For projects without an onsite fuel supply, securing adequate, long term feedstock supplies can be expensive and difficult. This research therefore combines biomass quantification and site optimization

Chapter 3 – Materials and Methods

3.0 Introduction

Research design is the general plan of how you will go about answering the research questions (Saunders, et al., 2009). Saunders further explained that it contains clear objectives, derived from your research questions and specifies resources which you intend to collect data from.

The site selection process involves not only technical requirements, but also economical, social, environmental and political demands that may result in conflicting objectives. Site selection is the process of finding locations that meet desired conditions set by the selection criteria. The selection process attempts to optimize a number of objectives desired for a specific facility. Such optimization often involves numerous decision factors, which are frequently contradicting. Today, a higher degree of sophistication is expected. Selection criteria must also satisfy a number of additional decision parameters as social and environmental aspects today are enforced by legislations and government regulations.

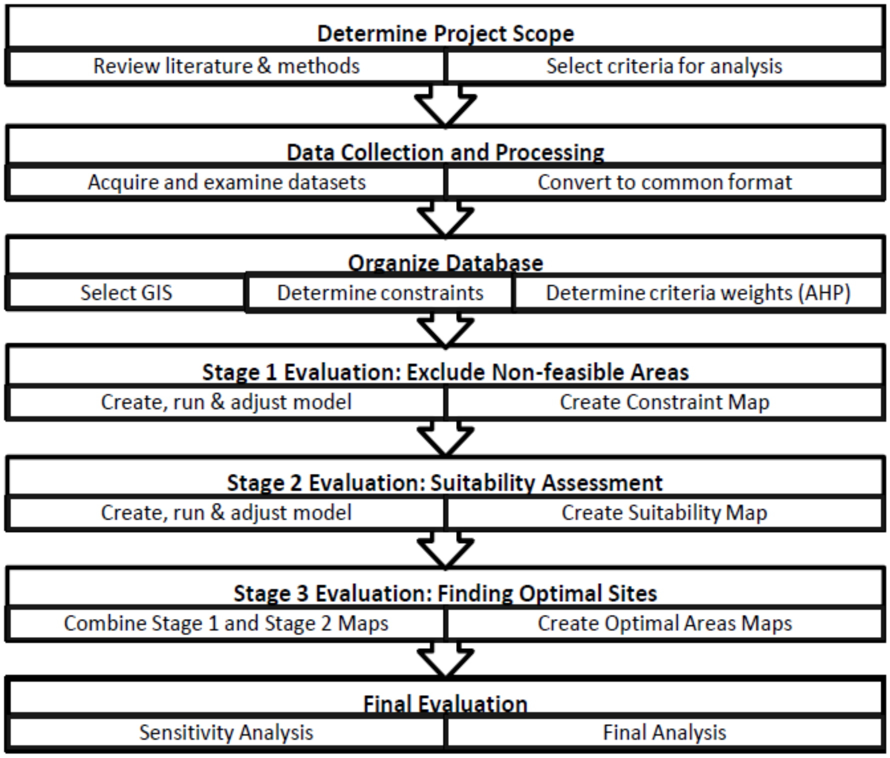

Figure 11: Schematic showing project workflow.

However, in this study, the economic model in bio-energy systems planning, that is the financial cost benefit analysis falls outside the scope of this research though an important component to a heuristic approach in the system design methodology.

This section presents work whose objective is, first, to quantify, the potential forest plantation biomass production in the Eastern districts of Manicaland. Secondly, using Multi Criteria Decision Modeling a methodology for defining optimum sites for the installation of biomass power plants using the available biomass distribution map and other datasets is employed. The study used a methodology based on AHP and Discrete Location Theory in the site optimisation procedure. The site location procedure took into account, among other factors, the following datasets: available biomass potential distribution map, current and established electricity power infrastructure datasets, road network dataset, protected spaces and national heritages, and land use zoning and characterisation with their relative importance on the decision function in the establishment of suitable land for biomass power plant location to make region specific optimization analysis. The general site optimization procedure can therefore be depicted as in the diagram below.

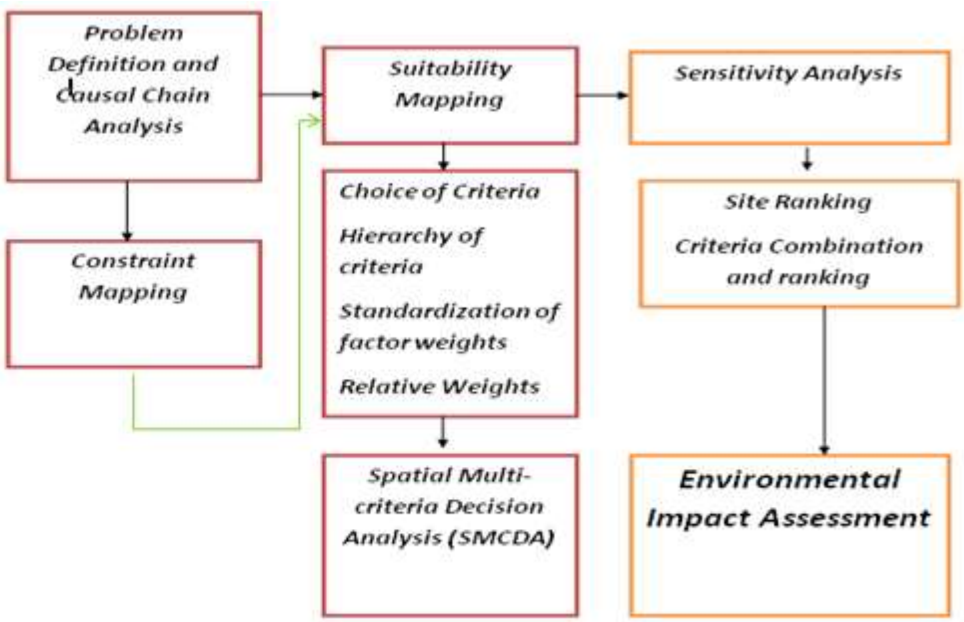

Figure 12: Overall Methodology for the site optimization Classification Model

3.1 Data sources-Setting and Participants

The major sources of data for this research are

1) Remote Sensing Imagery for the quantification of biomass and production of biomass potential maps. Cloud-free images acquired in August and September 2016 was obtained

from USGS Earth Resource Observation and Science Centre archive (http://earthexplorer.usgs.gov).

2) ZETDC database of current network infrastructure
3) Land use dataset from Diva GIS and the Zimbabwe Department of Physical Planning
4) The EMA protected areas database
5) Rural District Councils with jurisdictions for the areas under consideration

3.2 Concept Flow Diagram

Basically, the methodology employed in this research can be divided into four main parts: biomass availability assessment modelling, , multi-criteria Analysis, suitability plus network analysis and, spatial optimization modelling to come up with the least cost sites for biomass power plant candidates' sites. A system design methodology, whose flow diagram is shown in Figure 13, shows the general stages of the design process.

The forest plantation Biomass Model involves forest plantation biomass distribution modelling to identify Biomass potential distribution. The Available Land Surface Model takes into account land use planning restrictions, the restrictions imposed by the Environmental Management Act, the Regional town and Country planning Act and other related Acts. A weighting assessment is used which employs the AHP modelling technique in Excel. The general stages of project development are summarized below.

1. Defining the site selection criteria. Of most importance is the quantification and mapping of forest plantation biomass potential in the sampled plantation forest within Manicaland Province.
2. Preparing criteria maps. Among the major considerations are defining the extent and boundary of analysis, converting datasets from vector to raster, reclassification and other GIS functions. At this stage the following are paramount to project success:
   - Quantifying the available potential biomass from each district under consideration.
   - Generate a forest plantation biomass model
   - Develop a land surface model taking into consideration physical, social, economic and other constraints.
3. Data standardization and transformation of datasets is also carried out.

4. Multi-criteria analysis to define the region with the best conditions for the installation of bio-energy power plants using AHP Model
5. Performing a GIS analysis for the determination of the most suitable location for a bioelectricity plant in the region considered using Weighted overlay Analysis.
6. Eventually most suitable sites for the location of forest plantation Biomass are identified.

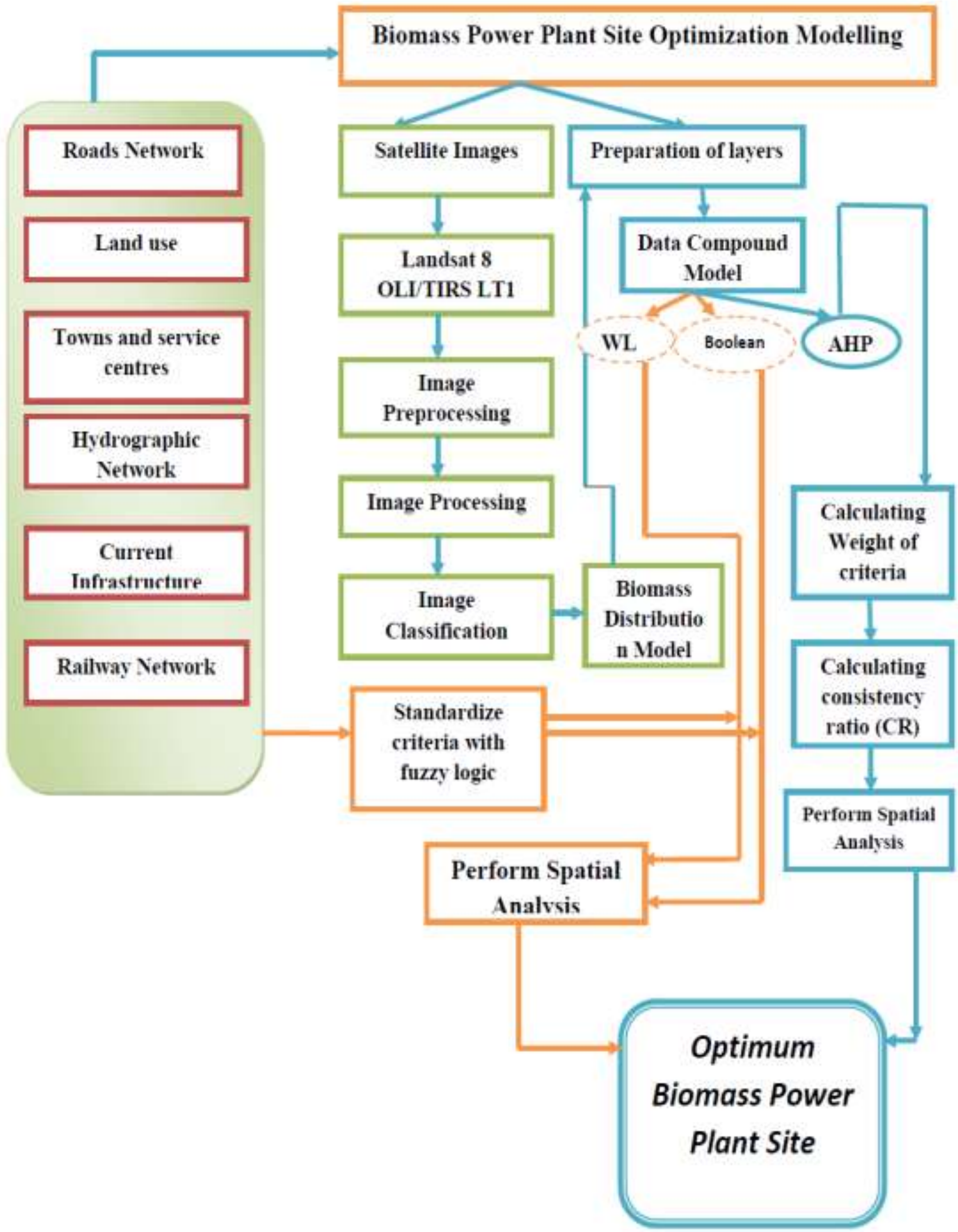

Figure 13: Site Location Multi-criteria Assessment - Concept Flow Diagram

The diagram above Fig: 13, shows the combined Forest Plantation Biomass model and site location and optimization model developed in this research.

3.3 Forest Plantation Biomass Model

In this research, due to limitations of data availability especially remotely sensed data, the research used Landsat 8 (L8 OLI/TIRS) data which was freely downloaded for use. The concept flow diagram for remotely sensed data handling is shown in Fig 14.

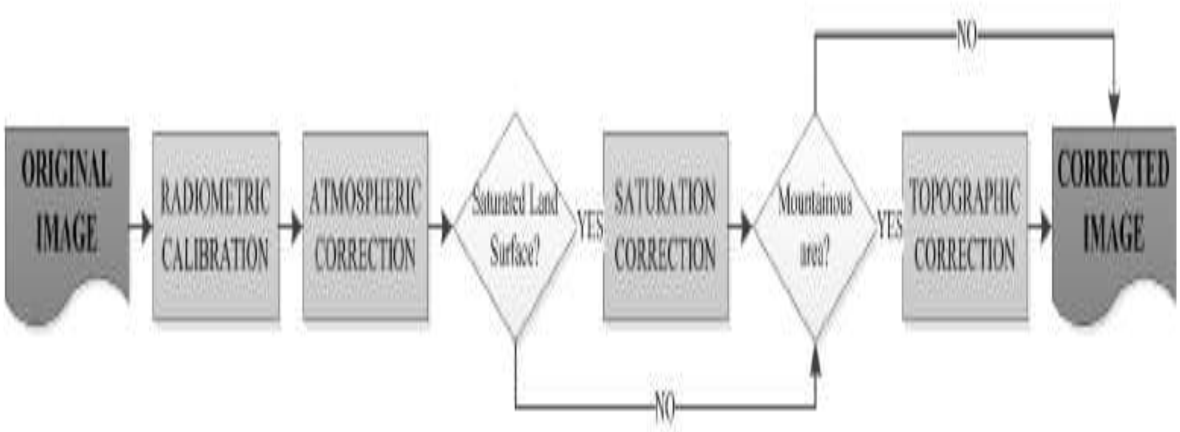

Figure 14: Landsat 8 Image Pre-Processing Concept Flow Diagram in ArcGIS

3.3.1 Image pre-processing

3.3.1.1 Remote Sensing Images Data acquisition

Landsat 8 OLI-TIRS satellite images were been used in this study. The level 1 product of this satellite image was downloaded from http://earthexplorer.usgs.gov/. This is the latest series of Landsat satellite program launched in 2013 and carried two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The OLI sensor has nine bands with 30 m spatial resolution for all bands (coastal/aerosol, blue, green, red, NIR, SWIR-1, SWIR-2 and Cirrus), except the 15 m panchromatic band, while the TIRS has two thermal bands (TIR 1 and TIR 2) with 100 m spatial resolution. The temporal resolution of this remote sensing system is 16days. The image acquisition dates were in August and September 2016. The selection was based on a minimum cloud cover percentage.

3.3.1.2 Image calibration

The pre-processing includes radiometric correction process. The final result of this process is image with Top of Atmosphere (TOA) reflectance value which is more suitable in generating vegetation indices. The conversion of Landsat DN value to TOA reflectance with sun angle correction uses the following formula:

$$\rho\lambda = (M_\rho Q_{cal} + A_\rho) / \sin(\theta_{SE})$$ (Shidiq & Mohd, 2016)

Where:

ρ_λ = TOA planetary reflectance with sun angle correction

M_ρ = Band-specific multiplicative rescaling factor from metadata

Q_{cal} = Digital Number (DN)

A_ρ = Band-specific additive rescaling factor from metadata

θ_{SE} = Local sun elevation angle

The Landsat-8 OLI image bands were converted from digital number format to reflectance. Landsat 8 OLI, conversion from DN to reflectance was implemented in ArcGIS10 using the raster calculator tool, following the approach described on the USGS website (http://landsat.usgs.gov). The Landsat 8 OLI scenes were converted to top of atmosphere (TOA) reflectance using post-launch calibration coefficients. The Apparent Reflectance raster function calibrates image brightness values (DN) for some satellite sensors. The main advantage of apparent reflectance function is to adjust the images to a theoretically common illumination condition, so there should be less variation between scenes from different dates and from different sensors. This can be useful for image classification, colour balancing, and mosaicking.

The function performs two calibrations. The first calibration is to convert the DN value to the top of atmosphere (TOA) radiance based on the sensor properties (i.e. gain/bias or LMAX/LMIN). The second calibration is to convert the TOA radiance to apparent reflectance, based on sun elevation and acquisition date.

The Landsat 8 OLI image was then atmospherically corrected to surface reflectance using the ArcGIS 10.

3.3.1.3 Composite Bands

This tool was used in order to render these raster datasets together to create a colour composite, with each band contained within a single raster dataset.

3.3.1.4 Image Pan sharpening

The panchromatic band was used for image pan sharpening to improve the spatial resolution of the images from 30m to 15m

3.3.1.5 Removing Image Black ends (No Data area)

A reclassification exercise was done in ArcGIS to eliminate the black no data areas. Two reclassification classes were used, that is 0 and 1 based on histogram characteristics. The reclassified images were then multiplied by the original raster in the raster calculator tool menu.

3.3.1.6 Mosaicking images

The images were then merged together. The MEAN mosaic type was used in this study - The output cell value of the overlapping areas will be the average value of the overlapping cells.

The research used the Matching Method of LINEARCORRELATION_MATCHING - This method will match overlapping pixels and interpolate the rest of the source dataset; pixels without a one-to-one relationship will use a weighted average.

3.3.1.7 Clipping to area of Interest Boundaries

The raster image was then clipped to the area of interest which in the Manicaland polygon map to reduce the processing extent in the datasets under use as well as to eliminate unwanted regions from the scenes.

3.3.2 Image processing

The Normalized Difference Vegetation Index (NDVI) was derived from Landsat 8 image with the following formula in raster calculator

$NDVI = (NIR - Red) / (NIR + Red)$..Equation (3)

Where:

NIR = Landsat 8 near infrared band (Band 5)

Red = Landsat 8 red band (Band 4)

3.3.3 Model generation

The statistical-based correlation analysis was used to develop the biomass model and examine the relationship between satellite image spectral reflectance and radar backscattering to stand parameter or biomass. The predictor variables are the individual Landsat 8 OLI bands for NDVI are shown below (Table 12).

Table 12: Landsat 8 OLI bands and vegetation indices (NDVI)

Variables	Utilized bands	Label
Individual Landsat 8 band	Band 1-9	B1-B9
NDVI	(Band 5 - Band 4)/(Band 5 + Band 4)	VI1

3.3.4 Unsupervised Classification for Forestry Plantation Biomass

Due to the fact that forest plantations in Manicaland stood out distinctly on Landsat 8 Images, an unsupervised classification was carried out. This technique performs unsupervised classification on a series of input raster bands using the ISO Cluster and Maximum Likelihood Classification tools. This tool combines the functionalities of the ISO Cluster and Maximum Likelihood Classification tools. It outputs a classified raster for forest plantation biomass in Manicaland. This was done using a python code, see code snippet in Annex 2

3.4 Available Land Surface Model – Site Optimization Modelling

The identification of areas with spatial land-use conflicts was conducted based on a multi-criteria analysis (MCA) before such areas were incorporated in the Weighted Overlay Analysis.

3.4.1 Economic Production Model

This part of the model falls outside the scope of this research and is only included here to emphasize its importance in the heuristic system design approach. It is therefore recommended for further research.

3.4.2 Site Location Algorithm

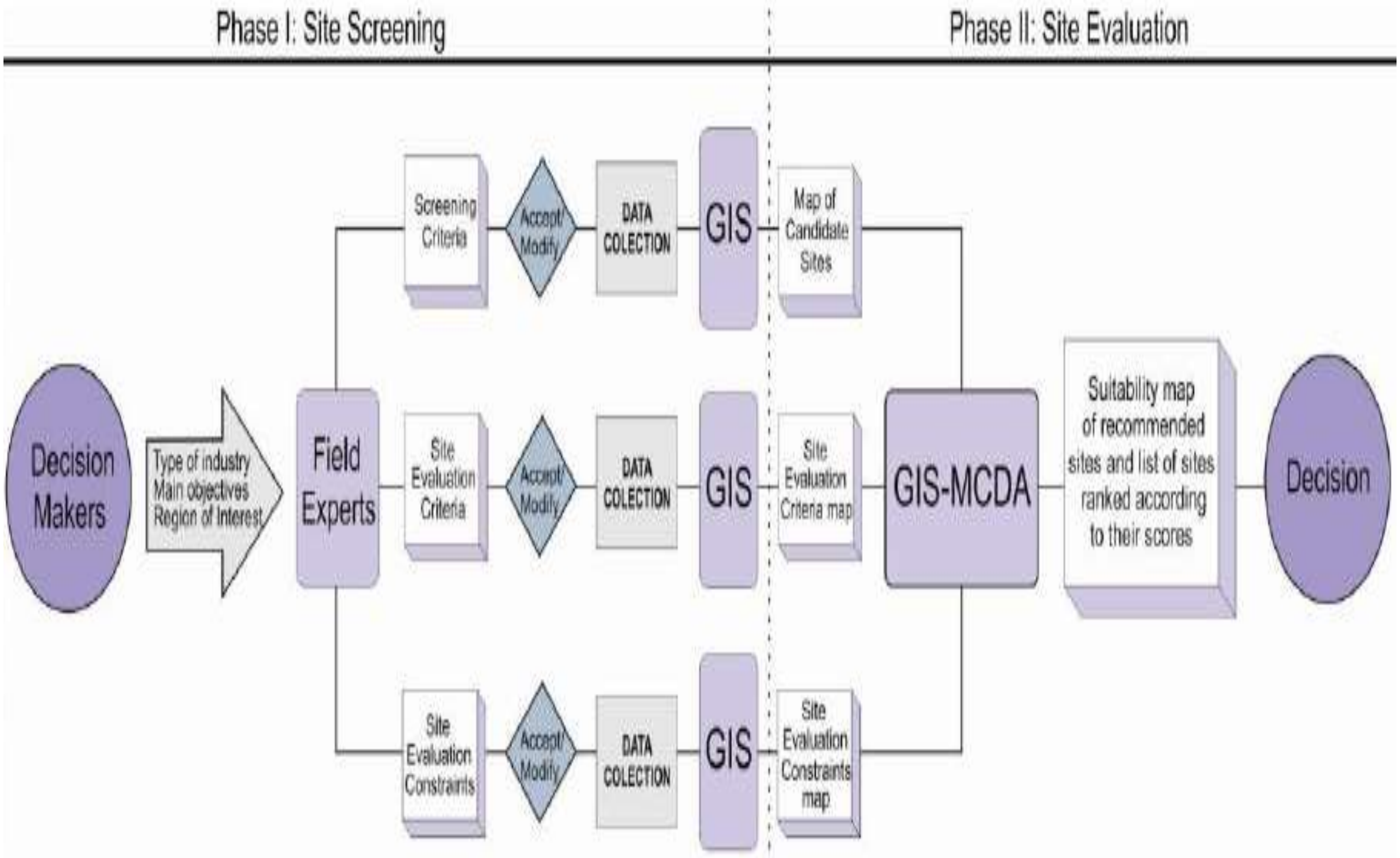

Figure 15: Architecture of the GIS based MCDA approach for Biomass power plant site selection.

The location problem dealt with in this research is directly linked to determining the most suitable areas for building a biomass power plant. The scheme in Fig. 16 shows the steps involved in the site location process.

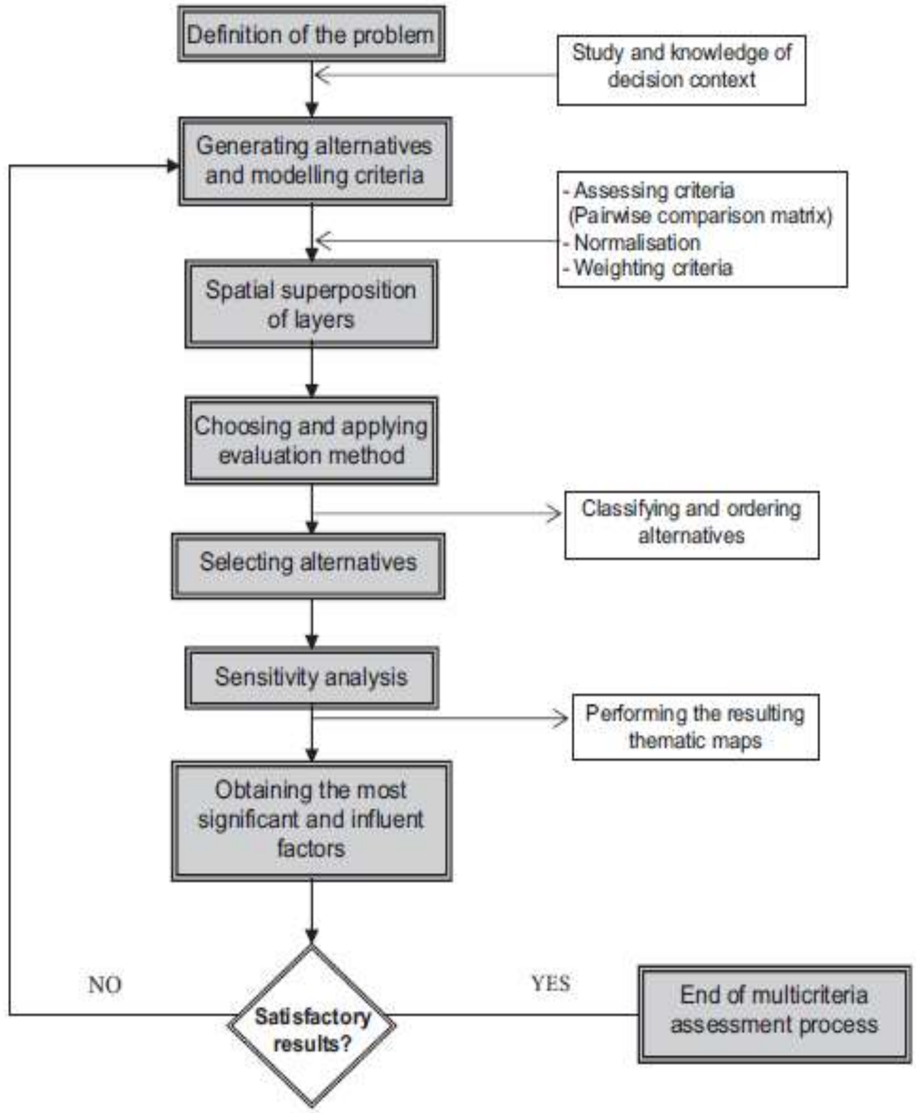

Figure 16: Scheme of MCA-GIS process.

3.4.3 Selecting spatial criteria: factors and constraints

The most important phase and the one with a strong influence in the evaluation of potential sites for an installation is the selection of the factors and criteria that will have a direct influence on the power plant facility to be developed. Many different factors can be taken into account in land use zoning, however the ones selected in this research are in accordance with the objectives, the easy availability of datasets to complete the research within the specified timeframe, and the researcher’s experience. In this study all the criteria (factors and constraints, see Table 12) are reflected in the corresponding GIS thematic classes. Even though consultation to an extensive bibliography ((Voivontas, 1998); (Gómez & Barredo, 2005); (Hubina & Ghribi, 2008); (Munier, 2004; Munier, 2004)), implementation of such consultation in this research could not be achieved because of the limited availability of usable datasets within the research delivery period. Experts were also consulted and the current standards were complied with. The region contains both natural and artificial areas with special characteristics that need to be preserved, many of which are protected by current legislation.

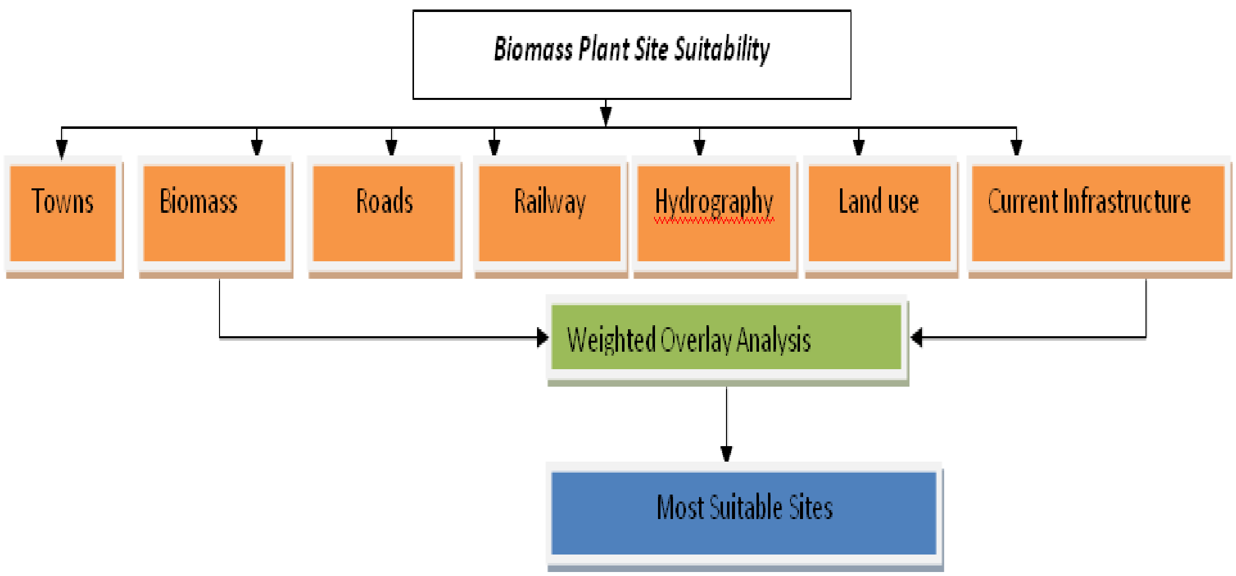

Figure 17: Site Optimisation Modelling

The ground-use regulations identify the areas where these plants can be built, on Manicaland's land classification map. Natural areas, protected zones, elements of the national heritage, natural monuments, flora, fauna, paleontological, archaeological and scientific sites, etc. are considered as irreplaceable assets and are subject to protection and conservation measures. This means that all such elements are surrounded by a protection area in which biomass site location is forbidden.

3.4.4 Valuation of factors using the Analytic Hierarchy Process (AHP) Model

In this research project, the AHP method was used to determine the weights of preferable criteria, instead of arbitrarily assigning intuitive or empirical weights, and the eigenvector approach is utilized for measuring the consistency of the proposed pair-wise comparison matrix.

An excel spreadsheet compilation was used to analyse factor weights in ranking the importance of identified factors of importance in the biomass power plant site location.

3.4.5 Cartographic data acquisition and Map generation

This next phase consists in obtaining a cartographic map for each of the analysis criterion that has been defined as having a comparative influence on the site location decision rule. The maps produced and overlaid include: Cartographic map about availability of biomass, roads network map layer, Cartographic map about protected natural areas, land use map for the study area and current infrastructure in the study are. The cartographic information is then superimposed to integrate all the factors in a single layer and quantify the values of each alternative in order to reduce the possible number of plant sitting points. This process can be understood as adding together the spatial frontiers of the data.

3.4.6 Applying the decision rules

After superimposing the spatial layers, the decision rules obtained from expert knowledge and statutes consultation were applied to the simple objective and multiple criteria problem in order to obtain the alternatives map according to suitability. A weighted influence of each criterion was fed into the Weighted Overlay Analysis in ArcGIS using the weights obtained from the AHP model Analysis as a percentage against each factor/criterion in the Weighted Overlay Analysis table.

3.5 Spatial Optimization Modelling – Site Location Data Processing and Analysis using ArcGIS Model Builder

3.5.1 Exclusive Analysis

In this research, exclusive analysis is used to identify areas where it would be unsuitable to construct power plants. In order to identify all those areas which are deemed unsuitable by exclusionary criteria, which are usually represented as buffer zones indicating suitable and unsuitable areas in a series of concentric buffers which corresponding to each considered criterion.

For each criterion, the cells falling within a constrained area which are unsuitable are assigned “0”, and cells falling in the suitable areas are assigned “1”.

The first step was to collect the necessary datasets and convert them into usable forms using ArcGIS 10.0 geo-processing tools. For this type of analysis, working with a grid system was the most effective means of calculating values for particular locations. This way each grid unit (or cell) in the study area would have an integer value and these values could be altered based on the weights assigned to them, yielding a *suitability score* for each cell. However, most datasets were available as vector-type data and so several of the datasets had to be converted to grid-based (raster) data prior to analysis in a Vector-to-Raster operation.

To further reduce the computation time of processing and analysis, all layers were first clipped to a common regional extent, (for most layers, the boundaries of Manicaland, Zimbabwe, were used for cartographic purposes). The Land cover, built up area and public transport layers required extensive pre-processing because of the incorrect ring ordering which required the repairing of geometries before input into the weighted suitability analysis model. The repair geometry function in ArcGIS was used with strings with null geometry being deleted.

Once all the datasets had been converted to a common format (i.e. same coordinate system, same cell size, proper extent, etc.), they were added to a geodatabase in ArcGIS.

The analysis was carried out in three stages using ArcGIS 10.0 Model Builder following the recommendations of the New York study as highlighted in Chapter 2. For Stage 1, the Euclidean distance was calculated from each feature to a maximum threshold distance using a Multiple Ring Buffering technique. The result was identified to the study area polygon and then a conversion to raster technique was employed, producing raster datasets as outputs. A reclassification exercise was then carried out to convert the new raster to a binary scale (Yes = 1/No = 0) using the *Reclassify* tool. Areas within the buffer thresholds were assigned values of zero, while the remaining areas were given a value of one. These outputs were then combined into a single layer through the *Mosaic-to-New Raster* tool with a minimum mosaic operator, and then the relevant areas (buffered features) were selected using the *Con* tool, which uses conditional statements to select only the desired cells (those with values of zero). Areas with values of ‘1’ were discarded in Stage 1 for illustrative purposes, but were reused in Stage 3 as a mask raster.

The *Euclidean Distance* tool accepts either feature class or raster as inputs and produces a raster as an output, thus effectively doing the same thing as buffering in a fraction of the time. The *Reclassify* tool could be used to set the buffer thresholds, and the *Con* tool could be used to select the cells that correspond to the buffered areas.

3.5.2 Exclusion of Non-feasible Areas - Suitability Analysis

Suitability analysis tools are commonly used for facility sitting. In this research the selection of suitable power plant candidate sites begins with identification of a set of criteria that can be used to differentiate those sites that are suitable from those which are not and to rank order suitable sites in terms of their desirability. Criteria that represent requirements that must be satisfied can be thought of as exclusionary because they eliminate certain areas from consideration. Other criteria may represent preferences rather than absolute requirements. Preferential criteria do not preclude development of a particular site but affect the site's ranking in comparison to other potential sites.

3.5.3 Preferable Analysis

Unlike exclusionary criteria which have to be met absolutely, the preferable analysis is employed to measure the suitability (high, medium, or low) of each factor considered. In this thesis, for each factor layer, the study area is classified into different cell values based on the corresponding criterion with a high cell value representing high suitability relative to the particular factor being considered. As well, each factor is assigned a weight representing its relative importance compared with the other factors in the suitability analysis.

3.5.4 Network Analysis

This requirement though so essential for the optimisation modelling was not carried out in this particular study and is recommended for inclusion in further model development.

3.6 Model Generation – Weighted Suitability Analysis

3.6.1 Multiple Ring Buffering

This tool was used to create multiple buffers at specified distances around the input feature up to a defined threshold distance. The threshold distances are governed by the RTCP Act, the Combination Master plan, Local Plans and Town Planning Schemes for the study area. Beyond the threshold distance a distance decay function was used to cater for the effect of distance from the inner buffer centre point.

In this research the Euclidean method of buffering was used. Euclidian buffers measures distance in a two dimensional Cartesian plane where straight line or Euclidean distances are calculated between any two points on the Cartesian plane. The Euclidian method works well when analyzing distances around features in a projected coordinate system concentrated in relatively small areas for example one UTM zone.

3.6.2 Identity

This was used to compute a geometric intersection of the input features and identity features. The input features or portions thereof that overlap identity features will get the attributes of those identity features

3.6.3 Feature to raster conversion

This tool was used to convert vector datasets to raster datasets which is a usable input data type in the weighted overlay analysis

3.6.4 Raster Reclassification

The raster reclassification technique in this research is an exclusionary measure to eliminate unsuitable sites in the Weighted Overlay Analysis.

3.6.5 Weighted Overlay Analysis

The weights developed in the AHP model expressed as a percentage were used as factor weights in the Weighted Overlay Analysis.

3.6.6 Feature to polygon conversion

This tool was used to convert the identified locations for biomass power plants into polygon vector and define shape area and extent in a bid to determine the amount of space that can be reserved for plant installation.

3.7 Ethical Considerations

3.7.1 Consistency analysis

Consistency is crucial to multi-criteria decision making because of the complexity of the criteria weighting process and the likelihood of bias (either intentional or unintentional) on the part of the different decision-makers. An improved consistency statistic does not necessarily mean that the judgments will lead to the best answer in regards to the “real world” objective, but it does mean that the judgments are significantly different from random. In this research a consistency index was calculated in the AHP model.

3.7.2 Sensitivity analysis of factors and weights

The next step is to carry out a thorough sensitivity analysis of the results of the previous stage. Sensitivity analysis (SA) is a prerequisite for model building since it determines the reliability of the model through assessment of uncertainties in the results. With growing interest in extending GIS to support multi-criteria decision-making (MCDM) methods, enhancing GIS-based MCDM with sensitivity analysis procedures is crucial. Sensitivity analysis should be involved in GIS-MCDM model evaluation that tests the robustness of a model and the extent of output variation when parameters are systematically varied over a range of interest. The most common approach is based on varying criteria or their weights which represents input parameters in order to understand the model behaviour and its limitations, with the aim of identifying the effect of factor and weight variations on the model results. This ensures the results are more reliable and identifies the factors by which they are significantly influenced. However in this research no sensitivity analysis was carried. This is therefore recommended in any further studies for the same geographical location.

3.7.3 Ethics Clearance for data handling

No ethics clearance was obtained for purposes of this study. However a letter of request from the University, Department of Surveying and Geomatics, signed and dated by the Departmental chairperson was used in seeking datasets from organizations in custodian of such.

3.7.4 Protection of privacy in information handling and use

The datasets obtained for this study were treated with confidentiality. The datasets were only used for purposes of this study and no other benefit was sought from such datasets other than for which it was requested from the respective organization.

3.7.5 Interview Handling Techniques for AHP Model Criteria Weights

In this study telephone interviews were used to enquire expert opinion on the relative significance of the factors to be used in the AHP Model. This was necessitated by the limited available time under which this research was carried out, since the Network Manager and the project Manager for ZETDC Eastern Region were not available in the office to respond to a properly designed questionnaire. This however might have a negative bearing on the weightings obtained since the Managers themselves did not truly understand the AHP weighting criteria.

3.8 Chapter Summary

In this chapter, GIS and its applications, the Analytic Hierarchy Process (AHP), discrete location models, and their application in location science, are applied. A Weighted Overlay Analysis was implemented containing the following layers: land use, administrative boundaries, roads network, the biomass distribution model, hydrographical network, current power infrastructure and Manicaland railway network to define potential areas for bio-energy power plants. GIS is an efficient data processing and analysis tool which can be used for biomass availability assessment, suitable sites selection when combined with the AHP method, and results visualization with GIS maps. In order to spatially locate the power plants and optimally allocate the available biomass, discrete location models are employed.

Chapter 4 – Results, Analysis and Discussion

4.0 Introduction

In this section, a GIS-based multi-factor weighted suitability analysis using AHP model for site selection is developed in ArcGIS 10.0.

4.1 Research Findings

4.1.1 Unprocessed Landsat 8 tiles against Manicaland boundaries shapefile

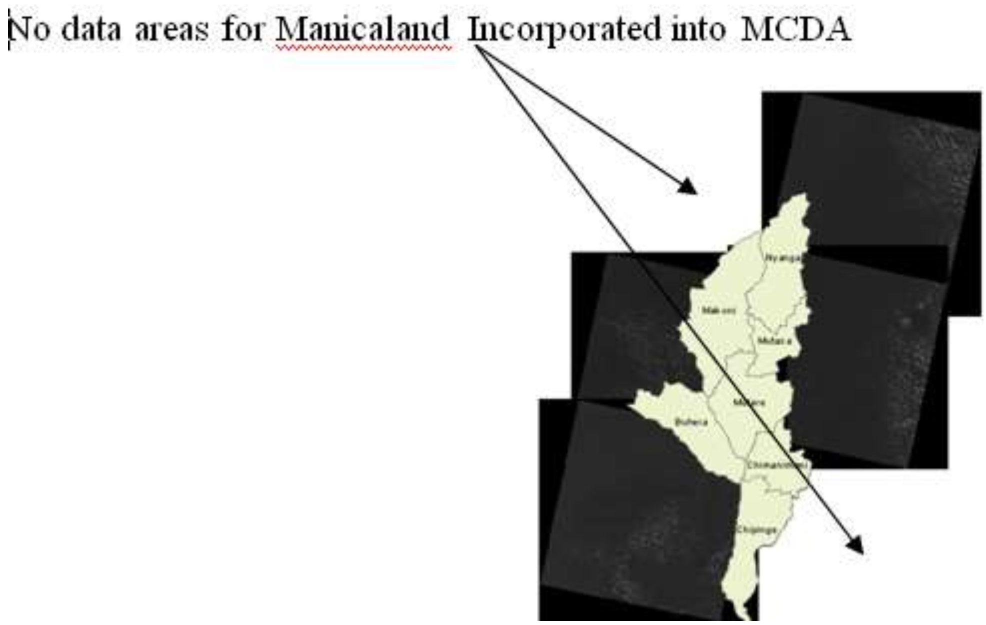

Figure 18: Manicaland shapefile versus unprocessed landsat 8 tiles covering the region

The diagram above shows Manicaland region shapefile against the unprocessed Landsat 8 tiles for use in the biomass distribution potential model. However the downloaded raster file for two tiles as indicated above were corrupted and could not be used in the analysis.

4.1.3 Pan sharpened Image for 168/73 for Vegetation Analysis

The result will be a natural colour image with higher resolution (15m).

4.1.4 Apparent Reflectance Raster Function for 168/73 pan sharpened

The main advantage of apparent reflectance function is to adjust the images to a theoretically common illumination condition, so there should be less variation between scenes from different dates and from different sensors. This can be useful for image classification, colour balancing, and mosaicking.

The function performs two calibrations. The first calibration is to convert the DN value to the top of atmosphere (TOA) radiance based on the sensor properties (i.e. gain/bias or LMAX/LMIN). The second calibration is to convert the TOA radiance to apparent reflectance, based on sun elevation and acquisition date.

4.1.4.1 DN Value to the top of atmosphere (TOA) radiance

Formula: Band specific reflectance_mult_band * DN Values + Reflectance_Add_Band

<u>Metadata files summary</u>

			Scene I.D				
Attribute	Band Number	Band Name	168/72	168/73	169/73	169/74	169/75
REFLECTANCE_ADD_BAND_4	4	*Red Band*	-0.100000	-0.100000	-0.100000	-0.100000	-0.10000
REFLECTANCE_MULT_BAND_4	4	*Red Band*	0.000020	0.000020	0.000020	0.000020	0.00002
REFLECTANCE_ADD_BAND_5	5	*NIR Band*	-0.100000	-0.100000	-0.100000	-0.100000	-0.10000
REFLECTANCE_MULT_BAND_5	5	*NIR Band*	0.000020	0.000020	0.000020	0.000020	0.00002
REFLECTANCE_ADD_BAND_6	6	*SWIR 1 band*	-0.100000	-0.100000	-0.100000	-0.100000	-0.10000
REFLECTANCE_MULT_BAND_6	6	*SWIR 1 band*	0.000020	0.000020	0.000020	0.000020	0.00002
REFLECTANCE_ADD_BAND_7	7	*SWIR 2 band*	-0.100000	-0.100000	-0.100000	-0.100000	-0.10000
REFLECTANCE_MULT_BAND_7	7	*SWIR 2 band*	0.000020	0.000020	0.000020	0.000020	0.00002
SUN_ELEVATION			47.657013	46.506800	43.43015	52.37561	46.2231
Sine (Sun_Elevation)_calculated			**0.739126**	**0.725456**	**0.687470**	**0.7920299**	**0.72204**

Table 13: Metadata Summary Statistics

4.1.2.2 TOA radiance to apparent reflectance (Correction for sun angle)

This raster function was combined with the previous output in the raster calculation for Apparent reflectance

4.1.3 Saturation correction

No saturation correction was applied to the datasets. Oversaturation occurs when a detector views an object that is much brighter than the maximum radiance the instrument was designed to handle. This causes the detector to deliver a voltage that is larger than expected by the 12-bit electronics, so the detector's value rolls over the 12-bit limit and is recorded as a very small integer. Thus, this artifact appears as dark spots in the middle of very bright objects.

For vegetation analysis this is a highly unlikely event, hence justifying why the correction was not applied.

4.2 Results Analysis

4.2.1 Calculating the Vegetation Indices from Landsat 8 image Using ArcGIS 10.0

"An NDVI is often used worldwide to monitor drought, monitor and predict agricultural production, assist in predicting hazardous fire zones, and map desert encroachment. The NDVI is preferred for global vegetation monitoring because it helps to compensate for changing illumination conditions, surface slope, aspect, and other extraneous factors" (Lillesand 2004).

4.2.1.1 Image Reclassification Statistics – NDVI

From the results shown below, a three standard deviation of the mean was used to exclude very sparsely vegetated areas from the model since these offer little significance on the contribution to site location effect from the biomass layer and a 0.3 threshold on NDVI was set.

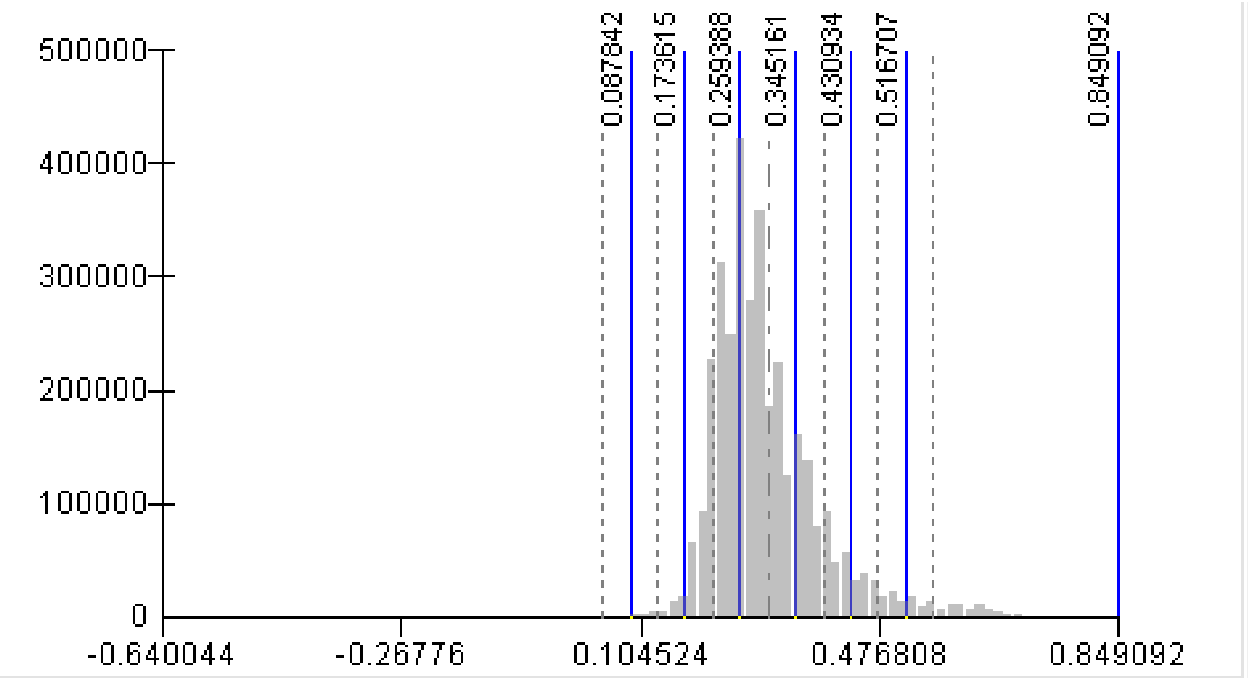

Figure 19: L816872 NDVI Reclassification Histogram using the Standard Deviation Method

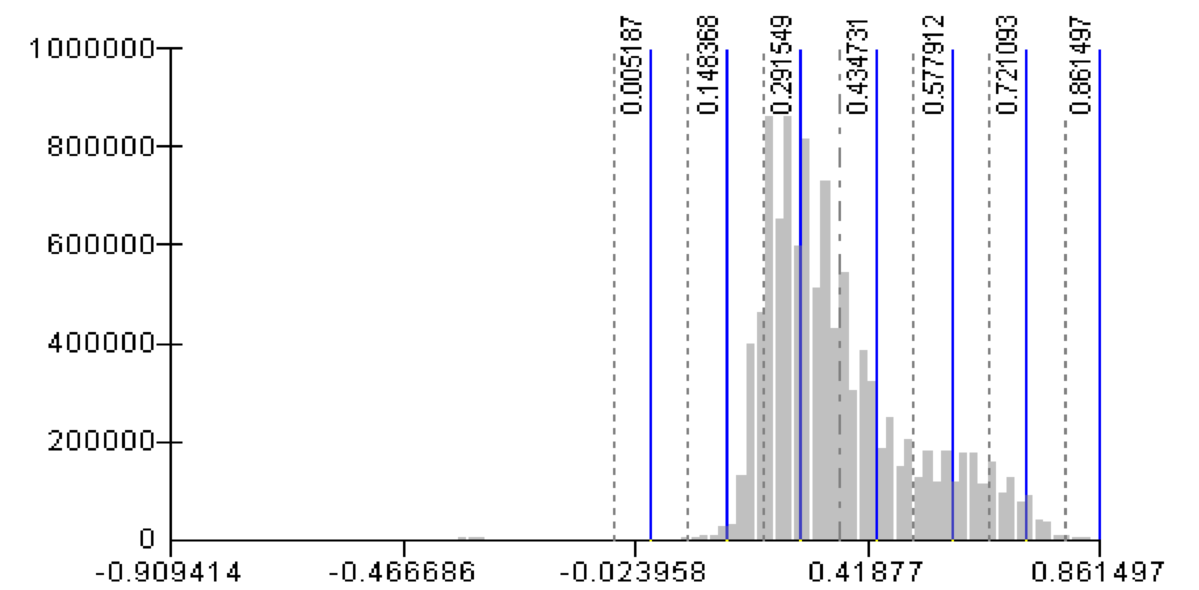

Figure 20: L816873 NDVI Reclassification Histogram using the Standard Deviation Method

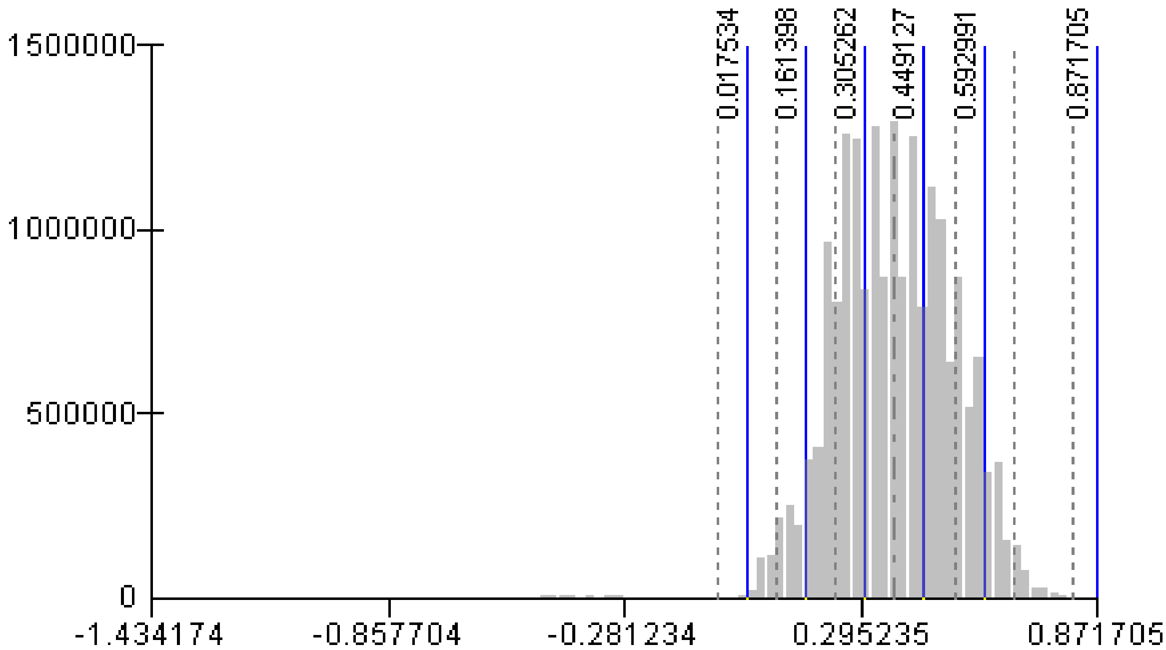

Figure 21: L816973 NDVI Reclassification Histogram using the Standard Deviation Method

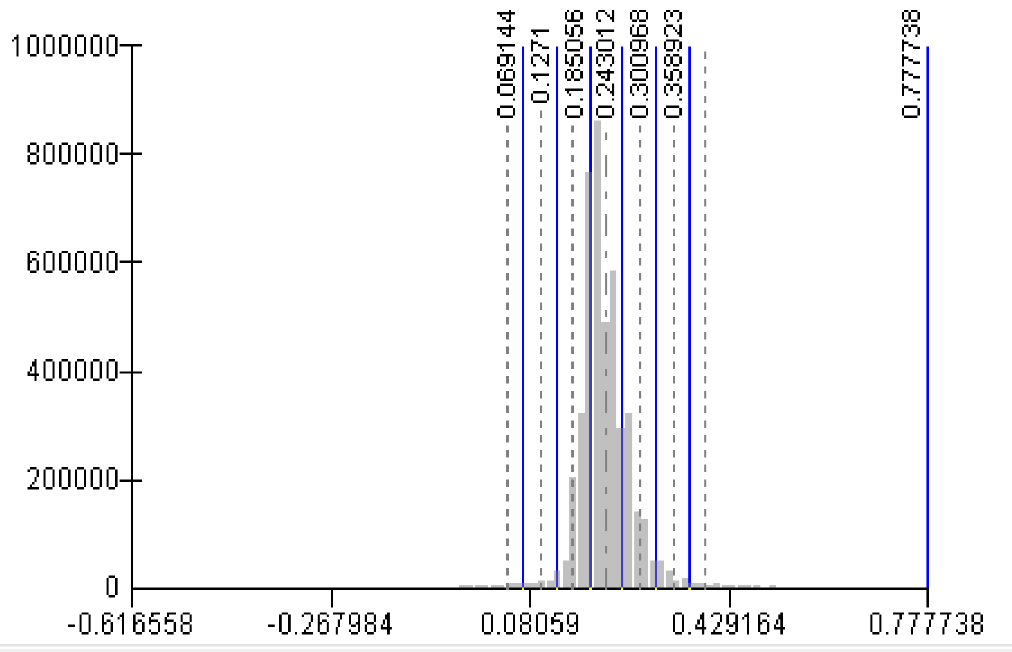

Figure 22: L816974 NDVI Reclassification Histogram using the Standard Deviation Method

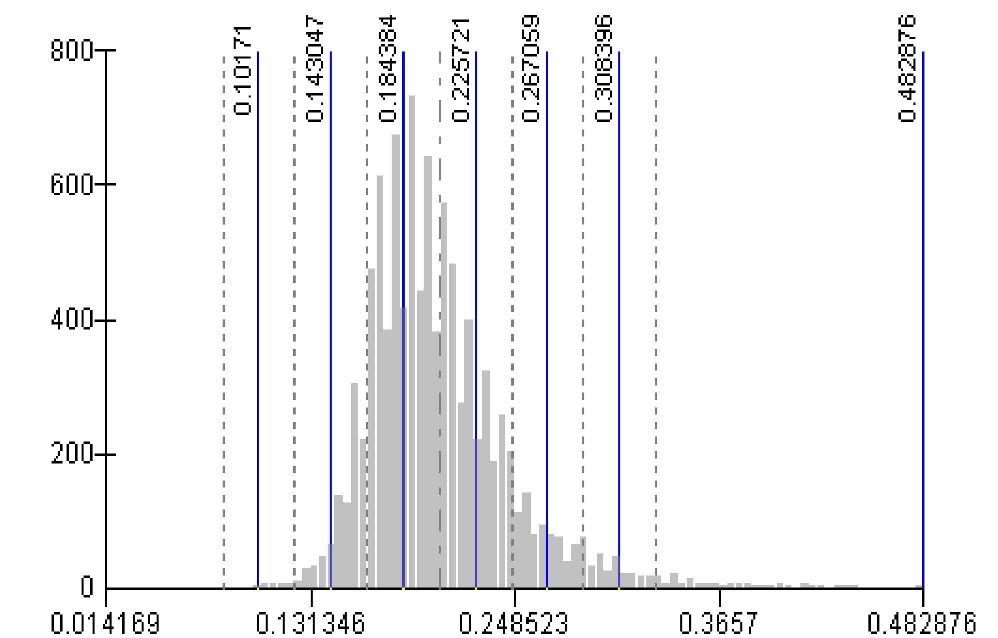

Figure 23: L816975 NDVI Reclassification Histogram using the Standard Deviation Method

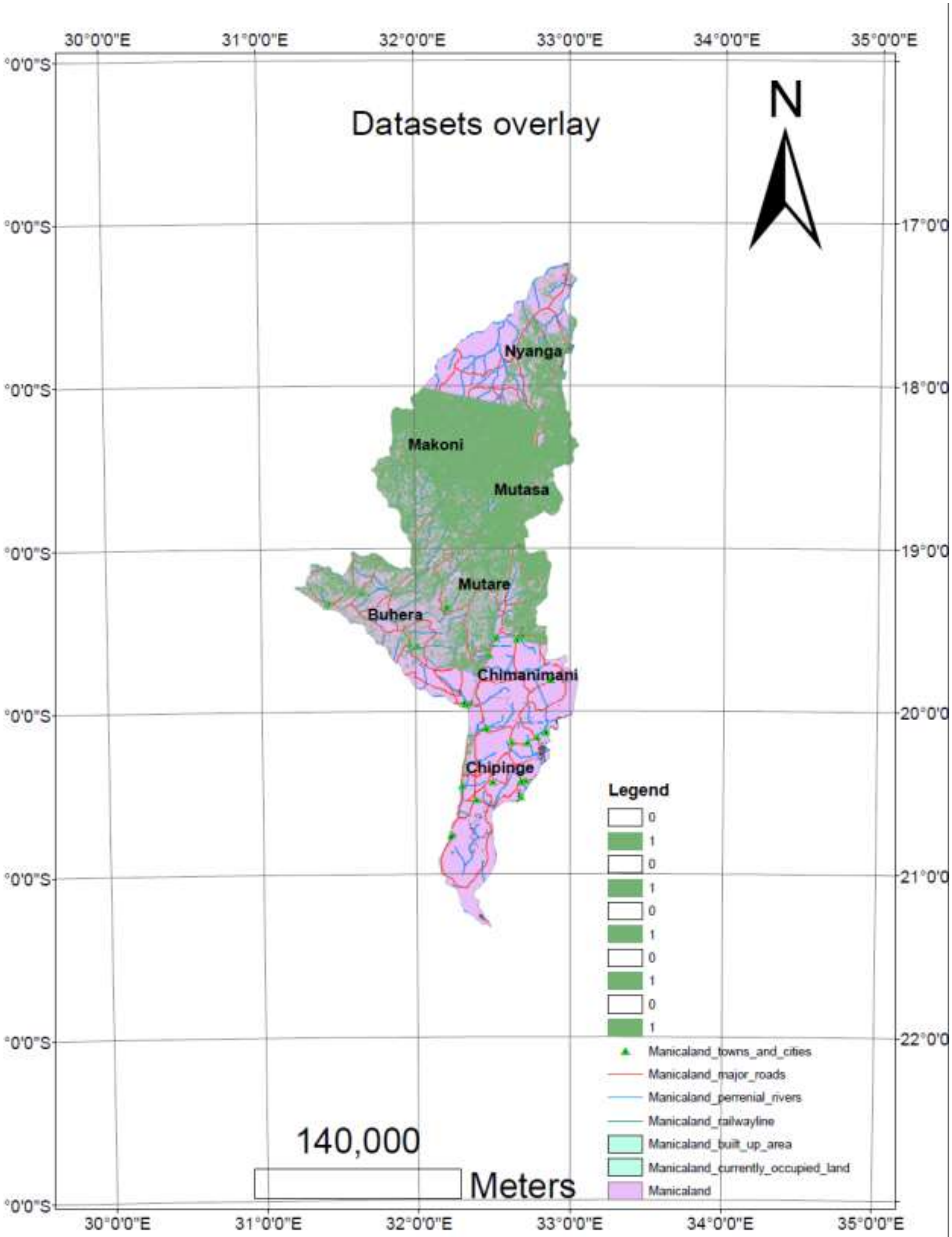

Figure 24: Manicaland Biomass Distribution Model from NDVI Indices

From the diagram the areas in RED represents areas with biomass content below an economic threshold for bio-energy production. The areas will automatically be excluded from the site optimization modelling in an exclusionary process to reduce the processing requirements of datasets involved in the analysis.

Water has an NDVI value less than 0, bare soils between 0 and 0.1, and vegetation over 0.1. Increase in the positive NDVI value means the greener the vegetation. This reclassification scheme was use to come up with biomass distribution as a function of NDVI. The Green parts represent areas with healthy vegetation cover in the study area.

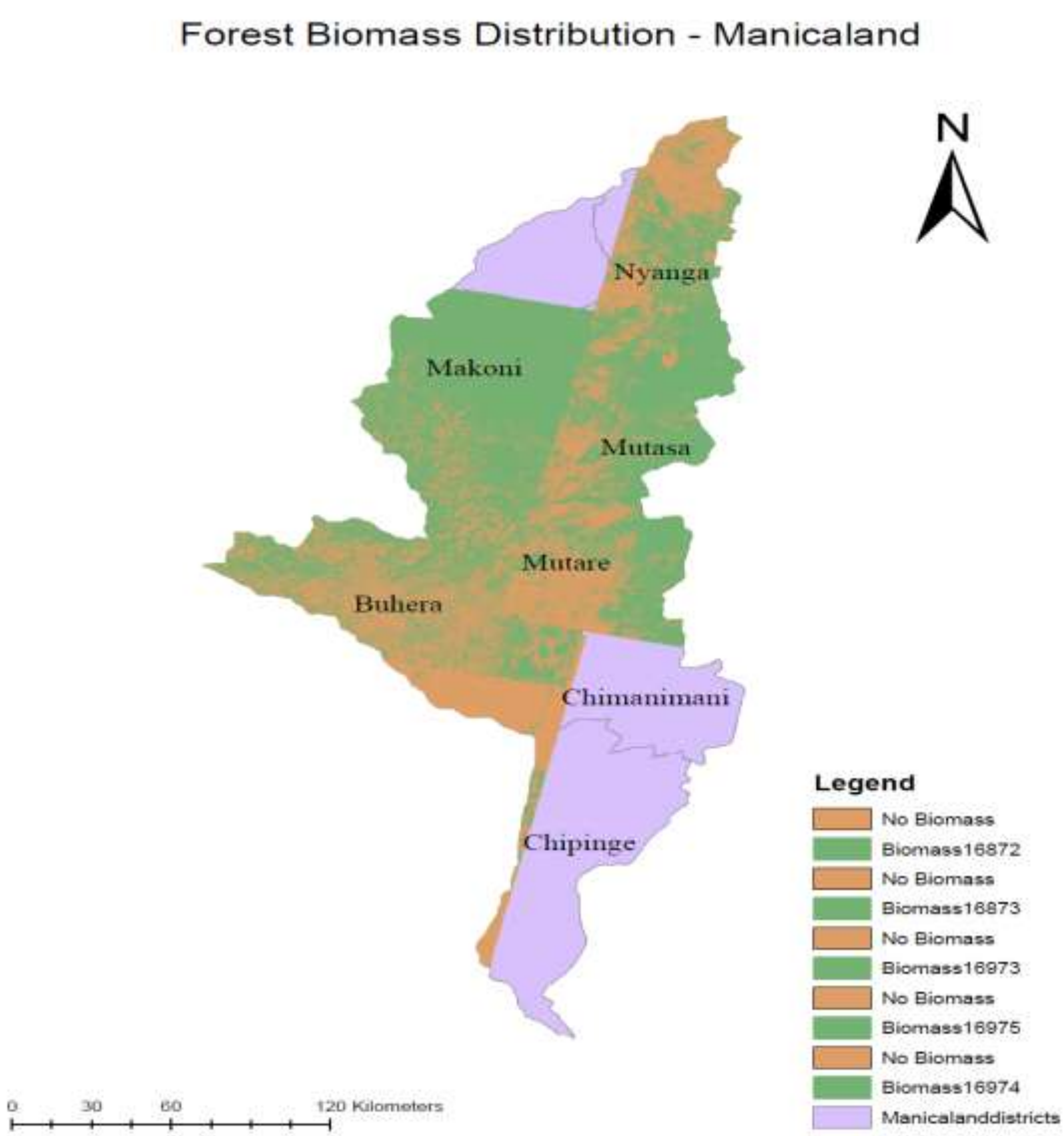

Figure 25: Manicaland Biomass Distribution Model at 0.3 threshold of NDVI

4.4 Site Optimization Results Analysis

4.4.1 Pairwise Comparison Matrix (AHP Template with n=7)

Table 14: AHP Template with 7 criteria

Analytic Hierarchy Template: n=	7	Criteria

Fundamental Scale (Row v Column)	
Extremely less important	1/9
	1/8
Very strongly less important	1/7
	1/6
Strongly less important	1/5
	1/4
Moderately less important	1/3
	1/2
Equal Importance	**1**
	2
Moderately more important	3
	4
Strongly more important	5
	6
Very strongly more important	7
	8
Extremely more important	9

The template above shows the assessment criteria for the Pairwise Comparison Matrix. The scale is for converting subjective opinion to objective measurement in the development of weights for use in the Multi-factor Weighted Overlay Analysis in ArcGIS. For later versions of ArcGIS this can be developed within the ArcGIS platform.

Table 15: Pair wise Comparison Matrix for Site Optimization

Criteria Rating for Biomass Power Plant Site Selection							
Pairwise Comparison Matrix							
	Biomass	Roads	Land Use	ServiceCentres	Hydrographical Network	ZETDC Infrastructure	Railway
Biomass	1	9	3	1	3	2	1
Roads Network	1/9	1	1/3	1/9	1/3	1/5	1
Land Use	1/3	3	1	1/3	1	1/2	1
Town and ServiceCentres	1	9	3	1	3	2	1
Hydrographical Network	1/3	3	1	1/3	1	1	1
Current Infrastructure	1/2	5	2	1/2	1	1	2
Railway Network	1	1	1	1	1	1/2	1

4.4.2 Factor weights and Consistency Index Calculation Results

Table 16: AHP Derived Weights and the Consistency Checking Results

Pairwise Comparison Matrix	AHP	Consistency check
Biomass Resources	0.234	Consistency OK 8%
Roads Network	0.043	
Land Use and Built Up Areas	0.088	
Towns & service centres	0.234	
Hydrographical network	0.098	
Current Infrastructure	0.146	
Railway network	0.158	

4.4.2 Normalized Factor weights, Eigenvector, Consistency Index and Matrix Consistency Ratio Calculation Results

Table 17: Consistency Weighting (Normalized) from AHP

Pairwise Comparison Matrix	Normalized					
	AHP-1	CA	Lambda		CI	CI/RI
Biomass Resources	0.245	1.04846	7.57070261		0.0951171	0.07205841
Roads Network	0.043	1.32261			Randomness Index,RI	
Land Use and Built Up Areas	0.090	1.02336		3	0.58	1.32
Towns & service centres	0.245	1.04846		4	0.9	
Hydrographical network	0.100	1.03557		5	1.12	
Current Infrastructure	0.151	1.0874		6	1.24	
Railway network	0.126	1.00485		7	1.32	

4.4.3 Factor Based Site Location Results

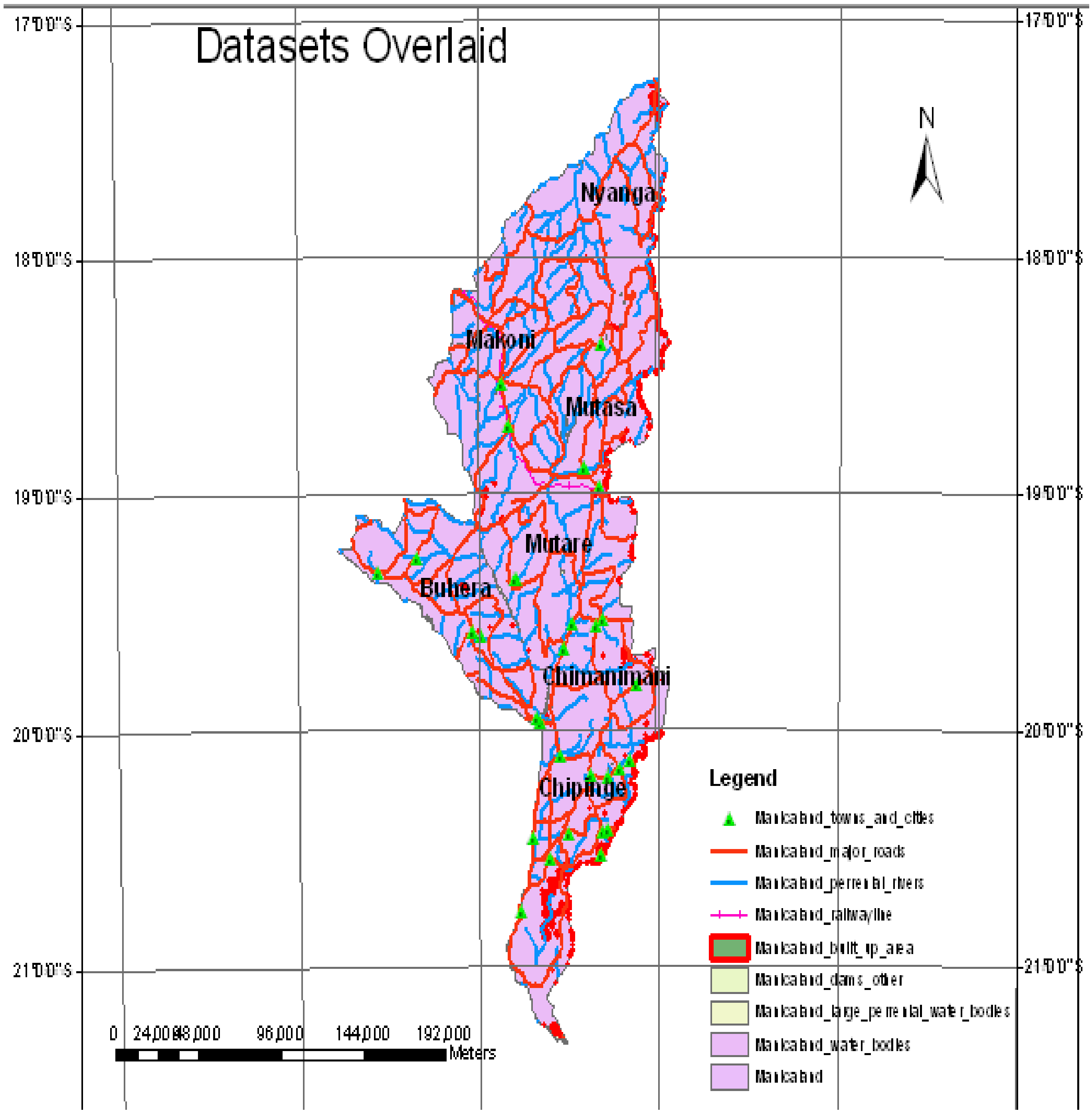

Figure 26: Overlaid datasets for consideration in site optimization model

4.4.3.1 Result Determined by the Layer Manicaland towns and Cities.shp

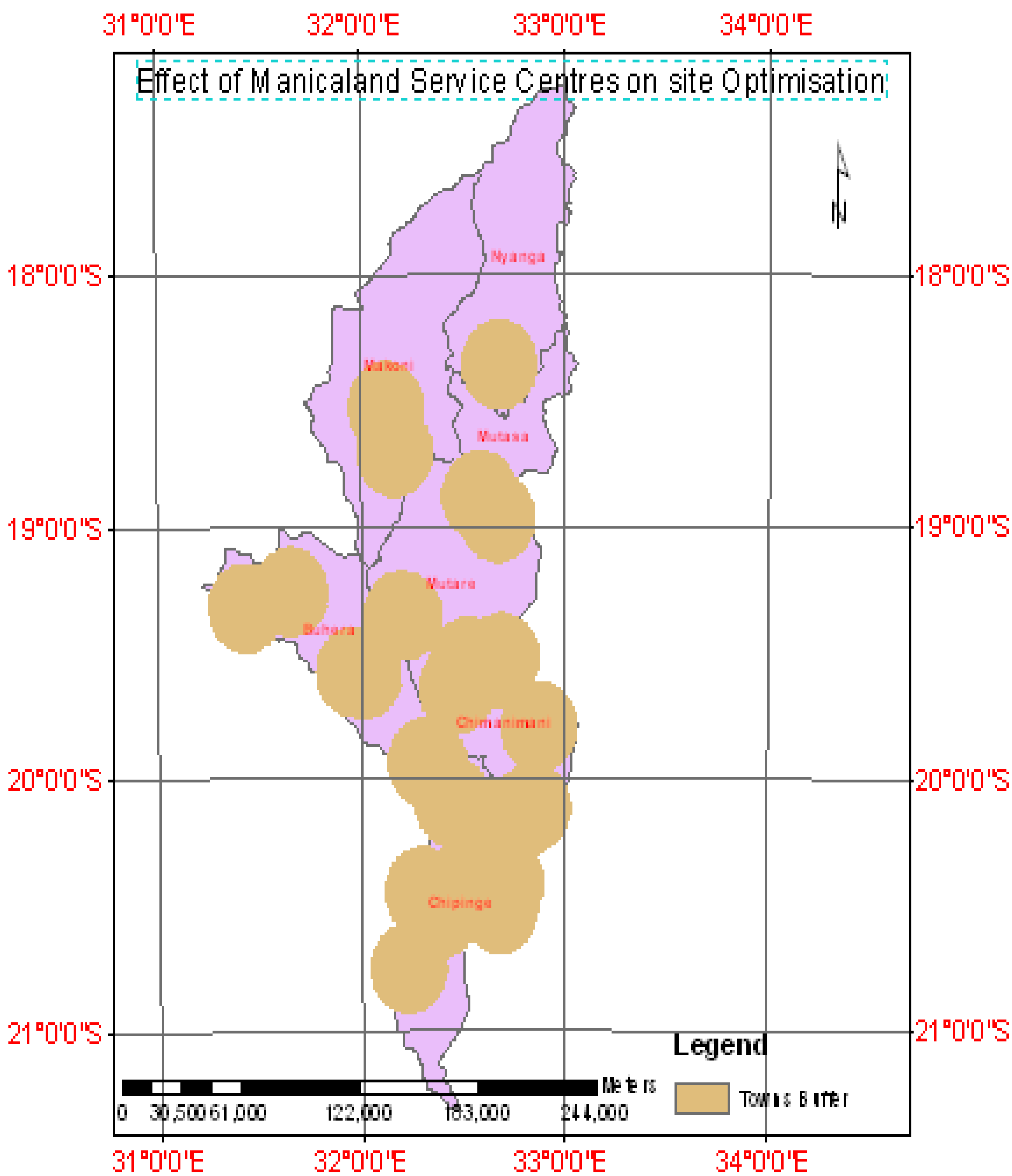

Figure 27: Excluded areas within a 10km Buffer of Urban Built up areas

The areas in brown indicate the excluded areas for power plant location based on a 10km Euclidian Distance Buffer around all the major towns, cities and service centres in Manicaland. This therefore leaves the remaining areas as the only candidate sites for biomass power plant location based on this factor.

After the overlaying of the three datasets, roads, railway network and service centres only the areas in light purple remains candidates for the installation of the proposed biomass power plants. However these candidate areas still had to be overlaid with the biomass distribution map layer.

4.4.3.4 Six factor combined effect on site optimisation

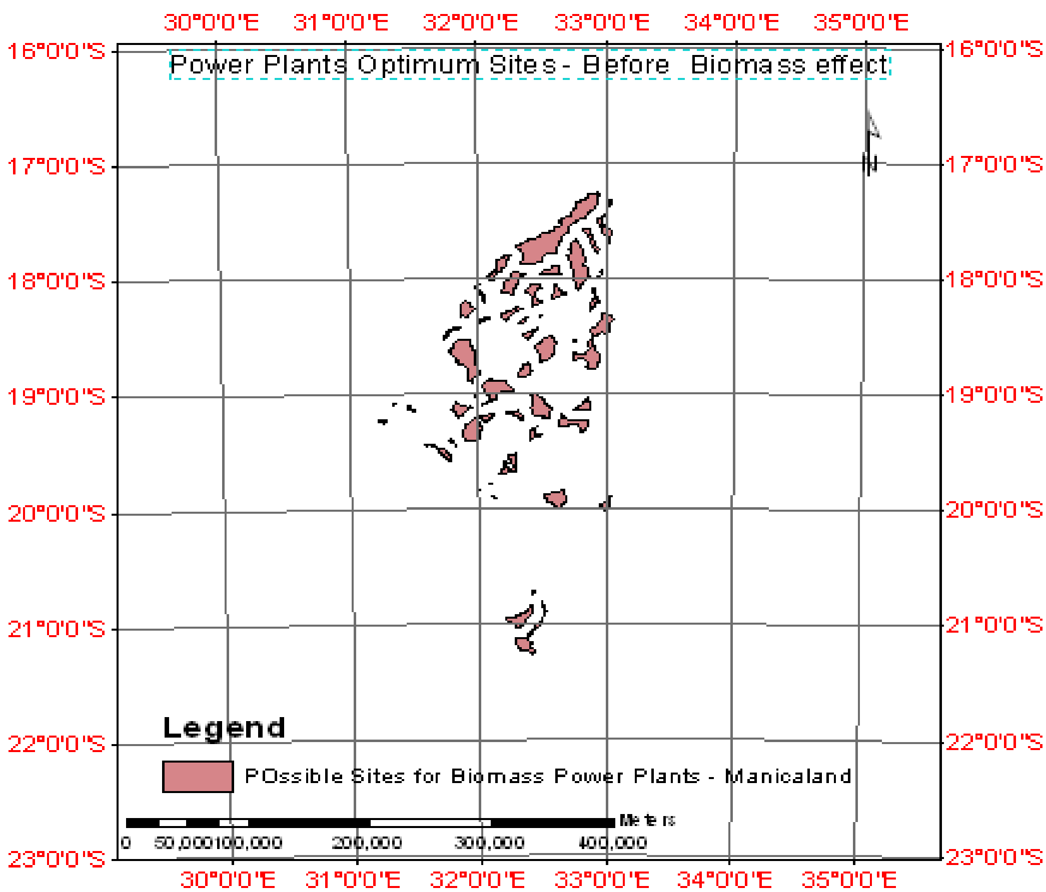

Figure 28: Manicaland possible sites for power plant location (Before adding biomass raster layer)

4.4.3.5 Results of the Weighted Overlay Analysis – Map presentation of optimum sites for power plant installation

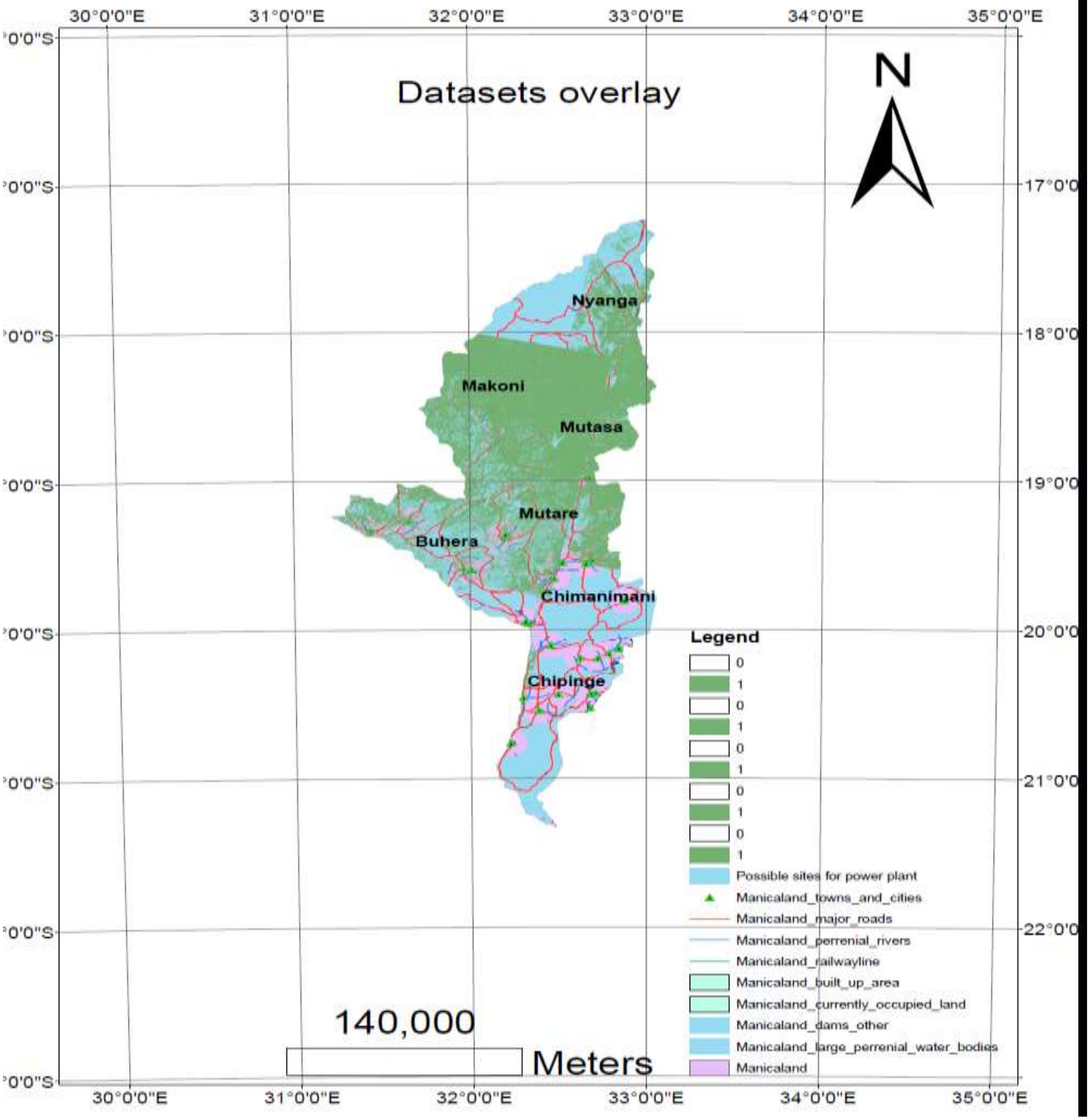

Figure 29: Weighted Overlay Analysis Results

Note: I represents optimum biomass sites for consideration in the facility modeling

4.5 Limitations

4.4.1 Format Conversion Generalisations

The image pre-processing technique employed in ArcGIS involves converting back and forth between raster data format and vector data format to make analysis in ArcGIS possible. However these conversions results in generalizations and accuracy loss. Raster-to-vector and vector-to-raster conversion are associated with many problems especially on polygon shape and size and also with grid cell size.

4.5.1 Criterion datasets availability in Usable Formats and Processing Software Limitations

Even though an AHP model was included as part of the objective criteria weighting this was limited by the availability of datasets in usable formats for the purposes of this research. As well the limitations imposed by the available processing software further compromised the results of the research.

4.6 Chapter Summary

Chapter four presented results from the Biomass model as well as the results of the site Optimization Model using the Weighted Overlay Analysis using the biomass distribution raster layer and other factor input layers for consideration in the site optimization procedure. The chapter presented a biomass distribution map as well as locations for biomass power plant installation as emphasized by the objectives of the research.

Chapter 5 – Summary, Conclusions, Contributions, Recommendations and Further study

5.1Research Summary

This research has been developed to assist decision makers in the process of developing a national bio-energy policy and strategy and/or assessing investment opportunities, by:

- Providing step-wise guidance on the key issues that need to be addressed when considering tradeoffs, and processes that need to be undertaken to optimize opportunities and minimize risks in the energy sector;
- Providing a set of technical resources and links to existing tools, guidelines, information and resources that are relevant to the country's critical risks and challenges in the energy sector;
- Offering guidance on identification and inclusion of stakeholders in the bio-energy decision-making process and on adopting transparent processes for good governance.

This research work has investigated the overall process of bio-energy system design. Some key aspects related to bio-energy systems planning, from biomass availability assessment to locating power plants and distribution of biomass, have been investigated and a review of previous research on the corresponding fields (i.e. biomass assessment, power plant sitting, and spatial optimization) was conducted.

5.2 Research Conclusion

The results indicate that, in the case of Manicaland, Zimbabwe, the Mutasa and Nyanga region is the most suitable for setting up bio-energy power plants.

Much has been made of the negative environmental impact of using fossil fuels. The assumption has often been made that anything that reduces use of fossil fuels will automatically benefit the environment. However, the reality is much more complicated. Everything has two sides and every technology introduces both benefits and costs. Exploitation of bio-energy is no exception. The application of biomass from forest plantations may cause environmental issues which we are trying to prevent by careful management, such as deforestation, soil erosion (soil carbon degradation), land use competition, water and air pollution (Abmann & Laumanns, 2006) and (Brown, 2003)

As one of the most promising renewable energy resource, bio-energy for power generation has a lot of benefits from both an environmental point of view or in terms of energy security and energy balance. An integrated methodology combining GIS, AHP, and discrete location allocation models is an important option in the decision criteria evaluation. This comprehensive design approach for bio-energy system planning addresses the difficulty resulting from the highly distributed biomass resources and promotes economically and environmentally sustainable development at the local or regional scale.

GIS based suitability analysis, network analysis and AHP methods have effectively promoted the design performance. The results obtained can not only provide decision making support for planners but also decrease the computational efforts in the spatial optimization models. This study demonstrated the potential of GIS and AHP as efficient methods for bio-energy systems planning.

The main contributions of this research include the following aspects:

1. Prior to this study, an integrated model for regional scale bio-energy systems design has never been fully addressed in the bio-energy literature for Zimbabwe. This study fills this gap by proposing an integrated method for comprehensive bio-energy systems planning at the regional and local scales;
2. The use of GIS based suitability analysis, network analysis and AHP for power plant sitting;

5.4Recommendations from the study

The accomplishment of Renewable Energies Transfer Systems (RETs) in the locale has been constrained by a blend of variables which include: poor institutional structure and framework; insufficient RET planning arrangements; absence of co-ordination and linkage in the RET program; estimating mutilations which have set renewable energy off guard; high introductory capital costs; weak dissemination strategies; absence of gifted labour; poor pattern data; and, powerless support administration and base. The following policy options could contribute to the development and dissemination of successful RETs programs in Zimbabwe:

- Long term RETs policy programmes within government
- Careful selection of RETs that are appropriate to Africa, and implementation of sustained capacity building programs

5.4.1 The inclusion of a proper economic model in the site optimization strategy

While the addition of an economic evaluation is a key component to the site optimization strategy, it is a bit problematic because the costs of the technology, the behaviour of the biomass resources, and the costs of producing bio-energy are not constant, and also bio-energy development is largely policy-driven at the regional, state, or local level. However the utilization of a p-UFLP location-allocation model for LUCE minimization in bio-energy systems design is one such core requirement of this model design. Another facility location problem model - the p-uncapacitated facility location problem model to minimize the levelized unit cost of energy to assess the viability of using bio-energy for electric power generation should also be incorporated for an all-encompassing decision modelling since these models are effective ways for spatial optimization in bio-energy systems design. Studies have shown that the nameplate capacity estimates are often significantly less than the realized values (Boccard, 2009), and this must be taken into consideration in any detailed economic evaluation.

5.4.2 The employment of a yield sensitivity analysis for forest plantation biomass based on different factors

The most complex models enable one to carry out a yield sensitivity analysis based on different factors, combining different types of soil, climate, cultivation, and management. Most of the model applications are related to management aspects such as fertilization or crop maintenance strategies, sowing dates, or crops with a different cycle, which have to be assessed in accordance with a historical series of climate data. This will feed more detail into especially the Return on Investment (ROI) Analysis which is pertinent in the site optimization modelling.

5.4.3 Cross platform and cross software data processing

Cross software data processing could not be used in this research because of the limitations imposed on data files, especially shapefiles. This would then mean that all files will have to be stored in a relational ArcSDE database. ArcSDE (Spatial Database Engine) is a server-software sub-system (produced and marketed by Esri) that aims to enable the usage of Relational Database Management Systems for spatial data. The spatial data may then be used as part of a geodatabase. This allows for the automatic checking and repairing of the geometries of transported spatial data files for example incorrect ring ordering in polygon datasets. ArcGIS applications are built with the assumption that the feature's geometry follows certain specifications. When the software encounters data which does not follow the specifications, the result can be unexpected software behaviours (including crashes) and incorrect analysis results. The exception to this is when the data is loaded to an SDE Geodatabase. Before it is stored in the feature class, each record's geometry is checked for geometry problems, and repaired if necessary.

5.4.4 Active remote sensing technology a better predictor of biomass quantities especially when accurate correlation between biomass and calorific content is required.

The ability to estimate forest biomass from passive satellite images is limited because the spectral responses in passive satellite images are primarily connected to the interface between sun radiance and stand crown closures. Therefore, in general, the relationship between AGB and spectral reflectance values is low. Therefore should a more accurate biomass assessment model be employed the research recommends the use of active remote sensing technology.

However, active remote sensing images require extra processing such as pre-processing, subtraction of noise, and image processing. Additionally, active remote sensing data is more expensive than other satellite images. Problems such as mixed pixels and image saturation in medium resolution satellite images are found when estimating AGB from them.

5.4.5 Network Analysis in Site Optimization Modelling

Many location-allocation problems are concerned with the provision of a service to satisfy a spatially dispersed demand which exists at a large number of widely distributed sites. To reduce costs, the service must be provided from a few, centralized locations to meet distributed demands.

Network analysis is a very important application in GIS. It is usually used to manage or optimize systems operation, such as utility, communication and transportation system operations. Utilities use network models to monitor and analyze their distribution systems. Businesses use network to find the optimal routes for the delivery of goods and services for example Biomass raw material hauling to candidate plants.

The three main types of network analyses are: network tracing, network routing and network allocation. The purpose of network tracing is to find a particular path through the network based on criteria such as shortest distance, fastest distance and minimum cost. Network routing determines the optimal path along a network. Network allocation deals with the designation of portions of the network to supply centres or demand points. It is widely recognized that network analysis can provide crucial insight into geographic and real world networks, and can be employed to obtain more accurate and appropriate solutions in these networks.

In bio-energy systems planning, network analysis can be employed to find the lowest transportation costs in delivering biomass feedstock and in allocating all the collectable biomass to the conversion facilities, e.g. biomass power plants. In this study, ArcGIS based network analysis was employed to:

1) Find the shortest road network distance for the delivery path of biomass feedstock;

2) Get the solutions of the p-median problem for locating the power plants and allocating the biomass supplies.

5.4.6 More datasets should be considered in the site selection delivery process

The most important phase and the one with a strong bearing on the evaluation of potential sites for an installation of a biomass power plant is the selection of the factors and criteria that will have a direct influence on the power plant facility to be developed. Many different factors can be taken into account in this respect; however the ones selected in this research are in accordance with the objectives, the easy availability of datasets to complete the research within the specified timeframe, and the researcher’s experience. However some datasets which are not considered in this concept research will and might also have a strong bearing on the selected sites' economic social and environmental suitability to site optimisation. In this study all the criteria (factors and constraints, see Table 12) are reflected in the corresponding GIS thematic classes. Even though consultation to an extensive bibliography ((Voivontas, 1998); (Gómez & Barredo, 2005); (Hubina & Ghribi, 2008); (Munier, 2004; Munier, 2004)), has been done in this research, the outcome was constrained by availability of datasets for the implementation of such consultation recommendations in this research. This could not be achieved because of the limited availability of usable datasets within the research delivery period. Experts were also consulted and the current standards were complied with. The region contains both natural and artificial areas with special characteristics that need to be preserved, many of which are protected by current legislation. These areas have been considered as constraints in the present study (see Table 12) For a more comprehensive site optimisation analysis a fuller consideration of datasets is required

5.4.7 The use of low-carbon energy sources and renewable energy supply to better the current energy mix

The world is at a critical juncture in its efforts to combat climate change. Since the first Conference of the Parties (COP) in 1995, greenhouse-gas (GHG) emissions have risen by more than one-quarter and the atmospheric concentration of these gases has increased steadily to 435 parts per million carbon-dioxide equivalent (ppm CO_2-eq) in 2012 (EEA, 2015). The International Panel on Climate Change (IPCC) has concluded that, in the absence of fully committed and urgent action, climate change will have severe and irreversible impacts across the world. The international commitment to keep the increase in long-term average temperatures to below two degrees Celsius (2°C), relative to pre-industrial levels, will require substantial and sustained reductions in global emissions. The research also highlighted the need for renewable and sustainable energy sources in the energy supply debate.

5.4.8 Energy policies and Incentive schemes for biomass energy production in Zimbabwe and Africa at large.

The energy sector needs to see a projection from political leaders at the highest level of clarity of purpose and certainty of action, creating a clear expectation of global and national low-carbon development. In addition, the research pointed out that since biomass can help to reduce CO_2 emissions, some economic measures and/or incentives should be adopted, such as CO_2 taxes, state subsidies for biomass-4red energy conversion plants, or reduced rates for electricity produced from biomass.

5.4.9 Sustainability Considerations key to bio-energy strategy implementation

Sustainability is to be achieved at all levels and is thus paramount in this action plan. When promoting bio-energy use, we must ensure that we do so without compromising the situation in other countries and particularly in developing countries where food shortfalls are critical.

5.4.10 Review of zoning regulations in Zimbabwe

Although planning is critical to ensuring the sustainability of buildings in Zimbabwe, it still relies heavily on the outdated building standards set by the British. The social, economic, and physical environment in which developments takes place has greatly changed. Under the current mantra of building operations guided by the current planning diktats and procedures, it is uncertain whether sustainable construction is achievable. Sustainable construction is defined as "... an emerging field of science that aims at incorporating the general sustainable development concepts into conventional construction practices" (Sarkis, et al., 2008).

Sustainable zoning embraces integrating success factors in the planning of projects. (Sarkis, et al., 2008) argued that when evaluating the built environment, "…it is important to take a broad view incorporating broader stakeholders and communities, beyond immediate investors [taking into account] the intergenerational aspect of sustainability [and] influencing the needs and requirements of future generations."

This emerging concept of sustainable zoning and construction addresses issues of the economy, society, and environment, and embraces infrastructural development as a way to create a better future for the users. In light of this, (Bakar, et al., 2006) affirm, "in order to be sustainable […] initiatives must be economically viable, socially acceptable, technically feasible and environmentally compatible."

Other less significant contributions as emphasized by the discussion in the literature of this document include:

5.4.11 A faster pace is essential to reach the 2030 goal of universal energy access

The world at large is falling short of its ambition to provide affordable, reliable, sustainable and modern energy for all. Despite the serious efforts already made, today an estimated 1.2 billion people – 17% of the global population – remain without electricity, and 2.7 billion people– 38% of the global population – put their health at risk through reliance on the traditional use of solid biomass for cooking. The newly agreed UN Sustainable Development Goals embrace a goal on energy, a move long advocated by the IEA, including the target to achieve universal access to energy by 2030.

5.4.12 Public Private Partnerships a must for bio-energy systems planning and implementation.

Due to the huge capital intensity involved in bio-energy projects implementation public private partnerships should be embraced if such project success should be guaranteed.

5.5 Further study

Future research on bio-energy systems planning should include modelling of the distribution of generated bio-power so that: (1) all acquired bio-power can be optimally injected into the local distribution grid, and (2) power plants and distribution substations can be selected by considering the local power demand to minimize power delivery costs. This research was limited to forest plantation biomass for the location of the optimum sites for plant installation however, more bio-energy resources, such as MSW and wood residues, in the regional and countrywide scale for power generation will be taken into account for bio-energy systems planning and as such quantification methods and their integration into the multi-criteria and factor evaluation should be considered in further researches in this respect.

Further development of the bio-energy systems design model may consider uncertainties and develop corresponding algorithms for solving the stochastic spatial optimization models.

The research did not delve into the econometrics of site location optimisation and therefore should the model be used to any meaningful benefit that area requires careful attention and expertise from people well versed with the subject.

References

Abmann, D. & Laumanns, U., 2006. *Renewable Energy: A Global Reveiw of Technologies, Polices and Markets,* London: Earthscan..

Arto, I. et al., May 2016. The energy requirements of a developed world. *Energy for Sustainable Development,* Volume 33, p. 1–13.

Asner, G., Hicke, J. & Lobell, D., 2003. Per-pixel analysis of forest structure: vegetation indices, spectral mixture analysis and canopy reflectance modeling.. In: M. Wulder & S. Franklin, eds. *Remote Sensing of Forest Environments: Concepts and Case Studies.* Boston: Kluwer Academic, p. 209–254.

Baccini, A., Friedl, M. & Warbington, R., 2004. Forest biomass estimation over regional scales using multisource data.. *Geophysical Research Letters ,* 31(1), pp. 1-4..

Bailis, R., Herzog, A. & Nhete, T., 2000. *Biomass Energy in Zimbabwe. Biomass Energy for Sustainable Economic, Social and Environmental Development in Eastern Zimbabwe.,* s.l.: s.n.

Bakar, A., Razak, A., Abdullah, S. & Awang, A., 2006. *"Project Management Success Factors For Sustainable Housing: A Framework"..* [Online]
Available at: http://eprints.usm.my/16076/1/ICCI09-_14_aidah_awang.pdf
[Accessed 09 October 2016].

Banks, D. I., Griffin, N. J. & Shackleton, C. M. S. E., 1996. Wood supply and demand around two rural settlements in semi-arid Savanna, South Africa. *Biomass and Bioenergy,* 11(4), pp. 319-331.

Baral, S. K. & Katzensteiner, K., 2015. Impact of biomass extraction on soil properties and foliar nitrogen content in a community forest and a semi-semiprotected natural forest in the central mid-hills of Nepal.. *Tropical Ecology,* Volume 56, pp. 323-333..

Beccalia, M., Columbab, P., D'Albertia, V. & Franzittaa, V., 2009. Assessment of bioenergy potential in Sicily: A GIS-based support methodology.. *BIOMASS AND BIOENERGY ,* 33(1), p. 79 – 87.

Beinat, E. & Nijkamp, P., 1998.. Multicriteria Analysis for Land-Use Management.. In: *Environment & Management.* Dordrecht: Kluver Academic Publishers.

Boccard, N., 2009. Capacity factor of wind power realized values vs. estimates. *Energy Policy,* Volume 37, pp. 2679-2688.

Bórdas, R., 2006. *Implementación de una herramienta basada en tecnología SIG y técnicas de decisión multicriterio para la obtención de mapas de orientación a la ubicación de instalaciones de gestión de residuos.,* Spain: s.n.

Boyd, D., Foody, G. & Curran, P., 1999. The relationship between the biomass of Cameroonian tropical forests and radiation reflected in middle infrared wavelengths. *International Journal of Remote Sensing,* 20(5), pp. 1017-1023.

Brown, R. C., 2003. *Biorenewable Resources-Engineering New Products from Agriculture.* s.l.:Blackwell Publishing..

Brown, S., 2002. Measuring carbon in Forests: Current status and future Challenges.. *Environmental Pollution,* 116(3), pp. 363-372.

Brown, S., Gillespie, A. & Lugo, A., 1989. Biomass Estimation Methods for Tropical Forests with Applications to Forest Inventory Data.. *Forest Science ,* 35(1), pp. 881-902..

Buchholz, T. S., Volk, T. A. & Luzadis, V. A., 2007. A participatory systems approach to modeling social, economic, and ecological components of bioenergy. *Energy Policy,* 35(12), p. 6084–6094.

Buckley, J. R. & Smith, A. M., 2010. “Monitoring grasslands with RADARSAT 2 quad-pol imagery”. *2010 IEEE Int. on Geoscience and Remote Sensing Symp. (IGARSS),,* Volume 1, p. 3090–3093.

Butchholz, T., Rametsteiner, E., Volk, T. & Luzadis, V., 2009. Multicriteria analysis for bioenergy systems assessments.. *Energy Policy,* Volume 37, p. 484–495.

Carlson, E. D., 1978. An approach for designing decision support systems. *ACM SIGMIS Database,* 10(3), pp. 3-15.

Case, B. S. & Hall, R. J., 2008. “Assessing prediction errors of generalized tree biomass and volume equations for the boreal forest region of west-central Canada,”. *Canadian Journal of Forestry Resources,* 38(4), p. 878–889.

Chave, J. et al., 2005. “Tree allometry and improved estimation of carbon stocks and balance in tropical forests,”. *Oecologia,* 145(1), p. 87–99.

Cheng-Dar, Y. & Grant Gwo-Liang, Y., 2007. Decision support system for exploiting local renewable energy sources: a case study of the Chigu area of southwestern Taiwan.. *Energy Policy,* Volume 35, p. 383–394.

Chen, G. & Wang, J., 2008. Spectral reflectance and aboveground biomass estimation of the grassland under protection condition. *Journal of Yunnan Agricultural University,* Volume 23, pp. 462-467.

Chen, K., Blong, R. & Jacobson, C., 2001. MCE-RISK integrating multicriteria evaluation and GIS for risk decision making in natural hazards.. *Environmental Modelling and Software ,* Volume 16, p. 387–397..

Chen, Q., 2013. “LiDAR remote sensing of vegetation biomass,”. In: Q. Weng & G. Wang, eds. *Remote Sensing of Natural Resources.* 3rd Edition ed. BocaRaton,Florida: CRCPress, p. 399–420.

Chen, Q., 2013. “LiDAR remote sensing of vegetation biomass,”. In: Q. Weng & G. and Wang, eds. *Remote Sensing of Natural Resources.* 1st Edition ed. Boca Raton,Florida: CRC Press, p. 399–420.

Cohen, W. B. & Spies, T. A., 1992. “Estimating structural attributes of Douglas-fir/western hemlock forest stands from Landsat and SPOT imagery,”. *Remote Sens. Environ. ,* 41(1), p. 1–17 .

Cote, A. & Grant, C., 2008. *“Codes and Standards for the Built Environment”, Chapter 3 in NFPA Fire Protection Handbook 19th Edition.* [Online]
Available at: http://www.nfpa.org/assets/files/pdf/codesfph.pdf
[Accessed 13 09 2016].

Crosetto, M. & Tarantola, S., 2001. Uncertainty and sensitivity analysis: tools for GIS-based model implementation.. *International Journal of Geographical Information Science ,* Volume 15, p. 415–437.

Culvenor, D., 2003. Extracting individual tree information: a survey of techniques for high spatial resolution imagery.. In: M. Wulder & S. Franklin, eds. *Remote Sensing of Forest Environments: Concepts and Case Studies.* Boston: Kluwer Academic, p. 255–277.

Cutler, M., Boyd, D., Foody, G. & Vetrivel, A., 2012. Estimating tropical forest biomass with combination of SAR image texture and LANDSAT TM data: An assessment of predictions between regions.. *ISPRS Journal of Photogrammetry and Remote Sensing,* 70(1), pp. 66-77..

DˇıOvidio, A. & Pagano, M., 2009. Probabilistic multicriteria analysis for optimal biomass power plant design.. *Electric Power Systems research ,* Volume 79, p. 645–652.

de Gier, A., 2003. *New Approach to woody biomass Assessment in woodlands and shrublands,* s.l.: GeoInformatics for Tropical Ecosystems.

Devi, L. & Yadava, P., 2009. Aboveground biomass and net primary production of semi evergreen tropical forest of Manipur:North Eastern India. *Journal of Forestry Research,* 20(1), pp. 151-155.

Devi, T. I., Yadava, P. S. & Garkoti, S. C., 2014. Cattle grazing influences soil microbial biomass in subtropical grassland ecosystems at Nambol, Manipur,northeast India.. *Tropical Ecology ,* Volume 55, pp. 195-206.

Drake, J., Knox, R. D. R., Clark, D. & Condit, R., 2003. Aboveground biomass estimation in closed canopy Neotropical forest using lidar remote sensing: factors affecting the generality of relationships.. *Global Ecology and Biogeography,* 12(1), pp. 147-159..

Dubayah, R. O. & Drake, J. B., 2000. “Lidar remote sensing for forestry,”. *Journal of Forestry,* 98(6), p. 44–46.

Dube, T. & Mutanga, O., 2015. Investigating the robustness of the new Landsat-8 Operational Land Imager derived texture metrics in estimating plantation forest aboveground biomass in resource constrained areas.. *ISPRS Journal of Photogrammetry and Remote Sensing, ,* Volume 108, p. 12–32.

Dusseux, P., 2014. “Combined use of multi-temporal optical and radar satellite images for grassland monitoring,”. *Remote Sens. ,* 6(7), p. 6163–6182 .

Eckert, S., 2012. Improved forest biomass and carbon estimations using texture measures from WorldView-2 satellite data.. *Remote Sensing,* 4(1), pp. 810-829..

Ene, L. et al., 2012. Assessing the accuracy of regional LiDAR-based biomass estimation using a simulation approach.. *Remote Sensing of Environement ,* 123(1), pp. 579-592..

Flannergy, T., 2005. *The Weather Markers,* Melbourne,Australia: Text Publishing..

Foody, G., 2001. Mapping the biomass of Bornean tropical rain forest from remotely sensed data. *Global Ecology and Biogeography,* 10(4), pp. 379-387.

Friedl, M., 1994. “Estimating grassland biomass and leaf area index using ground and satellite data,”. *Int. J. Remote Sens. ,* 15(7), p. 1401–1420 .

Gao, S., Sundaram, D. & Paynter, J., 2004. *Flexible support for spatial decision making..* Honolulu, Hawaii., s.n.

Geertman, S., 2006. Potentials for planning support: A planning-conceptual approach.. *Environment and Planning B: Planning and Design,* 33(6), p. 863–880.

Gibbs, H. et al., 2007. Monitoring and estimating tropical forest carbon stocks: Making REDD a reality.. *Environmental Research Letters,* 2(1), pp. 1-13..

Gibbs, H., Brown, S., Niles, J. & Foley, J., 2007. Monitoring and estimating tropical forest carbon stocks: Making REDD a reality.. *Environmental Research Letters,* 2(1), pp. 1-13.

Gómez, M. & Barredo, J., 2005. *Sistemas de Información geográfica y evaluación multicriterio en la ordenación del territorio,* Madrid: s.n.

Government of Zimbabwe, 2012a. *Zimbabwe’s Second National Communication to the United Nations Framework Convention on Climate Change,* Harare: s.n.

Government of Zimbabwe, 2012b. *Baseline Report on Economic Development and Climate Change,* Harare: s.n.

Government of Zimbabwe, 2014. *Zimbabwe National Climate Change Response Strategy,* Harare: s.n.

Grabaum, R. & Meyer, B., 1998. Multicriteria optimization of landscapes using GIS-based functional assessment.. *Landscape and urban planning,* Volume 43, p. 21–33..

Grabitzki, S., 2004. *Classification of Miombo Forest Based on SPOT 4 Image Analysis I-TOO Working Paper No. 19.* Albert-Ludwigs - Universitaet Freiburg, Freiburg, Germany., s.n.

Graham, R. L. & English, B. C., 2000. "A Geographic Information System-Based Modeling System for Evaluating the Cost of Delivered Energy Crop Feedstock.". *Biomass and Bioenergy,* 18(4), pp. 309-329.

Grassi, G. & Bridgwater, A. V., 1993. "The Opportunities for Electricity Production from Biomass by Advanced Thermal Conversion Technologies.". *Biomass and Bioenergy ,* 4(5), pp. 339-345.

Gwaze, D. P. & Marunda, C., 30 November - 4 December 1998.. *The Status Of Forestry Statistics In Zimbabwe..* Mutare, Forestry Commission, Zimbabwe..

Hall, F. G. et al., Nov. 2011. “Characterizing 3D vegetation structure from space:Mission requirements,”. *Remote Sensing. Environment,* 115(11), p. 2753–2775.

Häme, T., Salli, A., A. K. & Lohi, A., 1997. A new methodology for the estimation of biomass of coniferdominated boreal forest using NOAA AVHRR data. .. *International Journal of Remote Sensing,* 18(1), pp. 3211-3243.

Harding, D., Lefsky, M., Parker, G. & Blair, J., 2001. “Laser altimeter canopy height profiles: methods and validation for closed-canopy, broadleaf forests,”. *Remote Sensing of Environment,* 76 (3), p. 283–297.

Hermann, L. et al., 2000. *Promoting the role of Renewable Energy among Governments in Africa.* Seville 2000, Proceedings, s.n., pp. 1413 - 1416.

He, Y., Guo, X. & Wilmshurst, J., 2006. Studying mixed grassland ecosystems: suitable hyperspectral vegetation indices. *Canadian Journal of Remote Sensing,* Volume 32, pp. 98-107.

Holdridge, L., 1967. *Life zone ecology,* San Jose: s.n.

Houghton, R., Hal, F. & Goetz S. J., Jun. 2009. “Importance of biomass in the global carbon cycle,”. *Journal of Geophysics. Remote sensing and Biogeoscience,* 114(G2), p. 1–13.

Hubina, T. & Ghribi, M., 2008. *GIS-based decision support tool for optimal spatial planning of landfill in Minsk region, Belarus.* Spain., Universidad de Girona.

Hudak, A. et al., 2012. Quantifying aboveground forest carbon pools and fluxes from repeat LiDAR surveys.. *Remote Sensing of Environment ,* 123: (1), pp. 25-40..

Hurcom, S. & Harrison, A., 1998. The NDVI and spectral decomposition for semi-arid vegetation abundance estimation.. *International Journal of Remote Sensing,* 19(16), pp. 3109- 3125.

Hurcom, S. & Harrison, A., 1998. The NDVI and spectral decomposition for semi-arid vegetation abundance estimation.. *International Journal of Remote Sensing,* 19(16), pp. 3109- 3125.

Hyde, P. et al., 2006. “Mapping forest structure for wildlife habitat analysis using multi-sensor (LiDAR, SAR/InSAR, ETMþ, Quickbird) synergy,”. *Remote Sensing of Environment,* 102(1–2), p. 63–73.

Hyde, P., Nelson, R., Kimes, D. .. & Levine, E., 2007. “Exploring LiDAR–RaDAR synergy—predicting aboveground biomass in a southwestern ponderosa pine forest using LiDAR, SAR and InSAR,”. *Remote Sensing Environment.,* 106(1), p. 28–38.

IBRD/WB, (. I. B. f. R. a. D. /. T. W. B., 2012. *"Doing Business 2012: Doing Business in a More Transparent World – Zimbabwe".* Washington DC , The International Bank for Reconstruction and Development / The World Bank..

IEA, 2006. *Key World Energy Statistics from the IEA,* s.l.: Organisation for Economic Co-operation and Development..

IMF, I. M. F., 2016. *Staff Report for the 2016 Article IV Consultation and the third review of the staff-monitored program-Press release; staff report;and statement by the Executive Director for Zimbabwe,* Washington, D.C.: s.n.

International Energy Agency, 2001. *World Energy Outlook 2001 Insight,* s.l.: DIANE Publishing..

International Energy Agency, 2006. *Key World Energy Statistics from the IEA,* s.l.: Organisation for Economic Co-operation and Development..

International Energy Agency, 2012. *"Energy Technology Perspectives 2012",* s.l.: s.n.

International Energy Agency, 2016. *Key Renewables Trends -RENEWABLES INFORMATION (2016 edition),* s.l.: IEA.

IPCC., 2006. *Guideline for National Green House Gas Inventories Volume 4 - Agriculture, Forestry and other Land Uses,* s.l.: s.n.

Jingyuan, D., 2008. *GIS and Location Theory Based Bio-energy Systems Planning,* Ontario, Canada: s.n.

Kanniappan, P. & Ramachandran, T., 1998. "Optimization Model for Energy Generation from Agricultural Residue.". *International Journal of Energy Research ,* Volume 22, pp. 1121-1132.

Karekezi, S. .. & Kithyoma, W., 2- 4 June, 2003. *RENEWABLE ENERGY DEVELOPMENT.* Novotel, Dakar, Senegal, AFREPREN, pp. 1-30.

Katharine, C. K. & Jason, C. N., 2014. Estimates of Aboveground Biomass from Texture Analysis of Landsat Imagery. *Remote Sensing,* Volume 6, pp. 6407-6422.

Kelbe, D., 2010. *Towards Scale-Invariant Aboveground Biomass Estimation in Savanna Ecosystems Using Small-Footprint Waveform Lidar,* United States of America: s.n.

Ketterings, Q. M. .. et al., 2001. "Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests,". *Forest Ecology and Management,* 146(1–3), p. 199–209.

Klinge, H. & Herrera, R., 1983. "Phytomass structure of natural plant communities on spodosols in southern Venezuela: the tall Amazon Caatinga forest,". *Vegetation,* 53(2), p. 65–84.

Kumar, L., Sinha, P., Taylor, S. & Alqurashi, A. F., June 16, 2015. Review of the use of remote sensing for biomass estimation to support renewable energy generation. *Journal of Applied Remote Sensing,* 9(1), pp. 1-19.

Lambert, M. C., Ung, C. H. & Raulier, F., 2005. “Canadian national tree aboveground biomass equations,”. *Canadian Journal of Forestry Resources,* 35(8), p. 1996–2018.

Lefsky, M. A., 2002. “Lidar remote sensing for ecosystem studies: lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes. *BioScience,* 52(1), p. 19–30.

Lefsky, M. et al., 2001. Lidar remote sensing of above-ground biomass in three biomes.. *Global Ecology and Biogeography ,* 11(1), pp. 393-399.

Lewandowski, I. & Weger, J., 2006. "The Potential Biomass for Energy Production in the Czech Republic.". *Biomass and Bioenergy ,* 30(5), pp. 405-421.

Liang, T. & Khan, M. A., 1996. "Spatial and Temporal Effects in Drying Biomass for Energy.". *Biomass and Bioenergy ,* 10(5-6), pp. 353-360.

Lim, K., 2003. “LiDAR remote sensing of forest structure,”. *Prog. Phys. Geogr.,* 27(1), p. 88–106.

Li, X., 2005. "Diversification and Localization of Energy Systems for Sustainable Development and Energy Security.". *Energy Policy,* 33(1), pp. 2237-2243.

Li, X. & Yeh, A. G.-o., 2005. "Integration of Genetic Algorithms and GIS for Optimal Locaiton Search.". *International Journal of Geographical Information Science ,* 19(5), pp. 581-601.

Lucas, R. M., 2010. Ecosystem Function in Savannas Measurement and Modeling at Landscape to Global Scales. In: M. J. Hill & N. P. Hanan, eds. *“Quantifying carbon in savannas,”.* 2nd Edition ed. Boca Raton, Florida: CRC Press, p. 155–174.

Lu, D., 2006. The potential and challenge of remote sensing-based biomass estimation.. *International Journal of Remote Sensing ,* 27(1), pp. 1297-1328..

Lu, D., 2005. Abovegrund biomass estimation using Landsat TM data in the Brazilian Amazon.. *International Journal of Remote Sensing ,* 26(1), pp. 2509-2525..

Madlener, R., 2001. *How to Maintain Competition and Diversity? A Socio-Ecological Economic Assessemtn of Bioerngy Options with a Focus on CHP..* Alberta,Canada, Centre for Energy Policy and Economics.

Malczeweski, J. & Jackson, M., 2000. Multicriteria spatial allocation of educational resources: an overview.. *Socio-Economic Planning Sciences ,* Volume 34, p. 219–235.

Malczewski, J., 1999. *GIS and Multicriteria Decision Analysis.* 2nd Edition ed. USA/Canada.: John Wiley & Sons.

Martinot, E. et al., 2002. Renewable Energy Markets in Developing Countries. *Environment and Resources,* 27(1), pp. 309-348.

Maynard, C., Lawrence, R., Nielsen, G. & Decker, G., 2007. Modeling vegetation amount using bandwise regression and ecological site descriptions as an alternative to vegetation indices. *GIScience and Remote Sensing,* 44(1), pp. 68-81.

McGlinchy, J., 2014. “Extracting structural vegetation components from small-footprint waveform lidar for biomass estimation in savanna ecosystems,”. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.,* 7(2), p. 480–490.

McKendry, P., 2002. "Energy Production From Biomass (Part 3): Overview of Biomass.". *Bioresource Technology,* Volume 83, pp. 55-63..

Mellqvist, F. & Palm, L., 1996. Co-generation of Power and Heat from Sawmills in Zimbabwe. *Rural Energy for Development,* 9(3-4).

Mena, C., Gajardo, J. & Ormazábal, Y., 2006. Modelación espacial mediante geomática y evaluación multicriterio para la ordenación territorial.. *Revista de la Facultad de Ingenieros. Universidad de Tarapacá,* 14(1), p. 81–89.

Mirchandani, P. & Francis, R., 1990. *Discrete Location Theory.* 2nd ed. s.l.:Wiley Publishers.

Mirik, M., 2013. “Evaluating biomass of juniper trees (Juniperus pinchotii) from imageryderived canopy area using the support vector machine classifier. *Adv. Remote Sens.,* 2(2), p. 181–192.

Mirik, M. & Ansley, R. J., 2012. “Utility of satellite and aerial images for quantification of canopy cover and infilling rates of the invasive woody species honey mesquite (Prosopis glandulosa) on rangeland,”. *Remote Sens.,* 4(7), p. 1947–1962.

Mitchell, C., 2000. Development of decision support systems for bioenergy applications. *Biomass and Bioenergy ,* Volume 18, p. 265–278.

Moghaddam, M., Dungan, J. & Acker, S., 2002. Forest variable estimation from fusion of SAR and multispectral optical data.. *IEEE Transactions on Geoscience and Remote Sensing,* Volume 40, p. 2176–2187.

Moller, B. & Nielsen, P. S., 2007. "Analysing Transport Costs of Danish Forest Wood Chip Resources by Means of Continuous Cost Surfaces.". *Biomass and Bioenergy ,* Volume 31, pp. 291-298.

Montès, N. et al., 2000. A nondestructive method for estimating above-ground forest biomassin threatened woodlands.. *Forestry Ecology and Management,* 130(1), pp. 37-46.

Munier, N., 2004. *Multicriteria Environmental Assessment,* The Netherlands: Kluwer Academic Publisher.

Munier, N., 2004. *Multicriteria Environmental Assessment. A Practical Guide.* Dordrecht: Kluver Academic Publishers.

Murali, K. S., Bhat, D. M. & Ravindranath, N. H., 2005. “Biomass estimation equations for tropical deciduous and evergreen forests,”. *Int. J. Agric. Resour. Governance Ecol.,* 4(1), p. 81–92.

Navár, J., 2009. Allometric equations for tree species and carbon stocks for forests of Northwestern Mexico.. *Forest Ecology and Management ,* 257(1), pp. 427-434.

Nelson, B. et al., 1999. Allometric regressions for improved estimate of secondary forest biomass in the Central Amazon.. *Forest Ecology and Management ,* 117(1), pp. 149-167.

Nelson, R., Kimes, D., Salas, W. & and Routhier, M., 2000. Secondary forest age and tropical forest biomass estimation using Thematic Mapper imagery.. *Bioscience,* Volume 50, p. 419–431.

Nelson, R., Krabill, W. & Tonelli, J., 1988. Estimating forest biomass and volume using airborne laser data.. *Remote Sensing of Environment ,* 24(1), pp. 247-267..

Noon, C. E. & Graham, R. L., 1996. *Transporation and Site Location Analysis for Region Integrated Biomass Assessment (RIBA)..* Nashville, Tennessee., s.n.

Omasa, K. et al., 2003. Accurate Estimation of forest carbon stocks by 3-D remote sensing of individual trees.. *Environmental Science and Technology ,* 37: (1), pp. 1198-1201..

Oswalt, S., Smith, W., Miles, P. & Pugh, S., 2014. *Forest Resources of the United States, 2012.,* Washington, DC: U.S. Department of Agriculture, Forest: Gen. Tech. Rep. WO-xxx (Review Draft).

Panichelli, L. & Gnansounou, E., 2008. GIS-based approach for defining bioenergy facilities location: A case study in Northern Spain based on marginal delivery costs and resources competition between facilities.. *Biomass and Bio-energy,* 32(1), p. 289 – 300.

Paradzayi, C. & Annegarn, H., 2012. Polarimetric Synthetic Aperture Radar (POLSAR) Above Ground Biomass Estimation in Communal African Savanna Woodlands. *International Journal of Applied Geospatial Research,* 3(1), pp. 53-62.

Patel, N., Saxena, R. & Shiwalkar, A., 2007. Study of fractional vegetation cover using high spectral resolution data. *Journal of the Indian Society of Remote Sensing,* Volume 35, pp. 73-79.

Patenaude, G., 2004. “Quantifying forest above ground carbon content using LiDAR remote sensing. ” *Remote Sens. Environ.,* 93(3), p. 368–380.

Patenaude, G., Milne, R. & Dawson, T., 2005. Synthesis of Remote Sensing Approaches for forest Carbon Estimation: Reporting to the Kyoto Protocol. *Environmental Science and Policy,* 8(2), pp. 161-178.

Popescu, S., 2007. Estimating biomass of individual pine trees using airborne idar.. *Biomass and Bioenergy ,* 31(1), pp. 646-655..

ProBEC., 2006. [Online]
Available at: http://www.probec.org
[Accessed 03 09 2016].

Rahman, A., Gamon, J., Sims, D. & Schmidts, M., 2003. Optimum pixel size for hyperspectral studies of ecosystem function in southern California chaparral and grassland. *Remote Sensing of Environment,* Volume 84, pp. 192-207.

Rahman, S.-u. & Smith, D. K., 2000. "Use of Location-Allocation Models in Health Service Development Planning in Developing Nations.". *European Journal of Operational Research,* Volume 123, pp. 437-452.

Ramachandra, T. V., 2007. Solar energy potential assessment using GIS. *Energy Education Science and Technology ,* 18(2), pp. 101-114.

Ravindranath, N. & Ostwald, M., 2008. Methods for estimating above-ground biomass.. In: *Carbon Inventory Methods:Handbook for greenhouse gas inventory, carbon mitigation and roundwood production projects..* s.l.:Springer Science + Business Media B.V, pp. 113-14..

Ritchie, J. & Lewis, J., 2003. *Qualitative Research Practice.* 3rd ed. London EC2A4PU: SAGE Publications Ltd.

Rosenqvist, A., Antony, L., Richard, I. & Mark Dobson, C., 2003. A review of Remote Sensing Technology in Support of the Kyoto Protocol. *Environmental Science and Policy,* 6(5), pp. 441-455.

Rowe, R. L. & Street, N. R., 2007. *"Identifying Potential Environmental Impacts of Large-Scale Deployment of Dedicated Bioenergy Crops in the UK.",* s.l.: ONLINE PUBLICATION (DOI:10.1016/J.RSER.2007.07.008)..

Rutledge, D. et al., 2008. Choosing regional futures: challenges and choices in building integrated models to support long-term regional planning in New Zealand.. *Regional Science Policy & Practice ,* 1(1), pp. 85-108.

Saatchi, S., 2011. "Impact of spatial variability of tropical forest structure on radar estimation of aboveground biomass,". *Remote Sens. Environ.,* 115(11), p. 2836–2849.

Saaty, T. & Kearns, K., 1985. *Analytical Planning; The Organization of Systems.* 2nd Edition ed. Oxford: Pergamon Press.

Saltelli, A., Chan, K. & Scott, E., 2000. *Sensitivity Analysis..* 12th Edition ed. Chichester.: John Wiley & Sons.

Saremi, H., 2014. "Sub-compartment variation in tree height, stem diameter and stocking in a Pinus radiata D. Don plantation examined using airborne LiDAR data,". *Remote Sensing,* 6(8), p. 7592–7609.

Sarker, L. & Nicho, J., 2011. Improved forest biomass estimates using ALOS AVNIR-2 texture indices.. *Remote Sensing of Environment ,* 115(1), pp. 968-977..

Sarkis, J., Meade, L. & Presley, A., 2008. *"Sustainability in the Built Environment: Factors and a Decision Framework".* [Online]

Available at: http://www.decisionsciences.org/Proceedings/DSI2008/docs/258-7433.pdf
[Accessed 9 October 2016].

Saunders, M., Lewis, P. & A., T., 2009. *Research methods for business students.* 5th ed ed. Harlow: Pearson Education.

Sawin, J. L. & Martinot, E., 2010. *RENEWABLES 2010 GLOBAL STATUS REPORT,* Paris: Paris: REN21 Secretariat.

Sawin, J. L. & Sverrisson, F., 2014. *REN21's Renewables 2014 Global Status Report ,* Paris, France: REN21 Secretariat.

Schlerf, M., Alzberger, C. & Hill, J., 2005. Remote sensing of forest biophysical variables using HyMap imaging spectrometer data. *Remote Sensing of Environment,* 95(2005), pp. 177-194.

Sebukeera, C., Muramira, E., Momokama, C. & Elkholei, A., 2006. *Chapter 6: Forest and Woodlands,* s.l.: UNEP Africa Environment Outlook 2.

Segura, M. & Kanninen, M., 2005. Allometric models for tree volume and total aboveground biomass in a tropical humid forest in Costa Rica.. *Biotropica ,* 37(1), pp. 2-8.

Shidiq, I. P. A. & Mohd, H. I., 2016. Stand age model for mapping the spatial distribution of Rubber trees using Remotely Sensed data. *Jurnal Teknologi (Sciences & Engineering),* 78(5), p. 239–244.

Simon, H. A., 1960. *The new science of management decision.* 2nd Edition ed. New Jersey: Englewood Cliffs.

Smil, V., 2000. "Energy in the Twentieth Century: Resources, Conversions, Costs, Uses, and Consequences.". *Annual Review of Energy and Environment,* 25(1), pp. 25-51.

Steininger, M., 2000. Satellite estimation of tropical secondary forest aboveground biomass data from Brazil and Bolivia.. *International Journal of Remote Sensing ,* 21(1), pp. 1139-1157..

Stover, D., 2011. *Bulletin of Atomic Scientists.* [Online]
Available at: http://www.thebulletin.org/myth-renewable-energy
[Accessed 17 08 2016].

Sugumaran, R. & Degroote, J., 2011. *Spatial Decision Support Systems: Principles and Practices.* 1st ed. London, New York: CRS Press.

Sumathi, V., Natesan, U. & Sarkar, C., 2008. GIS-based approach for optimized siting of municipal solid waste landfill. *Waste Management,* Volume 28, p. 2146–2160.

Swezey, B. G. & Porter, K. L., 1995. "The Potential Impact of Externalities Considerations on the Market for Biomass Power Technologies.". *Biomass & Bioenergy ,* 8(4), pp. 207-220.

Thomas, V., 2006. “Mapping stand-level forest biophysical variables for a mixed wood boreal forest using lidar: an examination of scanning density,”. *Canadian Journal For Remote Sensing,* 36(1), p. 34–47.

Todd, K. W., Csillag, F. & Atkinson, P. M., 2003. “Three-dimensional mapping of light transmittance and foliage distribution using lidar,”. *Canadian Journal of Remote Sensing,* 29(5), p. 544–555.

Toriro, P., 2007. “Town Planning in Zimbabwe: History, Challenges and the Urban Renewal Operation Murambatsvina. In: K. K. C. S. Chapter 11 in Maphosa F, ed. *Zimbabwe's Development Experiences since 1980: Challenges and Prospects for the Future.* Addis Ababa: OSSREA.

Tremeer, G. B., 2007. *Opportunities for Biomass Energy Programmes - Experiences and Lessons Learned by UNDP in Europe and the CIS..* London, UNDP, p. 94.

Uran, O. & Janssen, R., 2003. Why are spatial decision support systems not used? Some experiences from the Netherlands.. *Computers, Environment and Urban Systems .,* 27(5), p. 511–526.

Van Delden, H., 2009. *Lessons learnt in the development, implementation, and use of integrated spatial decision support systems..* Cairns, Australia., s.n.

Venema, H., 2004. *An Ecosystem Approach to Climate Policy : the Role of Rural Renewable Energy Design,* s.l.: Systems Design Engineering..

Venema, H. D. & Calamai, P., 2000. "Multi-Objective Spatial Design Principles for Rural Biomass Energy Planning.". *Journal of Environmenatl Studies and Policy ,* 3(1), pp. 1-19.

Venema, H. D. & Calamai, P. H., 2003. "Bioenergy Systems Planning Using Location-Allocation and Landscape Ecology Design Principles.". *Annals of Operations Research,* 123(1-4), pp. 241-264..

Vincent, V. & Thomas, R., 2013. *An agricultural survey of Southern Rhodesia: Part I: agro-ecological survey.,* Salisbury: Government Printer.

Voivontas, D., 1998. Evaluation of renewable energy potential using GIS decision support system.. *Renewable Energy,* Volume 13, p. 333–344.

Voivontas, D. D., . Assimacopoulos, D. & Koukios, E., 2001. "Assessment of Biomass Potential for Power Production: a GIS Based Method.". *Biomass and Bioenergy,* 20(2), pp. 101-112..

Von Maltitz, G. P. & Scholes, R. J., 1995. The burning of fuelwood in South Africa: When is it sustainable?. *Environmental Monitoring and Assessment,* 38(1), pp. 243-251.

Vonk, G., Geertman, S. & Schot, P., 2005. Bottlenecks blocking widespread usage of planning support systems.. *Environment and Planning ,* Volume 37, p. 909–924.

Wallerman, J., 2010. *“Forest mapping using 3D data from SPOT-5 HRS and Z/I DMC,”.* s.l., s.n., p. 64–67.

Wang, L. & Cheng, Q., 2006. *Web-based collaborative decision support services:Concept, challenges and application..* Vienna., s.n.

Warren, C., Lumsden, C., O'Dowd, S. & Birnie, R., 2005. Green on green: public perceptions of wind power in Scotland and Ireland.. *Journal of Environmental Planning and Management,* 48(6), p. 853–875..

Williams, R., 2000. *"Environmental Planning for Sustainable Urban Development".* Trinidad, s.n.

Wu, W. P. & Helldén, U., 2013. Assessing woody biomass in African tropical savannahs by multiscale remote sensing.. *International Journal of Remote Sensing,* Volume 34, pp. 4525-4549.

Xiao, N., 2007. *Considering diversity in spatial decision support systems..* Ireland., s.n.

Xie, Y., 2009. "A comparison of two models with Landsat data for estimating above ground grassland biomass in Inner Mongolia, China,". *Ecol. Model.,* 220(15), p. 1810–1818.

Zhao, K., Popescu, S. & Nelson, R., 2009. "Lidar remote sensing of forest biomass: a scaleinvariant estimation approach using airborne lasers,". *Remote Sensing of the Environment,* 113(1), p. 182–196.

Zheng, D. et al., 2004. Estimating aboveground biomass using Landsat 7 ETM+ data across a managed landscape in northern Wisconsin, USA.. *Remote Sensing of Environment,* 93(3), pp. 402-411.

ZimAsset BluePrint Document, October 2013- December 2018. *Zimbabwe Agenda for Sustainable Socio-Economic Transformation (ZimAsset) - "Towards an Empowered Society and a Growing Economy",* Harare: Printflow.

Appendices

Annex 1 Unit Abbreviations

Unit abbreviations

bcm	billion cubic metres	**MBtu**	million British thermal units
Gcal	gigacalorie	**Mt**	million tonnes
GCV	gross calorific value	**Mtoe**	million tonnes of oil equivalent
GW	gigawatt	**MWh**	megawatt hour
GWh	gigawatt hour	**PPP**	purchasing power parity
kb/cd	thousand barrels per calendar day	**t**	metric ton = tonne = 1 000 kg
kcal	kilocalorie	**TJ**	terajoule
kg	kilogramme	**toe**	tonne of oil equivalent = 10^7 kcal
kJ	kilojoule	**TWh**	terawatt hour
kWh	kilowatt hour	**USD**	United States dollar

Figure 30: Unit Abbreviations

Annex 2 Python Code Snippet to perform Unsupervised Classification in ArcMap

```
# Name: IsoClusterUnsupervisedClassification_Ex_02.py
# Description: Uses an isodata clustering algorithm to determine the
#    characteristics of the natural groupings of cells in multidimensional
#    attribute space and stores the results in an output ASCII signature file.
# Requirements: Spatial Analyst Extension

# Import system modules
import arcpy
from arcpy import env
from arcpy.sa import *
```

```
# Set environment settings
env.workspace = "C:/arcgis/dissertation"

# Set local variables
inRaster = "Biomass"
classes = 6
minMembers = 50
sampInterval = 15

# Execute IsoCluster
outUnsupervised = IsoClusterUnsupervisedClassification(inRaster, classes, minMembers,
sampInterval)
outUnsupervised.save("c:/users/desktop/outunsupbiomass.tif"
```

ID	Class Name	Value	Color	Count
1	Forest	1		21990
2	Water	2		109
3	Grassland	3		2235
4	Agricultural	4		2357
5	Residential	5		13796
6	Commercial/Ind...	6		5296

Figure 31: Unsupervised Classification Results – Classes created