WIND RESOURCE POTENTIAL FOR ELECTRICITY GENERATION USING
MICRO - HYBRID SYSTEMS IN NORTHERN KENYA

By

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A Thesis Submitted in Partial Fulfilment of the Requirement for the award of the
Degree of Master of Environmental Science in the School of Environmental Studies of
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DECLARATION

This thesis is my original work and has not been presented for a degree in any other university or any other award.

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I dedicate this Research report to my late Mum (Wanjira Njiru) who inspired me to work hard in school for the fruits of education are always sweet and their taste lingers longer than short time pleasures.
ACKNOWLEDGEMENT

I am very grateful to my lecturers at Kenyatta University (KU) who modelled me to this level. Special thanks to my two supervisors Dr. G. Kirubi and Dr. E. Ndunda for standing on their very important and busy schedules to advice and guide this research to the final end.

I recognise the kind words of encouragements from by peers and work mates at the Institute for Meteorological Training and Research (IMTR) Nairobi, who always took time to enquire about the progress in my studies. Thank you very much.
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### ABBREVIATIONS & ACRONYMS

<table>
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<th>Description</th>
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<tbody>
<tr>
<td>CORDEX</td>
<td>Coordinated Regional Downscaling Experiment</td>
</tr>
<tr>
<td>CV</td>
<td>Coefficient of variability</td>
</tr>
<tr>
<td>ECMWF</td>
<td>European Centre for Medium Range Weather Forecasts</td>
</tr>
<tr>
<td>GCM</td>
<td>Global Circulation Model</td>
</tr>
<tr>
<td>GrADS</td>
<td>Grid Analysis and Display System</td>
</tr>
<tr>
<td>GW</td>
<td>Gigawatt</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>IPP</td>
<td>Independent Power Producers</td>
</tr>
<tr>
<td>KW</td>
<td>kilowatt</td>
</tr>
<tr>
<td>KWh</td>
<td>kilowatt hour</td>
</tr>
<tr>
<td>Mb</td>
<td>Milibar</td>
</tr>
<tr>
<td>ME&amp;P</td>
<td>Ministry of Energy and Petroleum</td>
</tr>
<tr>
<td>MSL</td>
<td>Mean Sea Level</td>
</tr>
<tr>
<td>MW</td>
<td>Megawatt</td>
</tr>
<tr>
<td>MWh</td>
<td>Megawatt hour</td>
</tr>
<tr>
<td>RCM</td>
<td>Regional Circulation Model</td>
</tr>
<tr>
<td>RCP</td>
<td>Representative Concentration Pathways</td>
</tr>
<tr>
<td>RE</td>
<td>Renewable Energy</td>
</tr>
<tr>
<td>DJF</td>
<td>December, January, February</td>
</tr>
<tr>
<td>MAM</td>
<td>March, April, May</td>
</tr>
<tr>
<td>JJA</td>
<td>June, July, August</td>
</tr>
<tr>
<td>SON</td>
<td>September, October, November</td>
</tr>
<tr>
<td>SEM</td>
<td>Standard Error of Mean</td>
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ABSTRACT

Currently the world is embracing renewable energy not only to enhance energy capacity but also to mitigate problems associated with greenhouse gas emissions. North eastern Kenya region lagged behind others parts of the republic in social economic indices. This may be attributed to the fast distance between the region and the electricity generation areas. Therefore northern Kenya is not connected to national electricity grid. Renewable energy from the wind can be used to supply electricity using off grid micro hybrid systems in the region. The study examined how variability in wind speeds may affect the potential for electricity generation using micro grid systems. The study therefore evaluated the spatial and temporal wind resource distribution, trends and the variability, assessed the electricity consumption per capita and the contribution of wind power resource to hybrid systems in the region. The study used the simulated model outputs extracted from Global Circulation Models (ECMWF-ERA) for winds at surface and 850mb level. Data period was from 1981-2015 for baseline with projections up to 2050. Other data considered were the electricity supply from the Kenya power company and the demographic totals for each of the five counties in the region sourced from the Kenya bureau of statistics Nairobi. The analyses were done using Grid Analysis and Display System, XLSTAT and SPSS. Findings indicated that region has good wind power potential to generate wind energy. Marsabit County had the highest long term mean wind velocity at 9m/s for the surface and 11m/s at the 850mb level. The models depicted wind speeds greater than the lowest wind speed (3-5m/s) that can be used to turn any rated turbine to generate useful wind energy. Data revealed low electrification rates with highest being 2.4% in Marsabit County where consumption was moderate at 556kWh per capita and the highest wind power density was 807W/m². Trend test posted p-values between 0.00 and 0.57 for 0.05 alpha. Mann Kendall test indicated positive but insignificant trends for baseline and projected winds up to 2050. The models also depicted low standard deviations at 0.22 - 0.46 with Coefficient of variation between 3.9 % - 5.8% for baseline and model projections. Thus study concluded that the northern Kenya regions have good wind power resource potential with low but insignificant long term mean wind speeds variability patterns. The seasonal wind patterns were intertwined with interseasonal and intraseasonal wind variability characteristics which influenced the distribution of the wind power resources across the region. However, June July August was the most dominant season compared to other seasons. The seasonal wind variability patterns were therefore significant. HadGEM2 model correlated well with baseline data. The correlation coefficients were 0.5 for the surface and 0.9 for the upper level winds, therefore modelling could be a better method for simulating winds for the region. The study recommended to both the national and the county governments to take advantage of good wind power potentials to put up wind farms to generate electricity using off grid micro grid systems. This will increase electricity access and trigger the much needed social and economic growth and development for people in the region.
CHAPTER ONE: INTRODUCTION

1.1 Background to the study

Renewable energy from the wind is probably one of the cheapest and the cleanest sources of energy today providing an alternative to conventional forms of energy (Kiariie, 2013). Provision of clean, reliable and affordable energy services is a strategy towards eradication of poverty and for community development (Kammen et al., 2015). Studies have identified renewable energy from the wind as an important component for electricity energy generation, and this potential is fairly distributed in Kenya (Kammen et al., 2015; Lukuyu & Cardel, 2014; Kiariie, 2013; Oludhe, 2008). This potential has been targeted to address challenges associated with limited electricity energy access locally with the goal to achieving sustainable universal electricity access by the year 2030 (MoEP, 2015).

Currently most governments in the developing world are targeting electrification as an important process that can help achieve national economic and social goals (Crousillat, Hamilton & Antmann, 2014). The study focused on use of renewable energy from the wind to reduce energy poverty by increasing electricity energy access in northern Kenya.

World over, enhanced upscale in wind power portfolio could be attributed to the economic advantages of wind as a resource compared to conventional energy sources (Valentine, 2011). Renewable energy resources are mitigating the risks associated with greenhouse gases (GHGs) emissions and acts as alternative sources of energy to exhaustible fossil fuels (Poudyay et al., 2012). More significantly, investments in renewable energy from the wind continue to grow probably due to the growing energy demand and lack of accessibility in marginalized areas and most importantly need for clean energy (Alstone, 2015; Akella, Saini, & Sharma, 2009). There are indicators that renewable energy can provide close to 77% of global primary energy supply with a potential to reduce carbon dioxide (CO₂)
emissions from 560Gigatonnes(Gt) to 220Gt (IPCC, 2013). Studies have shown that
developed nations are embracing renewable energy more than the developing countries
where energy poverty is most prominent (Sahu, Hiloidhari, & Baruah, 2013). Statistics
show electrification rate in sub Saharan Africa (SSA) was 28.5% compared to 98.9% in
northern Africa, 92.7% in Latin America and averaged at 72% in most developing
countries (Crousillat et al., 2014). Notably Egypt, Morocco and Tunisia were the only
nations in SSA that made substantial investments at 550MW translating to 95% share of
Africa’s’ installed wind capacity (Kammen et al., 2015). At the same time Kenya had
installed a 5MW wind power farm in Ngong’ with plans underway for construction of the
biggest wind farm in Africa, the 300MW Turkana wind farm in Marsabit County (Kammen
et al., 2015; Newell et al., 2014; Sahul et al., 2013). Completion of this project will greatly
contribute to local electricity access equation based on the renewable energy systems.

One of the impediments to scaling up investments in electrification in Kenya and the SSA
at large could be due to lack of sufficient financial and technological capacity (Kammen et
al., 2015). In particular challenges to grid extension to rural areas have been identified as
due to dispersed rural population, low purchasing power and high connectivity fee (MoEP,
2014; Yadoo & Cruickshank, 2012; Kirubi et al., 2009). Yet in Kiplagat et al. (2011),
Kenya spends substantial amounts of foreign income earnings to import petroleum products
to fuel the economy. This erodes the local capacity for investment in alternative energy
systems and also compromises the low carbon policy in energy development (Newell et al.,
2014; MoEP, 2014). Renewable energy from the wind can be used to mitigate GHG
emissions and more so provide a leap towards achieving universal electricity energy access.
Already Kenya has a strategic plan to generate a mix of 5000MW in forty (40) months, of
which 61% was expected to be generated from renewable energy sources (Kammen et al.,
2015; MoEP, 2014). Policy framework to move this project included the Feed in Tariff (FiT) policy and the affirmative budget allocations to the energy sector (Marques and Fuinhas, 2012). Other strategies towards local electrification includes the last mile connectivity strategy including research on suitable renewable energy resources that could be used to provide critical base load to mitigate use of fossil fuels (MoEP, 2013). There were many wind power projects planned in Kenya and intended to bridge the local electricity energy gap (MoEP, 2013; Newell et al., 2014). However, renewable energy from the wind can be influenced by climate variations. Climate variability may have direct effects on supply, demand and the distribution of wind energy resource (IPCC, 2011; Pryor, Barthelmie, & Kjellström, 2005; McInnes et al., 2011; Jury, 2013; Graabak et al., 2016).

Variability in the wind would therefore affect the power output from a rated wind turbine designed to operate with steady wind speeds as shown in Figure 1 below. Figure 1 depicts the minimum wind speed of (2 - 4m/s) when a wind turbine commences to output usable wind power also called the cut in speed. For any wind turbine, wind power generation is optimized at a limit called the rated output power or the rated output speed. The rated output wind speed could fall anywhere between 12 -17m/s and the point of cut out speed is 25m/s, being the wind speed when the wind turbine locks itself to avoid destruction by high winds (Kong et al., 2014). High variability in the wind may lead to breakages with implications to both the investor and the consumer. Variability can be studied in hourly, diurnal, seasonal & spatial characteristics (Graabak et al., 2016). Long term wind resource variability is associated with global climate patterns. The IPCC (2011) warned that the impacts of GHG emissions and global warming may alter future climate patterns with direct effect on wind energy resource. Climate variability also influences the base load and design capacity for wind farms (Bilal et al., 2011).
The study therefore assessed the temporal and the spatial wind speeds variability patterns in the north eastern Kenya regions. Knowledge on local wind patterns forms a crucial component for predictability of future wind characteristics and design technology for wind farms (Greene, Morrissey & Johnson, 2010; Graabak et al., 2016). In fact, Diamond (2011) warned that wind farm developers may have blind expectations of turbine outputs if they were not aware of future wind characteristics. Variability in wind patterns are not isolated from global synoptic systems hence the use of global climate models (GCMs) that are able to capture the present and simulate the future wind resource characteristics to inform the development of wind power systems (Foley et al., 2012; Kong et al., 2014; Graabak et al., 2016).

Figure 1: Typical wind turbine power output with steady wind speed

Source: Wind-power-program.com/turbine characteristics.htm, last accessed on 14/04/2017
1.2 Statement of the Problem

From the ministry of energy and petroleum (MoEP), rural electricity energy access in Kenya was 22% out of 88% strategic target by 2030 (GoK, 2009). Penetration rate stood at 30% in high density urban areas and 10% in other areas despite the fact that 94% of households lived within and adjacent to the electricity grid lines. A recent study showed that Kenya’s economy was projected to be growing at more than 5% per annum (Kammen et al., 2015). However this development record was backed mainly by the 29% of electricity grid connected population in Kenya. Northern Kenya experiences energy isolation barriers identified by Bazilian; Nussbaumer et al. (2010) as attributed to multiple dimensions of geographic remoteness, economic and political stresses and long transmission distances with diffuse population. Thus, the region is currently not connected to national electricity grid. Locally electricity supply comes from thermal plants restricted mainly to the major urban centres like Garissa, Wajir, Mandera and Marsabit. Majority of the local households depend on Kerosene and biofuels predominantly firewood and charcoal which degrades the environment. Essential services in hospitals, communications, security, education and private enterprises that require electricity connection are scarce due to limited electricity access. Population within the villages suffer from chronic health issues associated to persistent indoor pollution from use of kerosene and bio fuels. Social insecurity and conflict of resources like water and pastures are common due to lack of alternative sources of livelihoods. New avenues for employment and business opportunities could easily be unlocked by the now lacking equitable electricity energy access. There are glaring social economic disparities between people living in urban areas compared to rural dwellers in the region. This is mainly due to lack of electricity connection to the rural people.
Studies have shown that there exists a link between the Human Development Index (HDI) and access to modern energy supply (Kammen et al., 2015; UNDP, 2005). Lack of electricity connection to the region may be due to distances to the grid connected areas. However, the region has potential for renewable energy from the wind and solar (Theuri & Hamlin, 2008; Oludhe, 2008; Lukuyu & Cardell, 2014). These could be used to mitigate problems of limited electricity energy access through development of off grid micro hybrid systems for electricity generation in attempt to meet the local demand.

1.3 Research questions

The study focused on three main research questions listed below;

(1) How does past and future variability in wind speeds affect the distribution and potential for wind energy generation in north eastern Kenya?

(2) What is the current electricity energy consumption per capita in the north eastern Kenya regions and to what extent can this demand be met using the available wind energy resource?

(3) What is the contribution of renewable energy resources to a typical hybrid system in the north eastern Kenya region and how does this resource mix influence energy supply reliability to local users?
1.4 Research Objectives

The main objective was to assess the variability of the wind resource potential and how this may affect electricity generation using micro hybrid systems in northern Kenya.

1.4.1 Specific objectives

(1) To analyze the spatial and temporal characteristics for wind resource (speeds) using the GCM/RCM simulated data and baseline data.

(2) To determine current electricity energy consumption per capita and assess the ability of available wind energy resource to supply this demand in northern Kenya.

(3) To assess the renewable energy resource contribution to hybrid systems using data for Merti, Habasweni and Marsabit hybrid power generation stations and evaluate the energy reliability given use of renewable energy components.

1.5 Research hypotheses

This study will be guided by the following hypotheses.

(1) Spatial and temporal wind resource (speeds- m/s) variability significantly affects the wind energy generation in northern eastern Kenya.

(2) There is significant wind resource potential (m/s) to meet the growing electricity energy demand in northern eastern Kenya.

(3) Hybrid electric micro grid systems can significantly improve electricity energy access and improve electricity energy reliability in northern Kenya.
1.6 Conceptual Framework

The conceptual model in Figure 2 shows that it is possible to increase electricity energy access in north eastern Kenya. Independent variables were the availability of the wind resource potential (m/s) and the spatial and temporal variability of the same, the electricity demand patterns and the type of technology applicable to convert the power from the wind. The intervening variables were based on factors that would influence investment in wind energy generation. These include the government policies on renewable energy development, availability of investment capital and the local demographic potential. Indicators for dependent variables considered were the development of off-grid micro systems for increased electricity energy access, increased electricity consumption per capita, energy security and sustainable development. Wind power resource availability and potential, coupled with spatial and temporal distribution of the same uniquely influences the technology for electricity generation using off-grid hybrid systems. Hybrid systems would mitigate the wind variability by ensuring a continuous supply of the base load required for the target population. Hence the issue of limited electricity energy access will be addressed and households will be able to enjoy a clean, cheap and reliable electricity supply.
1.7 Justification of the study

More than fifty years after independence Upper Eastern and North Eastern Kenya remains under developed in terms of infrastructure and other social economic amenities compared to other areas in the republic. Although this region lies in the arid and semi arid (ASAL) areas, it still is a beacon of opportunity with potential for renewable energy harvesting, mining, irrigation agriculture, ranching, tourism, resorts cities and industrial parks. However, this potential remains untapped mainly due to lack of local capacity to roll out renewable energy projects in the area. Several studies have been conducted on how to harness renewable energy potential in the region (Oludhe, 2008; Theuri & Hamlin, 2008;
Lukuyu & Cardell, 2014). Researchers focused on northern eastern Kenya probably after noting the challenges of integrating the region with the conventionally generated electricity from the other parts of the country (Crousillat et al., 2014) and mainly because there is potential for renewable energy within the region. However none of these studies dwelt on effects of wind resource variability on potential for electricity generation. The study therefore assessed the distribution of wind resource potentials based on the fact that assessment of wind speeds is critical to the wind turbine design and site planning even in estimation of energy production (Masseran, Razali & Ibrahim, 2012; Meyer & Odeku, 2009). The wind power resource varies from year to year or day to day hence the importance of evaluating the long-term averages of wind speed and direction in order to estimate the power output from a given site (Oludhe, 2008).

The wind speeds were analyzed at two levels, surface wind measured at 10m vertically above the topographic surface and the upper level winds simulated at 1500m or (850mb level) above mean sea level (MSL). The 1500m above MSL is meteorologically taken to be the lowest level where winds flow freely without interference from surface features in the atmospheric boundary layer. The rationale to visualize wind at two levels was to find out whether patterns observed near the surface could also be traced at higher elevations (Greene et al., 2010). This would give a signal to the best locations for sitting wind turbines given that wind speeds increases with height. Study also sought to assess the current electrification levels in the study area. So that knowledge of the current power supply per capita and the level of electrification would inform key decisions on priority areas for putting up off grid micro grid systems. At the same time, assessment of the contribution of the wind power to current electricity supply in the region was to show that integration of
the wind power resource could be used to mitigate problems of limited electricity access in
the region.

1.8 Significance of the study

Electricity supply in the study area is currently generated using thermal diesel generators
restricted mainly within the urban centres at Garissa, Wajir, Marsabit, Mandera and Merti
town in Isiolo. Thermal generation is expensive and may have implications on
environmental pollution associated with release of green house gases (GHGs). Analysis of
wind flow characteristic in northern Kenya availed tangible information required by policy
makers and investors on wind energy generation. At the same time study findings not only
provide reference materials on wind resource variability in the region but also act as an
indicator towards the identification of ideal locations for construction of off-grid wind
farms. Finally knowledge of the local wind resource variability provides basis to inform
decisions on best technology to adopt for wind energy generation in the north eastern
Kenya region.
CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of past studies relevant to the current research topic. The review follows thematic issues related to the objectives of the study. Literature review basically tried to establish knowledge gaps and at the same time define terms used in the research.

2.2 Assessment of wind resource characteristics using GCM outputs and baseline data.

In the assessment of wind energy resource distribution Oludhe (2008), employed the fitting Weibull frequency distribution method and observed surface wind data for wind power potentials in Kenya. Marsabit region depicted the highest wind power potential of about 1000W/m$^2$ backed by mean wind speeds between 10m/s - 11m/s. A similar study in Senegal showed that wind power densities available were greater during dry season than in the rainy seasons (Bilal et al., 2011). While Choge et al. (2013), using power law found potential for wind power averaging between 70W/m$^2$ to 107.5W/m$^2$ by simulation of wind speeds and densities from surface to 40m heights in Uashin Gishu County, Kenya. The findings were consistent to assertions in Kubik et al. (2011), that the most important level is the hub height where the turbines harvest the wind energy.

In another study Fant and Schlosser (2012) used 19 Global Circulation Models (GCMs) to simulate the wind and solar resource flow for southern African region up to 2050. Most models showed slight changes in wind energy potential by 2050. Also Pryor et al., (2005) conducted a study on the effects of climate change on wind speeds and wind energy production in 2071-2100 over northern Europe.
Based on emission scenarios A2 and B2, study found evidence of a small increase in annual wind energy resource over northern Europe with a significant increase in energy density during winter seasons. Study by other researchers showed that downscaling of climate models could be used to simulate wind speeds at finer scales. That climate models can be used for prediction of wind power patterns to assess the wind resource variability at different timescales including local, regional and global scales (Bloom et al., 2008; Foley et al., 2012). In fact Foley et al. (2012) discussed the wind speed and wind power forecasting techniques using Numerical Weather Prediction (NWP) and the use of different climate models including methods for benchmarking and the uncertainty analysis to validate individual model out puts. While Kubik et al. (2011) noted that resource assessments play an integral part in planning, managing electricity-energy markets, infrastructure designs and the optimization of cost effectiveness. In a recent study Carta, Cabrera & Matias (2015) used the Measure-Correlate-Predict (MCP) method to come up with wind resource predictions using reference data from different weather stations. Results showed good correlations in filter based approach (FA) compared to other techniques employed for data manipulations. Further in Valentine (2011), some three qualities seen to have sizeable influence on wind power costs were identified as the overall wind speeds, consistency of the wind speeds and wind directions. Wind speeds affect the rotor speed; therefore this dictates the optimal size of wind turbines to be deployed in a certain area. The study noted that wind varies with time and sudden variations in wind speed and directions may damage the power systems. That is why in Hernandaz-Escobedo et al. (2014), spatial and temporal wind resource assessment was recommended as the initial stage in the wind generation projects. Therefore, the need for studies based on average wind speeds to investigate the wind speed distribution patterns for generation of wind power electricity.
2.3 Global Circulation Model (GCM)

The GCM is a mathematical model that incorporates several atmospheric processes based on physical and thermodynamic exchanges in the environment. The dynamic nature of climate models employs several equations as a basis for complex computer programs and statistical packages used for simulating the global climate (Foley et al., 2012). GCMs therefore mimic the dynamics of how solar radiation, the atmosphere, land and oceans interact to generate weather and climate. The model assimilates point data from observing stations together with satellite observations coupled with ocean and sea-ice models. This enables the simulation or forecasting (Numerical Weather Prediction-NWP) of global climate parameters at grid points from surface to upper levels (Foley et al., 2012). Model data have an advantage for it was possible to analyse output wind speeds at finer spatial details and at different heights as opposed to surface observations (Bloom et al., 2008). It was also possible to simulate future predictions of the wind resource distribution and potential. However GCM outputs are coarse with resolutions running between 100kms to 400kms hence not able to capture sufficient details on topography and local scales. This resolution gap was closed by use of GCM outputs as boundary conditions for RCMs and their ensemble average to simulate climate datasets with higher spatial resolutions (Giorgi and Mearns, 1999; Bloom et al. 2008; Nikulin et al., 2012). Therefore able to simulate weather and climate at finer scales up to 7 km or less. The following are important equations used by GCMs.
Conservation of momentum; \[ \frac{Dv}{Dt} = -2\Omega \times v - \rho^{-1} \nabla p + \mathbf{g} + \mathbf{F} \] ................. (i)

Conservation of mass; \[ \frac{D\rho}{Dt} = -\rho \nabla \cdot v + C - E \] ......................... (ii)

Conservation of energy; \[ \frac{DI}{Dt} = -P \frac{\partial \rho^{-1}}{\partial t} + Q \] ......................... (iii)

Ideal gas law; \[ P = \rho RT \] ................................................................. (iv)

Where:

- \( D \) = Total time derivative, \( t \) = time,
- \( \Omega \) = Angular Velocity of the earth,
- \( v \) = Velocity relative to the rotating earth,
- \( \rho \) = Atmospheric density,
- \( \nabla \) = Del operator,
- \( P \) = Atmospheric pressure,
- \( g \) = Apparent gravitational acceleration,
- \( Q \) = Heating rate per unit mass

- \( F \) = Friction, \( R \) = Gas constant,
- \( T \) = Temperature,
- \( C \) = Rate of creation of atmospheric constituents
- \( E \) = Rate of destruction of atmospheric constituents
- \( I \) = Internal energy per unit mass \((c_v T)\),
- \( c \) = Specific heat of air at constant volume

Sailor, Smith & Hart (2008) used GCMs to evaluate impact of climate change on wind speeds and wind power density. Results for Northwest United States showed that in summer time wind speeds may decrease by 5 - 10% in the next 50 – 100 years with insignificant changes in winter (Sailor et al., 2008). These results however noted that given that wind power density is a function of the cube of mean wind speeds projected decrease in the wind power density may be as high as 40%.

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In a similar work by Pryor and Barthelme (2010), results showed that natural variability exceeds the climate change signal in the wind energy resource and extreme wind speeds. This study observed indication of small changes in wind speeds and a slight increase in higher and extreme wind speed events in northern Europe. These studies however were not explicit on certainty of future wind speeds characteristics with respect to wind power generation. Therefore need for further studies to establish future patterns and trends in wind speeds and wind power density.

2.4 Equitable electricity energy access and distribution of renewable energy resources

Recent studies on the regional energy gap cite the developments of the East African Power Pool (EAPP) as a tool to eliminate energy poverty and limited electricity access in the region (Kammen et al., 2015). The researchers observed that in eastern Africa energy consumption per capita was less than 1000kWh with exception of Egypt. Therefore need to improve interconnectivity and distribution of power supply within the region. In a different study Bazilian et al. (2010) defined energy poverty in three levels. The basic human needs where electricity is only used for lighting, health, education, communication and community services with between 50 – 100kWh per capita. Energy poverty was also seen in the level of productive uses. Here electricity, modern fuels and other energy services are used to improve productivity in agriculture, transport and other industries. Finally the level of modern society needs. This applies to modern energy services for many more domestic appliances for cooling and heating services and private transportation to a tune of about 2000kWh per capita (Kammen et al., 2015).

Bhatia & Angelou (2015), suggested that energy access could be achieved through a variety of technologies. Hence measurement of energy access should be technologically neutral.
Therefore, energy poverty and electricity access gap may not be alleviated by focusing only on traditional methods of expanding the grid and investing in large centralized projects. Successful energy access requires a combination of institutional and technical considerations including other benchmarks. Such benchmarks include the human development index (HDI) and the Energy for Development Index (EDI). HDI combines wealth distribution, level of institutional development and size of urban population as an indicator to community progress to assess the energy development index (Kammen et al., 2015). HDI is a tool developed by United Nations development programme to assess levels of community development including life expectancy, health, knowledge and education and the standards of living as a function of gross domestic product (GDP) (UNDP, 1990). The EDI on the other hand is a tool used to assess the role of electricity to human development index. EDI tracks energy development country by country considering energy development at household level and community level (Mainali et al., 2014). EDI also combines three indicators like the per capita commercial energy consumption, share of commercial energy in total energy use and share of population with access to electricity (Bazilian et al., 2010). With limited electricity energy access the EDI and HDI are generally low in north eastern Kenya.

Around the world regions the ratio of electricity generation capacity per million inhabitants is very low in Sub-Saharan Africa (SSA) (Kammen et al., 2015). Total average per capita annual consumption in Africa excluding the Republic of Southern Africa (RSA) was 155kWh compared to 4770kWh/per capita in RSA (Bazilian et al., 2012). Study by World Bank group (Crousillat, Hamilton & Antmann, 2010) showed that 1.5 billion people worldwide lacked access to electricity in 2008, 85% of those lived in the rural areas mainly in Sub-Saharan Africa and South Asia. This study indicated that SSA had by far the lowest
urban and rural access rates at 58 and 12 per cent. Researchers highlighted some barriers to electricity energy access as being related to the high costs of supplying rural and peri-urban households, lack of appropriate incentives, weak implementing capacity, electricity generation shortage and population growth. Noting that the world requires an annual investment of about 35 billion US dollars per year in the energy sector to meet the universal electricity access by 2030, researchers cautioned that it may not be possible to meet this challenge (Crousillat et al., 2010). In fact most low income countries have competing budgets where priority to electrification is almost always overshot by other pressing social and infrastructure needs.

2.5 Renewable energy technologies and adoption of off-grid hybrid energy systems

Martinez-Diaz et al. (2013) proposed four aspects to be studied for design of a hybrid power system including, demand load characteristic, potential and availability for renewable energy resource, restriction of the system and the optimization criteria. In another study, Singh & Ganguli (2010) observed that using a hybrid system can fulfil the load demand and reduce price of electricity. Similarly Lipu et al. (2013) studied hybrid systems in remote areas of Bangladesh. Results showed that average daily solar radiation at 4.36 KWh/m² and wind force at (3m/s - 5m/s) was ideal for a hybrid system. Locally Lukuyu & Cardell (2014) used a Multi-Attribute Trade-Off Analysis that simulated and tested five different hybrid configurations. A wind-diesel-battery system was recommended for a successful Feed in Tariffs (FiT) policy in Kenya. Researchers cautioned on the risk of incorporating a standalone wind resource to power grids due to intermittent nature of wind resource. In a different study Shafiullah et al. (2010) used meteorological station wind and solar radiation data with HOMER simulation model for a hybrid generation.
Results for Queensland Australia indicated that a 5.65m/s wind and mean solar radiation at 5.68kWh/m²/day was ideal for a hybrid system. This study showed that wind energy plays a very significant role in hybrid systems. That wind blows throughout the day providing over 50% in a hybrid system capacity compared with the possible 6 to 8 hours of sunshine.

2.6 Hybrid power systems

Hybrid systems include one or more renewable energy source as a primary and a thermal generator as a backup resource (Martinez-Diaz et al., 2013; Hessami et al., 2010; Sreeraji et al., 2010; Hassan et al., 2010). Hybrid systems use renewable energy sources including hydro, wind and solar to reduce the burden of fossil fuels and at the same time mitigates the emission of green house gases. Mini and micro hybrid systems therefore provide a continuous and reliable electricity supply to isolated regions and villages not connected to the national grid (Lukuyu & Cardell, 2014). Hybrid systems may integrate use of different renewable energy technologies (RETs) to optimise advantages of each. However, Lipu et al. (2013) showed that hybrid systems were faced by challenges of reliability due to seasonality of the renewable energy resources. Hence, the need to integrate an inverter and a battery bank for a continuous supply of energy. This also makes the hybrid systems dispatchable therefore able to handle different loads when demand increases and adjust during low peak demands.

2.7 Research Gaps

The main use of electricity energy for people in rural areas is for lighting. Other basic requirements include running of the rural health and education centres. Such were the factors used to define energy poverty at the basic level. Most studies on development of renewable energy in northern Kenya focused mainly on potential and type of technology to
deploy. While the wind energy potential for north eastern Kenya was not in doubt no study dwelt on effects of wind variability on the potential and distribution of the wind energy resource in northern Kenya. The study therefore identified the uncertainty of the wind resource variability and its implication for generation of wind power electricity as a gap in the regional energy development. The study also identified the gaps in wind resource mapping and the background of the Kenya Power company to enhance capacity using hybrid generation systems in northern Kenya. Modelling is one of the tools used to carry out research on wind resource characteristics. The study therefore identified two models borrowed from the CORDEX project for Africa and used them together with the Global model (ECMWF) to carry out the project. Results for the study were used to build the certainty required by governments and investors as a guide to policy on development of systems to increase electrification in northern Kenya.
CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

Chapter Three presents the area of study and the methods used to achieve the study objectives. It elaborates data acquisition procedures, research design and the methods applied in the data analysis. Purpose of data analysis was to organise and provide structures that can elicit meaning in research data (Polit & Beck, 2008). The study used different forms of data acquisition including primary and secondary information from different sources. The methods applied to present the results included tables, the time series plots, graphical maps output from GraDs and box plots analysis.

3.2 The area of study

The study covered some regions in Eastern and North Eastern counties of Kenya which fall in arid and semi arid zones. These include the counties of Mandera, Marsabit, Wajir, Garissa, and the adjacent counties of Isiolo, Laikipia and Meru for data comparisons as shown in Figure 3. Electricity connection is mainly restricted to the urban centres of Mandera, Marsabit, Wajir, Elwak, Habaswein, Merti and Garissa. Each town is served by an off grid thermal generator backed by the wind and solar components in some stations (Lukuyu & Cardell, 2014). The winds are fairly strong due to persistent north easterly and southerly easterly monsoons. These winds are mainly governed by the seasonal migration of the sun north and south of the equator. Rainfall though coming in two seasons is not sufficient for a robust agro activity without irrigation. Pastrolism is therefore the main economic activity for local people. Thus human population are mainly concentrated within the urban centres and localized wetlands scattered across the region where duellers found access to water for their livestock. The region has potential for wind energy harvesting as suggested in (Oludhe, 2008; MoEP, 2013; Lukuyu & Cardell, 2014).
Figure 3: County Map of Kenya showing the area of study (shaded)

Source: Author, 2015
3.3 Research Design

The study employed a modeling design where the global and regional climate models were used to simulate wind data at grid points. The model data were extracted from the Coordinated Regional Climate Downscaling Experiment (CORDEX) datasets (Giorgi, Jones & Asrar, 2009). Data was extracted using the Grid Analysis and Display System (GrADS) software. Two models were purposively selected for the purpose of the study.

These models were (HadGEM2) from Hadley centre United Kingdom (UK) and ICHEC from Germany. The rationale for using the two models was because they formed part of the ten (10) Regional Climate Models (RCMs) participating in the ongoing Coordinated Regional Downscaling Experiment in Africa (CORDEX-Africa) project. The aim of the CORDEX-Africa project was mainly to recommend models that demonstrate high skill in simulating African weather. Selected RCMs used a similar domain (SMHI RCA35 Sveriges Meteorologiska institute, Sweden) with a spatial resolution of approximately fifty kilometres (50 km) that yield good climate results. Secondly, the two RCMs (HadGEM2 and ICHEC) have been validated to simulate data that correlated well with observed historical datasets for temperature and precipitation in the region. The observed precipitation data showed significant improvement compared to GCMs outputs for African region, therefore useful to simulate climate projections over Africa (Nikulin et al., 2012; Kalognomou et al., 2013).

3.4 Data acquisition

Data used for the study was basically quantitative data in both the primary and secondary categories. The primary data sets included the simulated and projected model outputs for surface winds at 10m above topographic surface and the upper level winds at 1500m above mean sea level or the 850mb level. Historical records (baseline data) also constituted the
primary datasets including the reanalyzed wind data extracted from the global model based at the European Centre for Medium-range Weather Forecasting reanalysis for climate data (ECMWF-ERA). On the other hand, the secondary data included the recent human population census from the counties of Marsabit, Mandera, Wajir, Isiolo and Garissa.

Secondary datasets also included the amount of electricity generated from the local hybrid systems in Kilowatts and the electricity supply and consumption for the same counties.

Baseline data (ECMWF) therefore were the simulated mean monthly wind velocity in metres per second (m/s) at grind points. Baseline winds extracted for locations of the seven meteorological stations in northern eastern Kenya at the surface and 850mb level were for the period 1981-2014. The winds at the 850mb level were compared with surface winds. The rationale being to find out whether patterns observed near the surface could be traced at higher elevations (Greene et al., 2010). Further the wind datasets included the projected wind speeds at the surface (10m) and at 1500m (850mb level) for entire area of study. Baseline and the simulated model outputs were for more than 30 years starting 1981 to 2014 plus model projections up to 2050. Baseline data was used to validate the simulated model outputs up to 2014 as a way of assessing the skill of the model in simulating local winds. The baseline or the reanalyzed datasets were the outputs from the European Centre for Medium Range Weather Forecasts reanalysis for climate datasets (ECMWF- ERA).

This is a global model that supplies boundary conditions for the regional circulation models (HadGEM2 and ICHEC). The global model (ECMWF) assimilates satellite observed data blended with surface observations to simulate a fine spatial coverage of the globe at grid points (reanalyzed data).
The blend of remote sensed data (satellite/radar), the human observed data and other climate data observed using automatic weather machines is called the reanalyzed datasets. The global model therefore provides data at 24hour intervals for sea level pressure and winds at different levels. Thus, the wind data were extracted at grid points including at locations of the seven meteorological stations in the study area shown in Table 1. Meru and Laikipia meteorological stations were included as reference stations to cover Isiolo County since there was no meteorological station in Isiolo County. The baseline data (1981 – 2014) were used to validate the model outputs based on Brimmo et al. (2017) that validation of data was paramount in ensuring future models simulate the wind speeds profiles with minimum error.

On the other hand model projection datasets (2015 - 2050) were generated using the Representative Concentration Pathways (RCPs). The RCPs provides an improved way of assessing levels of greenhouse gas (GHG) concentrations pathways that leads to global warming (Giorgi, Jones & Asrar 2009). The study used the medium and high concentration pathway referred to as RCP4.5 and RCP8.5, respectively. These RCPs correspond to IPCC Special Report on Emission Scenarios (SRES) B1 and A1B, respectively. The RCP4.5 assesses the global warming under moderate and controlled emissions while RCP8.5 depicts the world under high industrial development. This implies high emission rates as industries strive to meet demand from increasing high to middle income classes and overall global human population growth. The projected wind regimes (2015 -2050) were used to investigate if there will be any significant change in the future wind resource characteristics compared to baseline period (1980 – 2014). The electricity generation and consumption data were for a period of five (5) years starting 2011 to 2015 and given in Giga watt hours (GWh).
Electricity generation data was from the hybrid stations at Merti in Isiolo county, Habaswени in Wajir county and Marsabit town in Marsabit county. However, the electricity supply and consumption data were from all counties in north eastern Kenya including Marsabit, Mandera, Wajir and Garissa. Electricity data was sourced from Kenya Power Company headquarters Nairobi. Finally the regional demographic (county human population) data was sought from the Kenya bureau of statistics Nairobi based on 2009 Kenya Population Census.

The following table presents the seven locations in the study area.

Table 1: Names and locations of the seven meteorological stations in Northern Kenya

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Latitude (Degrees)</th>
<th>Longitude (Degrees)</th>
<th>Elevation (m)</th>
<th>County</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moyale</td>
<td>3.530</td>
<td>39.050</td>
<td>1097</td>
<td>Marsabit</td>
</tr>
<tr>
<td>Marsabit</td>
<td>2.320</td>
<td>37.980</td>
<td>1104</td>
<td>Marsabit</td>
</tr>
<tr>
<td>Mandera</td>
<td>3.930</td>
<td>41.870</td>
<td>230</td>
<td>Mandera</td>
</tr>
<tr>
<td>Wajir</td>
<td>1.750</td>
<td>40.070</td>
<td>244</td>
<td>Wajir</td>
</tr>
<tr>
<td>Garissa</td>
<td>-0.470</td>
<td>39.630</td>
<td>138</td>
<td>Garissa</td>
</tr>
<tr>
<td>Meru</td>
<td>0.083</td>
<td>37.650</td>
<td></td>
<td>Meru</td>
</tr>
<tr>
<td>Laikipia</td>
<td>0.050</td>
<td>37.033</td>
<td></td>
<td>Laikipia</td>
</tr>
<tr>
<td>Air Base</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Author, 2015

* Meru and Laikipia meteorological stations were used as reference for Merti hybrid power station in Isiolo County where there was no Meteorological stations.
3.5 Estimation of the wind power resource potential and the turbine height

Motion in the atmosphere is triggered by differential heating on adjacent surfaces that develops the atmospheric pressure gradients (Burton et al., 2001; Manwell et al., 2010). Wind is the moving air horizontally on a surface or at the upper levels. Wind changes are affected by local, regional and global changes in air temperatures on adjacent surfaces, local vegetation cover and land use changes. Wind power is proportional to the cube of the wind speed; therefore assessment of the most feasible location for mounting wind turbine requires understanding of the average wind speed, vertical wind gradient and frequency distribution. The sitting of a wind turbine is guided by estimation of the mean power produced by a specific wind turbine at one or more specific locations (Eric et al., 1997). Wind turbines convert kinetic energy in the wind into electricity based on the wind power equation (Arjun et al., 2013). However, in Kong et al. (2014) the minimum wind speed to extract energy from a wind turbine ranges from 3 – 5 m/s, reaching maximum power at 17m/s and may become disastrous to the wind turbine if wind speed exceed 25m/s. Therefore, the amount of energy extracted from the wind by any rated wind turbine depends on the coefficient of performance, called the Beltz ratio, equivalent to 16/27 or 0.593 and the capacity factor of the wind turbine deployed.

\[
\text{Power in wind (P}_{\text{wind}}) = \frac{1}{2} (\rho A v^3) w / m^2 \]

Where: \( \rho \) = density of air taken as 1.225 kg/m³

\( v \) = Monthly mean wind velocity in m/s

\( A \) = Area of wind turbine swept by the wind in square metres (m²)
Estimation of turbine height to assess level with optimum wind energy was done using the power law empirical (Kubik et al. 2011; Bekele, 2009).

Wind velocity; \[ u_2 = u_1 \left( \frac{z_2}{z_1} \right)^\alpha \] .................................(vi)

Where; \( U_1 \) = wind speed at height \( Z_1 \)

\( U_2 \) = wind speed at height \( Z_2 \)

\( Z_1 \) = reference height

\( Z_2 \) = computed height

\( \alpha \) = wind shear coefficient or power exponent that depends on surface roughness.

The study adopted the \( \frac{1}{7} \) power rule that assumes a constant factor of 0.143 which do not depend on topographic features and ambient environment of the observing station (Apratim, 2012).

3.6 Data Analysis

Data analysis process applied different procedures and techniques to describe, illustrate and evaluate the results. The study applied several methods including manipulation of simulated model datasets in GrADS for spatial and temporal maps including use of XLSTAT and Ms EXCEL software for trends, stationary and significance tests. Results were presented in tables, maps, time series and box plots. The methods applied in this study sought to find answers to the research questions that informed the objectives of the study. So that before the evaluation of spatial and temporal distribution of wind power potential in objective one, several test were done for decisions on data using the following methods.
3.6.1 Trend and significance tests

Annual and seasonal statistics extracted from baseline and simulated model outputs were used for statistical significance tests. Lag correlations were used to test for stationarity with Mann-Kendall and Spearman’s Rank Test used to identify variability, trends and statistical significance in the data (Mann, 1945; Hirsch & Slack, 1984; Önçöz & Bayazit, 2003). Test parameters were used to make decisions on data results using the following equations.

3.6.1.1 Mann-Kendall Test (S)

Mann-Kendal is a rank based non-parametric Test used to detect statistically significant trends. Equations used were as follows:

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sig}(x_j - x_i) \]

\[ \text{sig}(x_j - x_i) = \begin{cases} +1 & \text{if} \ (x_j - x_i) > 0 \\ 0 & \text{if} \ (x_j - x_i) = 0 \\ -1 & \text{if} \ (x_j - x_i) < 0 \end{cases} \]  \quad \text{(vii)}

\[ V(S) = \frac{1}{18} [n(n-1)(2n+5) - \sum_{p=1}^{q} t_{p} (t_{p} - 1)(2t_{p} + 5)] \quad \text{......... (viii)} \]

\[ Z = \begin{cases} \frac{S - 1}{\sqrt{\text{VAR}(S)}} & \text{if} \ (S > 1) \\ 0 & \text{if} \ (S = 0) \\ \frac{S + 1}{\sqrt{\text{VAR}(S)}} & \text{if} \ (S < 0) \end{cases} \quad \text{......... (ix)} \]
Where: \( S \) = Mann-Kendall’s statistical value,

\[ V(S) = \text{Variance of } S \]

\( Z \) = Standardized test statistic.

\( x_i \) and \( x_j \) are time series observations in chronological order.

\( n \) = number of variables

\( t_p \) = the number of ties for \( p^{th} \) value

\( q \) = number of tied values

In this test, a positive \( Z \) value indicates an increasing trend and negative \( Z \) values indicate a decreasing trend in the series. The test hypothesis for this test is \( H_0 \) for no trend and \( H_1 \) for existence of a trend in the data series. For \( |Z| > Z_{1-\alpha/2}, (H_0) \) is rejected and significantly statistical trend exist. The critical value of \( Z_{1-\alpha/2} \) for \( p - value \) of 0.5 from standard table is 1.96

### 3.6.1.2 Spearman’s rho Test \( (R_{sp}) \)

Spearman’s rho test is a rank based non parametric method for trend test analysis. The test was used for comparison with Mann-Kendall Test. Method assumes that long term data were independent and identically distributed. For this test the null hypothesis \( (H_0) \) like Mann-Kendall Test is for no trend and the alternative hypothesis \( (H_1) \) for existent of a trend. Spearman’s rho Test statistic \( (R_{sp}) \) and standardized statistics \( (Z_{sp}) \) were calculated using the following formulas.
\[ R_{sp} = 1 - \frac{6 \sum_{i=1}^{n} (D_i - i)^2}{n(n^2 - 1)} \] ............................................ (x)

\[ Z_{sp} = R_{sp} \sqrt{\frac{n - 2}{1 - R_{sp}^2}} \] ............................................ (xi)

Where: \( D_i \) = Rank of \( i \)th observation

\( i \) = Chronological order number

\( n \) = Total length of the time series data

\( Z_{sp} \) = Student’s \( t \) – distribution with \((n - 2)\) degrees of freedom (df)

So that Positive \( Z_{sp} \) values indicates increasing trend while negative values presents a decreasing trend. Spearman’s Test was also used to test for interseasonal and intra-seasonal variability based on long term mean (LTM) wind speeds for baseline and model outputs at surface and 850mb level. For the value of \( \left| Z_{sp} \right| > t_{(n-2,1-\frac{\alpha}{2})} \), reject null hypothesis that trend is not significant and accept the alternative hypothesis that trend was significant.

### 3.6.2 Coefficient of Variability Test and the standard error of mean (SEM)

Coefficient of variation (CV) was used to show how much of the sample data could be explained using the mean and the standard deviation or the levels of individual data variations from the mean hence a pointer to the degree of variability. On the other hand the standard error of mean estimates the variability between samples.
The CV was used to indicate variability levels between stations data and compare variability between different model outputs. Both the CV and the SEM ranges between 0-100 percent (%). High values of the C.V would suggest high wind variability levels and also high SEM values would indicate high variability between samples. SEM is also an indicator of how the mean of a sample estimates the population mean. So that small values of SEM indicate a precise estimate of population mean. Coefficients of Variability and SEM in the wind were computed by using the standard deviation over the long term mean and standard deviation over the square root of total data entries (N) as shown below:

\[
\text{C.V} = \frac{\sigma}{\bar{X}} \times 100\% \quad \text{.................................................. (xii)}
\]

\[
\text{SEM} = \frac{\sigma}{\sqrt{N}} \quad \text{.......................................................... (xiii)}
\]

Where: \(\sigma\) = Standard deviation,

\(\bar{X}\) = Long Term Mean in wind

\(N\) = the number of data entries.

3.7 Wind power density and the energy consumption per capita in northern Kenya

Wind power density was calculated using the power in wind equation. While the electricity energy consumption per capita was calculated by cumulating all the electricity energy generated and consumed in an area divided by the total population in the area (Sahul et al., 2013).
For purpose of this report, electricity energy consumed per capita was calculated by dividing the cumulated electricity energy supplied and consumed in year 2015 by number of active customers for same period. That way it was possible to evaluate the electricity energy consumed per capita for different locations. Assessment of per capita supply was done to identify areas that required urgent supply using micro-hybrid systems.

3.8 Assessment of the contribution of the hybrid power stations in north eastern Kenya

This was carried out by plotting the total electricity energy generated together with the wind and solar energy components as a contribution to energy generation at Merti, Habaswени and Marsabit hybrid power stations. Results were evaluated in percentages of renewable energy component compared to the total energy generated per station using the mix in the individual hybrid electricity generation station.
CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Introduction

Chapter four presents the results from the analysis carried out on baseline and simulated model outputs for wind speeds at different levels together with electricity data. It also includes discussions on pertinent observations gathered from results compared with the literature. The graphical maps were used to present the spatial and temporal distribution of wind speeds, direction and its variability. These maps presented direct output from GrADs displaying lines of latitudes in the y-axis and longitudes in the x-axis to optimize visualization at grid points. The charts were also used to show the wind vectors which had indications of wind direction and the magnitudes of the wind. The length of the wind vectors therefore displays the strength of wind at a particular location compared to the others. On the same chart, the color codes presented different wind power potentials as shown on the bar codes. It was therefore possible to discuss the wind resource variability for particular locations using geographical references shown in Table 1. Results were organized based on the specific objectives after the initial stages for stationary, trend and the significance test as follows.

4.2 Stationary test using Mann-Kendall and Spearman’s Rank Test

Data were fed into the XLSTAT in Excel and the output values were summarized in Tables 2, 3, 4 and Table 5 as shown below. In this test computed $P$-value greater than tabulated value $alpha (\alpha )$ at 0.05 or 95% significance level, implied that data was stationary and the opposite was true. Table 2 shows results for Mann Kendall stationary test for Garissa Meteorological station. Data show that the computed $p$-value was greater than the critical value $alpha (\alpha )$ at 0.05 for all cases implying that mean monthly winds for Garissa were stationary. The same test was repeated for all other stations returning a stationary series.
Table 2: Mann-Kendall test for mean monthly winds for Garissa station

KPSS test (level/lag Short)

<table>
<thead>
<tr>
<th>Month</th>
<th>Eta (Observed)</th>
<th>Tau</th>
<th>P-Value</th>
<th>Alpha (α)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>0.368</td>
<td>0.462</td>
<td>0.097</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Feb</td>
<td>0.387</td>
<td>0.462</td>
<td>0.085</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Mar</td>
<td>0.384</td>
<td>0.462</td>
<td>0.087</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Apr</td>
<td>0.301</td>
<td>0.462</td>
<td>0.154</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>May</td>
<td>0.171</td>
<td>0.462</td>
<td>0.389</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Jun</td>
<td>0.236</td>
<td>0.462</td>
<td>0.242</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Jul</td>
<td>0.293</td>
<td>0.462</td>
<td>0.162</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Aug</td>
<td>0.313</td>
<td>0.462</td>
<td>0.142</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Sept</td>
<td>0.267</td>
<td>0.462</td>
<td>0.158</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Oct</td>
<td>0.261</td>
<td>0.462</td>
<td>0.201</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Nov</td>
<td>0.293</td>
<td>0.462</td>
<td>0.162</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Dec</td>
<td>0.367</td>
<td>0.462</td>
<td>0.098</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
</tbody>
</table>
Data in Table 3 below show the results for the long term mean (LTM) from baseline outputs for each station at surface (10m) and 1.5km (850mb) level. The KPSS test for LTM wind speeds per station yielded mixed signals with results depicting \textit{p-values} less than \textit{alpha (\(\alpha\))} in most cases. However, \textit{p-values} at 0.57 was greater than (\(\alpha\)) in Meru and Moyale both at the surface and 850mb levels suggesting stationary series. Further analysis showed that, when data was lagged results depicted a constant critical value (\textit{Tau}) at 0.45 for all stations both at the surface and 850mb level. This suggests that the non stationary portrayed in low \textit{p-values} with respect to \textit{alpha} for these stations was not significant hence stationary series. However, it is worthy to note that variability of climate variables can cancel out in the long term (Foley \textit{et al.}, 2012). There was need therefore to carry out significant test to establish the significance of the results shown in Table 3 which confirms the stationary series for wind data in north eastern Kenya.
Table 3: Stationary tests for wind data at surface and 1500m (850mb) level

<table>
<thead>
<tr>
<th>Stations</th>
<th>Level</th>
<th>Eta</th>
<th>Tau</th>
<th>p-value</th>
<th>Alpha (α)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garissa</td>
<td>850mb</td>
<td>0.99</td>
<td>0.45</td>
<td>0.00</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.99</td>
<td>0.45</td>
<td>0.00</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td>Marsabit</td>
<td>850mb</td>
<td>0.55</td>
<td>0.45</td>
<td>0.02</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.55</td>
<td>0.45</td>
<td>0.02</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td>Moyale</td>
<td>850mb</td>
<td>0.12</td>
<td>0.45</td>
<td>0.57</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.12</td>
<td>0.45</td>
<td>0.57</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>Mandera</td>
<td>850mb</td>
<td>0.94</td>
<td>0.45</td>
<td>0.001</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.94</td>
<td>0.45</td>
<td>0.001</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td>Wajir</td>
<td>850mb</td>
<td>0.83</td>
<td>0.45</td>
<td>0.002</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.83</td>
<td>0.45</td>
<td>0.002</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td>Laikipia</td>
<td>850mb</td>
<td>0.55</td>
<td>0.45</td>
<td>0.02</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.55</td>
<td>0.45</td>
<td>0.02</td>
<td>0.05</td>
<td>Stationary*</td>
</tr>
<tr>
<td>Meru</td>
<td>850mb</td>
<td>0.35</td>
<td>0.45</td>
<td>0.01</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td></td>
<td>Surface</td>
<td>0.35</td>
<td>0.45</td>
<td>0.11</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
</tbody>
</table>

Stationary*: *P-Values* less than *alpha (0.05)* for non-stationary series, however critical Value *tau* was constant at 0.45 indicating that non stationary signal was not significant. Note; *Eta*=Observed value; *Tau*= Critical value; *P-value* - one tailed.
Table 4 below represents seasonal outputs for baseline data at the surface. In Table 4, DJF represents December January February season, MAM is for March April May season, JJA for June July August season and SON for September October November season. Results from data for seasonal means depicts that the p-values were consistently greater than (α) at 0.05 and this was backed by a constant tau at 0.46 implying a stationary series. Results in Table 4 were consistent with Table 3 implying that the seasonal wind speeds for north eastern Kenya had a stationary series.

**Table 4: Stationary test for simulated seasonal wind totals in northern Kenya**

<table>
<thead>
<tr>
<th>Seasons</th>
<th>Eta</th>
<th>Tau</th>
<th>P-Value</th>
<th>alpha (α)</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJF</td>
<td>0.30</td>
<td>0.46</td>
<td>0.15</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>MAM</td>
<td>0.33</td>
<td>0.46</td>
<td>0.13</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>JJA</td>
<td>0.19</td>
<td>0.46</td>
<td>0.33</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
<tr>
<td>SON</td>
<td>0.29</td>
<td>0.46</td>
<td>0.17</td>
<td>0.05</td>
<td>Stationary</td>
</tr>
</tbody>
</table>

*Key: Eta=Observed value; Tau= Critical value; P-value –one tailed*

The summary statistics were presented in Table 5 below. Results show that simulated average wind potential was highest in Marsabit at 8.7m/s with a standard deviation (s.d) of 0.46, 0.05 the standard error of the mean (SEM) and coefficient of variation (C.V) at 5.8%. Results show that Meru had the lowest wind power potential at 4.1m/s, s.d of 0.22, SEM at 0.03 with the C.V at 5.5%. Other stations had mean wind speed values between 6.2 – 8.0m/s, s.d of 0.26 – 0.46, the SEM between 0.05 & 0.09 with C.V values ranging between
3.9% - 5.8% for baseline and 3.8% - 5.8% for model data. The mean wind speeds at the surface ranged between 4m/s – 10m/s. These values were higher than suggestions by Lipu et al. (2013) that average wind speeds at 3 – 5 m/s were ideal for wind power generation. Study results relate well with findings by Oludhe (2008) and recently by Kammen et al. (2015) that region had high potential for wind power generation. Table 5 results indicates that both simulated and baseline winds depicted low standard deviations between 0.22 – 0.46 and C.V values ranging between 3.9% – 5.8% suggesting low wind variability levels in the area. Further observations depicts low standard error of the mean ranging between 0.03 - 0.09 suggesting low long term wind resource variability in northern Kenya. The results were in line with findings by Fant and Schlosser (2012), that showed slight changes in wind power potential by 2050 based on model simulation for wind speeds from 19 GCMs for Southern Africa region. Valentine (2011) came up with the factors that may have sizeable influence in the wind power cost including the mean wind speed, the consistency of the wind speeds and the wind directions. The results in Table 3, 4 and 5 show that north eastern Kenya region have stable winds that are consistent in speed and direction. Results therefore suggesting less impact on wind power cost related to wind variability in the area.
Table 5: Summary of winds for baseline at the surface in northern Kenya

<table>
<thead>
<tr>
<th>Variable</th>
<th>MIN</th>
<th>MAX</th>
<th>Mean</th>
<th>s.d ($\sigma$)</th>
<th>S.E($\bar{x}$)</th>
<th>Models C.V(%)</th>
<th>Baseline C.V(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garissa</td>
<td>6.2</td>
<td>7.5</td>
<td>6.9</td>
<td>0.3</td>
<td>0.05</td>
<td>4.7</td>
<td>4.2</td>
</tr>
<tr>
<td>Laikipia</td>
<td>6.4</td>
<td>8.5</td>
<td>7.5</td>
<td>0.5</td>
<td>0.09</td>
<td>5.8</td>
<td>3.7</td>
</tr>
<tr>
<td>Mandera</td>
<td>6.0</td>
<td>7.4</td>
<td>6.5</td>
<td>0.3</td>
<td>0.05</td>
<td>5.2</td>
<td>5.0</td>
</tr>
<tr>
<td>Marsabit</td>
<td>6.8</td>
<td>9.0</td>
<td>8.7</td>
<td>0.5</td>
<td>0.09</td>
<td>5.8</td>
<td>5.8</td>
</tr>
<tr>
<td>Meru</td>
<td>3.6</td>
<td>4.5</td>
<td>4.1</td>
<td>0.2</td>
<td>0.03</td>
<td>5.5</td>
<td>5.5</td>
</tr>
<tr>
<td>Moyale</td>
<td>6.4</td>
<td>7.3</td>
<td>6.8</td>
<td>0.3</td>
<td>0.05</td>
<td>3.9</td>
<td>3.8</td>
</tr>
<tr>
<td>Wajir</td>
<td>6.3</td>
<td>7.4</td>
<td>6.8</td>
<td>0.3</td>
<td>0.05</td>
<td>4.3</td>
<td>4.2</td>
</tr>
</tbody>
</table>

* $[S.E(\bar{x})]$ is for the standard error of mean (SEM)

4.2.1 Test for trend and significance for winds in northern Kenya

Results on Table 6 below depicts trend and significance test for simulated wind values at the surface (10m) and the lowest level of free flow of the wind at 1.5km or 850mb above mean sea level. The study used the non parametric Mann-Kendall and the Spearman’s Rank Test to compare the results for model outputs for the baseline and the projected periods. In Table 6 the asterisks (*) appears on the negative Z values (-3.0 & - 0.1) indicating a decreasing trend for baseline and ICHEC model outputs at surface and 850mb level respectively. However, $|Z|$ values at 3.0 & 2.6 with asterisks in baseline and ICHEC RCP8.5 at the 850mb level were greater than critical value of 1.96 for a positive significant trend.
In the Spearman’s rho Test, the standardized test statistics ($|Z_{sp}|$) was positive for the baseline and model outputs reflecting an increasing trend. ICHEC model simulated a decreasing trend for winds at 850mb level at $Z = -1$, this result however conflict with the Spearman’s rho Test which posted a positive $R_{sp} = 0.4$ for increasing trend. The same scenario was shown in the baseline at the surface with $Z = -3$ and $R_{sp} = 0.03$ for baseline implying that results were not significant. Figure 6 show that in most cases the models simulated increasing trends same as the baseline data. This fact suggests that the models were capturing the local wind characteristics but with different sensitivities compared to baseline outputs. These results were similar to findings by Jury (2013) that showed slight increase in trend for wind speeds in Southern Africa for some areas and stable winds in others up to 2050. In Graabak et al. (2016), results indicated that the increase or decrease in wind resource was dependent with a signal to increase wind speeds in winter compared to summer seasons. Therefore trends in wind speed in northern Kenya could be collaborated with other parts of the globe given that local wind characteristics were also impacted by the global wind patterns.
Table 6: Mann-Kendall and Spearman’s Rank Test for trend and significance

<table>
<thead>
<tr>
<th>MODELS</th>
<th>Mann-Kendall Test</th>
<th>Spearman’s Rank Test</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S</td>
<td>Z</td>
<td></td>
</tr>
<tr>
<td>Baseline Surface</td>
<td>3</td>
<td>-3*</td>
<td>3*</td>
</tr>
<tr>
<td>Baseline- 1.5km</td>
<td>3</td>
<td>3</td>
<td>3*</td>
</tr>
<tr>
<td>HadGEM2 Surface</td>
<td>1.1</td>
<td>0.2</td>
<td>0.05</td>
</tr>
<tr>
<td>ICHEC Surface</td>
<td>1.4</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>HadGEM2 1.5km</td>
<td>1.8</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>ICHEC 1.5km</td>
<td>0.4</td>
<td>-0.1*</td>
<td>0.1</td>
</tr>
<tr>
<td>HadGEM2 RCP4.5</td>
<td>1.0</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>ICHEC RCP4.5</td>
<td>1.4</td>
<td>1.3</td>
<td>1.3</td>
</tr>
<tr>
<td>HadGEM2 RCP8.5</td>
<td>1.3</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>ICHEC RCP8.5</td>
<td>1.1</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>HadGEM2 RCP8.5</td>
<td>1.3</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>ICHEC RCP8.5</td>
<td>2.6</td>
<td>2.6</td>
<td>2.6*</td>
</tr>
</tbody>
</table>

4.2.2 Seasonal trends and variability for baseline at surface and 850mb level

The seasonal trends were used to test significance of each seasonal mean wind speeds in relation to long term mean. The test for interseasonal and intra-seasonal wind speeds variability was carried out to assess if there was a significant difference between long-term variability and seasonal wind characteristic in northern eastern Kenya. Interseasonal wind speed variability patterns were computed from season to season mean data based on the long term wind for the baseline at surface and 850mb level. The intra-seasonal variability
assessed the wind variability within the seasons assuming a lag between the presiding seasons to the next season (Xie et al., 2007).

The trends for seasonal outputs were presented in Table 7. Results showed that for baseline data the \( p\)-value was consistently greater than critical value \( \alpha \) at 0.05 for all seasons both at the surface and the 850mb level for significant winds. However, comparing the individual seasonal outputs with baseline, \( p\)-values were considerably lower than the critical value of 1.96 at 95% significant level. The results therefore suggest that seasonal winds had positive trends but not significant. The JJA season with \( p\)-values at 0.65 for surface winds and 0.67 for upper winds indicates a positive trends way above the other seasons. This result therefore suggests that JJA had a significant contribution to the local wind power potential compared to the other seasons. Results also depict different values for variance of the statistical parameter \( \text{VAR}(S) \) being 28.3 at the surface and 44.3 at 850mb level. This difference suggests that seasonal variability in wind were slightly higher at 850mb level compared to the winds at the surface (10m).
Comparison for the individual seasonal means with LTM wind speeds for the baseline was presented in Table 8. The results were used to show interseasonal relationship in the data. Data showed a negative correlation between LTM and DJF at surface and 850mb level. The results for JJA and SON indicate a strong positive relationship for surface winds and also positive relationship for winds at 850mb level. This could be attributed to the strong seasonal pulses of wind speeds in JJA season that raises the seasonal mean with respect to LTM. The change in the season introduces significant changes in wind speed and direction. In Han et al. (2004), changes from one season to the other were accompanied by varying
amplitudes in the wind speed and direction that may influence the wind power. The intraseasonal variability therefore has significant implications on the seasonal and annual wind potentials.

Results also depicted significant positive correlation coefficient for both JJA and SON seasonal outputs compared to LTM. The t-test depicts positive values between 0.5 – 0.8 for significant correlation coefficients which suggest that there was significant interseasonal variability. It is however notable that the negative relationship between LTM with DJF and MAM seasons would likely cancel out with positive signals in the JJA and SON seasons. This therefore suggests a slightly positive trend for the long-term mean (LTM) wind patterns in the northern Kenya region. These results were consistent with the assertions in Pryor et al. (2005) that the near surface wind speeds for northern Europe were expected to increase by 5-10% between 2070-2100.

Table 8: Relationships between LTM and Seasonal winds for northern Kenya

<table>
<thead>
<tr>
<th>Seasons</th>
<th>Correlation at Surface</th>
<th>T-test</th>
<th>Correlation at 850mb</th>
<th>T-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>LTM/DJF</td>
<td>-0.5</td>
<td>0.5</td>
<td>-0.6</td>
<td>0.8</td>
</tr>
<tr>
<td>LTM/MAM</td>
<td>-0.2</td>
<td>0.8</td>
<td>-0.3</td>
<td>0.8</td>
</tr>
<tr>
<td>LTM/JJA</td>
<td>0.9</td>
<td>0.5</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>LTM/SON</td>
<td>1.0</td>
<td>0.5</td>
<td>0.7</td>
<td>0.8</td>
</tr>
</tbody>
</table>
Table 9 below presented the intraseasonal wind variability tests based on the lagged seasonal means for interlinked seasonal wind speeds at surface and 850mb level. Data show a moderate negative correlation for the lagged DJF and MAM seasonal winds at the surface and 850mb level. There was a weak positive correlation between MAM and JJA seasons. At the same time correlation coefficient between JJA and SON seasons was strong at 0.9 for both levels. The positively strong relationship between JJA and SON seasons may be attributed to the natural lag in atmospheric systems. This implies that the persistent wind pulses in JJA season sometimes spill over into the SON season influencing the observed wind potentials (Xie et al., 2007). The strong wind pulses were indications of high variability patterns within the season depicted by persistence and changing wind direction with time. The results therefore collaborates well with the findings in Wu et al. (2005) which showed that the intraseasonal signals were introduced during changes in wind direction within the seasons. Results depicted the t-test for JJA/SON seasons were 0.9 and 0.8 for the surface and 850mb level winds respectively for a significant wind resource variability.

<table>
<thead>
<tr>
<th>Seasons</th>
<th>Correlation at Surface</th>
<th>T-test</th>
<th>Correlation at 850mb</th>
<th>T-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJF/MAM</td>
<td>-0.7</td>
<td>0.3</td>
<td>-0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>MAM/JJA</td>
<td>0.1</td>
<td>0.4</td>
<td>0.1</td>
<td>0.04</td>
</tr>
<tr>
<td>JJA/SON</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>SON/DJF</td>
<td>1.0</td>
<td>-0.5</td>
<td>-0.5</td>
<td>0.8</td>
</tr>
</tbody>
</table>
Results in Figure 4 below were used to show graphical comparisons for seasonal winds for baseline (LTM) and at different seasons. Figure 4 was also used to highlight strengths of different models in simulating the local winds based on baseline data. Data showed that models simulated winds at very close range to baseline (LTM) at surface and 850mb level. The HadGEM2 model simulated slightly high wind speeds while ICHEC models depicted slightly low wind speeds compared to the baseline outputs. Highest wind speed of 8.7m/s was simulated by the HadGEM2 model in JJA season at the 850mb level. Results also showed that the lowest wind speeds (4.0m/s) were output by the ICHEC model mainly at the surface. Further tests indicated that HadGEM2 model results for seasonal winds correlated well with baseline outputs. Data for baseline and HadGEM2 model depicted a moderate correlation coefficient at 0.5 while, baseline (LTM) and ICHEC had a negative correlation coefficient at -0.7 and -0.2 at surface and 850mb level respectively.

The student T-test for the relationship between baseline and HadGEM2 was 0.1 suggesting a significant relationship. Therefore, comparing the HadGEM2 and ICHC model performance, these results indicates that HadGEM2 model was fairly good at simulating the seasonal winds for northern eastern Kenya. The results for seasonal variability related well with findings by Xie et al. (2007) which showed that the intra-seasonal wind variability was not controlled by local systems. The seasonal and intra-seasonal wind variability patterns were mainly influenced by synoptic and planetary systems. This result related well with the findings by Wu et al. (2005) where the intra-seasonal variability of the local wind stress curl was attributed to the alternation of flow direction. Results showed that the local wind variability patterns could also be tied to persistent systems linked to
contrasting maritime and continental temperature imbalances. The results were therefore consistent with conclusions in Han et al. (2004) that intraseasonal atmospheric forcing can cause seasonal to inter-annual variability in the tropical ocean atmosphere systems.

Figure 4: Seasonal wind speeds variability in northern Kenya
4.3 Determination of spatial and temporal wind resource distribution

Spatial and temporal distribution of wind power potentials were presented on grinded charts as outputs from GrADs. On these maps values on the horizontal (x-axis) represent the lines of longitudes running north to south while the values on the vertical axis (y-axis) represent the lines of latitudes. The array of arrows inside the charts represents the magnitude and direction of wind vectors. The actual wind velocity may be decoded from the representative colors shown on the barcode below the maps. Baseline data was represented by the output from the ECMWF model while the other two Models i.e. HadGEM2 and ICHEC represented the simulated and projected winds at surface and 850mb levels. The charts were used to compare the baseline and model outputs since all the wind features could be seen both on surface (10m) and at the upper level (1500m or the 850mb level).

4.3.1 Long term mean wind speed distribution in at the surface and 850mb Level

In figure 5 & 6 below the ECMWF, HadGEM2 and ICHEC model outputs depict the surface (10m) and upper level winds at 850mb levels respectively. Results show that surface winds in Figure 5 depicted similar variability patterns compared to upper level winds in Figure 6. Baseline (ECMWF) outputs had a long term Mean (LTM) of 6.0m/s at the surface and a LTM of 8.0 m/s at the 850mb level. HadGEM2 model had a LTM of 6.0m/s at the surface and a LTM of 10m/s at 1500m or the 850mb level. On the other hand ICHEC model depicted a LTM of 4.5m/s at the surface and a LTM of 7.5m/s at the upper level. The results indicate that there were higher wind speeds at the upper level compared to the winds at the surface. However, baseline and models depicted similar characteristics for the direction of the winds at both levels.
Data showed that Marsabit County had the strongest LTM wind power potential averaged to above 8.0m/s on the surface and over 10m/s at 850mb level.

Spatial distribution of the mean wind power potential reduces to the south east direction from Marsabit County crossing over to Wajir and Garissa Counties. By comparing baseline and model outputs, Mandera County had the lowest LTM wind power potential averaged at 3.5m/s at the surface and above 5m/s at 850mb level. The close relationship between baseline (ECMWF) and model (HadGEM2 & ICHEC) model outputs in Figures 5 & 6 suggests that models outputs could be used to represent the baseline data. Marsabit station depicted the highest wind speeds in the region in consistent with results by Oludhe (2008), who showed that Marsabit had the highest wind speeds averaged above 11m/s. The strong winds in Marsabit County informed the ongoing construction of the largest (300MW) wind farm in Africa (Turkana wind farm) suggesting that models could be used to identify sites for setting up wind farms. The spatial wind patterns were also consistent with findings in Ajayi et al. (2014) in the assessment of wind potential for ten selected sites in southern western Nigeria. That some sites with high wind speeds between 2.9 - 5.8m/s were adequately suitable for large scale generation projects while others with low wind speeds qualified only for small scale generation.
Figure 5: Long Term Mean wind speed distribution at surface in northern Kenya
Figure 6: Long Term Mean wind speed distribution at 850mb in Northern Kenya
4.3.2 Seasonal wind speeds distribution at the surface in northern Kenya

The following were the results for seasonal wind resource variability (spatial and temporal wind resource characteristics) in north eastern Kenya. Figures 7, 8, 9 & 10 below presents the spatial distribution of the seasonal wind power potential following the monsoonal swings in the global circulation system. Figure 7 showed the wind resource distribution pattern in December, January, February (DJF) season. The highest wind speeds at 6m/s were observed in Marsabit as output by ECMWF model compared to HadGEM2 and ICHEC values for the same season. The HadGEM2 and ICHEC models depicts that in DJF season the wind resource potentials are distributed mainly through the north easterly trade winds system.
Figure 7: Spatial Wind Patterns in December January February (DJF) in northern Kenya
Figure 8 below presented the wind distribution patterns for March, April, May (MAM) season. Results for MAM showed that the maximum wind speeds observed around Marsabit County decreases towards Mandera, Wajir and Garissa Counties. Figure 8 show that the baseline depicted winds with a strong southerly component which accelerates with a south easterly component as it transverses the Marsabit county. At the same time HadGEM2 model outputs winds with a southeasterly component which accelerates as it transverses the Marsabit county. The ICHEC model on the other hand depicts winds with a near easterly flow that sweeps across northern Kenya regions distributing the wind power potentials fairly well as it exits through Marsabit County. Both models therefore output wind speeds that accelerates as they enter Marsabit County from the east and exit to the west of the county. The result suggests presence of some distinct topographic features that triggers the observed increase in wind speed regimes as they enter Marsabit County propagating west wards to the open shores of Lake Turkana and beyond. It is observed that there were some distinct differences in the wind direction components displayed by each model. This observation could be attributed to the fact that MAM is a transitional season where for the sun moves from southern to northern hemisphere. The synoptic systems are not completely stabilized hence different model sensitivities (Xie et al., 2007). However it’s observable that models displayed an easterly to southerly component indicating that the seasonal wind resource potentials may vary during the transitions with changing wind directions and speed (Wu et al., 2005).
Figure 8: Spatial wind patterns in March April May (MAM) in northern Kenya
The maximum average seasonal wind velocity of about 9m/s was depicted in ECMWF (baseline output) during the June, July, August (JJA) season in Figure 9 below. HadGEM2 model depicted mean wind speeds at 9m/s while ICHEC outputs had a maximum of 7m/s for the same season. The model outputs in Figure 9 show that the wind directions for JJA season were persistent for baseline and models outputs compared to MAM season in Figure 8. The HadGEM2 and ICHEC models depicted winds with a very strong southerly component consistent with the baseline data. But, in contrast to other seasons the wind resource potential in JJA season was fairly distributed across the north eastern Kenya regions. This was depicted in the Baseline and HadGEM2 outputs which show the wind power potentials distributed to the widest part of the region from the south to the north in equal measures. The slight difference observed in the ICHEC model output in the spatial distribution of the wind power resource could only be attributed to different model sensitivities. Concurrence in model outputs in JJA season therefore suggest that the models could be used for assessment of the wind resource characteristics for north eastern Kenya. The results therefore indicates that JJA season with strong amplitudes in the wind speed regimes had some effects to the seasonal and the long term wind resource potentials within the northern Kenya regions. Results were therefore consistent with the conclusions in Han et al. (2004) on effects of intra-seasonal wind speeds variability to the long term wind resource potentials in the tropics.
Figure 9: Spatial wind distribution for June July August (JJA) in northern Kenya
Finally, Figure 10 below presented the wind velocity patterns in September, October, November (SON) season. In the SON season maximum wind resource potentials were well distributed around Marsabit regions decreasing towards Mandera and Wajir Counties. Average wind speeds observed in SON season indicates that ECMWF had 7m/s, HadGEM2 7m/s and ICHEC 6m/s. Models depicted wind vectors with a persistent south easterly component similar to observations in the MAM indicating a transition as the sun crosses the equator from the northern to the southern hemisphere. However, the strong wind speed signal in SON season suggests a lag in the strong wind speed pulses that persisted in the JJA season. The observation therefore suggests presence of interseasonal dependence in the wind resource potentials across the region.

The seasonal wind characteristics for north eastern Kenya depicts unique seasonal characteristics but also displays some similarities in the climatological wind regimes. The most dominant season was the JJA season where the observed wind speeds were highest at 9m/s. JJA season had a persistent southerly component depicted in all the models compared to the other seasons. High surface pressure gradients between the southern hemisphere winter and northern hemisphere summer enhance strong southerly currents in JJA season across the northern Kenya regions. Never the less, results show that baseline and model outputs depicted similar spatial and temporal wind resource variability patterns governed by monsoonal systems. The only marked departure from this observation was in DJF season that depicts contrasting results for baseline compared to HadGEM2 and ICHEC outputs (Figure 7). In the DJF season the ECMWF output indicates presence of high wind power potentials in Marsabit County while HadGEM2 and ICHEC depicted high wind power potentials in Mandera County. However the wind direction regimes persisted with
similar components in all locations for the same season. Overall, the high wind speeds in Marsabit County could be attributed to the fact that Marsbit County has surface topographic features that enhances the wind force through the channeling effect. The results therefore suggest that variability in the regional wind speeds were hinged mainly to the global synoptic systems and the local features that aids the redistribution of the wind resource to locations within the region. The observed seasonal wind resource variability was characterized with intraseasonal pulses introduced by the dynamics of changing wind direction and speeds as observed in Han et al. (2004); Wu et al.(2005) and Hernandaz-Escobedo et al. (2014).
Figure 10: Wind speeds for September October November (SON) in northern Kenya
4.3.3 Seasonal wind resource variability at 850mb level in northern Kenya

From Figure 11 and Figure 12, both baseline and model outputs at the 850mb level respectively show that the distribution of mean wind speeds follow similar patterns as for the winds at the surface (Figures 7, 8, 9 & 10). Data on Figure 11 show that mean wind values were high at (10m/s) almost doubling in 850mb level compared to surface at a maximum of over 9.0m/s. Results indicates that the 850mb level winds matched with the surface winds in terms of orientation and distribution of the wind power resources.

Figure 11: Wind speed variability for DJF & MAM in northern Kenya at 850mb level
In the Figure 12 below, results show that the JJA season was the most dominant season in the upper level winds. The results were consistent with the surface observations on Figure 9. These results therefore suggest that there were no major differences between the seasonal wind resource characteristics on surface and at the 1500m above mean sea level.

Figure 12: Seasonal wind patterns for JJA & SON in northern Kenya at 850mb level
The comparison between the baseline and the models outputs at the surface and the 850mb level was summarized in Table 10 below. Table 10 shows the range of simulated wind values for historical period (LTM). Also included were the seasonal outputs being the simulated and the projected mean wind resource potentials for baseline (ECMWF), HadGEM2 and ICHEC models. The table was used to compare the LTM for the baseline and model outputs at the surface and upper levels (1500m or the 850mb Level) and for the different seasons (DJF, MAM, JJA and SON). Results on Table 10 therefore, show that variability in the LTM wind regimes was high at 850mb levels compared to the surface for the baseline and model outputs up to 2050. Data show that there were very slight variations between simulated outputs using the RCP4.5 and RCP8.5 at both levels for close model sensitivity. These results therefore suggest that the observed wind variability in the baseline period is likely to obtain even to the future and that the observed wind resource potentials are sustainable.
Table 10: Baseline and model outputs at surface and the 850mb for northern Kenya

<table>
<thead>
<tr>
<th>Models</th>
<th>Levels</th>
<th>LTM (m/s)</th>
<th>DJF (m/s)</th>
<th>MAM (m/s)</th>
<th>JJA (m/s)</th>
<th>SON (m/s)</th>
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<td>3.5 – 6.0</td>
<td>3.0 – 6.0</td>
<td>3.5 – 6.0</td>
<td>3.0 - 8.0</td>
<td>3.5 – 6.5</td>
</tr>
<tr>
<td></td>
<td>850mb</td>
<td>4.0 - 11</td>
<td>3.0 – 7.5</td>
<td>3.5 – 8.0</td>
<td>4.0 - 11</td>
<td>3.5 – 9.0</td>
</tr>
<tr>
<td>HadGEM2</td>
<td>Surface</td>
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<td>3.5 – 6.0</td>
<td>3.0 – 5.0</td>
<td>3.5 – 6.5</td>
<td>3.5 – 6.5</td>
</tr>
<tr>
<td></td>
<td>850mb</td>
<td>4.0 - 10</td>
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<td>4.0 - 11</td>
<td>4.0 - 13</td>
<td>4.0 - 10</td>
</tr>
<tr>
<td>ICHEC</td>
<td>Surface</td>
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<td>3.5 – 6.0</td>
<td>3.5 – 5.5</td>
<td>3.5 - 4.5</td>
<td>3.5 – 4.8</td>
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<tr>
<td></td>
<td>850mb</td>
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<td>4.0 - 11</td>
<td>4.0 – 9.0</td>
<td>4.0 - 11</td>
<td>3.5 – 7.5</td>
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<tr>
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<td>2.0 – 5.0</td>
<td>2.5 – 6.0</td>
<td>2.5 – 7.0</td>
<td>2.5 – 6.5</td>
</tr>
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<td>4.0 - 10</td>
<td>3.0 – 11</td>
<td>4.0 - 12</td>
<td>3.0 - 10</td>
</tr>
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<td>RCP8.5</td>
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<td>4.0 - 11</td>
<td>3.0 - 10</td>
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</tr>
<tr>
<td>RCP4.5</td>
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<td>2.0 – 7.5</td>
<td>3.0 - 11</td>
<td>3.0 – 9.0</td>
<td>4.0 - 11</td>
<td>3.5 – 7.5</td>
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<td>ICHEC</td>
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<td>3.5 – 4.5</td>
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<tr>
<td>RCP8.5</td>
<td>850mb</td>
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<td>3.0 – 10</td>
<td>3.0 – 8.5</td>
<td>3.0 - 11</td>
<td>3.5 – 7.8</td>
</tr>
</tbody>
</table>

4.3.4 Graphical presentation for wind variability in Baseline and Projected periods

Figures 13 & 14 showed the line graph and radar (with marks) respectively depicting the mean monthly wind resource variability for baseline and projected periods. Results in Figure 13 and Figure 14 depict similar monthly wind characteristics patterns for the baseline and the projected period respectively. The highest winds were observed between
the months of June to August followed closely by the December, January, February (DJF) season. This potential decreases from March to May and that minimum winds obtain between the months of September and November.

In Figure 13 for baseline outputs therefore, HadGEM2 model depicted the highest simulated wind speeds in the month of July at above 9.5 m/s followed by the baseline at above 8.0 m/s over the same period. The lowest monthly mean wind speeds were depicted by the ICHEC model at 2.5 m/s in the month of November at the surface. Monthly variation of wind speeds indicates that for baseline wind speeds starts increasing in the month of April reaching the peak in July from where it decreases to the minimum in November. This wind characteristic pattern was also captured by HadGEM2 and ICHEC models at the surface and the 850mb levels suggesting that models were able to simulate wind values consistent with the baseline data.
Figure 13: Simulated (1981 – 2015) winds on the Surface in northern Kenya

Figure 14 below for the projected wind speeds show that the winds will follow similar pattern as the depicted by the historical monthly wind patterns in Figure 13. The highest mean wind speed of (10m/s) was projected by the HadGEM2 and ICHEC models forced by RCP8.5 at 850mb level during the JJA season. The lowest wind speeds were projected to be around 3.0 m/s using ICHEC RCP4.5 in the month of November. The results for projected wind regimes suggest that northern eastern Kenya will continue observing low wind resource variability as in the baseline period for certainty in the development of wind energy farms.
4.3.5 Projected (2016 to 2050) wind resource distribution in northern eastern Kenya

Figures 15 - 20 below shows the projected outputs from HadGEM2 and ICHEC models for data simulated using the RCP4.5 for controlled carbon dioxide emissions and RCP8.5 for enhanced carbon emission levels. The results were used to compare the model outputs being the HadGEM2 and ICHEC results for surface and 850mb level for long term mean (LTM) and the seasonal wind speed patterns. Figure 15 therefore presents results for the projected long term mean (LTM) wind characteristics at surface and 850mb levels. Data show that the highest average wind values will continue to be observed in Marsabit County.
Both models project an average wind ranging between 3.5 m/s at the lower end to 12 m/s at the upper end. Compared with ICHEC model outputs, HadGEM2 model projects slightly higher mean wind speed values both at the surface and at 850mb level. Data shows that HadGEM2 projects mean wind speeds at 10 m/s against a mean of 7.5 m/s by ICHEC model at 850mb level. However, the projected mean wind speeds for the surface and 850mb level depicts a similar spatial distribution patterns by both models.

![Wind patterns for Surface and 850mb using the RCP4.5 in northern Kenya](image)

**Figure 15:** Wind patterns for Surface and 850mb using the RCP4.5 in northern Kenya
Figures 16 on the other hand present the long term mean wind resource characteristics at surface and 850mb level using the RCP8.5. Results depict similar spatial distribution patterns for upper level winds and the surface winds presented Figure 15. However, in Figure 16 models projected slightly high wind speed regimes compared to wind speeds forced under the RCP4.5 in Figure 15. Nevertheless, the results show that models were able to capture the surface and the upper level wind features appropriately for no significant difference between the surface and upper level winds in north eastern Kenya region.

Figure 16: Wind speeds at the Surface and 850mb for RCP8.5 in northern Kenya
Results for projected seasonal wind speeds using representative concentration pathways (RCP 4.5 and the RCP8.5) were presented in Figures 17, 18, 19 & 20. Projected seasonal wind distribution patterns reflected a similar pattern for surface and 850mb level as shown in the LTM wind patterns in Figures 15 and 16 above. Comparing the seasonal wind outputs in Figures 17, 18, 19 & 20, results show that JJA season will dominate the projected wind resource potentials in north eastern Kenya. Data show that in the projected period, the seasonal wind variability patterns oscillate with the monsoonal flow as was observed with baseline period. These results however show that models projects slightly high wind potentials for RCP8.5 compared to the RCP4.5 at the same level. Data for the projected seasonal wind patterns in north eastern Kenya therefore indicates a significant seasonal variability patterns which influences the spatial distribution of the regional wind resource potentials. However, the seasonal characteristic of the local winds depicts cyclical patterns that are strongly tied to the global monsoonal patterns. The monsoons are intertwined by both seasonal and intraseasonal wind variability pulses influencing the wind power resource potentials. The results therefore suggest that seasonal variability patterns were significant compared to long term mean wind variability that exhibited low variability levels shown in baseline period in Table 5. These results are consistent with observations in Wu et al. (2005) and Xie et al. (2007) on intraseasonal wind variability. Also the results support the findings by Oludhe (2008); Theuri and Hamlin (2008); Lukuyu & Cardell (2014) and recently by Kammen et al. (2015) that region has good wind resource potentials that can be used for wind power generation. Figures 17, 18, 19 & 20 are shown in the following charts as discussed above.
Figure 17: Projected Seasonal wind speeds at surface - RCP8.5 in northern Kenya
Figure 18: Projected Seasonal wind speeds at 850mb- RCP8.5 in northern Kenya
Figure 19: Projected Seasonal wind speeds at surface - RCP4.5 in northern Kenya
Figure 20: Projected Seasonal wind speeds at 850mb - RCP4.5 in northern Kenya
Results so far indicates that northern eastern Kenya region have high wind resource potentials distributed over most locations. Investigating the wind resource characteristics however would not be complete without the consideration of frequency distribution of the wind speeds for the baseline and the projected periods. The frequency analysis thus provided insights on the level of deviations in the (baseline) historical and (model) projected datasets. Figure 21 below show that out of the possible 34 cases of data period, baseline had 22 cases reporting about 4.8m/s compared with 34 cases projected at 5.0m/s. Similarly baseline had 30 cases reporting wind speeds above 7.0m/s relative to 33 cases projected at 7.5m/s. Records show that 19 cases reported wind speeds greater than 8m/s in the baseline with models projecting 28 cases with mean wind speeds greater than 8.5m/s.

The results in Figure 21, suggest that highest number of observed and projected winds in north eastern Kenya were skewed towards high values above 7m/s in baseline and the projected periods. Data show that baseline and model outputs depicted high frequency of wind speeds values above 5m/s compared to the frequency of the wind speed less than 4m/s. These findings therefore suggested that region has high potential for wind power generation. The results depict high wind speed values greater than the literature value for lowest wind speeds required to turn a rated wind turbine to generate useful energy at 3 – 5m/s (IRENA, 2012; Lipu et al., 2013; Manwell et al., 2009). The study results were therefore consistent with findings by (Kammen et al., 2015; Lukuyu & Cardell, 2014; Kiarie, 2013; Oludhe, 2008) for good wind power potentials in northern Kenya.
Figure 21: Frequency of winds for baseline and Projected periods in northern Kenya

**4.3.6 Relationship between Baseline and Model outputs at Surface and 850mb**

The analysis for the relationship between the baseline and model outputs were carried out to find out how individual model outputs correlated with the baseline model (ECMWF). Correlation results were used to recommend the model to be used in wind resource assessment for northern Kenya. Results in Table 11 show that baseline, HadGEM2 and ICHEC model outputs yield mixed correlation coefficients for the historical and the projected periods. However, the observed negative correlation between ICHEC model outputs with the baseline (ECMWF) data, suggests that ICHEC model was less sensitive in simulating winds for north eastern Kenya. HaGEM2 model depicted moderate to strong
correlation coefficients with the baseline model both at historical and projected periods. Results therefore suggest that HadGEM2 model performed better than the ICHEC model.

Observed spatial, long term, seasonal and monthly wind characteristics suggests existence of a good relationship between the baseline and models outputs both in the historical and projected periods. The Positive correlation coefficient between baseline and model data validates the models outputs for wind speeds in north eastern Kenya. The results were therefore consistent with suggestions by Foley et al. (2012) that model outputs can be validated using observed meteorological data or the reanalyzed datasets from global models downscaled to regional conditions. Secondly, the results suggest that models data can be used in assessment of wind resource characteristics in different locations (Jury, 2013).

It is evident that the projected wind speed patterns closely matched with the simulated baseline and model output. Although the long term mean wind patterns depicted low variability characteristics, JJA season presented persistently high wind speeds. The interseasonal and seasonal wind pulses were intertwined with intraseasonal amplitudes with implications to the seasonal and annual wind characteristics. The seasonal wind variability patterns were therefore significant. Trend test results and the coefficient of variability tests suggest no significant differences between baseline, simulated and the projected winds resource characteristics for the region. In most cases baseline and models outputs simulate high frequency of wind speeds greater than 7m/s. This indicates that northern Kenya regions have high wind speeds above the literature value of wind speeds between 3 – 5m/s as the minimum wind that can turn a rated wind turbine to generate useful power (IRENA, 2012; Lipu et al., 2013; Manwell et al., 2009). Thus north eastern Kenya region has good wind resource potentials for generation of electricity using off grid hybrid systems.
These results were consistent with the findings by Oludhe (2008); Lukuyu & Cardell (2014) and recently by Kammen et al. (2015) that region has good potential for generation of wind power electricity.

Table 11: Correlation Coefficients for baseline and the Model outputs

<table>
<thead>
<tr>
<th>Models Correlated</th>
<th>Levels</th>
<th>Correlation Coefficient (r)</th>
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</thead>
<tbody>
<tr>
<td>ECMWF HadGEM2</td>
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<td>0.5</td>
</tr>
<tr>
<td></td>
<td>850mb</td>
<td>0.4</td>
</tr>
<tr>
<td>ECMWF ICHEC</td>
<td>Surface</td>
<td>-0.2</td>
</tr>
<tr>
<td></td>
<td>850mb</td>
<td>-0.03</td>
</tr>
<tr>
<td>ECMWF HadGEM2</td>
<td>Surface</td>
<td>0.8</td>
</tr>
<tr>
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<td>850mb</td>
<td>0.8</td>
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<td>RCP4.5</td>
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</tr>
</tbody>
</table>
4.3.7 Assessment of wind resource variability using Box plots

From the seasonal variability patterns study sought to assess the wind resource variability using the box plots. Box plots were used to show the variability levels in station data for baseline and model outputs at surface and 1500m above mean sea level. Box plots show the location and data range using the quartile values, skewers, tail length and outlying data points (McGill, Tukey & Larsen, 1978). Data location was summarized by the median, while the length of the box shows the spread and the length of the whiskers indicates the outliers. Figures 22, 23 and 24 below depict the box plot outputs of the wind resource variability at surface and 850mb level in the baseline and projected period. Figure 22 show the wind resource variability as simulated from ECMWF model data extracted at the locations represented by local Meteorological stations in north eastern Kenya. From the chart the length of the boxes presents the inter quartile range (distance between the 25th and 75th percentile); horizontal line inside the box indicates the median and the vertical line (whiskers) are for the maximum and the minimum values in the data. Results show that Marsabit County had the highest annual wind resource variability based on the range between the highest and lowest simulated wind values at surface and at 850mb level. In Marsabit the median value was located at 6m/s for the surface wind and at 8.0 m/s for the winds at 1500m above mean sea level or the 850mb level. Other results show that the lowest wind resource variability was observed at Meru and Laikipia.
Figure 22: Box plots for the baseline winds at the Surface & the 850mb level

Figure 23 below compares the variability of the wind resource in the historical period using different models at surface and the 850mb level. Data showed that there were marked differences between simulated wind values at surface and at the 850mb level. Figure 23 show that the median values for output winds at surface ranged between 3 - 5m/s while the upper level winds ranged between 6 - 8.5m/s. Highest wind speeds were depicted by HadGEM2 model at 850mb level while the lowest was output by the ICHEC model at the surface. The most variable wind was exhibited by the IHEC model at 850mb level based on the distance between the lower and upper quartiles and the range between the highest and lowest winds simulated at the surface.
Results in Figure 24 below depict the projected winds for period 2016 - 2050 under different scenarios. Data indicates a marked difference between surface and upper level winds as output by models based on RCP4.5 and RCP8.5. The boxes at the lower end show the surface winds while the upper level winds were depicted by the upper box plots. Data show that baseline and HadGEM2 model outputs low variable winds at the surface compared to 850mb level winds. HadGEM2 simulated the highest wind as 850mb level while the lowest wind was output by ICHE model at the surface. Thus in Figures 22, 23 & 24 the model and baseline outputs moderate median values for wind speed oscillating between 4 - 6m/s. The upper level winds were located between 8 - 9m/s therefore more variable than winds simulated at the surface for historical and projected datasets. Most median values were lying at the centre of the boxes and there were comparatively short distances between the 25th quartile and the 75th quartile values. Further analysis showed
that the maximum and minimum values overlapped for long term mean winds in the baseline considering the surface and the 850mb level winds (Figure 22).

The results in Figure 22 therefore suggest that north eastern Kenya had a moderately low wind variability patterns. In Graabak et al. (2016) it was shown that location specific wind characteristics have inherent impact to power system costs. The observed variability patterns therefore suggest that it is economical to invest in wind power systems in northern Kenya. However, it is notable from data that there was a significant difference in wind resource variability between surface and upper level winds (Figure 23 & 24). This indicates that wind speed increases with height a factor of consideration when putting up wind farms (Kubik et al. 2011; Jury, 2013; Lukuyu and Cardell, 2014).

Figure 24: Projected winds at RCP4.5 & RCP8.5 for 2016 – 2050 in northern Kenya
4.3.8 Variation of the Wind Resource Potential using Geographical Information Systems

In this analysis wind data was visualized using the geographical information systems (GIS) outputs of averaged wind values at surface and 850mb and using RCP4.5 with RCP8.5. The GIS data was extracted using County boundaries for the study area and results tabulated by averaging at the location of each of the seven meteorological stations in north eastern Kenya. GIS maps present grids indicted by lines of latitudes in the vertical y-axis and lines of longitudes in the horizontal x-axis. Based on the grid analysis it was possible to extract and average data for the seven stations at surface and 850mb level. The GIS outputs were presented by Figures 25 & 26 below. Each GIS map represents outputs at different levels, for data extracted on the location of the seven Meteorological stations in north eastern Kenya. GIS maps were also used to show the elevation of each location above mean sea level. This was because the surface topographic features have some effects on wind profiles in an area.

Data in Figure 25 show that HadGEM2 simulated slightly high mean wind values compared to ICHEC at the surface. It is observed that Marsabit Meteorological station sits in a region between two ranges one in northern and the other to the southern side. The presences of the two ranges on either side channels the moving air to the narrow passage in between the ranges making the air to accelerate as it exists to the other end. The feedback therefore generates strong air currents depicted by strong winds in Marsabit and its environments. GIS output at surface show that the highest long term mean (LTM) wind speed for Marsabit Meteorological station was 5.4m/s by HadGEM2 and 4.2m/s by ICHEC model. Mandera County in the lowly elevated areas had the lowest mean wind speed at
2.5m/s by both HadGEM2 and ICHEC models outputs. GIS wind outputs for the surface and upper levels were consistent with spatial wind characteristics simulated by models using GraDs. However data show that GIS outputs low wind speeds compared to output wind speeds from the GraDs software. This could be attributed to fact that GIS averaged winds at a point (Stations) while GraDs averaged winds for the whole County.

![GIS wind outputs](image)

**Figure 25:** GIS outputs for winds speeds at the surface (10m) in northern Kenya

Figure 26 below presents the projected mean wind speed values for the GIS outputs for models scenarios at surface and 850mb level. The highest wind observed was output by HadGEM2 RCP8.5 at the 850mb level at 9.4m/s while the lowest wind was 3.5m/s by ICHEC RCP4.5 at the surface. With a mean wind speed of 10m/s Marsabit Meteorological station depicted the highest wind projected while Mandera Meteorological station depicted the lowest mean wind values projected in the region. Like in the model outputs GIS
depicted low wind variability levels at 3.0 - 5.5m/s in low potential areas to between 3.4 – 9.4 m/s in the high potential areas. These results were consistent with baseline and model outputs summarized in Table 8. Model data therefore can be used for wind variability characteristic as shown in (Bloom et al., 2008; Foley et al., 2012; Fant & Schlosser, 2012; Jury 2013; Graabak et al., 2016). Results also show that GIS could be used in the development of wind atlas or a wind GIS database for northern Kenya. Therefore consistent with results by Huld et al. (2012) for the Potovoltaic Geographical Information System (PVGIS) web application for estimating the performance of PV systems in Europe and Africa. GIS out puts depict that the wind resource potentials are site specific therefore study suggest the use of off grid Microsystems and hybrid electricity generation systems. The off grid generation will mainly target to supply the small villages (Bura) that are scattered widely in northern Kenya region.
Figure 26: GIS output for projected winds at Surface & 850mb in northern Kenya
4.3.9 Comparison for Historical and Projected wind variability in northern Kenya

Figure 27 below depicts the graphical presentation for the baseline and the projected wind resource variability in north eastern Kenya. Data used to generate the time series plots was extracted from model outputs in the historical and projected periods. The chart was used to visualize the temporal characteristics of the baseline and projected wind speeds output by baseline (ECMWF) and models at the surface and 850mb levels. Results show that the baseline and model simulations followed similar temporal patterns at the surface and 850mb level. Data indicates that the ICHEC model simulated wind speed values below the Baseline (ECMWF) model outputs. In the historical period HadGEM2 curve crosses the baseline curve for the surface data. In most occasions however HadGEM2 model seems to be overestimating wind speeds at 850mb level compared to baseline output. Data show that projected wind patterns in northern eastern Kenya will obtain similar characteristic patterns at the baseline period but with slight increase at upper levels.

Time series plots depict a moderate positive correlation coefficient of 0.5 for baseline and HadGEM2 model outputs in the historical period. Results also indicate a strong positive correlation coefficient of 0.8 for baseline and the HadGEM2 model outputs in the projected period. There was a weak negative correlation of -0.1 for ICHEC model and baseline in the baseline period and some mixed signals in the projected period. The time series plots indicate a small range between the maximum and minimum points of data throughout the baseline and the projected periods. This observation is good for wind power generation based on the fact that extreme winds interfere with the efficiency of the wind turbines (Diamond, 2011; Lipu et al., 2013; Manwell et al., 2009). Diamond (2011), showed that less energy will be produced if turbines were shut to avoid damage by extreme winds.
which hurts both the consumers and the investors. Nevertheless results show that baseline and models simulated winds greater than 3 – 5m/s recommended as the lowest wind that can generate useful electricity extracted by a turbine at any level (Manwell, McGowan & Rogers, 2010; Kiarie, 2013). The results therefore suggest that prevailing wind power potentials in the north eastern Kenya region are good for generation of off grid wind power electricity. The observed LTM wind speeds variability therefore, would not affect the prevailing wind power potential in the northern Kenya region now and in the future up to 2050.

Figure 27: Baseline and model outputs with projected wind speeds in northern Kenya
4.4 Variation of wind speed with height using the power-law relation

The tabulation of the changes of the wind velocity with height was done for selected locations in northern Kenya. Graph was generated using the mean wind velocity for baseline datasets at the surface (10m) and the power law formula. Surface wind was therefore taken as the reference height and computed heights included 20m, 50m, 80m, 100m and 120m above the topographical surface. The power law coefficient or the friction coefficient (\( \alpha \)) was taken to be \( \left( \frac{1}{7} \approx 0.143 \right) \) (Apratim, (2012); Arya, 1988), since it was not possible to ascertain the friction coefficient for each location.

Results in Figure 28 showed that wind speeds increased with height up to about 80m - 100m where the graph starts to bend at a decreasing rate. This suggests that ideal wind turbine height could be anywhere between 50m - 80m. So that mounting the wind turbines above 80m may not justify the cost of height extension given the marginal increases of wind velocity with height above 80m. Data show a distinct distance between Marsabit and other stations curves demonstrating that highest wind power potentials were concentrated in Marsabit region. Isiolo County depicts the lowest wind power potential. Results indicates that wind resource potential was distributed fairly across the region given the clustering of Garissa, Mandera, Wajir and Moyale data sets at the same point. Figure 28 therefore demonstrates that, it was possible to achieve optimum levels for setting up wind turbines following assertions by Kubik, et al. (2011) that the most important level was the hub height where the wind turbines harvest the wind energy.
Figure 28: Variation of wind speeds with height using power law in northern Kenya.

4.4.1 Electricity energy consumption per capita in north eastern Kenya.

Analysis of electricity energy consumption data was used as an indicator to the current electricity demand in north eastern Kenya. Knowledge of the current demand will inform and motivate the independent power producers (IPPs) to invest in wind energy generation. Results may also be a pointer to areas that require urgent electricity connection from off grid hybrid systems. Off grid micro systems may be the best idea for electricity access in northern Kenya given the long distances between the local settlements Buras and the market centres. This could also be an indicator to whether the available wind resource potentials were adequate to satisfy the local demand. The electricity consumption data used was for five years spanning 2011-2015.
The data was used to determine the electricity consumption per capita for individual counties in north eastern Kenya. Results were presented in Figure 29, Table 12 and Table 13.

Figure 29 show that Garissa County had the highest annual electricity energy consumption that picked to 19 Million kilowatt-hours compared to the consumption of 5 million kilowatt-hours in Marsabit County in the year 2014. Highest electricity consumption totals were therefore recorded in Garissa for the year 2014. Trends in Electricity energy consumption increased for all stations between 2010 and 2014 where the trend stabilized for Wajir and Mandera with a decline in Garissa and Marsabit in 2015. Observed decline could be attributed to increase in international price of petroleum with direct impact on local cost of electricity. Increased cost of electricity leads to a direct adjustment in electricity consumption patterns to save on costs. However sustained increase in electricity consumption was a good indicator to the growing demands for electricity. Therefore need for enhanced electricity connectivity using the renewable energy resources in the counties within the north eastern Kenya.
Figure 29: Electricity energy consumption in the northern Kenya region

Table 12 show Wajir County depicting the highest electricity consumption per capita at 1023kwh per capita while the lowest consumption was reported in Marsabit County with 556kWh per capita. However, results indicated that there was only 1.0 % of electrified population in Wajir County compared to 0.6% at Mandera County. Garissa and Marsabit Counties had a slightly high number of electrified populations at 4.1% and 2.4% respectively. These numbers seem to suggest that although Wajir had a higher per capita energy consumption, penetration rate was quite low compared to Garissa and Marsabit. Data show that the electricity energy consumption per capita was decreasing with time for all areas. This was probably because the number of customers continued to grow while the local generation capacity remained almost the same.
The results for energy consumption per capita and the electrification rates suggest that northern Kenya region requires urgent attention to bridge the electrification gap. These results were consistent with findings by Bazilian et al. (2010) that in SSA electricity consumption per capita were below 1000KWh with low electricity access levels. The results for northern Kenya partially confirm that region lags behind in development record consequent of limited electricity access. Low levels of performance in electricity development index (EDI) directly affect the human development index (HDI) that links to community emancipation from disease, ignorance and poverty (UNDP, 1990; Kammen et al., 2015). The results were also consistent with findings in Martinez (2008), which showed existence of a strong relationship between the human development index and the per capita energy consumption. Other data not in Table 12 showed that the number of electrified customers in Isiolo County doubled from 5,117 in 2013 to 10,056 by the end of 2015. This meteoric rise in customer base could be attributed to the fact that thermal grid connection was integrated with 10MW PV solar systems at Merti coupled with the recent connection of Isiolo County to the national grid indicating that increased capacity will lead to increased electricity access.

Table 12: Electricity energy consumption per capita (2015) in northern Kenya

<table>
<thead>
<tr>
<th>Description</th>
<th>COUNTIES</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Garssa</td>
</tr>
<tr>
<td>Total Consumption (2015)</td>
<td>18,257,400</td>
</tr>
<tr>
<td>Connected Population (2015)</td>
<td>25,730</td>
</tr>
<tr>
<td>Per Capita Consumption (kWh)</td>
<td>709</td>
</tr>
<tr>
<td>Electrified Population (%)</td>
<td>4.1</td>
</tr>
</tbody>
</table>
Wind power density (WPD) is the amount of wind power available per unit area perpendicular to the wind flow Choge et al. (2013). WPD therefore could be a good indicator for the local wind resource distribution and potentials (Oludhe, 2008). Wind power density was calculated for the seven locations being the local meteorological stations in the north eastern Kenya region assuming standard air density to be 1.225kg/m$^3$ (Arjun et al. 2013; IRENA, 2012). WPD was calculated using the mean wind velocity for the baseline data at the surface. Results in Table 13 show that the highest WPD was found in Marsabit with 807W/m$^2$ and lowest at Meru with 84W/m$^2$. Studies have shown conflicting WPDs’ for Marsabit where Kiarie (2013) used mean wind speed of 6m/s over Marsabit and showed a WPD of 362W/m$^2$. The study used mean wind speed of 8.7m/s for Marsabit for WPD at 807W/m$^2$. Results therefore suggest that variability in the wind may interfere with the steady flow of the wind impacting the WPD. Changes in WPD influence the capacity of rated wind turbines to generate electricity (IRENA, 2012). Thus low wind variability regimes are good for stable and reliable wind energy generation. Results suggests that north eastern Kenya regions depicts high wind power potentials compared to the 70W/m$^2$ and 107.5W/m$^2$ shown for Uashin Gishu county in the north rift regions (Choge et al., 2013). Thus the findings were consistent with literature that region has good potential for generation of electricity from the wind power (Oludhe, 2008; Lukuyu & Cardell, 2014; Kammen et al., 2015).
Table 13: Wind Power Density for mean wind speeds in north eastern Kenya

<table>
<thead>
<tr>
<th>Stations</th>
<th>Wind (m/s)</th>
<th>Wind Power Density (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marsabit</td>
<td>8.7</td>
<td>807</td>
</tr>
<tr>
<td>Laikipia</td>
<td>7.5</td>
<td>517</td>
</tr>
<tr>
<td>Garissa</td>
<td>6.9</td>
<td>402</td>
</tr>
<tr>
<td>Wajir</td>
<td>6.8</td>
<td>385</td>
</tr>
<tr>
<td>Moyale</td>
<td>6.8</td>
<td>385</td>
</tr>
<tr>
<td>Mandera</td>
<td>6.5</td>
<td>336</td>
</tr>
<tr>
<td>Isiolo</td>
<td>4.1</td>
<td>84</td>
</tr>
</tbody>
</table>

4.5 Contributions of renewable energy resources to Hybrid systems in northern Kenya.

The assessment of the share of renewable energy resources to a typical hybrid station was done to demonstrate capacity of renewable energy potential in northern Kenya. The functioning hybrid systems in north eastern Kenya include Merti station in Isiolo, Habaswein in Wajir County and Marsabit hybrid plant in Marsabit town. These stations started as thermal diesel plants and on later converted to hybrid systems by addition of the wind and solar components. The renewable energy components therefore were progressively being developed to mitigate costs through enhancement of base load capacity (Gichungi, 2013).
Results in Figure 30 show the amount of electricity energy generated from diesel, wind and solar energy in Marsabit, Merti and Habaswein stations. Data show that out of 2400kW diesel capacity, Marsabit achieved a 20% increase in energy generated from wind in 2012 compared to 4% contribution from the wind in 2011. At the same time Merti in Isiolo grew its solar energy component from 3% of total energy generated in 2011 to over 10% share in 2012. Growth in solar energy component in Merti continued with an addition of another 10% of solar PV capacity in 2015. The results indicate that Habaswein in Wajir County boosted its solar PV capacity by 5% and 2% of wind components added to the total energy generated between 2011 and 2012. This effort continued with an addition of 2% solar PV capacity by the end of 2015.

Figure 30 shows that Marsabit County had the largest share of electricity energy generated from the wind. The results support the assertions by Nedaei (2012) that wind energy generation was expected to increase in future based on the fact that wind energy is clean and freely available. Thus results depict a sustained effort towards integration and growth in the hybrid systems in northern Kenya, consistent with Chu & Majumdar (2012) that access to clean, affordable and reliable energy was the key to economic development. This was a government strategy to convert the existing thermal diesel plants into hybrid systems through integration of 30% renewable components (Gichungi, 2013; Kiarie, 2013). The continuous implementation of hybrid systems in northern Kenya would contradict the assertions in Wolfram (2012) that nearly all increase in use of fossil fuels for the next 25 to 30 years were forecasted to come from the developing world. Hybrid systems will not only minimise use of fossil fuels but also mitigate poverty level by reducing the price of electricity (Singh & Ganguli, 2010). The results therefore indicate a path to boost the reliability of electricity energy supply in northern Kenya in consistent with Crousillat et al.
(2014) that nations consider electrification for increased social and economic developments. The result from Figure 30 therefore confirms that it is possible to mitigate the growing need for electricity using the hybrid systems in northern Kenya. One of the basic advantages of a hybrid system was to maximize on the use of the renewable energy sources to supply the base load requirement and only engage the use of thermal component during peak hours (Singh & Ganguli (2010); Lipu et al., 2013). That way it would be possible to mitigate emission of GHG and have a cheap and sustainable electricity supply for northern Kenya region.

Figure 30: Energy Generated using hybrid systems in northern Kenya
CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the conclusions and recommendations of the study based on the findings and in line with the study objectives.

5.2 Summary

The study sought to understand the effects of wind resource variability to distribution and potential of wind velocity (wind power potential) for generation of electricity using the off grid micro-hybrid systems in northern Kenya.

Initial tests indicated that baseline and model outputs were stationary. Statistical tests using the Mann-Kendall and the Spearman’s Rank tests depicted that stations data had $p$-values less than critical value $\alpha$ of 0.05 and 95% confidence interval implying that some stations data was not stationary. However, further tests by lagging showed that the surface and 850mb level seasonal data had a constant $\tau$ at 0.45 suggesting that data was stationary. Stationary tests for seasonal means for baseline and model simulations at surface and 850mb level had $p$-value of 0.15 and 0.13 respectively which were greater than 0.05 ($\alpha$) therefore stationary series. Models simulated increasing trends in the data which were however not significant. Further, Mann-Kendall results showed that the seasonal data had $p$-values greater than $\alpha$ 0.05 for stationary seasonal series. Data showed a slightly higher range between the upper level wind speeds compared to the surface winds. Therefore higher seasonal variability in 850mb level wind speeds compared to surface datasets. Results for the baseline and model outputs showed that region had moderate seasonal wind speed variability patterns governed by the global monsoon regimes which aids in the distribution of the wind power resource. The JJA season had the highest wind power resource potential and compared to DJF, MAM and SON seasons.
The seasonal variability patterns were intertwined with interseasonal and the intraseasonal winds speed variability patterns that influenced the distribution of the wind power potentials across the region. The seasonal wind resource variability patterns were therefore significant.

On variability analysis the baseline and the models simulated long term mean data that demonstrated a value of 0.4 standard deviations, coefficient of variation (CV) below 5.8% and low standard error of mean (SEM) ranging between 0.03 - 0.09 for low wind resource variability characteristics. The seasonal variability patterns revealed that winds in northern Kenya were mainly controlled by monsoonal wind systems. The box plots analysis depicted moderately small margins between the maximum and minimum wind speeds for baseline and model outputs with overlapping ends which suggests low LTM wind resource variability. Based on the above, it is evident that region is dominated by low spatial and temporal wind resource variability patterns. Spatial maps had indication of matching surface and upper (850mb) level wind features. Projected winds at surface and 850mb level depicted similar wind patterns as those observed in the baseline at the same levels. The relationship between HadGEM2 model outputs with baseline data had a moderate correlation coefficient of 0.5 for surface winds and 0.9 for 850mb level winds. At the same time ICHEC model depicted some mixed signals with the baseline outputs for surface and for upper level winds. This therefore implies that the HadGEM2 model demonstrated skill in simulating baseline data compared to the ICHEC model. The GIS maps on the other had showed that Marsabit station lays in a region between two ranges that channels moving air through a narrow opening thus accelerating the wind speeds as they pass through the narrow channel. The time series plots depicted slight positive trends in wind resource
potentials up to the year 2050. However, the trends in the temporal variability patterns were not significant.

The highest electricity energy consumption per capita was realized in Wajir County with 1023kWh per capita. However, Wajir County was the least electrified in the region with only 1% of total population connected to electricity. This demonstrates that northern Kenya region have high electricity poverty levels. Highest contribution of renewable energy resource to hybrid generation was in Marsabit County where the wind power resource contributed to over 600MWh in 2012 which rose to more than 780kWh by the end of 2015.

5.3 Conclusions
The study results have shown that there exist significant good wind resource potentials in the north eastern Kenya regions. The highest winds speed was simulated in Marsabit County at 9m/s and lowest wind speed at Mandera station at 4.6m/s. Results indicated that the baseline and model outputs depicted similar spatial and temporal long term mean wind speed distribution patterns for the surface and the 850mb level. Study therefore concludes that the north eastern Kenya region is characterized by low wind variability patterns hence observed long term variability patterns and trends were not significant. However, seasonal wind variability patterns were intertwined with inter-seasonal and intraseasonal wind speed characteristics that aid the distribution of the wind resource across the region. Therefore, seasonal wind patterns were significant to the development of wind power generation systems. In the other findings, Marsabit County depicted the highest wind resource
potential at 9m/s and wind power density (WPD) at 807W/m$^2$. The most ideal level for mounting the wind turbines across the northern Kenya region was found to be between 50m - 80m to maximize the harvesting of the observed wind power potentials. On the other hand, the highest electricity consumption per capita was found in Wajir County at 1023kWh per capita followed by Marsabit at 556kWh per capita. However, results also revealed very low electrification rates in Wajir at 1%, 2% in Garissa and 2.4% in Marsabit. Study therefore concluded that north eastern Kenya region have very high electricity poverty levels. Hence the region requires urgent development of off grid micro-hybrid systems to bridge the low electrification access gaps.

Finally study presented performance of three active hybrid electricity generation stations in Marsabit, Habaswein and Merti. Other hybrid station where data was not available includes Hola and El Walk. Highest contribution to hybrid systems was observed in Marsabit County with wind contributing over 780kWh of local electricity energy consumption in the year 2015. Implementation of 30% of renewable energy components into the existing thermal plants would boost reliability of electricity generation and supply in north eastern Kenya. The study also found that HadGEM2 model outputs had a positive correlated with the baseline wind data at the surface and the 850mb levels. Therefore, HadGEM2 model performed well compared to the ICHEC model. Thus based on the results modeling could be a better method of simulating wind maps (wind data) for assessment of wind resource characteristics in the north eastern Kenya.
5.4 Recommendations

(1) The study has shown that there is significant wind power potential distributed over most places in the northern Kenya region. This therefore calls on the national government of Kenya working together with the respective County governments to consider policies likely to attract investments in wind energy for the northern Kenya region.

(2) Government and private investors in wind power generation to take advantage of the observed high and stable wind power potential to put up off grid wind farms for electricity generation to mitigate high electricity poverty levels in the northern Kenya region.

(3) The national and county governments need to provide incentives to the independent power producers (IPPs) and also boost security and provide infrastructures that will attract population to local centers. Increased population will in turn provide critical mass required to absorb the increased electricity energy generated using the micro-hybrid systems in the area.

(4) Further studies to be carried out to find out the exact nature of interseasonal and intraseasonal wind speed characteristics and how such could impact the local wind power potentials.

(5) Feasibility studies be carried out to find out specific locations for setting up wind farms even the most desirable wind turbine technology and heights to optimize exploitation of the available wind power potential for sustainable electricity energy access.
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