GEOSPATIAL ANALYSIS OF SOLAR ENERGY POTENTIALS IN PARTS OF NORTHCENTRAL NIGERIA

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ABSTRACT

All over the world, solar energy is indispensable for economic and socio-development activities. Many African countries, especially those in the process of development, are not able to produce enough solar energy. Northcentral Nigeria is located within the solar region, thus has tremendous solar energy potentials, the region lacks solar radiation information which is a critical prerequisite for exploiting solar energy. Geospatial techniques have been used lately to study solar energy potentials in different parts of the world. This study uses geospatial techniques to integrate ground-measured solar radiation data with temperature to assess solar energy potentials in Niger, Kogi and Nasarawa States of Northcentral Nigeria. Inverse Distance Weighted (IDW) interpolation was used in order to map the ground-measured data. The variability analysis was done using a standardised index (I). The findings over the study period showed increase in temperature and decrease in solar irradiance over the period spanning from 1988-2018. Maximum insolation of averagely 5.94kWh/m^2/day was observed in the months of February, March and April; while minimum insolation of averagely 4.36kWh/m^2/day was observed in July, August, and September, over the study area. Then, weighted overlay and analytic hierarchy process were used to determine the solar energy potential sites in the area. However, spatial variations exist among the three states in terms of the pattern of solar radiation. In addition, findings revealed that the amount of exploitable solar power in Niger, Kogi and Nasarawa states were 414.651 x 10^6 MWh, 147.971 x 10^6 MWh and 144.262 x 10^6 MWh respectively. However, spatial variation exists among the three states due to the pattern of solar radiation. A positive correlation was found between the ground insolation and satellite derived temperature data in the study areas Geospatial techniques should be used to produce a more comprehensive solar radiation atlas of Niger, Kogi and Nasarawa states covering all the local government areas in the three states. The best periods for exploiting solar energy in the area (February – April) should be used to harness and conserve solar power. Areas with very high solar energy potentials should be used in siting of utility scale solar farms and Concentrating Solar Power plants while Photovoltaic solar panels can be used in areas with moderate solar energy potentials. The information provided in this study can be used to diversify the energy supply mix in Nigeria in a bid to addressing the power problem in the country.

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LIST OF ABBREVIATIONS

kWh/m^2 /day	Kilowatts hour per meter square per day
PV	Photovoltaic Cell
GIS	Geographical Information System
^{o}C	Degree Celsius

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

The energy arriving at the Earth's surface from the sun is called solar energy. A large portion of this energy is in form of radiation from the "visible" frequencies. Visible radiation and radiation with more limited frequencies, for example, ultraviolet radiation is classified "shortwave" (Graham, 1999). The World's environment framework continually changes to keep a harmony between the approaching and out-going radiation. This is alluded to as Earth's "radiation Budget". The parts of the Earth framework that are vital for the radiation budget are the Earth's surface, atmosphere, and clouds (Graham, 1999). In light of the guideline of conservation of energy, the Earth's radiation budget involves the incident, reflected, absorbed, and emitted energies by the Earth framework.

Solar energy is the most sustainable renewable energy source (Pettazzi and Salsón, 2012). It's more predictable than wind energy and less vulnerable to changes in seasonal rainfall patterns (Muneer *et al.*, 2005). Still, comprehensive information on the spatio-temporal pattern of yearly mean values of global solar radiation reaching the Earth's face is Needed in the design and development of solar energy systems, as shown in Figure 1.1 (Rehman and Ghori, 2000).

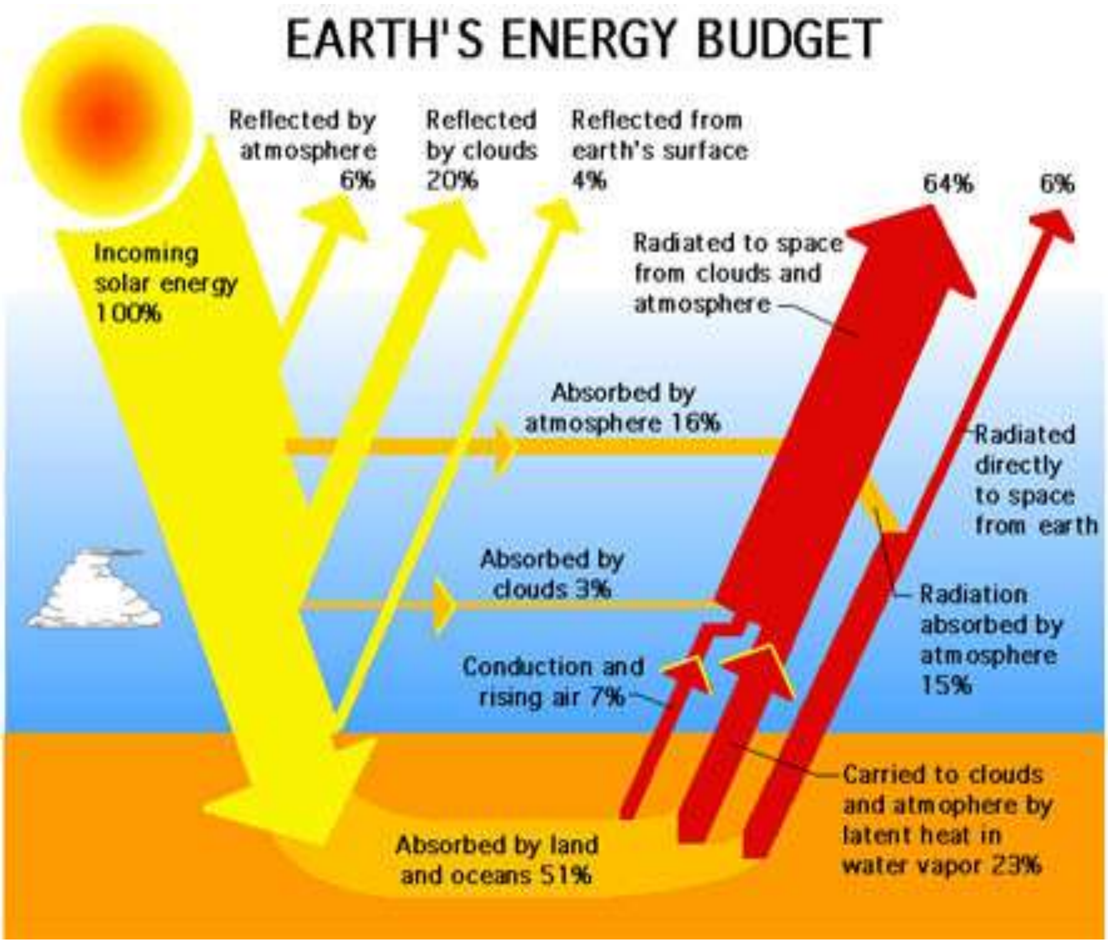


Figure 1.1: The Earth's Radiation Budget

Source: NASA (2016)

This radiation budget addresses the accounting of the harmony between approaching radiation, which is totally sunlight based radiation, and out-going radiation, which is halfway reflected solar based radiation and partly terrestrial radiation, including the atmosphere (NASA, 2010).

The potential of solar energy in Africa is naturally high. The mainland is located between authorizations 37 °N and 32 °S and spans a vast area that crosses the equator and both tropics. African countries admit a veritably high number of periodic sun hours and the average solar irradiation is relatively fairly distributed (though areas of Sahara, Sahel, and the south-west tip of the mainland and the horn of Africa are exceptionally sunny). This means that policy and fiscal restrictions away, solar technologies could supply heat and power to nearly everyone, indeed the most remote communities. African countries are blessed with a huge and still untapped renewable energy potentials. Estimates of power generation implicit in the mainland are 350 GW for hydroelectric, 110 GW for wind, 15 GW for geothermal and a stunning 1000 GW for solar (AfDB, 2017). Solar energy is indeed promising in terms of geographical distribution albeit with varying capabilities. This type of energy could be exercised nearly every place in Africa.

Nigeria is endowed with abundant solar energy capabilities which vary spatially and temporally. These capabilities can be exploited to increase the energy force blend in the country. Several studies have been carried out on solar energy capabilities in different corridor of Nigeria using empirical models similar as Akpabio *et al*. (2004), Chiemeka (2008), Augustine and Nwabuchi (2009), Sanusi and Abisoye (2011), Falayi *et al.* (2011), Ibeh *et al.* (2012), Musa *et al.* (2012), Ogbaka and Silikwa (2016). These studies have concentrated substantially on southern Nigeria and some corridor of northern Nigeria.

Regionally, there's difference in terms of solar energy development and application among the countries of Africa. For case, in 2013, the world's biggest solar power factory was launched in Morocco and was anticipated to supply electricity to over one million people in the country. Lately, forty solar power stations with the capacity of producing 2000MW of power were developed in Aswan city of Egypt. Other countries like Tanzania and Kenya have gone far ahead of Nigeria in terms of solar energy development and application. Although solar is now getting a feasible indispensable source of power in Nigeria, utmost studies on solar energy capabilities have concentrated on Southern Nigeria, in malignancy of the fact that Northern Nigeria has further solar energy capabilities which can be exercised to incompletely address the aboriginal problem of power force in the country. There's thus the need to study the abundant solar energy capabilities in Northcentral Nigeria, which is the region where this study is positioned, in order to grease solar energy development in the region. The region of Northcentral Nigeria is the fourth most populated and well concentrated profitable and marketable activities in Northern Nigeria. Thus, there's high demand of energy for domestic, industrial and marketable activities in the region.

Information on the quantum of both direct and verbose solar radiation is essential for solar energy exploitation. Conventionally, similar information is attained from a thick network of solar radiation monitoring stations covering an area of interest. A thick network of similar stations equipped with pyranometers, and other data acquisition systems are needed to collect solar radiation data at locales of interest. Still, the stations that give further dependable solar radiation data are veritably precious to maintain and limited in terms of content especially in Africa (Journee and Bertrand, 2010).

Rehman and Ghori (2000) observed that in developing countries where the number of radiation data collection stations is limited and direct measures of solar radiation is insufficient; the value of global solar radiation and sunshine duration for numerous geographic locations can be deduced or estimated. This is because in the absence of factual measured data, radiation data can be calculated from other available meteorological parameters to give necessary data content for a geographic position or region (Ramachandra, 2007). To achieve this, empirical modeling is needed.

1.2 Statement of the Research Problem

Nigeria's incapability to achieve stable power force is a problem to worry about, and a pointer to the fact that its over-dependence on gas and hydroelectric power sources alone need to be reviewed. Though gas, due to its profuseness in Nigeria appears to be the most cost-effective and effective means of power generation and hydro is also cost-effective due to its profuseness, experts are of the view that other indispensable energy sources like solar, wind, biomass should be considered by the Federal Government to broaden the country's energy blend and help insure stable power force.

Northcentral Nigeria falls within the solar belt and thus has enormous solar energy potentials but solar radiation information which is a key demand for employing solar energy in the region is relatively poor. Few studies have assessed solar energy potentials for different locations in North central Nigeria. Such studies include the works of

Sambo (1988), Muhammad and Dama (2014) and Mohammed *et al.* (2015) whom employed various statistical techniques to model solar radiation directly from insolation data, or, indirectly from other climatic variables.

Still, attempt has not been made to use geospatial ways to integrate ground-based solar radiation measurements with temperature data so as to assess solar energy potentials in Northcentral Nigeria, in spite of the capability of the geospatial methods in estimating solar radiation with high degree of trustability. Reliable assessment of the available solar radiation in the region revealed the enormous solar energy potentials which can be exercised to grease socioeconomic development of the region and also revive industrialisation in the region. Thus, this study applied geospatial ways to assay solar energy capabilities in the three countries of Northcentral Nigeria (Kogi, Nasarawa and Niger) using ground-measured insolation and satellite temperature-deduced data.

This study therefore seeks to find answers to the following research questions:

i. How efficient is geospatial technique in analysing solar energy potentials in the study area?
ii. What are the similarities and differences between temperature and solar radiation data in the area?
iii. What is the spatiotemporal variation of solar energy potentials in the area?
iv. Where are the optimum sites for solar energy development in the area?

1.3 Significance of the Study

This study identifies implicit sites for deploying both photovoltaic so that solar energy can be harnessed for power generation in study area. Solar energy capabilities in the area have the capability to resuscitate industrialisation thereby creating employment opportunities and providing additional source of revenue generation for the government. It will also provide the energy needed by manufacturing and small-scale industries which will result to wealth creation in the region. Solar energy can also go a long way to boost irrigation farming and enhance agriculture as a whole in the region where a large percentage of the population is engaged in agriculture. Other important application of solar energy include: monitoring plant growth and disease control; evaporation and power generation; solar heating system design and use; weather and climate prediction models.

1.4 Aim and Objectives of the Study

The aim of this study is to analyse solar energy potentials in parts of Northcentral Nigeria with a view to revealing the solar energy potentials in the three states.

The specific objectives are to:

i. generate solar radiation maps of Kogi, Nasarawa and Niger States of Northcentral Nigeria using solar irradiance data;
ii. analyse the variability of solar irradiance, and ambient temperature in the area;
iii. determine the spatio-temporal variation of solar energy potentials across the area, and

iv. identify the solar energy potential sites in the three states.

1.5 Scope of the Study

This study is concerned with geospatial analysis of solar energy potentials in parts of Northcentral Nigeria. It covers three states namely: Kogi, Nasarawa and Niger. The study integrated ground-measured solar radiation data to map solar energy potentials in the study area. Variability analysis of solar irradiance and ambient temperature was made and analysed the spatiotemporal variability of solar energy in the area. The study also identified the distributions of solar energy potential sites in the area. Also the amount of exploitable solar power in each of the three states as well as the optimum periods for harnessing solar energy in the area was determined. Thirty years data was used for this study spanning from 1988 to 2018.

1.6 Study Area

The study area comprises of three states Kogi, Nasarawa and Niger in North-central Nigeria. The area is found between latitudes $7^{o}00'$-11^{o} North of equator and longitudes 4^{o} – $11^{o}00'$ East of the Greenwich meridian as shown in figure 1.2

1.6.1 Niger State

Niger State is a state in the Northcentral region of Nigeria and the largest state in terms of land mass in the country, with the capital in Minna. The area is found to between latitude $10^{o}00'$N and longitude $6^{o}00'$E of the Greenwich meridian.

The cross sectional area of the state is about 76,363km^2, Niger State enjoys the tropical continental climate characterised by wet and dry seasons. The temperature is high almost throughout the year except during hamattan period which begins in November and lasts till February. The North-central region cut across the three savanna belts and has a hot and semi-arid climate. The climate of the region is controlled mainly by the two dominant air masses affecting the sub-region (Wikipedia, 2019).

1.6.2 Kogi State

Kogi State is a state in the Northcentral region of Nigeria, with the capital in Lokoja. The area is found to between latitude 7^{o}30'N and longitude 6^{o}42'E of the Greenwich meridian.

Kogi State is the only state which shares boundary with ten states with cross sectional area of the state is about 29,833km^2, Kogi State enjoys the tropical continental climate characterised by wet and dry seasons. The temperature is high almost throughout the year except during hamattan period which begins in November and lasts till February. The North-central region cut across the three savanna belts and has a hot and semi-arid climate. The climate of the region is controlled mainly by the two dominant air masses affecting the sub-region (Wikipedia, 2019).

1.6.3 Nasarawa State

Nasarawa State is a state in the Northcentral region of Nigeria, with the capital in Lafia. The area is found to between latitude 8^{o}32'N and longitude 8^{o}18'E of the Greenwich meridian.

Nasarawa State is bounded in the north by Kaduna State, in the west by FCT, in the south by Kogi and Benue States and in the East by Taraba and Plateau States, the cross sectional area of the state is about 27,117km^2, Nasarawa State enjoys the tropical continental climate characterised by wet and dry seasons. The temperature is high almost throughout the year except during hamattan period which begins in November and lasts till February. The North-central region cut across the three savanna belts and has a hot and semi-arid climate. The climate of the region is controlled mainly by the two dominant air masses affecting the sub-region (Wikipedia, 2019).

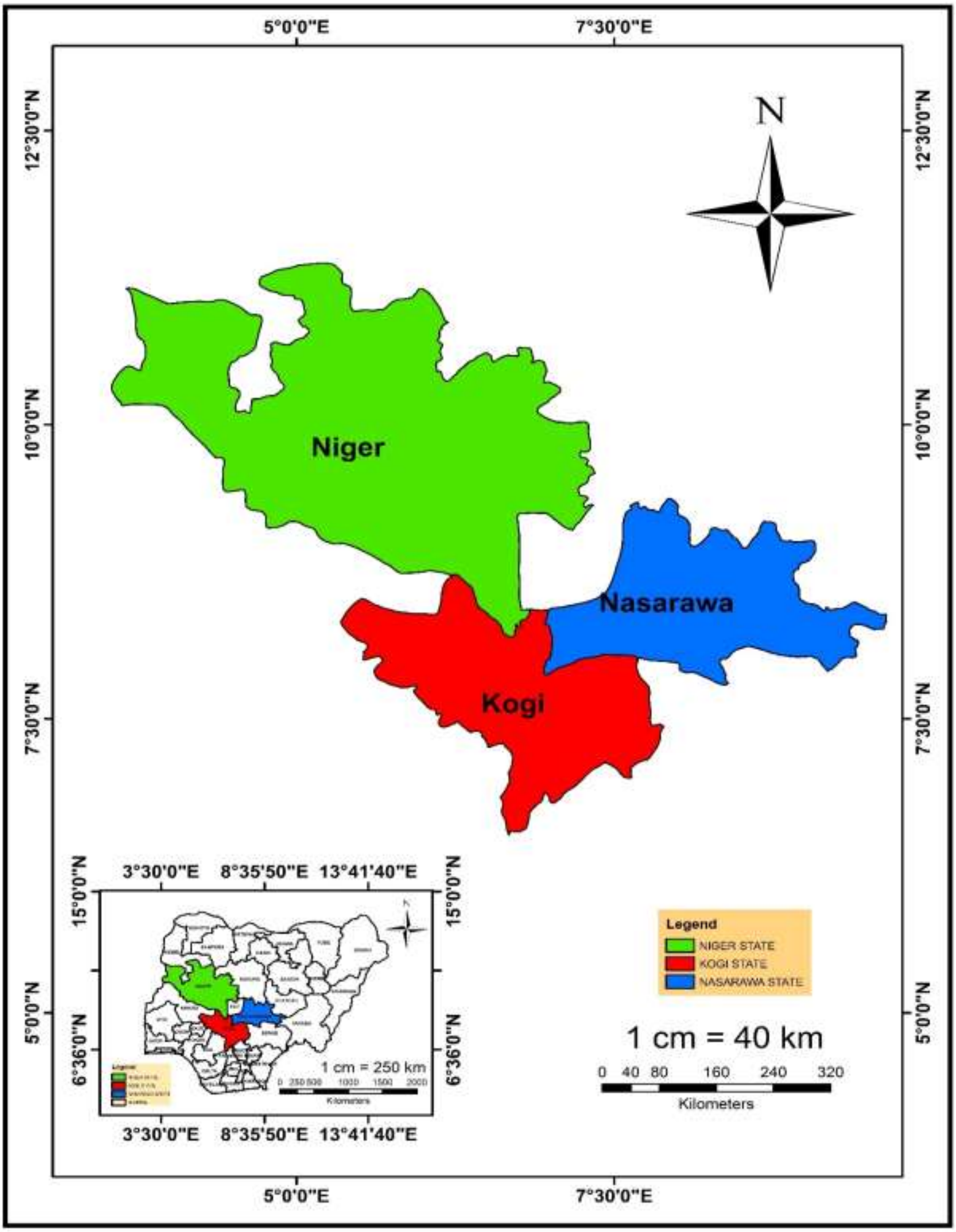


Figure 1.2: The Study Area in North Central Nigeria

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Review of Related Literature

Researchers in Nigeria, have assessed solar energy potentials in various parts of the country. One of the earlier studies was carried out by Ojosu (1990) in which he produced iso-radiation map for Nigeria using measured solar radiation data attained from experimental stations and estimated solar radiation from empirical formulae, but the iso-radiation maps did not easily show spatial variation in solar radiation across the country. Latterly, researchers like Udo (2002), Akpabio *et al.* (2004) , Chiemeka (2008), Augustine and Nwabuchi (2009), Sanusi and Abisoye (2011), Okundamiya and Nzeako (2011), Falayi *et al*. (2011), Ibeh *et al.* (2012), Musa *et al.* (2012), Medugu *et al.* (2013) used different climate parameters to estimate solar radiation in different corridors of Nigeria.

Few studies have assessed the solar energy potentials for various locations in northwestern Nigeria. Such studies include Sambo (1988) in Kano; AbdulAzeez (2011) in Gusau; Gana and Akpootu (2013) and Gana *et al*. (2014) in Kebbi; These studies employed various statistical techniques to model solar radiation directly from insolation data, or, indirectly from other climatic variables.

Information on global solar radiation is essential for research, engineering applications, studying Earth's climatic system dynamics and for power supply. In spite of its importance as a prospective alternative energy source, global solar radiation measurement is still scarce in Nigeria. There are various ways to address the scarcity of information on solar radiation in an area or region. Rehman and Ghori (2000) proposed the application of spatial mapping in estimating the amount of solar radiation in an area. Other researchers such as Becker (2001), Monedero *et al.* (2007), Gadiwala *et al.* (2013) used empirical models to estimate global solar radiation in various locations.

Alternatively, maps of global solar radiation can be derived by spatial interpolation of ground-based measurements, but the spatial density of solar radiation data required for interpolation is often very limited and therefore the interpolation errors can be high (Perez *et al.*, 1994). To complement the sparse network of ground-based measurements, numerous algorithms have been developed to estimate the surface incoming global solar irradiance from satellite images. Initially, empirical models were used to estimate solar radiation from available meteorological data.

An alternative approach to analyze solar energy potentials is the application of geospatial techniques (Rehman & Ghori, 2000; Ramachandra, 2007). Geospatial technique has the ability to analyse the spatial variation in solar energy potentials, and to determine the most suitable locations for harnessing solar energy in an area or region (Ramachandra, 2007).This study employs geospatial technique to map the potential sites for exploiting solar energy in North Central Nigeria; and to determine the spatial extent and the amount of solar energy that can be exploited in the study area.

There are several empirical models which have been employed to estimate the global and diffuse solar radiation using available climatology tools such as sunshine duration, cloud cover, relative humidity and ambient temperatures. For example, Angstrom

(1924), Black *et al.* (1954), Glover and McCulloch (1958) used the sunshine hours; while Gopinathan (1988) used the relative humidity and sunshine hours. Besides, Kalidindi *et al*. (2014) used a global climate model in testing the climate response to Solar Radiation Management by stratospheric aerosols and reduced solar constant. Their results showed that the climate conditions produced by a reduction in solar constant and addition of aerosols into the stratosphere are approximately the same. Gaetani *et al.* (2015) used climate models in assessing the future energy potential from photovoltaic solar and wind energy for Europe. In addition, Oloo *et al.* (2016) analysed atmospheric transmissivity and topography using spatial modeling to assess the potential of photovoltaic solar energy in Kenya.

Moreover, the use of satellite data as an alternative method to derive solar energy information was employed by Journee *et al.* (2011) and Janjai (2013). However, Journee and Bertrand (2010) and Basir *et al.* (2013) established that the integration of ground measurements with satellite data is currently used by researchers to estimate solar radiation in different parts of the world. In which case, the satellite data are processed, analyzed and validated with data from ground based stations. Therefore, this study adopts the current method of integrating ground based measurements with satellite data to derive solar radiation information for some parts of North-central Nigeria, which can be used for solar energy development and utilisation in the area.

2.2 Models for the Estimation of Global Solar Radiation

The models for the estimation of global solar radiation can be classified into models for the estimation of global solar radiation on horizontal and inclined/tilted surfaces.

2.2.1 Models for the estimation of global solar on horizontal surface

These models can be classified into Sunshine-based model, Temperature-based model, Cloud based model, Meteorological parameters-based model and hybrid parameter-based models (Bashara *et al.*, 2013).

2.2.1.1 *Sunshine-based models*

These models use sunshine data that are usually obtained from weather stations to estimate solar radiation in an area or region. These types of models were used by Gana and Akpootu (2013), Ogbaka and Silikwa (2016) to estimate solar radiation in Kebbi and Yola states of Nigeria respectively. The models are usually employed due to availability of sunshine data in most weather stations.

2.2.1.2 *Cloud-based models*

Examples of the application of these models are found in Flores and Baldasano (2001), Basir *et al*. (2013). These models are usually applicable in temperate climate and regions experiencing high cloud cover.

2.2.1.3 *Temperature-based models*

This model use temperature data to model solar radiation as demonstrated by Sanusi and Abisoye (2011), Okundamiya and Nzeako (2011).

2.2.1.4 *The hybrid parameter-based models*

This model integrates meteorological and geographical parameters to predict the solar radiation on a horizontal surface as demonstrated by Bois *et al*. (2008). Although this model can predict solar radiation in an area, many of the required parameters are not readily available at most locations (Bashara *et al.*, 2013).

2.2.2 Models for the estimation of diffuse radiation on horizontal surface

The models that can be used to estimate diffuse radiation on horizontal surfaces can be classified into two types: Parametric Models and Decomposition Models.

2.2.2.1 *Parametric models*

The parametric models require specific information on environmental conditions of an area such as atmospheric turbidity, fractional sunshine, cloud cover and perceptible water content as input parameters of the model. Examples are Ashrae Model, Nijegorodov's Model and Parishwad's Model (Maleki *et al.,* 2017).

2.2.2.2 *Decomposition models*

Decomposition models determine diffuse radiation from solar radiation data. The models are based on a correlation between the diffuse and global radiation on a horizontal surface. This correlation is defined as a function of the hourly clearness index (Maleki *et al.,* 2017). Examples of decomposition models include Erbs' Model, Jacovides' Model, Muneer's Model, Spencer's Model, Lam and Li's Model, Liu and Jordan's Model. A review of these models is found in Maleki *et al.* (2017).

2.3 Models for the Estimation of Global Solar Radiation on Inclined Surface

These models can be classified into isotropic and anisotropic sky models. There are several isotropic and anisotropic models, some of which are discussed below

2.3.1 Isotropic models

The isotropic models include Liu and Jordan, Koronakis and Badescu models.

2.3.1.1 *Liu and Jordan's model*

This model is based on the assumption that solar radiation on inclined surface is composed of the beam radiation, the reflected radiation from the ground and the diffuse fraction (Shukla *et al.,* 2015). This model presumes that diffuse radiation intensity is distributed uniformly over the whole sky (Maleki *et al.*, 2017).

The mathematical expression is given thus:

$$I_{d\beta} = \left(\frac{1 + COS\beta}{2}\right) \times I_d \qquad (2.1)$$

2.3.1.2 *Koronakis' model*

Koronakis modified the assumption of isotropic sky diffuse radiation and proposed that the slope ß = 900 provides 66.7% of diffuse solar radiation of the total sky dome (Shukla *et al.*, 2015).

The mathematical expression is given thus:

$$I_{d\beta} = \frac{1}{3}\left[\frac{1}{2 + COS\beta}\right] \times I_d \qquad (2.2)$$

2.3.2 Anisotropic models

Examples of anisotropic models include Hey and Davies, Perez' Model, Klucher's Model, Temps and Coulson's Model.

2.3.2.1 *Hay model*

This model is also known as Hay and Davies model. They assumed that the diffuse radiation from the sky is comprised of an isotropic and circumsolar component only, whereas the horizontal brightening parts was not considered. It was assumed that the diffuse component coming directly from the sun's direction is circumsolar and diffuse component reaching through the rest of the sky dome is isotropical (Shukla *et al*., 2015).

The mathematical expression is given thus:

$$I_{d\beta} = I_d \left[f_{Hay} \left(\frac{Cos\theta}{Cos\theta_z} \right) + \left(\frac{1 + Cos\beta}{2} \right) \left(1 - f_{Hay} \right) \right] \quad (2.3)$$

2.3.2.2 *Perez model*

This model is based on the in-depth applied mathematics analysis of the sky's diffuse components. The model divides diffuse radiation into three components: isotropic background, circumsolar, and horizon zones (Maleki *et al*., 2017).

The mathematical expression is given thus:

$$I_{d\beta} = I_d \left[\frac{1 + COS\beta}{2} (1 - F_1) + F_1 \frac{d_1}{d_0} + F_2 Sin\beta \right] \quad (2.4)$$

2.3.2.3 *Temps and Coulson's model*

This model is based on the modification of the isotropic model of Liu and Jordan, in which two terms representing diffuse radiation by assuming a clear sky condition was introduced (Maleki *et al.*, 2017).

The mathematical expression is given thus:

$$I_{d\beta} = \frac{1}{2} I_d (1 + Cos\beta) P_1 P_2 \quad (2.5)$$

2.3.2.4 *Klucher's model*

This model is based on the models by Temps and Coulson and Liu and Jordan. Klucher discovered that Liu and Jordan's isotropic model provides good result for overcast skies but ignores radiation for some sky conditions, such as partly overcast and clear skies. To address such, the Temps and Coulson model was refined by introducing a function fk that determines the degree of cloud cover (Maleki *et al*., 2017).

The mathematical expression is given thus:

$$I_{d\beta} = I_d \left[\frac{1}{2}\left(1 + Cos\left(\frac{\beta}{2}\right)\right)\right] [1 + f_k Cos^2\theta(Sin^3\theta_z)] \left[1 + f_k Sin^3\left(\frac{\beta}{2}\right)\right] \quad (2.6)$$

Although Maleki *et al*. (2017) found that the most accurate isotropic models are those of Liu-Jordan and Koronakis, while the Perez, Temps-Coulson, Klucher and Bugler models were the most accurate anisotropic model; the choices of model depend on the availability of data, geographical location and time.

2.4 Models for Estimation of Global Solar Radiation from Satellite Data

The models used to estimate global solar radiation from satellite data can be classified into empirical and theoretical. The empirical method establishes a relationship between the satellite data and the measurements made on the surface; while the theoretical method uses radiative transfer models in order to relate the satellite data with the surface measurement (Flores and Baldasano, 2001). The estimation of solar radiation from satellite data usually requires the use of Geographic Information System (GIS) techniques. The application of these models is found in the works of Ramachandra (2007), Pettazzi and Salson (2012), Janjai *et al*. (2013).

2.4.1 Factors that influence satellite estimation of global solar radiation

Several factors affect satellite retrieval of solar radiation data which include clouds and atmospheric constituents. Cloud detection is important when attempting to obtain precise estimates of global solar radiation (Flores and Baldasano, 2001). Therefore, estimating the total atmospheric transmission factor and the cloud-cover index for the satellite images are critical steps in estimating solar radiation from satellite images. Solar radiation implies the electromagnetic radiation of the sun. As the solar radiation passes through the atmosphere, it undergoes absorption of scattering by various constituents (gases, water droplets and particulates) of the atmosphere (Natural Resources Canada, 2015). The amount of solar radiation finally reaching the earth surface depends quite significantly on the composition and concentration of various atmospheric constituent (Camfer University, 2017) at any point in time. Also, solar irradiance, which is the incident energy per unit area is influenced by geographical factors and therefore varies with season and time of the day due to the various sun's position. Therefore, knowledge of the effects of geographical factors on irradiance is vital for developing location-specific solar energy applications. Likewise, information on global radiation is essential for research, engineering applications, for studying earth's climatic system dynamics, and for power supply. In spite of its various applications and viability as a prospective alternative energy source, global solar radiation measurement is still scarce in Nigeria. There are various ways to address the scarcity of information on solar radiation in an area or region.

Rehman and Ghori (2000) proposed the application of spatial mapping in estimating the amount of solar radiation in an area. Spatial mapping in this case involves developing solar database which can be used for solar energy analysis. Other researchers such as Becker (2001), Monedero *et al*. (2007), Gadiwala *et al.* (2013) used empirical models to estimate global solar radiation in different parts of the world. Hence, spatial mapping and empirical modeling provide sources of solar information gathering and analysis.

Alternatively, maps of global solar radiation can be derived by spatial interpolation of ground-based measurements. But, the spatial density of solar radiation data required for interpolation is often very limited and therefore the interpolation errors can be high (Perez *et al.*, 1994). To complement the spares network of ground-based measurements, numerous algorithms have been developed to estimate the surface incoming global solar radiation from satellite images. Initially, empirical models were used to estimate solar radiation from available meteorological data. Empirical modeling approach has been adopted by several researchers.

Angstrom (1924) was the first scientist known to use empirical model to mathematically relate two solar properties (the average actual sunshine hours per day and the maximum possible sunshine hour per day) as a fraction of the global solar radiation of clear-sky day. Later on, the Angstrom formula was modified to estimate solar radiation at different locations. However, recent studies by Journee *et al.* (2011) and Pettazi and Salson (2012) have demonstrated the advantages of merging ground-measured and satellite-derived values of the global solar radiation to provide reliable high resolution maps of global solar radiation. For example, Journee and Bertrand (2010) carried out a study to improve the spatiotemporal estimation of the surface solar radiation over Belgium, by merging ground and satellite measurements. They found that the best estimation of the distribution of surface solar radiation is obtained when both satellite and ground data sources are combined to compensate errors inherent to the satellite data with accurate ground measurement.

Likewise, Pettazzi and Salson (2012) utilised twenty three years long series of satellite data together with in situ measurements distributed across Galicia (NW Spain) for detailed analysis of the solar radiation in the region. Both spatial and temporal analyses were performed.

Analysis of solar energy potentials in a region start from acquiring solar radiation data from available radiation stations, the data can be complemented through empirical modeling or satellite remote sensing. Empirical modeling of solar radiation has the disadvantage of being time consuming and computationally complex while satellite derivation of solar radiation requires some technical knowledge of remote sensing and is prone to errors. In this study, merging ground-based measurements of solar radiation and satellite-derived data is considered because it gives better results based on the finding of Journee and Bertand (2010) and Pattazzi and Salson (2012).

2.5 Renewable Energy Resource Information in Africa

There is general scarcity of information on potential of energy resources in Africa compared to the rest of the world, making it difficult to compare the potential for the different alternative sources of energy which is fundamental for investing in and harvesting alternative energy sources in the continent. This lack of information is even more obvious for renewable energies such as wind and solar which have been used in many countries to provide electricity in the rural areas. According to an elaboration of the International Energy Agency (IEA) data by the Alliance for Rural Electrification (ARE, 2011), about 589 million people in the African continent had no access to electricity in 2008. This shows the extent of energy poverty among the people in the continent. However, the pervasive energy poverty in the continent can be reduced by increasing access to electricity. Access to electricity in Africa and Nigeria in particular can be significantly improved by harnessing the available renewable energy resources in the country. However, knowledge of the potentials of renewable resources in an area is required to be able to harness them properly.

Hermann *et al.* (2014) used a GIS-based approach to estimate the renewable energy potential in Africa. Their findings revealed that with the exception of Central African countries, solar energy resources have a significant potential in large parts of the continent but with remarkable differences when applied through different solar technologies – PV or CSP plants. They also reported that the bioenergy potential of the continent is enormous but characterised by extreme disparities between regions; while wind energy has the largest regional disparities in the continent.

Also, a scientific and technical report by the Joint Research Centre of the European Commission reported some information regarding renewable resources in Africa (Monforti-Ferrario *et al.*, 2011). The report assembled geographical data on solar radiation, wind weather patterns, biomass resources of forests, agriculture and residues as well as water resource data in the continent. According to the report, the potential of smaller scale (<50kW) wind-energy systems within hybrid solar/biodiesel generator/wind electricity systems has not been studied.

Apart from the report by the Joint Research Centre, few studies have been carried out to assess solar energy potentials in Africa. An attempt to map solar radiation in Africa is found in the work of Diabaté *et al.* (2004). Such a map is very useful for understanding solar radiation pattern as well as for preliminary assessment and modeling of solar energy systems in Africa. However, the climate zone classification proposed by Diabaté *et al.* (2004) only gives information about similar values of the monthly mean of the daily clearness index, making it unsuitable for direct solar energy calculations. In addition, Diabaté *et al.* (2004) acknowledged the limitations of the zoning adopted in their work to estimate the solar radiation climate in Africa. This is because it was observed that the zoning they adopted was inconsistent all over the map. The reason for this being lack of stations in some places within the continent. One way to increase the quality of the zoning according to them would be to use satellite-derived clearness index, which will be available at each pixel within the whole area. Such a dataset (satellite-derived data) which would have implied much larger computational resources is presently available (Diabaté *et al*., 2004).

The present study integrates available satellite data with ground measurements to map solar radiation in Northcentral Nigeria as proposed by Diabaté *et al*. (2004) and has been experimented in few African countries.

In developing countries like Uganda, solar radiation data is scarce due to the high costs involved in buying and maintaining solar measuring equipment. As a result of this, the long-term global solar radiation data is measured in very few locations in the country where the measuring instruments are installed and then estimated in other places where there is no equipment (Angela *et al.*, 2011). The same situation is found in Nigeria and specifically in the Northwestern region of the country where there are very few meteorological stations. There is therefore the need to devise methods of assembling solar radiation data as an important preliminary step for solar energy resource exploitation in Africa.

There are different methods that can be used to assemble and analyse solar radiation data for the development of solar energy in Africa. For instance, Hussein (2012) developed a mathematical model to estimate the hourly global solar radiation on horizontal surfaces in the Delta of Egypt, using the available meteorological data, which are sunshine duration and cloud cover, as well as maximum, minimum and daily mean of ambient temperature covering the year 2009. Similarly, Angela *et al*. (2011) employed the artificial neural network to estimate the monthly average of daily global solar irradiation on a horizontal surface in Kampala, based on sunshine hours in the area. Likewise, Lealea and Tchinda (2013) estimated the diffuse radiation of four stations in North and Far North of Cameroon. The results obtained by these studies can be improved, in view of the fact that indirect methods were used in estimating solar radiation which are prone to errors. The results can be improved by using other climatic variables or through alternative methods. The need to improve the results is particularly important in order to have relatively accurate estimate of the amount of solar radiation in the areas which is required for design and exploitation solar energy in the African countries.

The successful design and effective utilisation of solar energy systems and devices for application in power and water supply, for industrial, agricultural and domestic uses, largely depend on the availability of information and the characteristics of solar radiation in the locations where the systems and devices are to be situated (Falayi *et al.,* 2011). As such, there are solar information systems that are developed for specific locations. For instance, Photovoltaic Geographical Information System (PVGIS) has been developed to provide a map-based inventory of solar energy resource and assessment of the electricity generation from photovoltaic systems in Europe, Africa, and South-West Asia (Huld *et al*., 2005). PVGIS is famous, widely used and validated tool which is suitable for further analysis on solar energy deployment. The PVGIS also provides solar radiation data for the three continents.

It is noteworthy that there are areas in Africa that are endowed with higher solar energy potentials than other parts of the world. In these areas, the same type of photovoltaic panel can produce averagely twice as much electricity in Central Europe (Monforti-Ferrario *et al.,* 2011). But the actual quantities of these resources in many of these areas have not been determined due to lack of sufficient solar radiation data in the areas. Hence the resources remained unharnessed and therefore unutilized.

In addition to the need for adequate information on solar radiation in an area, Monforti-Ferrario *et al.* (2011) affirmed that sufficient knowledge of the existing and viable energy infrastructures is an essential requirement for comprehensive assessment of the economically utilisable renewable energy in an area. He therefore recommended mapping the physical availability of renewable energy infrastructures as an important step in understanding their exploitability. Renewable energy maps serve as veritable tools for visualising renewable energy distribution, and geographic variations in renewable potentials, which will guide policy formulation and investment in renewable energy development.

Solar and Wind Energy Resource Assessment (SWERA) is an example of such a veritable information system for the analysis of renewable energy potentials. SWERA is a pilot project designed to compile such data in thirteen developing countries and to facilitate investments in solar and wind energy projects. SWERA is developing new informational tools for energy planners and project developers. These tools include regional and national maps of solar and wind energy resources and a GIS that will allow easy access to the detailed information contained in these maps. A similar application can be developed for Northcentral Nigeria and the preliminary steps have been taken by this study.

Solar energy information is required as input for solar energy mapping, assessment and exploitation. Such information is usually obtained from meteorological stations. However, the number of stations to provide sufficient data is very few in Africa. Therefore, solar radiation data is not available for many African countries like Nigeria which cannot afford the cost of managing and maintaining more stations. Hence, radiation data in Nigeria is usually derived or estimated from other related data. There are several models that relate global radiation to other climatological parameters which have been used to estimate solar radiation at various geographical locations in Nigeria. These models are reviewed in the following section.

2.6 Statistical Modeling of Solar Radiation in Nigeria

In Nigeria, a number of studies have modeled solar radiation on the basis of the more readily available meteorological data in the country. Some of the studies developed models and empirical correlations involving global solar radiation and sunshine hours for different locations in Nigeria. For example, Sambo (1988) developed a correlation with solar radiation using sunshine hours for Kano with the regression coefficients for all the months between 1980 and 1984. Another attempt was done by Ojosu (1990) in which he produced iso-radiation map for Nigeria using measured solar radiation data obtained from experimental stations, estimated solar radiation from empirical formulae using meteorological data, and the converted solar radiation data from the Meteorological Office in Nigeria. However, the iso-radiation maps do not clearly show the spatial variation in solar radiation in Nigeria.

Other studies developed theoretical and empirical correlations of broad applicability to provide solar data for systems design in Nigerian cities. For instance, Udo (2002) used monthly average daily values of clearness index and relative sunshine covering a period of two years, to develop two equations (linear and quadratic) of the Angstrom-Prescott model for the estimation of global solar irradiation at Ilorin in northcentral Nigeria. Besides, multiple linear regression models were developed by Akpabio *et al*. (2004) to estimate the monthly average daily global solar radiation using ten parameters during a period of sixteen years (1984 - 1999) for Onne, in southwestern Nigeria. The parameters were extraterrestrial radiation, average daily temperature, ratio of minimum and maximum daily temperature, relative humidity, ratio of sunshine duration, solar declination, average soil temperature, average pan evaporimeter, average rainfall and average daily dew. Similarly, Chiemeka (2008) employed the Hargreaves equation using temperature data to estimate the solar radiation at Uturu in Abia State of southeastern Nigeria.

It is evidenced from the abovementioned studies that there are various approaches to solar radiation modeling as there are variant climatic parameters which can be used in the modeling, depending on the availability of the parameters. Therefore, Augustine and Nwabuchi (2009) investigated set of models that can used to relate global solar radiation and sunshine hours in Calabar, Port Harcourt and Enugu respectively in southsouthern and southeastern Nigeria. They used seventeen-year (1999-2007) monthly mean daily data for global solar radiation and sunshine hours in Calabar, Enugu and Port Harcourt to develop a number of regression equations, Also, a correlation equation of the Angstrom type has been developed by Augustine and Nwabuchi (2009) to predict the monthly mean daily global solar radiation incident on a horizontal surface in Warri of South-Southern Nigeria. The researchers compared measurements of global solar radiation with those predicted using the equation, and a positive correlation between them was observed. The positive correlation observed by Augustine and Nwabuchi (2009) could be validated or compared with the results from a hybrid model which combines several climatological parameters as done in some other studies.

Augustine and Nwabuchi (2009) developed a number of multilinear regression equations for Enugu town in southeastern Nigeria, to predict the relationship between global solar radiation with one or more combinations of the following meteorological parameters: fraction of sunshine, maximum temperature, cloudiness index and relative humidity for seventeen years (1991 – 2007). Likewise, Augustine and Nwabuchi (2009) used the monthly mean daily global solar radiation, sunshine hours, maximum temperature, cloudiness index and relative humidity data for some selected cities, Owerri and Enugu in southeastern Nigeria, Warri and Calabar in southsouthern Nigeria. The data covered a period of seventeen years (1991 - 2007), and was used to generate several linear and multilinear regression equations.

The methods used in the aforementioned studies are more of cloud-based integrating sunshine duration rather than the temperature-based methods which provide an alternative way of modeling and can be used to evaluate the performance of other solar radiation models. Sanusi and Abisoye (2011) evaluated the behaviour of three empirical models based on the difference between maximum and minimum temperatures at Ibadan in southwestern Nigeria. This was done by using monthly data on solar radiation and minimum and maximum temperature for a period of six years (2001–2006). The corresponding monthly value of extraterrestrial solar radiation (Ra) was calculated for each data. The shortcoming of this method is the short period of six years that may not give reliable results in studies of this nature which requires a long time period.

Also, Okundamiya and Nzeako (2011) proposed a temperature-based model of monthly mean daily global solar radiation on horizontal surfaces for selected cities, representing the six geopolitical zones in Nigeria. The monthly mean daily global solar radiation on horizontal surfaces and monthly mean daily ambient temperatures (minimum and maximum) for a ten-year period (1996–2005) from six cities (Abuja, Benin, Katsina, Lagos, Nsukka, and Yola) were used as input parameters. The modeling was based on linear regression theory.

In addition, Falayi *et al.* (2011) estimated the diffuse solar radiation for eight stations (Sokoto, Maiduguri, Port Harcourt, Enugu, Owerri, Abeokuta, Yola, Jos) in Nigeria. The data used for the study were the monthly means of daily global solar radiation on horizontal surface, ambient temperature (minimum and maximum), relative humidity and sunshine duration of the eight locations for sixteen years (1995-2010). The validity of the individual correlations were measured using the two widely used statistical indicators, MBE and RMSE. Besides, Ibeh *et al.* (2012) estimated the global solar radiation with meteorological parameters at Calabar city in southsouthern Nigeria. The daily mean temperature and relative humidity for seventeen years (1991-2007) and the global solar radiation data were used. The artificial neural network and multiple regression models were used for the estimation. Based on their findings, they observed that better results were obtained from correlation with the measured, which indicates that artificial neural network model is a better model for estimation. Therefore, they recommended the use of this model for estimation of global solar radiation at locations with similar weather conditions.

Beisdes, Isikwue *et al.* (2012) proposed the coefficients for Angstrom Prescott type of model for the estimation of global solar radiation in Makurdi of northcentral Nigeria, using relative sunshine duration alongside the measured global solar radiation data for the period of 2001-2010. Also, Musa *et al.* (2012) used the daily sunshine duration to estimate average global solar radiation for Maiduguri in northeastern Nigeria. The daily sunshine hour were measured for five years (2004-2007) from which the monthly mean values were determined. Angstrom model was then used to estimate the global solar radiation based on the monthly mean sunshine hour. The researchers observed that the monthly global solar radiation in the area is not uniform throughout the period of study.

In addition, a correlation between measured and predicted values of solar radiation in Mubi town of Adamawa State in Nigeria was presented by Medugu *et al.*

(2013). In this case, a series of daily measurements of the global solar radiation on a horizontal surface was recorded in with the aid of a constructed pyranometer. The monthly average value was determined. The monthly average daily solar radiation on horizontal surface was also determined using sunshine duration. These parameters were input in some radiation models to compute the solar radiation.

Finally, a prediction of the global solar radiation from climatological data was attempted. Then predicted values were compared with the corresponding measured values. Similarly, Osueke *et al.* (2013) examined the solar irradiance variation in four locations in Nigeria (Enugu, Lagos, Abuja and Maiduguri) using NASA meteorological data for twenty-two year period. This was achieved by developing models that were based on statistical regression analysis. Their findings revealed that the models developed from the statistical analysis showed good levels of linear conformity with correlation coefficients of 0.78 - 0.8 except for Abuja which had a fair value of 0.546.

The above mentioned studies indicate that in places where there is no direct measurement, solar radiation can be estimated using models and empirical correlations as highlighted. However, the accuracy of the models and empirical correlations can still be improved using alternative methods. An alternative method to derive solar radiation data is satellite remote sensing. Recently, satellite images have provided appropriate and up-to-date data on global solar radiation. The satellite data is usually analysed in a GIS to provide solar energy information in an area or region.

2.7 Radiation and the Atmosphere

The radiation reaching the earth's surface passes through the atmosphere. The atmospheric components in form of particles and gasses can affect the incoming light and radiation. These effects are caused by the mechanisms of scattering and absorption (Natural Resources Canada, 2015).

2.7.1 Atmospheric scattering

Scattering occurs when particles or large gas molecules present in the atmosphere cause the electromagnetic radiation to be redirected from its original path during radiation-atmosphere interaction. The extent of scattering depends on several factors including the wavelength of the radiation, the abundance of particles or gasses and the distance the radiation travels through the atmosphere. There are three types of scattering which take place in the atmosphere. These are:

a) Reyleigh scattering

b) Mie scattering

c) Nonselective scattering (Natural Resources Canada, 2015).

a) Rayleigh scattering occurs when particles are smaller compared to the wavelength of the radiation. These could be particles such as small specks of dust or nitrogen and oxygen molecules. Rayleigh scattering affects shorter wavelengths of energy much more than longer wavelengths. It is the dominant scattering mechanism in the upper atmosphere (Natural Resources Canada, 2015).

b) Mie scattering occurs when the particles are almost the same size as the wavelength of the radiation. Dust, pollen, smoke and water vapour are causes of Mie scattering which usually affect longer wavelengths than those affected by Rayleigh scattering. Mie scattering mostly affect the lower portions of the atmosphere where larger particles are more abundant and dominates when cloud conditions are overcast.

c) Nonselective scattering: This occurs when the atmospheric particles are much larger than the wavelength of the radiation. Water droplets and large dust particles can cause this type of scattering. All wavelengths are scattered almost equally by nonselective scattering (Natural Resources Canada, 2015).

2.7.2 Absorption

Absorption is another process resulting from interaction of electromagnetic radiation with the atmosphere. In contrast to scattering, this phenomenon causes molecules in the atmosphere to absorb energy at various wavelengths. Ozone, carbon dioxide and water vapour are the thre main atmospheric which absorb radiation (Natural Resources Canada, 2015).

2.7.3 Effects of the earth's atmosphere on incoming solar radiation

Greenhouse gasses in the atmosphere absorb most of the Earth's emitted longwave infrared radiation, which heats the lower atmosphere. In turn, the warned atmosphere emits longwave radiation, some of which radiates toward the Earth's surface, keeping our planet warm and generally comfortable. Increasing concentrations of greenhouse gases such as carbon dioxide and methane increase the temperature of the lower atmosphere by restricting the outward passage of emitted radiation, resulting in global warming or global climate change (NASA, 2016).

2.8 Radiation and Clouds

The nature of clouds and their characteristics, their occurrence and geographical location plays a significant role in the understanding of climate change (Graham, 1999). Low, thick clouds principally reflect solar radiation and col the surface of the Earth. High thin clouds primarily transmit incoming solar radiation; at the same time, they trap some of the outgoing infrared radiation emitted by the Earth and radiate it back downward, thereby warming the earth surface. The amount of heat transmitted by clouds to the Earth's surface depends on several factors such as the altitude of the cloud, it size and the composition of the particles that form the cloud (Graham, 1999).

When a cloud absorbs long wave radiation emitted by the Earth's surface, the cloud remits a portion of the energy to outer space and a portion back toward the surface. The intensity of the emission from a cloud varies directly as its temperature and also depends upon several other factors, such as the cloud's thickness and makeup of the particles that form the cloud (Graham, 1999).

The high, thin cirrus clouds are highly transparent to shortwave radiation, but they readily absorb the outgoing long wave, infrared radiation both out to space and back to the Earth's surface. Also, in the presence of cumulonimbus cloud, the energy radiated to outer space is lower, because the cloud tops are high and clod (Graham, 1999).

2.8.1 Radiation budget and the earth's surface

2.8.1.1 *Reflection*

Energy goes back to space from the Earth system in two ways: reflection and emission. Part of the of the solar energy that comes to Earth is reflected back to space in the same, short wavelengths in which it came to Earth (Graham, 1999). This is referred to as reflection.

2.8.1.2 *The concept of Albedo*

The fraction of solar energy that is reflected back to space is called the albedo. Different parts of the Earth have different albedos. For example, ocean surfaces and rain forests have low albedos, hence, they reflect only a small portion of the sun's energy (Graham, 1999).

2.8.2 Analysis of solar radiation using satellite remote sensing and GIS approach

Satellites are now considered as important sources of solar radiation data which is retrieved through the Remote Sensing and GIS techniques. GIS is a computer based information system for collection, storing, analysis and transformation of geographic data into geographic information. GIS has recently been used in the analysis of energy resources and energy systems as reported in the literature on Energy Geographies. Since solar radiation is measured at very few weather stations, it is often estimated from the duration of bright sunshine or from mean daily cloudiness. In the absence of these variables, irradiance can be estimated by means of standard meteorological observations, spatial interpolation techniques or satellite images (Bindi and Miglietta, 1991).

Satellite remote sensing has provided an efficient alternative approach to derive solar radiation data. An extensive review of satellite methods to derive surface shortwave irradiance is found in Pinker *et al*. (1995). In addition, Dagestad (2005) discussed the Heliosat algorithm which estimates solar radiation at ground level from satellite images. The study analysed the performance of various versions of the algorithm and suggested modifications. Appropriate information on solar resources is required for the development of solar energy systems and applications. Because ground-based measurements of solar radiation are usually scarce, several methods have been proposed to estimate the solar radiation incoming on a horizontal surface at ground level from images taken by satellites, and in particular by geostationary satellites (Journee *et al.*, 2011).

Geostationary meteorological satellites record backscattered solar radiation from the Earth-atmosphere system at high temporal frequencies, thereby providing means of estimating surface solar irradiance. Some models have been proposed to derive solar radiation from satellite data. These models have been employed by different researchers and they are reviewed in the following paragraphs.

A model was presented by Flores and Baldasano (2001) for the determination of hourly global solar radiation from National Oceanic and Atmospheric Administration-

Advanced Very High Resolution Radiometer NOAA-AVHRR satellite data, which provides wide coverage, together with adequate spatial resolution (around 1.1 km at the nadir). The process is divided into three steps: the first step consists of a cloud detection procedure; the second step determines the cloud index for each point on the satellite image, which is then used for the third step, which is the application of the global solar radiation statistical model. The coefficients for the model were determined by regression from the data obtained using pyranometers from eleven global surface solar radiation measurement stations. Then, a surface interpolation was performed in order to obtain the entire coefficient field for the area under study with the objective of applying the model. The estimates obtained from the model were compared to data from another ten ground radiation measurement stations in Catalonia, Spain. This model was tested for the eleven consecutive months beginning in February 1998, and a good correlation was obtained between the estimate provided by the model and the data from the measurement stations. This resulted in a coefficient of determination greater than 0.98 in all cases, together with RMSE of between 9.6% and 15.8% and a bias that varied from -9.5% to 1.3%. Ramachandra (2007) employed GIS to map and analyse spatial variation in solar potential in Karnataka state of India, based on global solar radiation data. In stations where measurements of global solar radiation were available, data was used directly, and for locations where the data was not available, indirect methods were used. Both the theoretically-based and empirical-based methods were used in the study. The study identified the area with the higher global solar radiation which is ideal for harvesting solar energy in Karnataka. The method employed by Ramachandra (2007) is applicable to Nigerian situation.

Bois *et al*. (2008) combined remotely sensed data and solar irradiation models based on topography to estimate the spatial and temporal variability of solar radiation interception of the Bordeaux winegrowing region in France over a twenty-year period (1985-2005). Their approach to solar radiation mapping of the area involved two steps: estimation of solar radiation on horizontal surfaces; and terrain integration for incoming solar radiation mapping. To achieve these, solar radiation data was retrieved from the HelioClim-1 database, elaborated from Meteosat satellite images, using the Heliosat-2 algorithm. Daily data was interpolated using ordinary kriging to produce horizontal solar radiation maps at a 500m resolution. Then using a digital elevation model, 50m resolution daily solar radiation maps with terrain integration were produced for the period 2001-2005. Then the Bordeaux winegrowing region was classified into three zones of low, medium, and high solar radiation areas (Bois *et al.*, 2008).

Pettazzi and Salsón (2012) utilised twenty years long series of satellite data together with ground-based measurements distributed all across Galicia in Northwestern Spain for detailed analysis of the solar radiation in the region. The data from the weather stations were validated using a clear sky model, in order to eliminate those values unusually too high (greater than 110% of clear sky irradiance) or too low (less than 3% of extraterrestrial radiation). A visual analysis to detect systematic errors in the pyranometers and comparisons between nearby stations, were also performed. Finally, monthly averages were calculated. The calibration of satellite data with ground-based measurements was achieved by means of residual techniques. First, differences between monthly values of insolation estimated by the Heliosat-2 algorithm and pyranometers data were calculated. Then, those differences were interpolated for Galicia, using Kriging geostatistical technique. Finally, climatic maps were produced by adding the residual calculated to the original data satellite (Pettazzi and Salsón, 2012). The resulting maps were validated using MBE, MAE and RMSE. There searchers compared the results obtained from their findings with previous works and concluded that their results showed some improvement over previous methods.

Basir *et al.* (2013) employed remote sensing in identifying the areas with maximum insolation in Pakistan by studying the cloud cover on Pakistan from June to August (Monsoon period having maximum clouds) in 2005-2009. The satellite data used for the study were obtained from NOAA-AVHRR images of June, July and August of year 2005-2009. Precipitation data and elevation maps were also included. The satellite images were processed by using ENVI image processing software through the following procedures: Georeferencing, Enhancement, Selection of Area of Interest for Classification (ROI), Supervised Classification (Maximum likelihood method), Subset (using Pakistan boundaries), Vector Conversion, Composite (Monthly Maps). In order to find out least cloudless area, GIS analysis was performed. The Union option was used to combine cloud vector layers of different years and resultant Union layer shows areas with and without clouds. Then, the Pakistan district vector layer was overlaid of on each Union layer, which provides location of least cloudless districts in Pakistan. The results indicated the locations with minimum cloud cover which have a great potential for solar energy. Janjai (2013) presented an improved model and demonstrated its application for mapping global solar radiation from satellite data in tropical environment of Thailand. Digital data from the visible channel of GMS4, GMS5, GOES9, and MTSAT-1R satellites collected during a 15-year period (1995–2009) was used as main input to the model. Satellite gray levels were converted into Earth-atmospheric reflectivity and used to estimate the cloud effect. The satellite data was further processed. In order to test its performance, the model was employed to calculate monthly average daily global solar radiation at thirty six solar monitoring stations across the country. Their finding showed that solar radiation calculated from the model and that obtained from the measurement are in good agreement, with a Root Mean Square Difference of 5.3% and a Mean Bias Difference of 0.3%. The model was used to calculate the monthly average daily global solar radiation over the entire country, and results were displayed as monthly and yearly maps. The maps showed that the geographical distribution of solar radiation in Thailand is strongly influenced by the tropical monsoons and local geographical features.

In Africa, GIS has also been used for the development of solar information system. For instance, Huld *et al.* (2005) presented a method for computing high resolution GIS database of global horizontal irradiation for Africa and the Mediterranean Basin. The primary solar radiation data used for the GIS database were previously computed from Meteosat satellite images by the Heliosat-2 method and stored in the

HelioClim-1 database. From this database, the long term monthly and yearly averages of global irradiation on horizontal plane over a period of 1985-2004 were derived. Using the PVGIS method, based on a clear-sky model, as well as the interpolation of the clear-sky index and terrain shadowing, the original spatial resolution of HelioClim-1 database (15') was enhanced to 2Km. Then, using the daily global irradiation from the enhanced PVGIS database, they estimated the electricity generation from a typical solar home system in Africa.

The interesting part of the method presented by Huld *et al.* (2005) is the use of satellite data to compute a high resolution GIS database of global solar radiation for a region of solar information scarcity, Africa. This can be regarded as a valuable contribution toward the development of solar information system for Africa. Similarly, Šúri *et al*. (2006) developed and presented an interactive web tools for map-based query of a solar radiation database and for assessment of the performance of solar photovoltaic systems. They adopted the PVGIS method in their design. The PVGIS provides an interface to a geographical database and tools designed for the assessment of photovoltaic systems in Africa, the Mediterranean Basin, and South-West Asia. The model presented by Flores and Baldasano (2001) is well grounded in the principles of Remote Sensing, and it has highlighted the relevance of the use of very high resolution satellite data like the NOAA-AVHRR to obtain good results. In addition, the model can be considered to be empirically proven considering the results obtained using the model. But the model as presented by Flores and Baldasano (2001) is a typical cloud-based model which is more applicable in temperate climate where cloud cover is highly influential in determining the amount of solar radiation received per unit area.

An alternative improved model for mapping global solar radiation from satellite data was presented by Janjai (2013). Their results further underscored the use of satellites as reliable sources of solar radiation data.

Ramachandra (2007) demonstrated the application of GIS as an alternative method in analysing spatial variation in solar energy potentials over an area or region, and its ability in determining the most suitable locations for harnessing solar energy in an area or region. Basir *et al*. (2013) employed Remote Sensing and GIS techniques in identifying the areas with maximum solar energy potentials. This is an alternative approach which combines Remote Sensing and GIS techniques. However, the application of this method is very rare in the analysis of solar energy in Nigeria.

Local geographical features Janjai (2013) and topography influence the solar radiation received in an area. Therefore, some GIS models like the r.sun have integrated the terrain effect in solar radiation mapping and modeling. Likewise, Bois *et al*. (2008) used a hybrid model which combined remotely sensed data and solar irradiation models based on topography to estimate the spatial and temporal variability of solar radiation.

Alternatively, Pettazzi and Salsón (2012) merged ground-based measurements and satellite data for detailed analysis of the solar radiation across Galicia in Northwestern

Spain. Their methods involved several steps which include interpolation using kriging, merging using residual techniques, calibration and validation processes.

The annual total solar radiation in an area is influenced by the slope, aspect, surrounding topography, and it varies spatially and temporally (Hussein, 2012). The spatial variability of solar radiation changes with time of day and time of year and in turn affects the variability of microclimate in an area (Effat, 2016). Also, the variations in elevation, slope and aspect have combined effect on the amount of solar radiation received at different locations. However, topography is a major factor that influences the spatial variability of solar radiation in an area.

The foregoing review has shown how satellite remote sensing has been able to provide a feasible source of information on solar radiation. In most cases, satellite remote sensing and GIS techniques are combined together for the analysis of solar radiation data in order to develop a solar information system which is discussed in the following section.

2.8.2 Improved solar information system for Nigeria

The scarcity of ground-based measurements of solar radiation in Nigeria has denied the country the opportunity to build and improve the solar radiation dataset over the country. These dataset are necessary for the development of a solar database which is an integral part of Solar Information System. A solar information system enables the assessment and analysis of solar energy potentials in the country. However, information derived from satellite images can be integrated with ground-based data to provide a comprehensive and reliable solar information system for Nigeria. In this study, attempt will be made to exploit the benefit of merging ground measurements of the global solar radiation and estimations derived from satellites to provide reliable solar radiation data in parts of Northcentral Nigeria. This method of merging ground data with satellite data has the capability to assemble the solar data required for research to enhance the development of solar energy and electricity supply in the country. It can also be used to increase access to electricity in Nigeria and reduce energy poverty among the people in the country. The literature review examined the available information on renewable energy resource in Africa. It was found that in spite of the enormous renewable energy potentials in Africa, information on the potentials is scarce in the continent. The review also found that several methods are used to analyse solar energy potentials, but statistical modeling is the most commonly used method in analysing solar energy potentials in different parts of Nigeria. The review of literature on the application of satellite Remote Sensing and GIS in the analysis of solar energy potentials started from a global perspective to the African continent. It was found that various geostatistical and geospatial techniques were used by different researchers in different locations, however, this study employed geospatial techniques to merge ground-based measurements of solar radiation with satellite-derived solar radiation data as an alternative approach to analyse solar energy potentials in the study area. The section concludes with a recommendation for the application of geospatial techniques in developing solar information system for Nigeria.

2.9 Multi-Criteria Decision Making Method

Multi-criteria decision making (MCDM) methodology is a branch of operation research models and a well-known method of decision making. These methods can manage both quantitative and qualitative criteria and can be used to analyse conflict in criteria and decision makers (Pohekar and Ramachandran, 2004). MCDM can be divided into two categories, namely multi-objective decision making (MODM) and multi-attribute decision making (MADM). In MODM, the decision-making problem is characterized by the existence of multiple and competitive objectives that should be optimized against a set of feasible and available constraints; in contrast, in MADM, a set of alternatives is evaluated against a set of criteria (Pohekar and Ramachandran, 2004). MCDM is helpful solving the complex interactions for decision making in renewable energy systems. Compared to the single-criterion approach, the advantage of MCDM methods is employing multiple-criteria or attributes to obtain an integrated decision-making result. MCDM includes several different methods, the most important of which involve the analytic hierarchy process (AHP), the preference ranking organization method for enrichment evaluation (PROMETHEE), elimination and choice translating reality (ELECTRE) and multi-attribute utility theory (MAUT) (Abu Taha and Daim 2013). MAUT is the most common MCDM method used in energy planning literature, followed by AHP, PROMETHEE, ELECTRE, and decision-support systems (DSS) (Pohekar and Ramachandran, 2004). A brief summary of the most well-known MCDM methods follows.

a) Multi Attribute Utility Theory (MAUT): One of the most popular MCDM methods in decision making, the theory considers the decision maker's preferences in the form of the utility function, which is defined over a set of attributes where the utility of each attribute/criterion does not have to be linear (Wang *et al*., 2010).

b) Analytic Hierarchy Process (AHP): A MADM method first introduced by Saaty (1980), AHP is a type of weighted sum method. In AHP, the problem is constructed as a hierarchy by breaking down the decision from the top to the bottom. The goal is at the first level, criteria and sub-criteria are in the middle levels and alternatives are at the bottom layer of the hierarchy. The input of experts and decision makers are considered as pair-wise comparison, and the best alternative can be selected according to the highest rank between alternatives (Abu Taha and Daim 2013).

The Analytical Hierarchy Process is an important method of estimating the relative value of a set of criteria and sub-criteria in order to achieve a certain objective. In this case, the objective importance of criteria and sub-criteria is measured and aggregated in order to reach a decision (Höfer *et al.,* 2014). AHP is a useful systematic decision-making tool which is capable of disintegrating complex multifactor problems into a hierarchical structure, and each hierarchy comprises of specific elements (Asakereh *et al.,* 2014).

In the literature the application of AHP in handling multi-criteria decision analysis is common. For example a study by Uyan (2013) used GIS and AHP to determine appropriate sites for solar farms in Karapinar region of Turkey. Asakereh *et al.* (2014)

developed a GIS-based fuzzy AHP model to locate the most suitable sites for solar energy in Shodirwan Region of Iran. Effat (2016) integrated the AHP with GIS using remote sensing data to identify the potential zones for solar energy around Lake Nasser, in Aswan, Egypt. Therefore, the AHP was employed to achieve the fifth objective of this study.

In this study, in order to find out the solar energy potential site over the study area, the insolation, DEM, slope, aspect will be used in the AHP model. Uyan (2013) opined that slope must be less than 3% for suitable solar farm sites. Another study by Li (2013) proposed a slope limit of less than 4%. However, Omitaomu *et al.* (2015) believed that the optimum slope value is site dependent, but a 5% threshold for slope should be applicable for most solar energy applications. Asakereh *et al.* (2014) assigned weights to varying degrees of slope, where the value of 1 was given to any cell with slope of 0-3%, and cells with slope 3-10% were valued from 0 to 1. Generally, Aspect angles (orientation) and slope degrees are categorized, the milder slopes are considered to be highly suitable since the most suitable sites are those where the ground is flat and with aspect angle oriented towards the south (Effat, 2016). Specifically, southeast to southwest facing orientation are appropriate locations for harnessing solar energy (Li, 2013).

In this study, four criteria namely: solar radiation, topography, slope and aspect will be weighted based on the Analytical Hierarchy Process (AHP). Then, the final weights of the four criteria and sub-criteria will be assigned. The output of this process will be solar energy potential sites in the study area.

c) Analytic Network Process (ANP): The ANP methodology is a general form of the AHP; Saaty (1996) introduced both. Although AHP is easy to use and apply, its unidirectional relationship characteristics cannot manage the complexity of many problems. ANP deals with the problem as a network of complex relationships between alternatives and criteria where all the elements can be connected. Cheng and Li (2005) provide an empirical example to illustrate the use of ANP.

d) PROMETHEE: This method is characterised by ease of use and decreased complexity. It uses the outranking principle to rank the alternatives and performs a pair-wise comparison of alternatives to rank them with respect to a number of criteria. The family of PROMETHE includes PROMETHEE I and II (Oberschmidt *et al*., 2010).

e) ELECTRE: This method is capable of managing discrete criteria that are both quantitative and qualitative in nature and provides complete ordering of the alternatives. The analysis is focused on the dominance relationship between alternatives and is based on the outranking relations and exploitation notions of concordance. The outranking method uses pair-wise comparison between alternatives (Wang *et al*., 2009). The family of ELECTRE includes ELECTRE I, II, III and IV. Abu Taha and Daim (2013) has notes that MCDM methods include four main stages: (1) structuring the decision process, alternative selection and criteria formulation; (2) displaying trade-offs among criteria and determining criteria weights; (3) applying value judgments concerning acceptable trade-offs and evaluation; and (4) final evaluation and decision making. The application of MCDA in energy-related matters includes energy planning and power plant allocation (Akash *et al*., 1999; Madlener *et al*., 2009), energy Review of current research 25 resource allocation (Ramanathan and Ganesch, 1993), energy policy (Greening and Bernow, 2004) and energy management (Ben Salah *et al*., 2008). Developing evaluation criteria and methods is a prerequisite for selecting the best alternative, identifying energy supply systems, informing decision makers of the integrated performance of the alternatives, and monitoring effects on the social environment. Weights are assigned to the criteria to indicate their relative importance and are determined by the variance degrees of criteria, the independency of criteria and the subjective preferences of the decision makers. The methods used to assign weights include equal weights and rank-order weights. However, the equal- weights method has been criticized because it ignores relative importance among criteria. Rank-order weighting methods are classified into three categories: the subjective weighting method, objective weighting method and combination weighting method. Criteria weights determined by the subjective weighting method depend only on the preference of decision-makers and not on the quantitative measured data of energy projects. Conversely, objective weights are obtained using mathematical methods based on the analysis of the initial data. Subjective weighting methods explain the evaluation clearly, while objective methods are relatively weak. Additionally, the judgments of decision makers sometimes depend on their knowledge or information. Thus, errors in assigning criteria weights are unavoidable to some extent. An integrated method could overcome these shortcomings and could be the most appropriate technique for determining criteria weights (Wang *et al*., 2009).

Pair wise comparison and AHP are the most commonly used methods in sustainable energy decision making. In the pair wise comparison method, participants are presented a worksheet and are asked to compare the importance of two criteria at a time, each time answering the question, ''Which one of these two criteria is more important, and how much more important?'' (Wang *et al*., 2009). Relative importance is scored using various scales; a scale of 0 (equal importance) to 3 (absolutely more important) is usually adopted. The results are consolidated by adding the scores obtained by each criterion when preferred to criteria with which it is compared. The classic MCDA methods generally assume that all criteria and their respective weights are expressed in clear values and, thus, that the rating and ranking of the alternatives can be carried out without any problem (Wang *et al.*, 2009). Nevertheless, in a real-world decision situation, the application of the classic multi-criteria evaluation methods may face serious practical constraints from the criteria, perhaps because of imprecision or vagueness inherent in the information. Due to the availability and uncertainty of information and the vagueness of human feeling and recognition, such as classifying agreement as 'equally', 'moderately', 'strongly', 'very strongly', 'extremely' and a 'significant degree', it is difficult for decision makers to assign exact numerical values to the criteria, make precise evaluation and convey their feelings about and recognition of objects (Wang *et al.*, 2009). Hence, most of the selection parameters cannot be provided precisely and the evaluation data of the alternative suppliers' suitability for various subjective criteria and the weights of the criteria are usually expressed in linguistic terms by the decision makers. Furthermore, it is also recognised that human judgment on qualitative criteria is always subjective and therefore imprecise. The fuzzy set theory introduced by Zadeh (1965) can solve this problem and play an important role in the decision situation. The combination of MCDM methods and fuzzy set theory has been applied in renewable energy cases.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Sources of Data

3.1.1 Ground-based solar radiation measurements

There are different sources of solar radiation data such as ground measurement and satellite retrieval, but none of them is considered to be faultless (PVGIS, 2016), so it is important to understand the strengths and weakness of each data source. Ground station measurement gives a more accurate estimate of the solar radiation at a particular place or region. However, the main advantage of satellite-based methods is that they give a fairly uniform coverage of large areas while ground stations are often very far apart. It is also possible to measure solar radiation with a high resolution satellite at a specified time intervals, typically every minute or even more often using the satellite method. However, the quality of satellite-based estimates must be checked by comparing the data with that of high-quality ground station measurements (PVGIS, 2016)**.**

The ground-measured solar radiation data used for this study was obtained from the Nigerian Meteorological Agency (NIMET). NIMET has several weather stations located mostly at Nigerian Airports. Until now the NIMET stations used Gunn-Bellani pyranometers, but presently the stations use Solarimeter to measure solar radiation in Watt per meter square (W/m^2), and Campbell-strokes sunshine recorder to measure sunshine duration in hours. Daily average solar radiation data covering a period of thirty years was provided by NIMET in millijoule per meter square per day ($MJ/m^2/day$). The data was converted into kilowatt hour per meter square per day (kWh/m^2/day) using the International Energy Agency (IEA) General Converter for Energy. This was done because solar radiation values are generally expressed in kWh/m^2/day, which is the amount of solar energy that strikes a square metre of the Earth's surface in a single day.

3.1.2 Satellite-derived temperature data

The satellite data used in this study was obtained from the following source:

NASA SSE Web Portal;

3.1.2.1 *NASA SSE web portal*

The NASA SSE web portal provides free solar radiation data with relatively good resolution. The temperature for SSE Release 6.0 (which is presently the latest version) was obtained from the NASA Science Mission Directorate's satellite and re-analysis research programs (NASA, 2016).

The temperature and cloud parameters contained in SSE 6.0 are derived from parameters available from the NASA/Global Energy and Water Cycle Experiment Surface Radiation Budgets (NASA/GEWEX SRB) Project Release 3.0 archive. The NASA/GEWEX SRB Project focuses on providing estimates of the Earth's Top of atmosphere (TOA) and surface radiative energy flux component. The datasets contains global 3-hourly, daily, monthly/3-hourly, and monthly averages of surface and TOA longwave and shortwave radiative parameters on a 2^0x2^0 grid. Primal inputs to the model include: visible and infrared radiances from International Satellite Cloud Climatology Project (ISCCP) pixel-level (DX) data, cloud and surface properties derived from those data, temperature and moisture profiles from GEOS-4 reanalysis product obtained from the NASA Global Modeling and Assimilation Office (GMAO) (NASA, 2016). NASA SSE provided daily averaged temperature data in ^{o}C.

3.2 Methods of Data Analysis

3.2.1 Spatial mapping of solar energy potentials

In order to achieve objective 1, spatial mapping of solar energy potentials was employed, in which case, the ground-measured and the satellite data over the study area were used to generate the solar radiation maps using Inverse Distance Weighted (IDW) interpolation. This was achieved using the Spatial Analyst tool in ArcGIS software (version 10.3). The solar radiation data were arranged in Microsoft Excel, saved as coma separated values (csv) and imported into the ArcGIS environment as points, using these points, the interpolation was carried out to produce the solar radiation maps.

IDW interpolation assumes that values that are closer are more related than those that are farther apart (ESRI, 2016). It gives greater distance (De Smith *et al.*, 2015). IDW was used in the study because it is the simplest interpolation method (Fisher *et al.*, 1987) and has the simplest technique for determining the weight values. In addition, the user has control over the mathematical form of the weighting function and the size of the neighborhood in IDW (Fisher *et al.*, 1987).

3.2.2 Variability analysis of solar irradiance and ambient temperature

The discrimination of high or low values of each climate parameter considered was done by computing the standardised variable index (I) created by McKee *et al.* (1993)

and which can be found in the study by Shukla *et al.*(2015) and Lawin *et al.*(2019). Then, the standardised variable index (I) is defined by equation:

$$I(i) = \frac{X_i - \overline{X}_m}{\sigma} \tag{3.1}$$

where $X_{i,}$is the value for the considered years or months $i; \overline{X}_m$ is the mean for the considered years or months $m; \sigma$ is the standard deviation for the considered years and months.

Thus, in this study it was considered that a month and year is normal when its standardised index falls between the value of -0.5 and +0.5. It will be in excess if its index is greater than +0.5, and it will be considered as deficit when its index is less than -0.5. This interval is criticised and relatively weak, but it allows differentiating between the deficit years and months from excess months and years (Lawin *et al.,* 2019).

The standardised variable index (I) makes it possible to analyse the seasonal and interannual variabilities of the variables at considered time scale. This is to achieve objective two of this study.

3.2.3 Visualising the spatial variability in solar energy potentials in the study are

In order to achieve objectives four and five of this study, the solar energy potential sites in the three states was determined using geospatial techniques. To achieve this, the solar radiation values, the digital elevation model (DEM), the slope and aspect of the study area was prepared in ArcGIS and used as input parameters.

Firstly, the study area was delineated in Google Earth using the base map of the area, then the coordinates of the extreme corners of the area was tabulated in a Microsoft Excel spreadsheet and used to create a georeferenced map based on the WGS 1984 Geographic coordinate system. Secondly, several points within the study area was marked and their coordinates and elevations was recorded in an Excel spreadsheet. Then, these was imported into ArcGIS as X, Y and Z data. Using the Spatial Analyst Tool in ArcGIS, interpolation process was carried out to create a DEM of the area. Then, the slope map and aspect of the area was generated from the DEM.

The Spatial Analyst Tool was also used to create slope map of the area as an output raster, in this case, the DEM was used as input raster, and the output measurement units and the z-factor were specified. Similarly, the Surface analysis tool was used to create the aspect of the study area as output raster; in this case, the DEM was used as input raster for the analysis. Then, the DEM, slope and aspect was integrated with the solar radiation data in Analytic Hierarchy Process (AHP) to produce a map of solar energy potential sites.

3.2.3.1 *The analytical hierarchy process (AHP)*

To identify the optimum solar energy potential sites and values for solar energy development in the area.

The optimum solar energy potential sites in the three states were identified using GIS weighted overlay and analytic hierarchy process. To achieve this, the solar radiation map, the digital elevation model (DEM), the slope and aspect maps of the study area were created in ArcGIS, these maps were then used as input parameters to identify the solar energy potential sites in the study area.

Firstly, the study area map was used to delineate the Digital Elevation Model of the area in ArcGIS environment. Then the maps were georeferenced based on the WGS 1984 Geographic coordinate system. Then, the slope and aspect maps of the area were generated from the DEM. Finally, the DEM, slope and aspect maps were integrated with the solar radiation data in Analytic Hierarchy Process (AHP) to produce maps of solar energy potential sites in the area.

However, in this study, four criteria namely: solar radiation, topography, slope and aspect were weighted based on the Analytical Hierarchy Process (AHP). Then, the final weights of the four criteria and sub-criteria were assigned. The output of this process is solar energy potential sites in the study area.

In order to determine the amount of exploitable power in each of the three states, the following formula was used: Cross sectional area X the average power intercepted at any time (Electropaedia, 2016).

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Result

The results and discussion of this study are in line with the objectives of the study presented in chapter one. The chapter is structured into the following sections: sections one and two present insolation maps separately based on climatic data; section three compares between ground measured solar radiation data and ambient temperature to highlight the similarities and differences between them. The fourth section analyses the pattern of solar radiation in Kogi, Nasarawa and Niger States; section five visualise the solar energy potential sites in the study area; section six estimates the potential solar electricity generation in the area; and the chapter concludes with a discussion on the economics of solar energy.

4.2 Insolation Maps Based on Ground Measured Data

Ground measured data forms one of the major sources of solar radiation data. In this section, maps of global solar radiation were produced using spatial interpolation of satellite data in order to examine the efficiency of geospatial concept in visualising the solar energy potentials in Kogi, Nasarawa and Niger states. Solar energy potential mapping using satellite data of solar radiation is a primal step in striking comparison with the ambient temperature, and subsequent analysis of the spatial variations in the solar energy potentials over the study area.

Table 4.1 shows the monthly mean values of solar radiation obtained from ground measured data in the entire study area over a period of thirty years.

Table 4.1: Monthly Mean Values of Global Solar Radiation (kWh/m^2/day) for 1988-2018 (NIMET,2020)

Station	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Niger	5.67	5.94	6.19	6.10	5.58	5.10	4.49	4.20	4.84	5.43	5.84	5.66
Nasarawa	5.82	6.03	6.08	5.71	5.34	4.81	4.46	4.16	4.55	5.21	5.38	5.79
Kogi	5.56	6.60	5.55	5.26	4.99	4.60	4.21	3.96	4.42	4.75	5.35	5.42

It can be observed from Table 4.1 that a maximum monthly mean solar radiation value of 6.19kWh/m^2/day was recorded in Niger state. It is also observed from Table 4.1 that the maximum solar radiation values were constantly recorded between March and April in the study area except for Kogi State whose highest value was observed in the month of February. This can be attributed to the fact that the months of February, March and April fall within the period of longer days and shorter nights experienced in the sahelian region of Nigeria. A longer day depicts longer sunshine hours per day, which results in greater amount of solar radiation received. The maximum insolation received over the study area is as a result of cloud attenuation reduction experienced during these periods.

Results from the study also showed that the minimum monthly mean solar radiation value of 4.20kWh/m^2/day was recorded in Niger state in August, while 4.96kWh/m^2/day and 3.96kWh/m^2/day were observed in Nasarawa and Kogi States respectively in August as presented in Table 4.1.

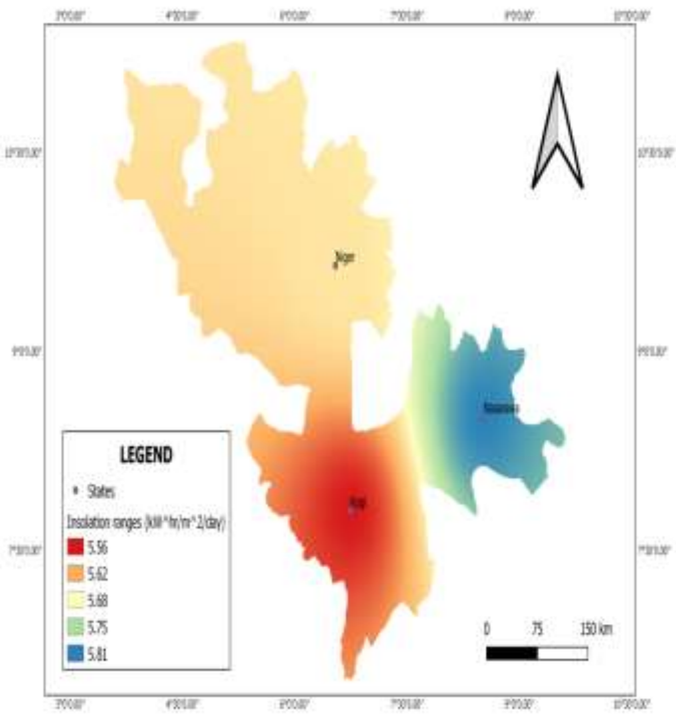
However, the lower insolation experienced during the months of July and August is attributed to the influence of cloud which significantly reduces the intensity of solar radiation reaching the Earth's surface. In addition, the minimum insolation recorded in both months can be attributed to the rainy season. This is because the Earth is a little farther from the Sun around July 4th annually, when the distance between the Sun and the Earth is about 152 million kilometres, a position known as aphelion (Rajan, 2017).

The rainy season is characterised by cumulonimbus clouds in the area, which have high capacity to intercept the incident solar radiation received in the area. A similar conclusion was reached by Ojosu (1990) who observed that in Nigeria, the rainy season also records low levels of solar radiation especially in the months of July and August. The implication of this is that lower solar energy can be harnessed during these periods. In order to improve the efficiency of photovoltaic solar technology deployed to harness solar energy in the area during the periods of minimum insolation, batteries should be serviced or changed regularly, and solar panels should be cleaned to maximise solar energy potentials during these periods.

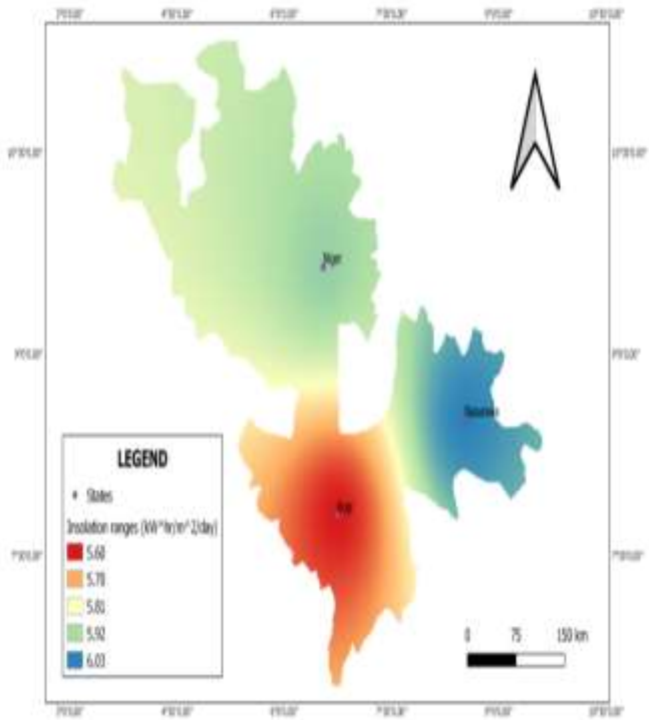
In addition, it is observed that the average monthly mean solar radiation throughout the study area is approximately equal to 5kWh/m^2/day, which is conducive for solar energy development. Based on this fact, there are many potential sites in the area that are good for solar energy development. This is because the amount of solar energy favourable to the Photovoltaic and Concentrating Solar Power technologies is at least 5kWh/m^2/day (USFS, 2005).

The research findings showed that the peak times for harnessing solar energy in the study area are the months of February, March and April. However, there are other months of the year that offer good times for harnessing solar energy which vary with locations within the study area as shown in Table 4.1.

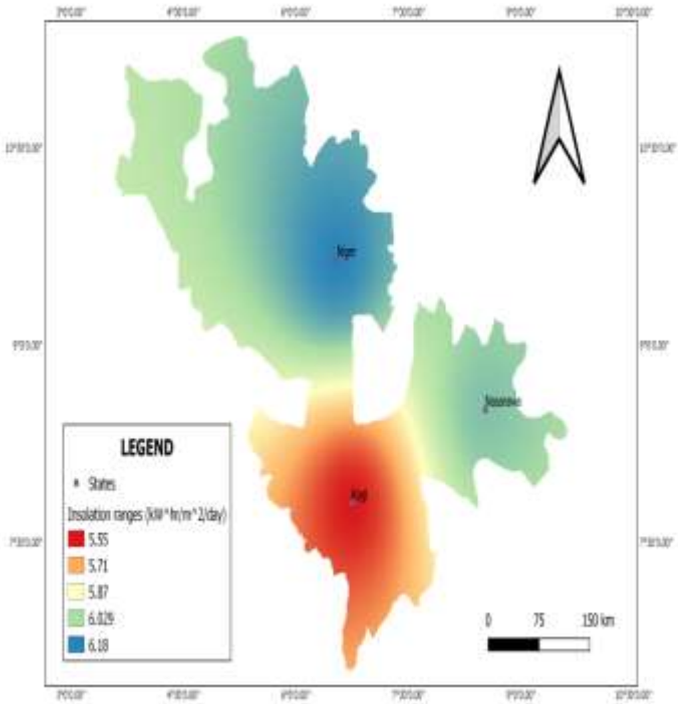
Figures 4.1a – 4.1l presents maps of solar radiation derived from ground measured data.



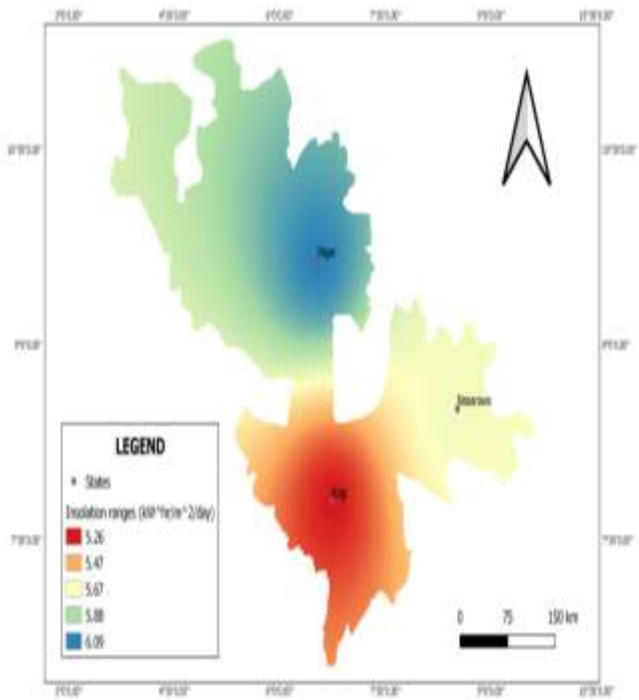
(a) January



(b) February

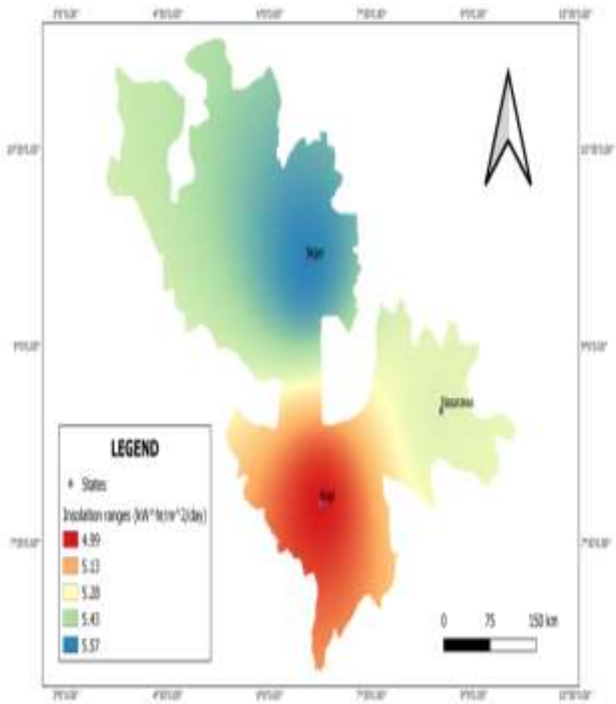


(c) March

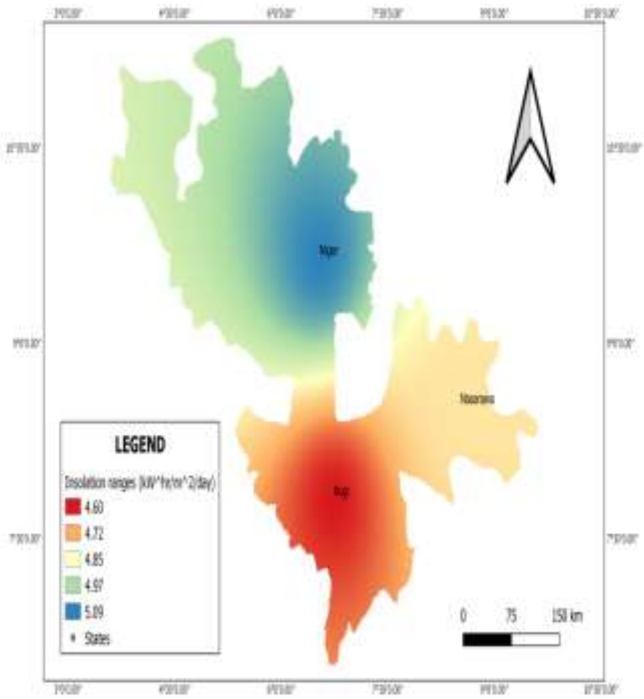


(d) April

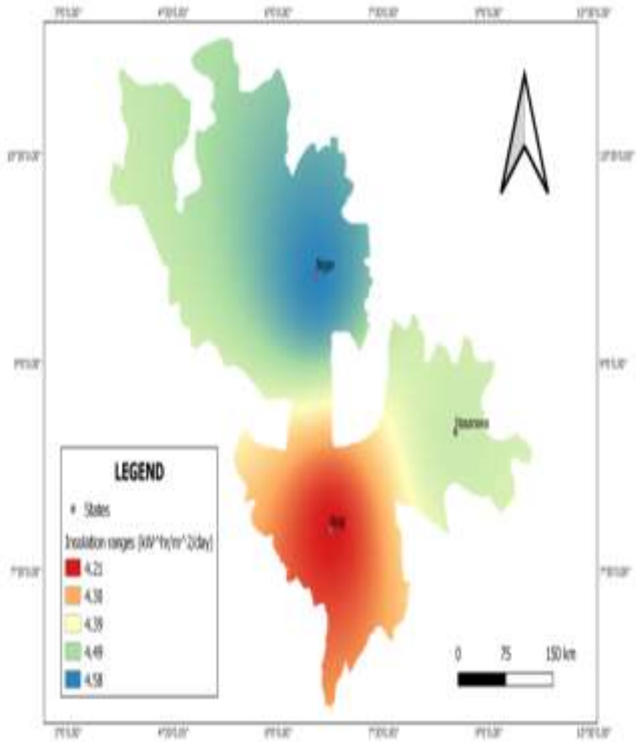
Figure 4.1: Monthly Mean Daily Values of Global Solar Radiation (kWh/m^2/day) for1986-2015



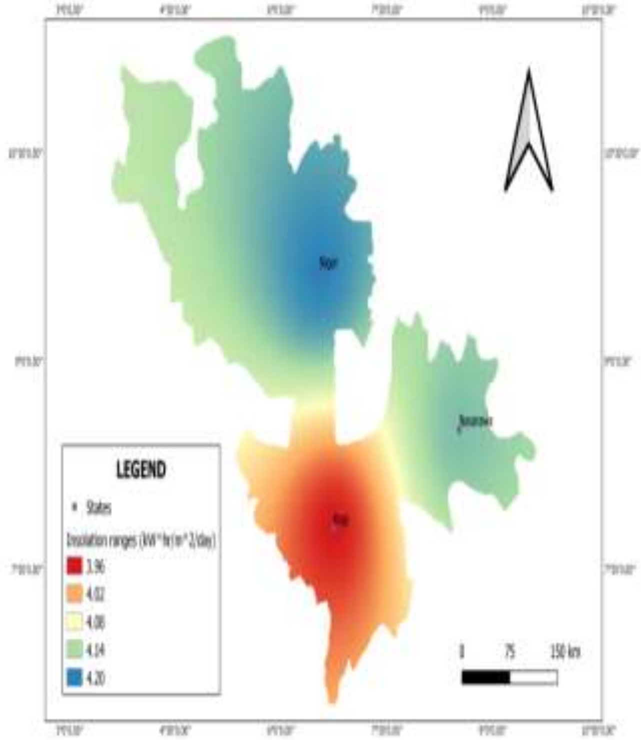
(e) May



(f) June

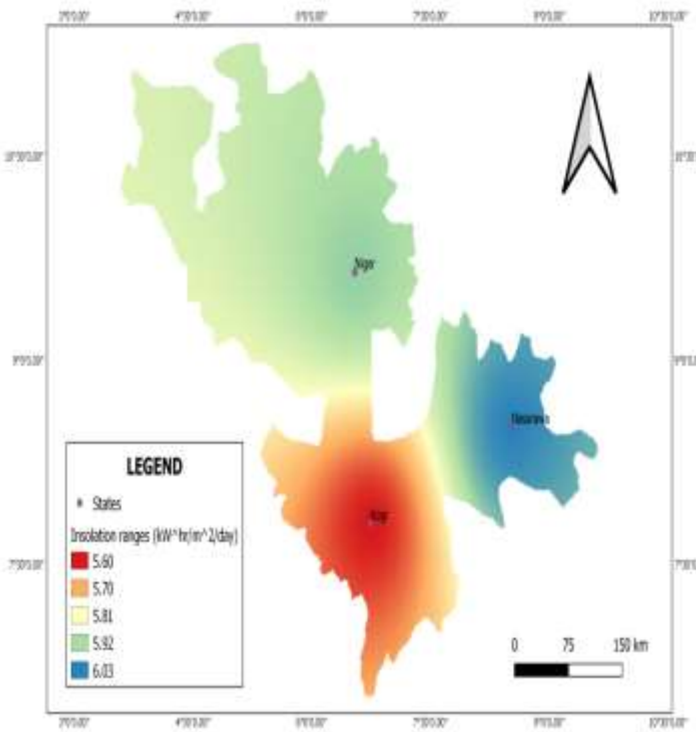


(g) July

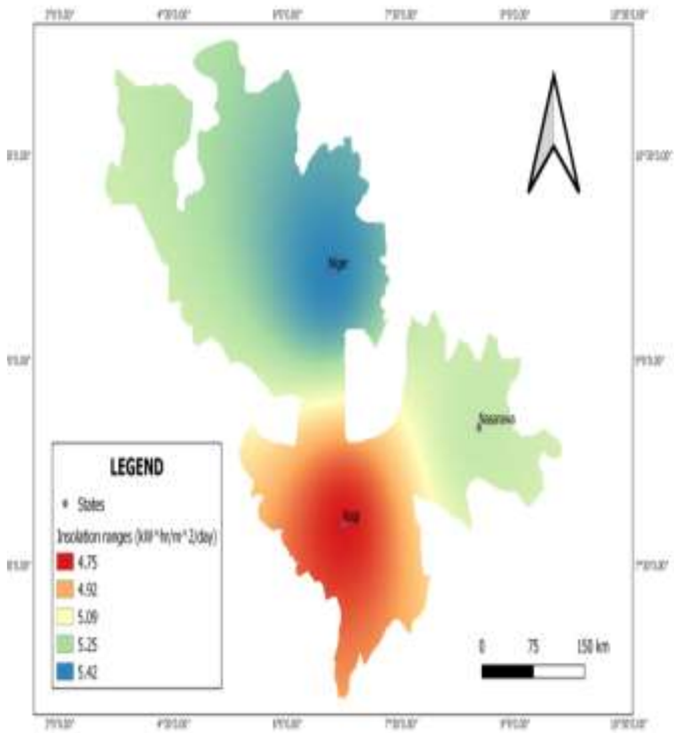


(h) August

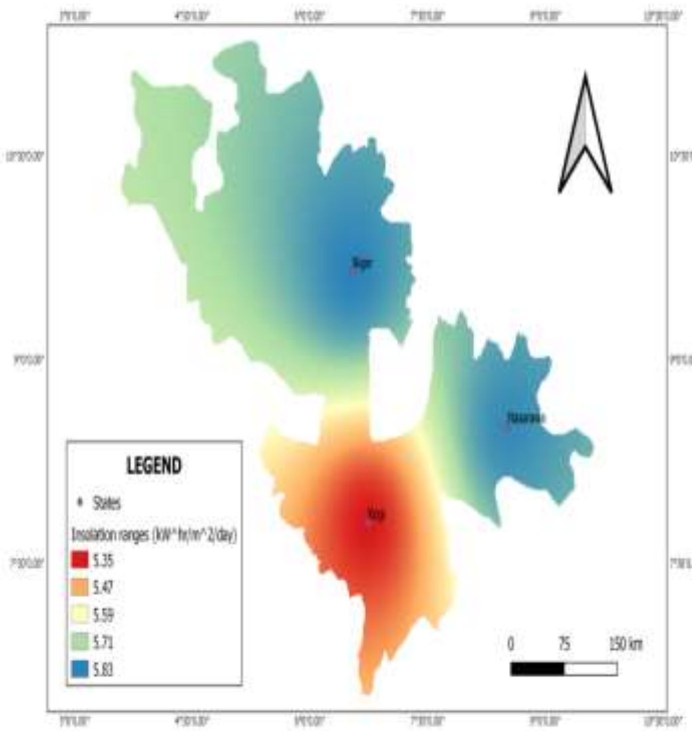
Figure 4.1 (Continued): Monthly Mean DailyValues of Global Solar Radiation ($kWh/m^2/day$)



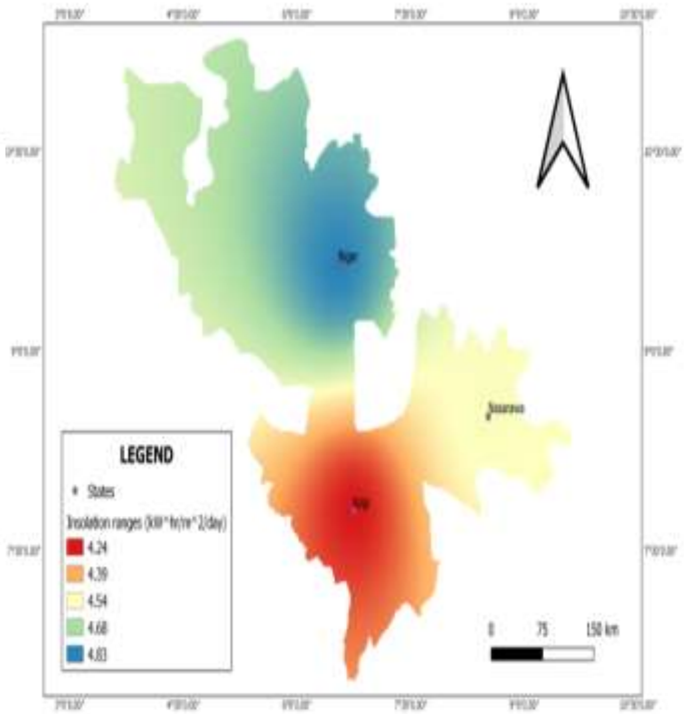
(i) September



(j) October



(k) November



(l) December

Figure 4.1 (Continued): Monthly Mean Daily Valuesof Global Solar Radiation(kWh/m^2/day)

The Figures showed that it is possible to map the surface solar radiation at every point location from satellite data. The use of ground measured data addresses the inconsistency observed in mapping solar radiation when climate zone classification is adopted as in the case of Diabaté *et al.* (2004). This also supports the hypothesis of Diabaté *et al.* (2004) that suggested the use of satellite-derived clearness index, which is available at every pixel to improve the quality of solar radiation mapping.

In addition, temporal variations in the monthly means of solar radiation among the three states can be observed from Figures 4.1a – 4.1l. Also, spatial variation in solar radiation across the three states was observed, whereby higher solar radiation value was recorded in Niger state during the month of November (Figure 4.1k); while higher values were observed in Nasarawa state during the months of January (Figure 4.1a) and December (Figure 4.1l); whereas, higher solar radiation values were recorded in Kogi state in the month of January (Figure 4.1a).

The information provided here are important parameters for the design, sizing, positioning of solar panels and for concentrating solar thermal applications. Also, the monthly variation in solar radiation is required by designers and engineers of solar energy conversion systems in order to ascertain the amount of solar energy available to a collector and how it varies monthly andannually.

4.3 Analysis of Seasonal and Inter-annual Solar Irradiance and Temperature

4.3.1 Seasonal solar irradiance (Niger State)

Figure 4.2 presents the monthly solar irradiance structures and respective standardised solar irradiance at Niger State over the period of 1988-2018.

The analysis of figure 4.2a depicts a bimodal seasonal cycle with peak value attained inFebruary, March,and April.

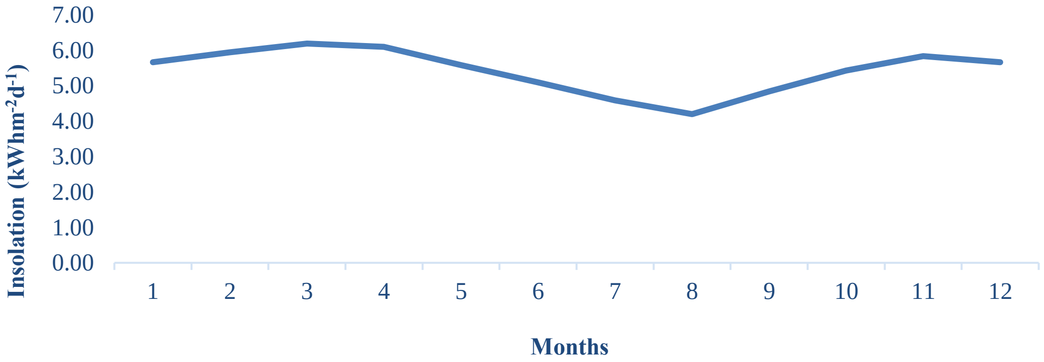


Figure 4.2a: Monthly insolation pattern (Niger State)

The month of August shows the lowest mean value of solar radiation, while the month of March shows the highest mean value of solar radiation as shown in Figure 4.2a.

Figure 4.2b presents the monthly standardised solar irradiance in Niger State over the study period.

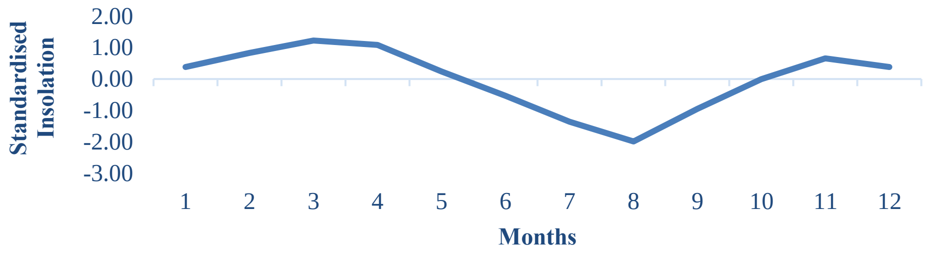


Figure 4.2b: Monthly standardised insolation

The analysis of this figure shows that four months (July, August and September) are in deficit of solar irradiance. The month with the lowest index value of -2.00 is August. The analysis shows also that three months (February, March and April) are in excess of solar irradiance. Normal months are January, May and December. The Month with highest index value of solar irradiance is March with 1.23.

The monthly mean solar irradiance for Niger State used to calculate the standardised variable index is 5.43kWh$m^{-2}d^{-1}$, whereas standard deviation is 0.62. This analysis shows that the months with highest values of solar irradiance are expectedly the dry seasonmonths which lead to the conclusion that there is an excess of solar irradiance during the dry season. Therefore, it is a period of high production of solar energy. Indeed, with low production in the dry season because of the reduction of the water level in the reservoir.

4.3.2 Inter-annual solar irradiance (Niger State)

Figure 4.3a gives the inter-annual solar irradiance pattern for the period 1988–2018.

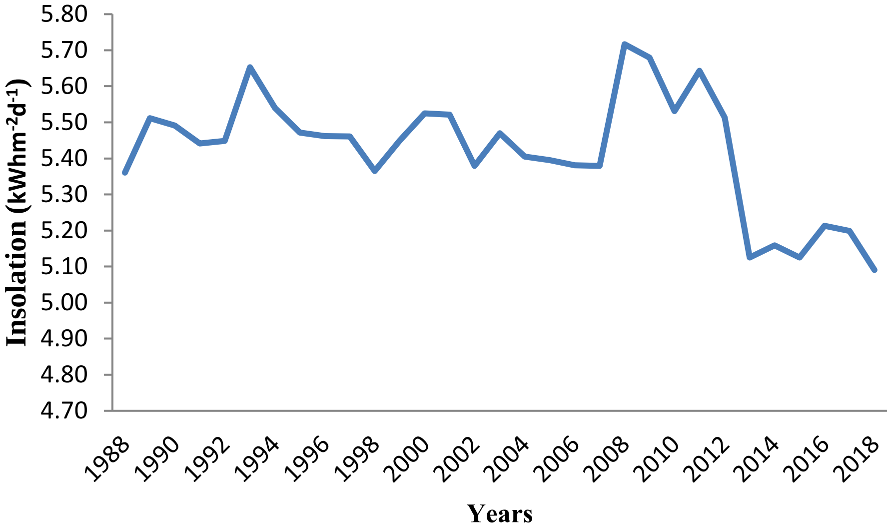


Figure 4.3a: Inter-annual Insolation pattern of Niger State (1988-2018)

This figure shows that year 2008 recorded higher value of solar irradiance than other years. It can also be observe that year 2018 recorded the lowest value of solar insolation values through the study period.

Figure 4.3b presents inter-annual standardised solar irradiance over the study period 1988–2018.

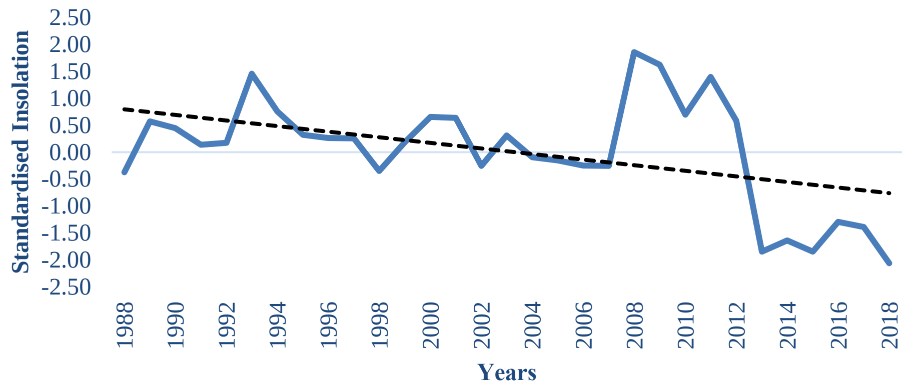


Figure 4.3b: Inter-annual Insolation pattern of Niger State (1988-2018)

The analysis of this figure points out three sub-periods including the first period spanning from 1988–1997 with high values of solar irradiance. The second sub-period 1998–2012 presents years with mixture of high, low and normal values of solar irradiance. The third sub-period 2013–2018 is marked by years with more low values of solar irradiance and a few normal values, but there is no year with high values of solar irradiance observed. The analysis also shows those 10 years with high values of solar irradiance and 6 years of low values of solar irradiance. These results reveal a trend of decline in average solar irradiance for the last sub-period 2013–2018.It also showed that the lowest value occurred in 2018, while the year with highest value of solar irradiance occurred in 2008. These analyses also show a general increase in average solar irradiance for the first sub-period. Furthermore, these findings agree with the results of several studies that reveal a subsequent increase (1–4W/m2) since the 1980s which is called “brightening” (Stanhill and Cohen, 2001) and a decrease of irradiation in some regions of the world. Solar irradiation is the principal resource of solar power output (PV); the decrease of this parameter affects negatively the production of solar energy.

4.3.3 Seasonal temperature (Niger State)

Figure 4.4a shows the monthly temperature pattern in Niger State over the study period 1988-2018 while Figure 4.4b shows the monthly standardised temperature index for the same period.

The analysis of Figure 4.4a shows that January and December have low mean values of temperature, whereas March and April recorded high mean values but the pattern does not show remarkable variations.

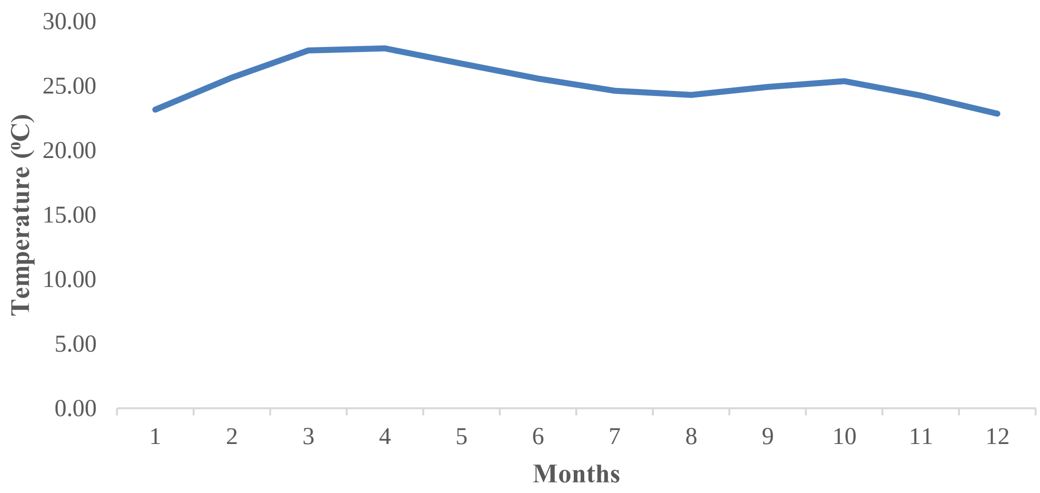


Figure 4.4a: Monthly temperature pattern (Niger State)

The means monthly temperature for Niger State used to calculate the standardised variable index is 25.24ºC, in the same way the standard deviation is 1.53. The analysis of Figure 4.4b shows that four months (January, August, November and December) are cooler. The coolest month with the lowest index value equal to -1.56 is December.

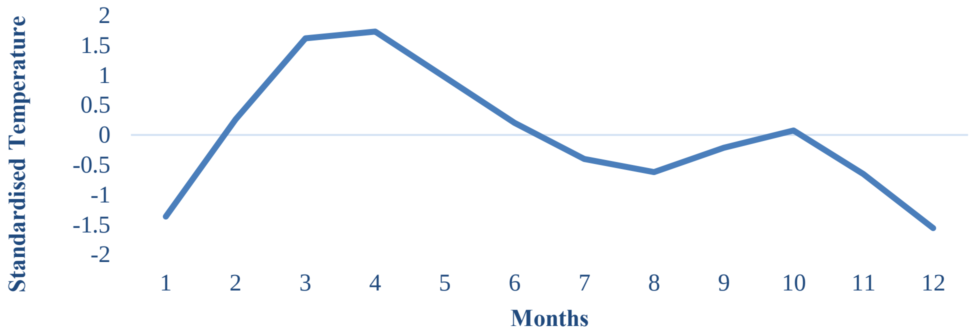


Figure 4.4b: Monthly standardised temperature (Niger State)

The analysis also shows that three months (March, April and May) are hotter in Niger State. Normal months in the year are February, June and October. The hottest month is April with the highest index values equal to 1.73.

4.3.4 Inter-annual temperature (Niger State)

Figure 4.5a presents the inter-annual temperature patterns for the period 1988–2018.

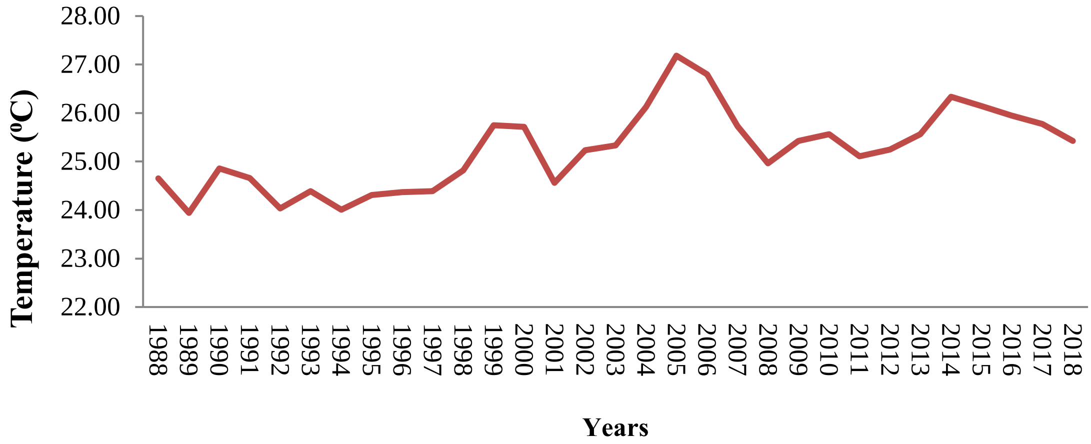


Figure 4.5a: Inter-annual temperature pattern of Niger State (1988-2018)

This result shows that 2005 is the hottest year with mean value of 27.1^{0}C. 1989 is the coolest year with 23.94^{0}C annual mean value. This high temperature over low land is due to low altitude and as can be seen, there is a trend of incremental variation.

Figure 4.5b shows inter-annual standardized temperature in Niger State over the period 1988–2018.

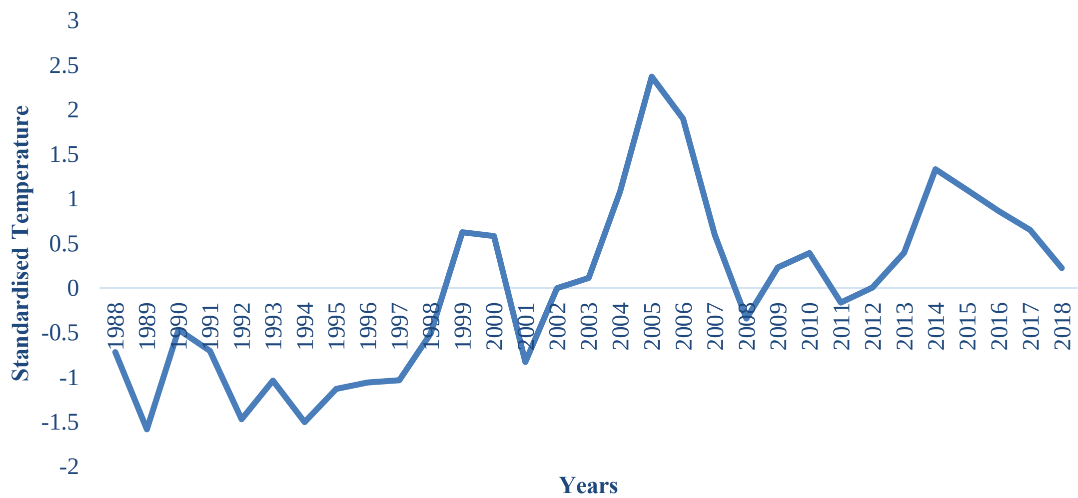


Figure 4.5b: Inter-annual Standardised Temperature over Niger State, Nigeria (1988 - 2018)

The analysis of this figure points out two sub-periods, including the first period 1988–2001 with very low temperature except 1999 and 2000, which have high values of mean temperature. The second sub-period includes the period is 2002–2018 characterised with hotter years except 2008 and 2011 which have low mean temperature. The analysis of the Figure 4.5b also shows that years 2002 and 2012 are within the normal range of temperature.

These results reveal an upward trend of average temperature for the last sub-period 2002–2018 and show that the hottest year was 2005 whereas the coolest year was 1989. Furthermore, these findings agree with the results of many studies which show increases in temperature over the end of last century (Brohan *et al.*, 2006; Safari, 2012 and Buhairi, 2010). More recently, Birara *et al*. (2018) analysed the trend and variability of Rainfall and temperatures in the Tana basin region, Ethiopia, for the period 1980–2015 and found significant increase of maximum, minimum and mean temperature for most of the stations considered. These increases in temperature may affect negatively the production of solar energy and increase evaporation which reduces water availability.

4.3.5 Seasonal solar irradiance (Kogi State)

Figure 4.6a presents the monthly solar irradiance structures and respective standardised solar irradiance at Kogi State over the period of 1988-2018.

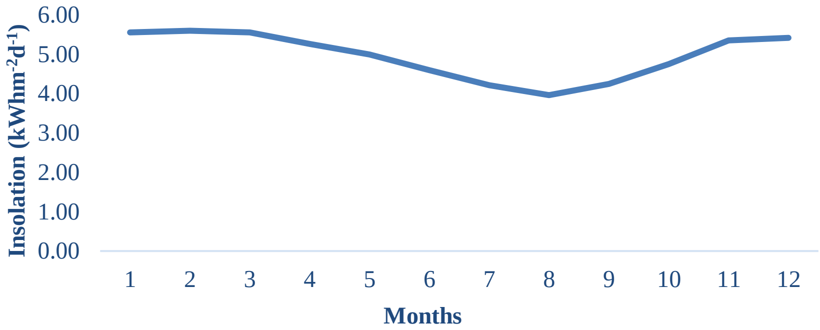


Figure 4.6a: Monthly insolation pattern (Kogi State)

The analysis of Figure 4.6a depicts a multiple seasonal cycle with peaks respectively attained in January, February, March, November and December. September shows the lowest mean value of solar radiation, while February shows the highest mean value of solar radiation.

Figure 4.6b presents the monthly standardised solar irradiance at Kogi State over the study period.

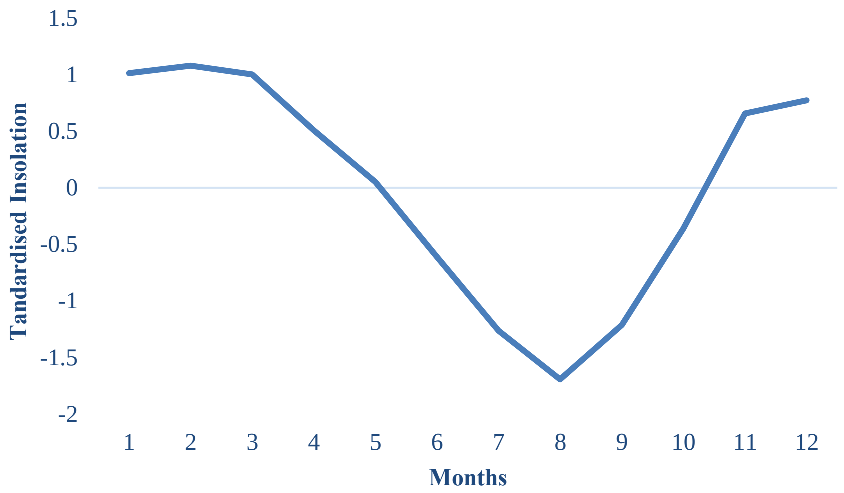


Figure 4.6b: Monthly standardised insolation (Kogi State)

The analysis of this figure shows that four months (June, July, August and September) are in deficit of solar irradiance. The month with the lowest index value of -1.69 is August. The analysis shows also that four months (January, February, March and December) are in excess of solar irradiance. Normal months are May and October. The Month with highest index value of solar irradiance is February with 1.07.

The monthly mean solar irradiance for Kogi State used to calculate the standardised variable index is 4.96k $Whm^{-2}d^{-1}$ whereas standard deviation is 0.59. This analysis shows that the months with highest values of solar irradiance coincide with the dry season, which leads to the conclusion that there is an excess of solar irradiance in the dry season and, therefore, it must be a period of high production of solar energy. Indeed, a solar power plant installed in this region could be in complementary with a hydroelectric plant with low production in the dry season because of the reduction of the water level in the reservoir.

4.3.6 Inter-annual solar irradiance (Kogi State)

The Figure 4.7a gives the inter-annual solar irradiance patterns for the period 1988-2018.

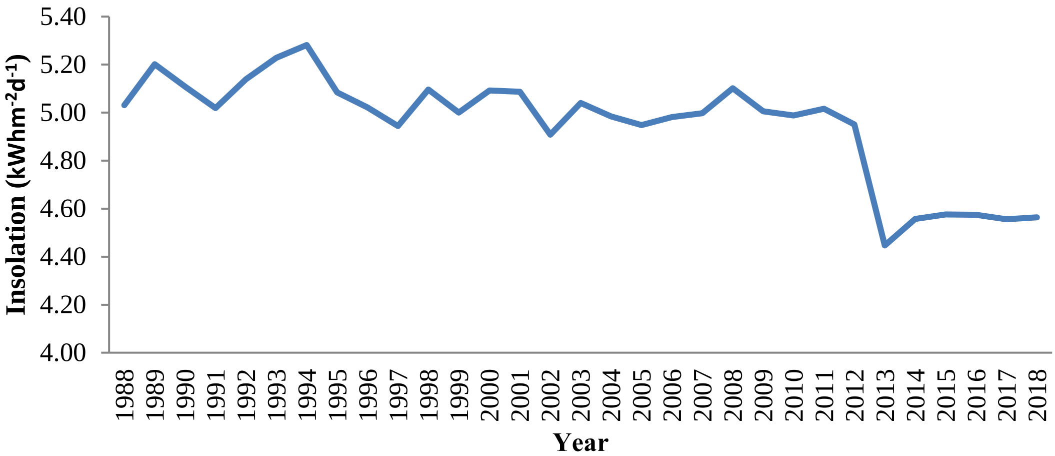


Figure 4.7a: Inter-annual insolation pattern of Kogi State (1988-2018)

This figure shows that the year 1994 indicates high value of solar irradiance than other years. It can also be observed that year 2013recorded the lowest value of solar insolation values through the study period.

Figure 4.7b presents inter-annual standardised solar irradiance over the study period 1988–2018.

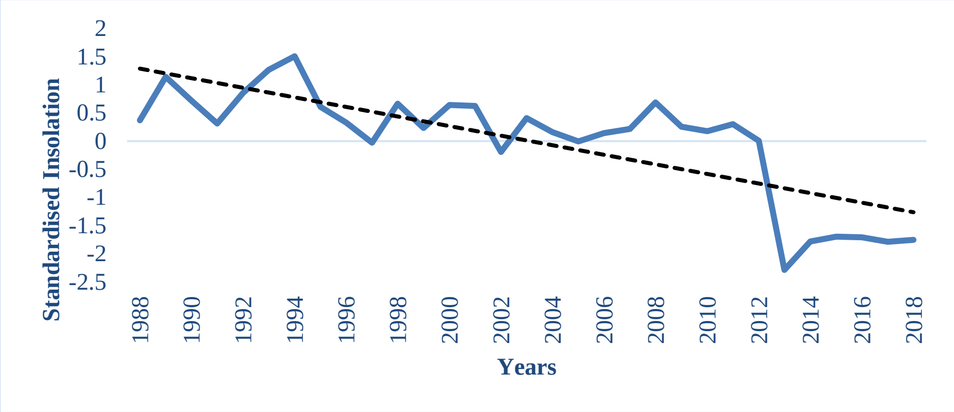


Figure 4.7b: Inter-annual standardized insolation pattern of Kogi State (1988-2018)

The analysis of this figure points out two sub-periods including the first period spanning from 1988–2011 with high values of solar irradiance and some years with normal values solar irradiance of the study area. The second sub-period 2013–2018 is marked by years with more low values of solar irradiance.

The analysis shows also 10 years with higher values of solar irradiance and 6 years of lower values of solar irradiance. These results reveal a trend of decline in average solar irradiance for the last sub-period 2013–2018.It also shows that the lowest value occurred in 2013 while the year with highest value of solar irradiance occurred in 1994. These analyses also show a general increase in average solar irradiance for the first sub-period. Furthermore, these findings agree with the results of several studies that reveal a subsequent increase (1–4W/m2) since the 1980s which is called “brightening” (Stanhill and Cohen, 2001) and a decrease of solar irradiation in some regions of the world. Solar irradiation is the principal resource of solar power output (PV); the decrease of this parameter affect negatively the production of solar energy.

4.3.7 Seasonal temperature (Kogi State)

Figure 4.8a shows the monthly temperature patterns at Kogi State over the study period 1988-2018 while Figure 4.8b shows the monthly standardised temperature index for the same period.

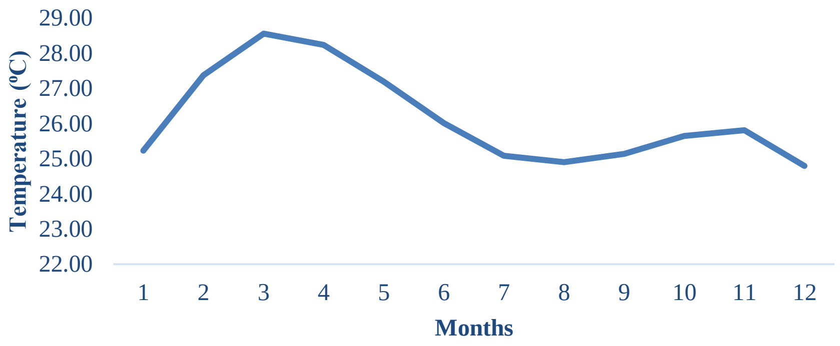


Figure 4.8a: Monthly temperature pattern (Kogi State)

The analysis of Figure 4.8a shows that January and December have low mean values of temperature, whereas March and April recorded high mean values but the pattern does not show remarkable variations.

The means monthly temperature for Kogi State used to calculate the standardised variable index is 26.16°C whereas then standard deviation is 1.33. The analysis of Figure 4.8b shows that five months (January, July, August, September and December) are cooler. The coolest month with the lowest index value equal to -1.03 is December. The analysis also shows that four months (February, March, April and May) are hotter in Kogi State. Normal months in the year are February, June, October and November. The hottest month is March with the highest index values equal to 1.80.

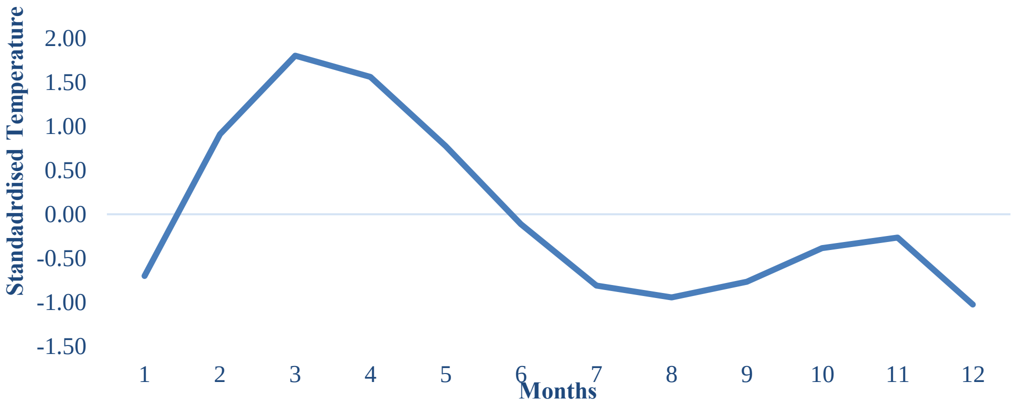


Figure 4.8b: Monthly standardised temperature (Kogi State)

4.3.8 Inter-annual temperature (Kogi State)

Figure 4.9a presents the inter-annual temperature patterns for the period 1988–2018.

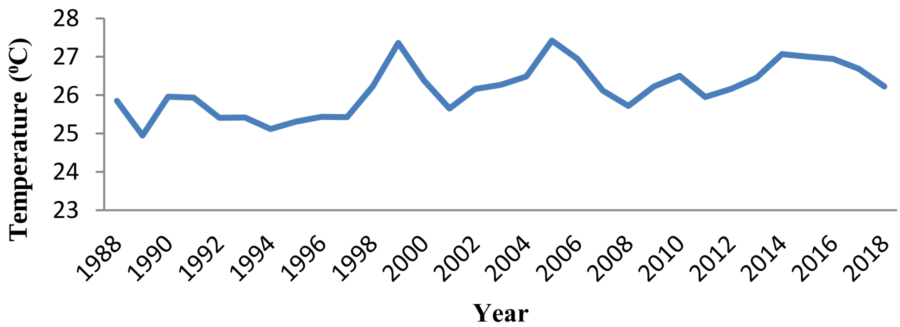


Figure 4.9a: Inter-annual temperature pattern of Kogi State (1988-2018)

This result shows that year 2005 is the hottest year with mean value of 27.42^0C. 1989 is the coolest year with 24.94^0C annual mean value. This high temperature over low land is due to low altitude and as can be seen that there is a trend of incremental variation.

Figure 4.9b shows inter-annual standardised temperature in Kogi State over the period 1988–2018.

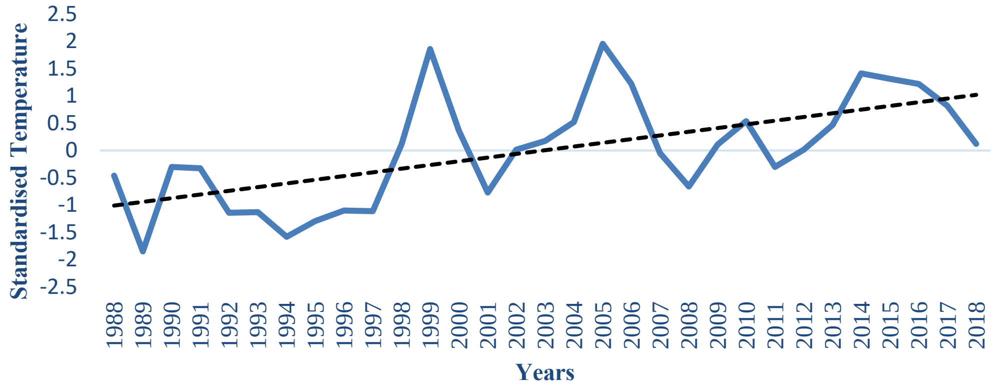


Figure 4.9b: Inter-annual standardised temperature pattern of Kogi State (1988-2018)

The analysis of this figure points out three sub-periods, the first period is 1988–1997 with very low mean temperature, except 1988, 1990 and 1991, which is within normal values of mean temperature. The second sub-period includes 1998–2012 with mixture of hot, normal and low values of mean temperature. The third sub-period 2013-2018 with hotter years except 2018 this is within normal mean temperature.

This result reveals an upward trend of average temperature from 2005–2017 and shows that the hottest year was in 2005 whereas the coolest year was in 1989. Furthermore, these findings agree with the results of many studies which show increases in temperature over the end of last century (Brohan *et al.*, 2006; Safari, 2012 and Buhairi, 2010). More recently, Birara *et al*. (2018) analysed the trend and variability of Rainfall and temperatures in the Tana basin region, Ethiopia, for the period 1980–2015 and found significant increase of maximum, minimum and mean temperature for most of the stations considered and an increase of 1.08^{0}C. These increases in temperature may affect negatively the production of solar energy and increase evaporation which reduces water availability.

4.3.9 Seasonal solar irradiance (Nasarawa State)

Figure 4.10 presents the monthly solar irradiance structures and respective standardised solar irradiance at Nasarawa State over the period of 1988-2018.

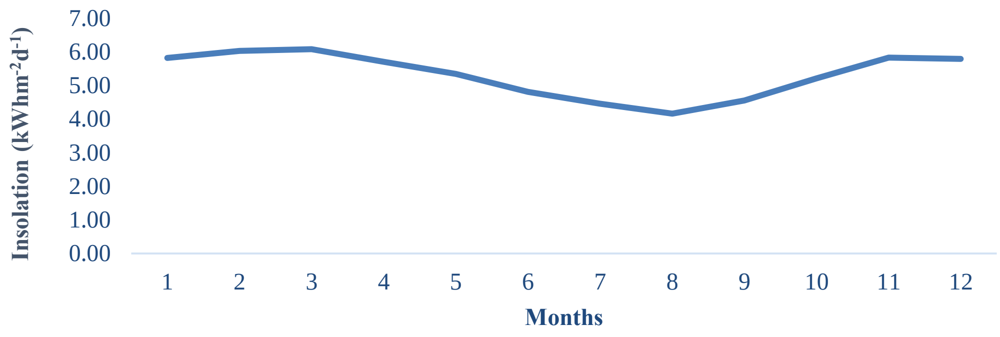


Figure 4.10a: Monthly insolation pattern (Nassarawa State)

The analysis of figure 4.10a depicts a bimodal seasonal cycle with peak values attained in January, February and March. The month of July and August shows the lowest mean value of solar radiation, where the month of March shows the highest mean value of solar radiation.

Figure 4.10b presents the monthly standardised solar irradiance at Nasarawa State over the study period.

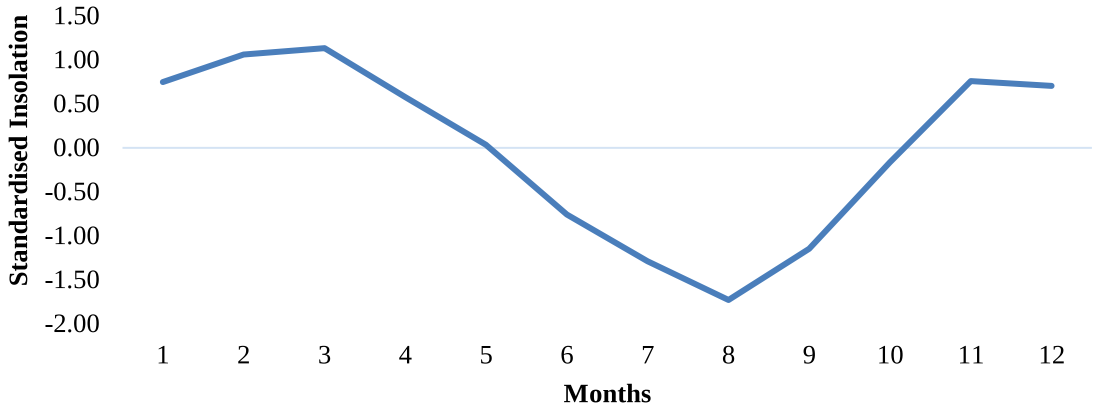


Figure 4.10b: Monthly standardised insolation (Nassarawa State)

The analysis of this figure shows that four months (June, July, August and September) are in deficit of solar irradiance. The month with the lowest index value of -1.73 is August. The analysis also shows that five months (January, February, March, November and December) are in excess of solar irradiance. Normal months are May and October. The Month with highest index value of solar irradiance is March with 1.13.

The monthly mean solar irradiance for Nasarawa State used to calculate the standardised variable index was 5.31k $Whm^{-2}d^{-1}$whereas the standard deviation is 0.70. This analysis shows that the months with highest values of solar irradiance expectedly the dry season months, which leads to the conclusion that there is an excess of solar irradiance during the dry season.Therefore, it is a period of high production of solar energy. Indeed, a solar power plant installed in this region could be in complementary with a hydroelectric plant with low production in the dry season because of the reduction of the water level in the reservoir.

4.3.10 Inter-annual solar irradiance (Nasarawa State)

The Figure 4.11a gives the interannual solar irradiance patterns for the period 1988–2018.

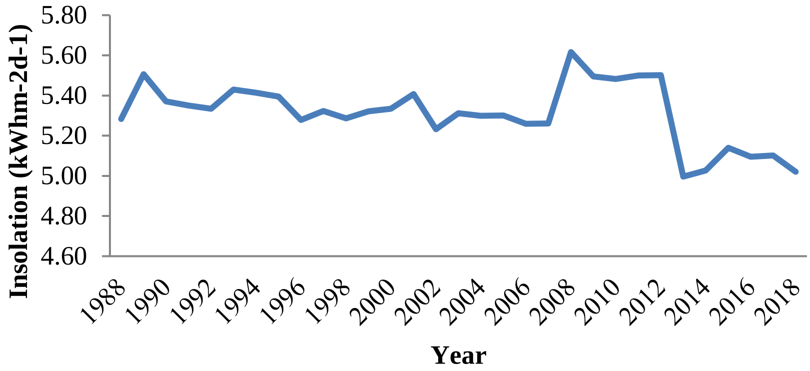


Figure 4.11a: Inter-annual insolation pattern of Nassarawa State (1988-2018)

This figure shows that the year 2008 higher value of solar irradiance than other years. It can also be observed that year 2013 recorded the lowest value of solar insolation values through the study period.

Figure 4.11b presents interannual standardised solar irradiance over the study period 1988–2018.

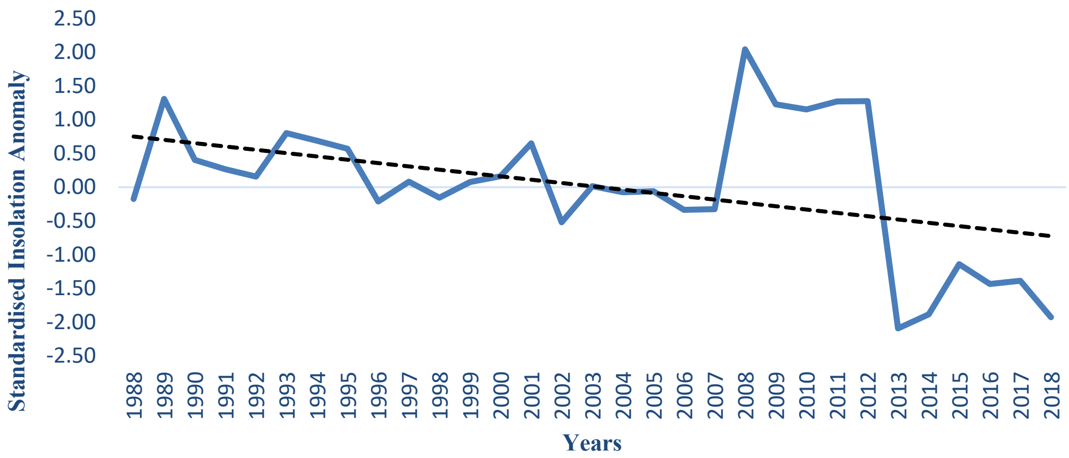


Figure 4.11b: Inter-annual standardised insolation pattern of Nassarawa State (1988-2018)

The analysis of this figure points out three sub-periods including the first period spanning from 1988–2001 with mixture of higher and normal values solar irradiance. The second sub-period 2002–2012 is marked by years with more high values of solar irradiance and a few normal values, but there is no year with low values of solar irradiance observed. The last sub-periods 2013-2018 there are significant lower values of solar insolation. The analysis of this implies that 10 years with high values of solar irradiance and 6 years have low values of solar irradiance. These results reveal a trend of decline in average solar irradiance for the last sub-period 2013–2018.It also showed that the lowest values was in 2013 whereas the year with highest values of solar irradiance was in 2008. These analyses show a general increase in average solar irradiance for the first sub-period. Furthermore, these findings agree with the results of several studies that revealed a subsequent increase (1–4W/m2) since the 1980s which is called “brightening” (Stanhill and Cohen, 2001) and decreasing of irradiation in some regions of the world. Solar irradiation is the principal resource of solar power output (PV); the decrease of this parameter affect negatively the production of solar energy.

4.3.11 Seasonal temperature (Nasarawa State)

Figure 4.12a shows the monthly temperature patterns in Nasarawa State over the study period 1988-2018 while Figure 4.12b shows the monthly standardised temperature index for the same period.

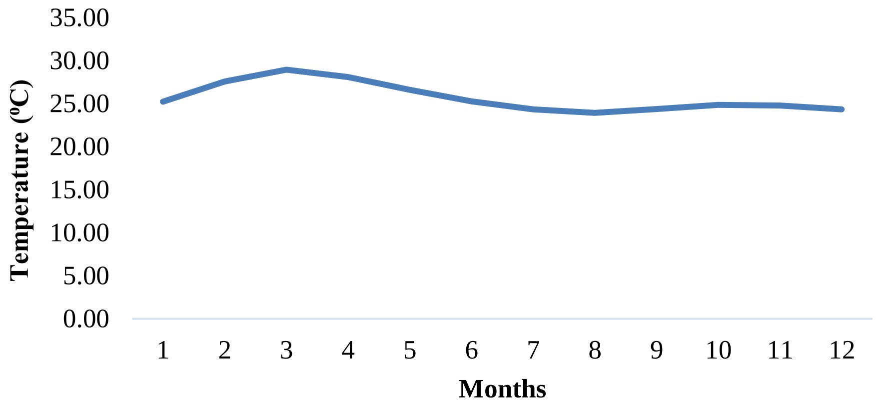


Figure 4.12a: Monthly temperature pattern (Nassarawa State)

The analysis of Figure 4.12a shows that July and August have low mean values of temperature, whereas March and April recorded high mean values but the pattern does not show remarkable variations.

The means monthly temperature for Kogi State used to calculate the standardized variable index is 25.71ºC and the standard deviation. The analysis of Figure 4.12b shows that four months (July, August, September and December) are cooler. The coolest month with the lowest index value equal to -1.05 is August. The analysis also shows that three months (February, March and April) are hotter in Nasarawa State. Normal months in the year are January, May, June and October. The hottest month is March with the highest index values equal to 1.94

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Figure 4.12b: Monthly standardised temperature (Nassarawa State)

4.3.12 Inter-annual temperature (Nasarawa State)

Figure 4.13a presents the inter-annual temperature patterns for the period 1988–2018.

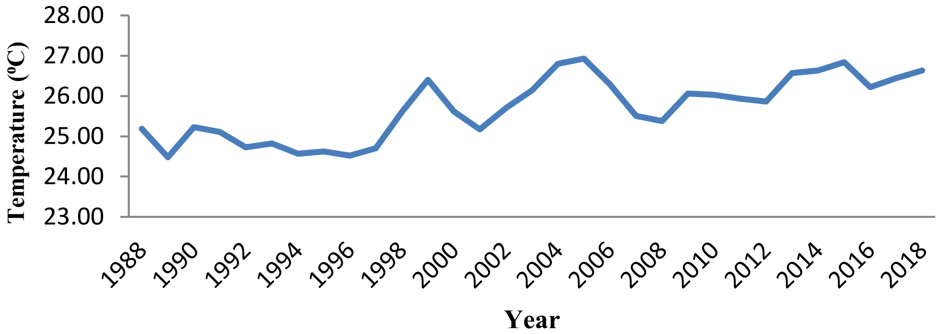

Figure 4.13a: Inter-annual temperature pattern of Nasarawa State (1988-2018)

This result shows that 2005 is the hottest year with mean value of 26.93 ^{0}C. 1989 is the coolest with 24.48 ^{0}C annual mean value. This high temperature over low land is due to low altitude and as can be seen there is a trend of incremental variation.

Figure 4.13b shows inter-annual standardised temperature in Nasarawa State over the period 1988–2018.

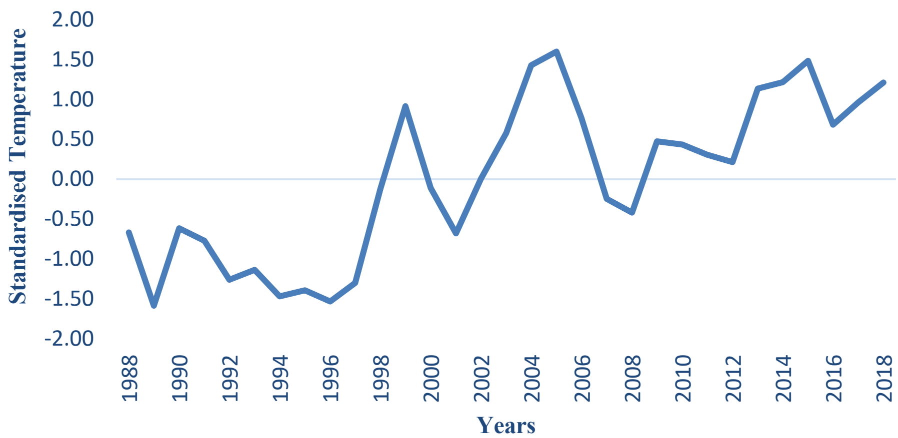

Figure 4.13b: Inter-annual standardised temperature pattern of Nasarawa State (1988 2018)

The analysis of this figure points out two sub-periods, the first period 1988–1998 with more cool years, except 1988 which is within normal values of mean temperature. The second sub-period 1999-2018 are with mixtures of higher and normal values.

These results reveal an upward trend of average temperature from 2003–2011and showed that the hottest year was in 2005 whereas the coolest year was in 1989. Furthermore, these findings agree with the results of many studies which show increases in temperature over the end of last century (Brohan *et al.,* 2006; Safari, 2012; Buhairi, 2010). More recently, Birara *et al*. (2018) analysed the trend and variability of Rainfall and temperatures in the Tana basin region, Ethiopia, for the period 1980–2015 and found significant increase of maximum, minimum and mean temperature for most of the stations considered and an increase of 1.08^{o}C. These increases in temperature may affect negatively the production of solar energy and increase evaporation which reduces water availability.

4.4 Solar Energy Potential Sites in Parts of Northcentral (Niger, Kogi and Nasarawa) Nigeria

The intensity of insolation in an area, the topography, the aspect of the area and the slope are all elements that influence the solar energy potentials in an area, as discussed in Section 3.2.3. As a result, this section discusses solar energy potential sites in the study area based on the parameters indicated above.

Figure 4.14 shows all of the solar energy potential sites in the study area.

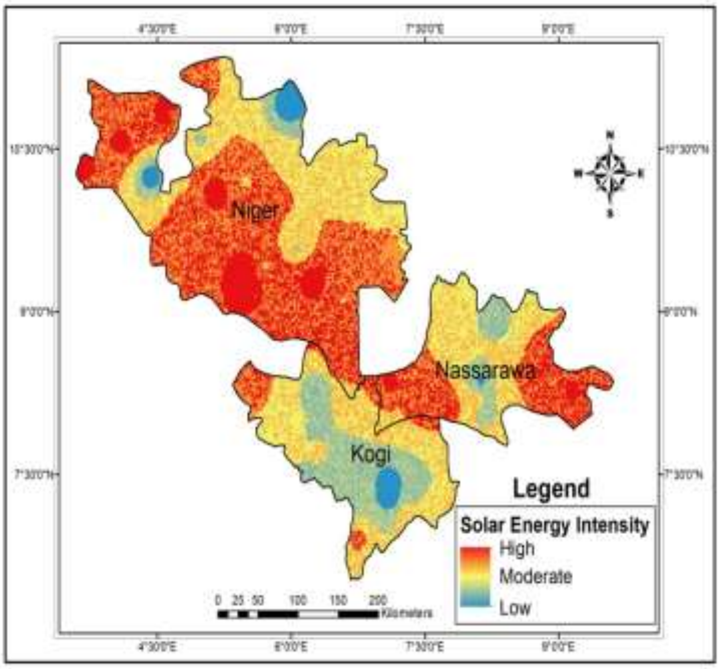

Figure 4.14: Solar Energy Potential Sites in Parts of Northcentral Nigeria (Niger, Kogi and Nasarawa) (Fieldwork,2018)

The result shows that many spot within the study have been identified as possible potential sites for solar energy production, while the strength of the potentials sites differs from one location to the next.

It is observed from Figure 4.14 that there is higher level of spatial variability of solar energy potentials present within the study area. From the Figure there are concentric zone of extremely high solar energy potential sites exists with Niger State, surrounded by a zone of high potentials, followed by a zone of moderate solar energy potentials in some parts of Niger state. It is also observed that there are some zones with a very low potential. From Figure 4.14 it can also be seen that the level of solar energy potentials increased with increasing distance from the centre outwards.

Also, Figure 4.14 points out the pattern of solar energy potentials in Kogi state is different from that of Niger state, where a region of high potential sites exists in the Northwestern part of the Kogi state interspaced by a narrow region of moderately low potentials in the heart of city. This is followed by a region of relatively very high potentials in the northern part of Kogi bordering Niger and Nasarawa states, and a region of lower potentials towards the heart of Kogi state. A further observation of Figure 4.14 shows that moderate potential sites in surrounds Kogi state.

Further analysis of Figure 4.14 depicts that there exist regions of high solar energy potentials in the eastern part which extends down Southeastern region of Nasarawa state and another region of very high potentials in Southwestern zone bordering Kogi State. In addition, areas of moderately high solar energy potentials are dispersed all over the state except for some zones. Also, areas of lower solar energy potentials are found in the center and Northern parts of Nasarawa state. However, areas of very low potentials are concentrated in the centre of the state.

4.4.1 Solar energy potential sites in Niger State

Figure 4.15 below shows the spatial variation of solar energy potentials in Niger State highlighting the areas with very high, moderate and low solar energy potentials in the state.

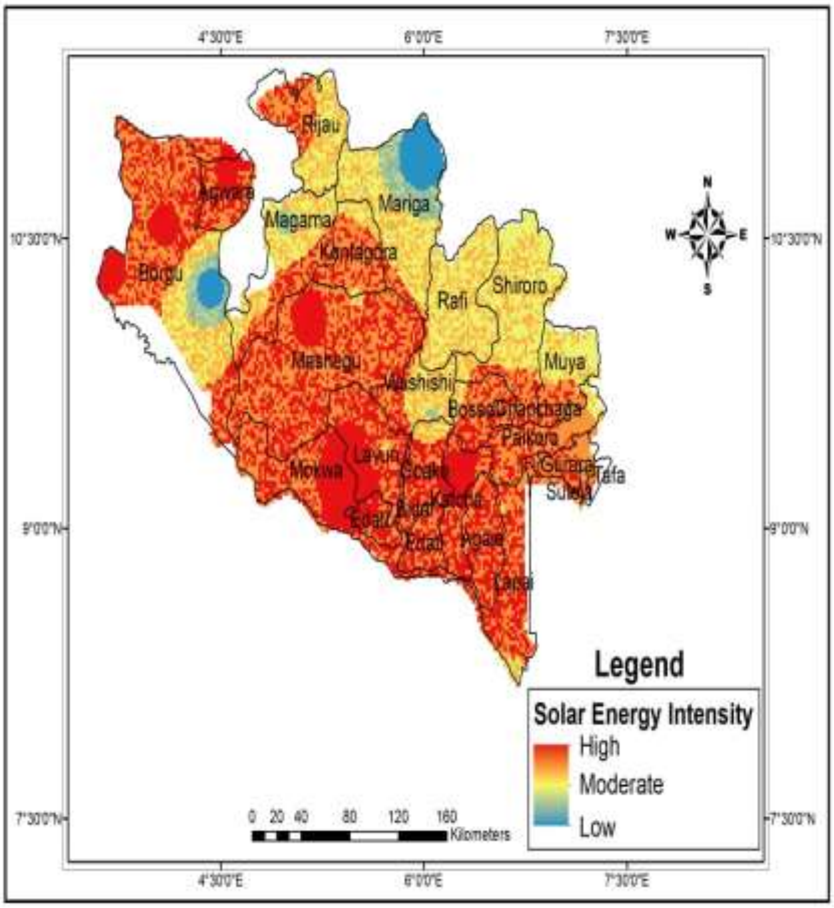

Figure 4.15: Solar Energy Potential Sites in Niger State (Fieldwork,2018)

Areas with very high solar energy potentials are: Agwara, Agaie, Bida, Edati, Gbako, Katcha, Kontagora, Lapai, Lavun, Mashegu and Mokwa Local Government Areas (LGAs). These are the most suitable potential sites for exploiting solar energy in the state. Areas with high potentials are: Bosso, Borgu, Chanchaga, Gurara, Paikoro, Suleja and Tafa LGAs.

Areas with moderate solar energy potentials are: Magama, Munya, Rijau, Rafi, Shiroro and Wushishi Local Government Areas. Areas with low potentials is Mariga LGA.

One of the most important parameters to consider when determining the actual prospective sites for PV and concentrating solar power technologies is that the direct and horizontal solar radiation at the site should be ≥5 $kWh/m^2/day$ (USFS, 2005). Manylocations in Niger state could be used to harness solar energy based on this information.

4.4.1.1 ***Available solar power in Niger State***

To determine the available solar power in an area, you will need to know the average solar radiation received and the cross-sectional area of the location. This is illustrated below:

Since Niger state's cross-sectional area =76,363 km^2;

and the average solar radiation in Niger State= 5.43 $kWh/m^2/day$;

Cross sectional area X the average power intercepted at any time (Electropaedia, 2016)

Thus, the average power intercepted at any time in the state = 76,363 X5.43

$=76,363 \times 5.43 = 414651.09 \times 10^6 = 414.651 \times 10^9$ kWh $= 414.651 \times 10^6$ MWh

= 35,653,568.40 tonne of oil equivalent.

4.4.2 Solar energy potential sites in Kogi State

Figure 4.16 below shows the spatial variation of solar energy potentials in Kogi State highlighting the areas with very high, moderate and low solar energy potentials in the state.

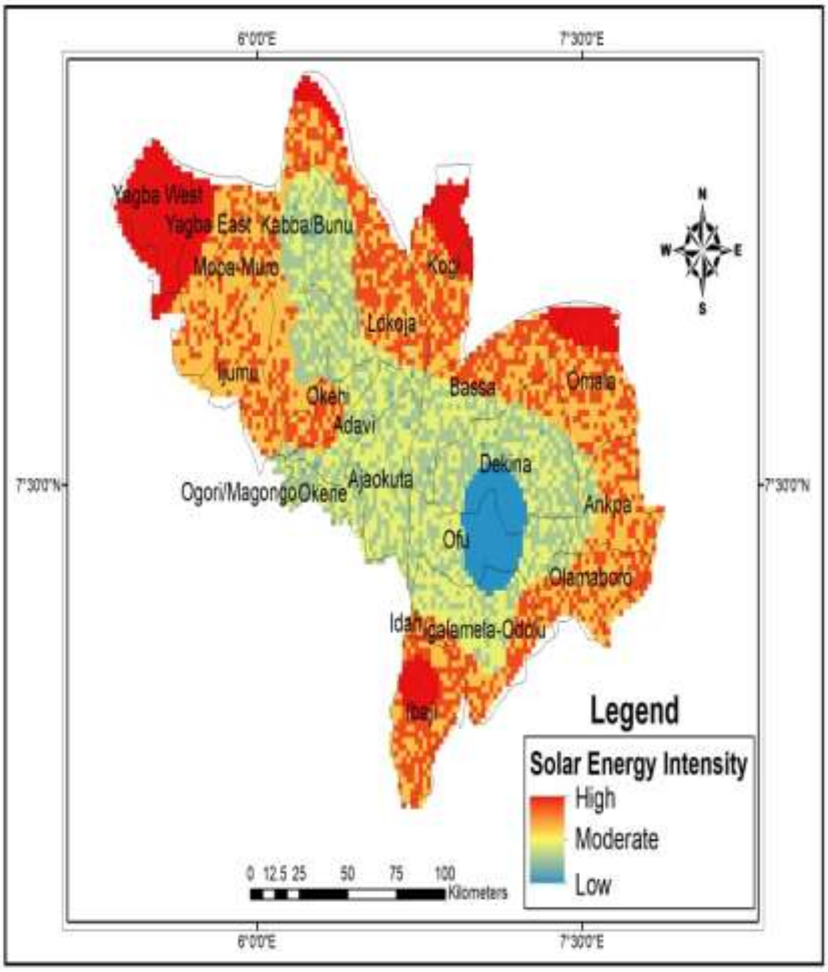

Figure 4.16: Solar Energy Potential Sites in Kogi State (Fieldwork, 2018)

Areas with very high solar energy potentials are: Ibaji, Kogi, Lokoja, Omala, Yagba East and Yagba West Local Government Areas (LGAs). These are the most suitable potential sites for exploiting solar energy in the state. Areas with high potentials are: Ankpa, Ibaji, Idah, Ijumu, Mopa moro, Okehi and Olamaboro LGA.

Areas with moderate solar energy potentials are: Bassa and Igalamela odolu Local Government Areas. Areas with low potentials are: Adavi, Ajaokuta, Dekina, Kabba Bunu, Okene, Ogori Magongo and Ofu LGAs.

4.4.2.1 Available solar power in Kogi State

Since Kogi state's cross sectional area =29,833 km^2;

and the average solar radiation in Kogi = 4.96 $kWh/m^2/day$;

thus, the average power intercepted at any time in the state =29,833 X4.96

$= 147,971.680^6 = 147.971 \times 10^9$ kWh $= 147.971 \times 10^6$ MWh

= 12,723,215.821 tonne of oil equivalent

4.4.3 Solar energy potential sites in Nasarawa State

Figure 4.17 below shows the spatial variation of solar energy potentials in Nasarawa State highlighting the areas with very high, moderate and low solar energy potentials in the state.

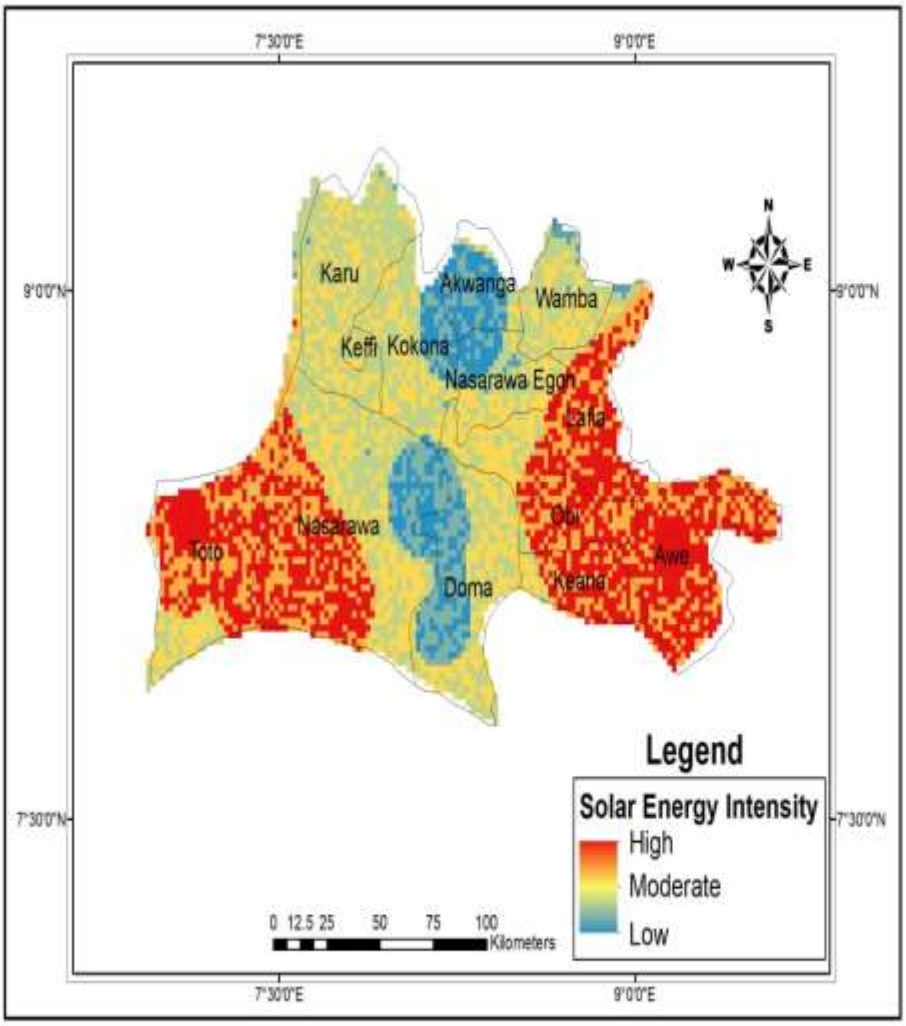

Figure 4.17: Solar energy potential sites in Nasarawa State (Fieldwork,2016)

Areas with very high solar energy potentials are: Awe, Keana, Lafia and Obi Local Government Areas (LGAs). These are the most suitable potential sites for exploiting solar energy in the state. Areas with high potentials are: Nasarawa and Toto LGAAreas with moderate solar energy potentials are: Karu, Keffi, Nasarawa Egon and Wamba Local Government Areas. Areas with low potentials are: Akwanga, Doma and Kokona

LGAs.

4.4.3.1 Available solar power in Nasarawa State

Since Nasarawa state's cross sectional area =27,117km^2;

and the average solar radiation in Nasarawa = 5.32kWh/m^2/day;

thus, the average power intercepted at any time in the state =27,117X5.32

= 144262.44X 10^6= 144.262 X 10^9 kWh = 144.262 X 10^6 MWh

= 12,404,299.226 tonne of oil equivalent

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Geospatial technique is an efficient method of solar radiation mapping used in analysing the solar energy potentials in the study area. The solar radiation maps produced in this study were found to be better than the climatic zone classification and iso-radiation mapping used previously to analyse solar energy potentials in Nigeria.

Based on ground-measured data, minimum insolation values were recorded in the months of July and August, while maximum insolation values were recorded between the months of February, March and April throughout the study area. Therefore, the months of February, March and April May provide the best periods for harnessing solar energy potentials in the study area.

The variability analyses of solar irradiance and ambient temperature have both similarities and differences. Based on the two sources of data, minimum values were recorded in July and August, while maximum values were in February, March and April throughout the study area. Thus, the months of February, March and April provides the best periods for exploiting solar energy potentials in the study area.

There is high level of spatial variability in solar energy potentials across the whole area of study. There are areas of very high, high, moderate and low solar energy potentials in Niger, Kogi and Nasarawa states of Northcentral Nigeria. It can thus be established that there is tremendous exploitable solar power in these states, which can be used to address the problem of power supply in the region.

Although the methods applied in this study have been used in other parts of the world, it is pertinent to mention that these methods have not been commonly used in Nigeria and as such there could be room for modifications and improvement.

This study emphasised that the Northcentral Nigeria is a potential area for the generation of solar energy, which can be used to provide electricity for domestic and industrial use. This will have multiplier effect on job creation leading to human capital development and economic sustainability in the region.

5.2 Recommendations

The findings of this study have demonstrated the capability of geospatial techniques in the analysis of solar energy potentials. Based on this, the followings are recommended:

1. Geospatial techniques should be used to produce a more comprehensive solar radiation map for Niger, Kogi and Nasarawa states covering all the local government areas in the three states, with a view to reveal the solar energy potentials at a finer scale in the state.

2. The best periods for exploiting solar energy in the area (between February, March and April) should be used to harness and conserve solar power, and during the periods of lower potentials such as July and August, other sources of energy can be relied upon. Therefore, there is the need to diversify the energy mix of the area.

3. Areas with very high solar energy potentials should be used in siting of solar farms and Concentrating Solar Power plants in order to maximize the available solar energy potentials in the region. Nevertheless, building-integrated or roof top solar panels can be used in areas with moderate solar energy potentials.

4. This study is based on NASA SSE satellite database which is of lower resolution than other emerging satellite temperature databases. There is the need to explore the use of satellite data with higher resolution in further studies.

5.3 Contributions to Knowledge

This study has contributed to the literature on solar energy, and specifically on the application of geospatial techniques in the analysis of renewable energy sources by producing the atlas of solar radiation in Niger, Kogi and Nasarawa states using geographical visualisation.

The application of geospatial techniques to identify solar energy potential sites in the study area has provided important knowledge that is required to maximally harness solar energy in the area. Therefore, geospatial approach has proven to be an alternative efficient method for the analysis of solar energy potentials.

The findings over the study period showed increase in temperature and decrease in solar irradiance over the period spanning from 1988-2018. Maximum insolation of averagely 5.94kWh/m^2/day was observed in the months of February, March and April; while minimum insolation of averagely 4.36kWh/m^2/day was observed in July, August, and September, over the study area.

This study has shown the possibility of using variability analysis of solar irradiance and ambient temperature in order to derive solar energy information for the study area. This is considered as a valid contribution to the existing literature on the current method of integrating solar irradiance and ambient temperature data, which has not been applied in the analysis of solar energy potentials in North Central Nigeria.

In addition, the amount of exploitable solar power in Niger, Kogi and Nasarawa states were 414.651 x 10^6 MWh, 147.971 x 10^6 MWh and 144.262 x 10^6 MWh respectively was determined in this study.

REFERENCES

African Development Bank, AfDB (2017).The new deal on energy for Africa. A transformative Partnership to light up and power Africa by 2025. Update of implementation.

Abu Taha, R., & Daim, T. (2013). Multi-criteria applications in renewable energy analysis, a literature review. In Research and Technology Management in the Electricity Industry. Springer London. (pp. 17-30)

Alliance for Rural Electrification, ARE (2011). Rural Electrification in Africa. *Technical report*, p 65. Retrieved from http://www.youtube.com/@ruralelec

AbdulAzeez, M.A. (2011). Artificial neural network estimation of global solar radiation. *Applied Science Research*, 3(2), 586–595.

Akpabio, L.E., Udo, S.O. & Etuk, S.E. (2004). Empirical Correlations of Global Solar Radiation with Meteorological data for Onne, Nigeria. *Turkey Journal of Physics*, 28, 205-212.

Akash, B. A., Mamlook, R., & Mohsen, M. S. (1999). Multi-criteria selection of electric power plants using analytical hierarchy process. *Electric Power Systems Research*, 52(1), 29-35.

Angela, K. Taddeo, S. & James, M. (2011). Predicting Global Solar Radiation Using an Artificial Neural Network Single-Parameter, *Model Advances in Artificial Neural Systems*, 2011, 1-7.

Angstrom, A.S. (1924). Solar and Terrestrial Radiation, *Meteorological Society*, 50, 121- 126.

Augustine, C. & Nwabuchi, M.N. (2009). Relationship between global solar radiation and Sunshine hours for Calabar, Port Harcourt and Enugu, Nigeria, *International Journal of Physical Sciences*, 4(4), 182-188.

Asakereh, A., Omid, M., Alimardani, R. & Sarmadian, F. (2014). Developing a GIS-based Fuzzy AHP Model for Selecting Solar Energy Sites in Shodirwan Region in Iran. *International Journal of Advanced Science and Technology*, 68, 37-48.

Basir, R., Aziz, N., Ahmad, S.S. & Wahid, A. (2013). Satellite remote sensing for identification of solar potential sites in Pakistan. *International Journal of Basic and Applied Sciences*, 2(2): 200-209.

Bashara, F., Dehghan, A. A. & Faghih, A. R. (2013). Emperical Models for estimating global solar radiation: a review and case study. *Renewable and Sustainable Energy Reviews*, 21(2), 798-21.

Becker, S. (2001). Calculation of direct solar and diffuse radiation in Israel. *International Journal of Climatology*, 21(1), 1561-1576.

Ben Salah, C., Chaabene, M., & Ben Ammar, M. (2008). Multi-criteria fuzzy algorithm for energy management of a domestic photovoltaic panel. *Renewable Energy*, 33 (2), 993–1001.

Bindi, M. & Miglietta, F. (1991). Estimating daily global radiation from air temperature and rainfall measurements. *Climatology Research*, 1(2), 117-124.

Birara, H., Pandey, R.P. & Mishra, S.K. (2018). Trend and variability analysis of rainfall and temperature in the Tanabasin region, *Ethiopia. Journal of Water Climatic. Change*, 9, 555–569.

Bois, B., Wald, L., Pieri, Ph., Van leeuwen, C., Commagnac, L., Chery, Ph., Christen, M., Gaudillère, J.-P. & Saur, É (2008). Estimating Spatial and Temporal Variations in Solar Radiation within Bordeaux Winegrowing Region Using Remotely Sensed Data. *Journal of International Science VigneVin*, 42(1), 15-25.

Black, J. N., Bonythou, C. W. & Prescett, J. A. (1954). Solar radiation and duration of Sunshine, *Q.J.R Meteorology Social Science.*, 80, 231-235.

Brohan, P, Kennedy, J.J., Tett, S.F.B. & Jones, P.D. (2006). Uncertainty Estimates in Regional and Global Observed Temperature changes: A New Dataset from 1850. *Journal of Geophysics Research*, 111(20), 1–12.

Buhairi, M.H.A. (2010). Analysis of Monthly, Seasonal and Annual Air Temperature Variability and Trends in TaizCity—Republic of Yemen. *Journal of Environmental Protection.*, 1 (2), 401–409.

Camfer University (2017). Remote Sensing & Image Analysis. Camfer University of Carlifornia at Berkeley. Retrieved on 26/01/2017 from http://nature.berkeley.edu/~penggong/textbook/chapter2/html/sect24.htm

Cheng, E. W. L., & Li, C. (2005). Analytic network process applied to project selection. *Journal of Construction Engineering and Management*, 131(4), 459-466.

Chiemeka, I.U. (2008). Estimation of solar radiation at Uturu, Nigeria. *International Journal of Physical Sciences*, 3(5),126-130

Dagestad, K-F. (2005). Estimating global radiation at ground level from satellite images. University of Bergen.

De Smith, M. J., Goodchild, M. F. & Longley, P. A. (2015). *Geospatial Analysis: A Comprehensive Guide to Principles, Techniques and Software Tools*. Fifth Edition. The Winchelsea Press, Winchelsea, UK.

Diabaté, L., Blanc Ph., & Wald, L. (2004). Solar Radiation Climate in Africa. *Solar Energy*, 76(2), 733-744.

Effat, H. A. (2016). Mapping Solar Energy Potential Zones, using SRTM and Spatial Analysis, Application in Lake Nasser Region, Egypt. *International Journal of Sustainable Land Use and Urban Planning*, 3(1), 1-14.

Electropaedia (2016). *Solar Power (Technology and Economics).* Retrieved on 16/01/2016 from http://www.mpoweruk.com/solar_power.htm

Environmental Systems Research Institute - ESRI (2016). *ArcGIS Desktop Help: "How Inverse Distance Weighted Interpolation Works"*. ESRI, Inc., USA.

Falayi, E.O., Rabiu, A.B. & Teliat, R.O. (2011). Correlations to estimate monthly mean of daily diffuse solar radiation in some selected cities in Nigeria. *Advances in Applied Science Research*, 2(4), 480-490.

Fisher, N. I., Lewis, T. & Embleton, B. J. J. (1987). Statistical Analysis of Spherical Data. Cambridge University Press, UK.

Flores, H. & Baldasano J.M. (2001). Solar Radiation Mapping from NOAA AVHRR Data in Catalonia (Spain). *Journal of Applied Meteorology*, 40(11), 1821-1834.

Freedman, D. A. (2005). *Statistical Models, Theory and Practice*. University Press, Cambridge.

Gadiwala, M.S., Usman, A., Akhtar, M. & Jamil, K. (2013). Empirical Models for the Estimation of Global Solar Radiation with Sunshine Hours on Horizontal Surface in Various Cities of Pakistan. *Pakistan Journal of Meteorology*, 9(18): 43-49.

Gana, N.N. & Akpootu, D.O. (2013). Estimation of global solar radiation using four Sunshine based models in Kebbi, North-Western, Nigeria. *Advances in Applied Science Research*, 4(5), 409-421.

Gana, N.N., Jitendra, K.R. & Momoh, M. (2014). Estimation of Global and Diffuse Solar Radiation for Kebbi, North-Western, Nigeria. *International Journal of Scientific & Engineering Research*, 5(1), 1654-1661.

Gaetani, M., Vignati, E., Monforti, F., Huld, T., Dosio, A. & Raes, F. (2015). *Climate modelling and renewable energy resource assessment*. European Commission Joint Research Centre. European Union, Italy.

Glover, J. & McCulloch, F. (1958). The empirical relationship between solar radiation and Hours of Sunshine. *Q.J.R. Meteorology of Social Science.*, 84(359), 56-60.

Gopinathan, K. K. (1988). A new model for estimating total solar radiation. *Solar and Wind Technology*, 5(1), 107-109.

Graham, S. (1999). Clouds & Radiation. NASA Retrieved on 21/03/2017 from https://earthobservatory.nasa.gov/Features/Clouds.

Greening, L. A., & Bernow, S. (2004). Design of coordinated energy and environmental policies: use of multi-criteria decision-making. *Energy Policy*, 32(2), 721–735.

Hermann, S., Miketa, A. & Fichaux, N. (2014). Estimating the Renewable Energy Potential in Africa, IRENA-KTH working *paper*. International Renewable Energy Agency, Abu Dhabi.

Huld, T., Súri, M., Dunlop, E., Albuisson, M. and Wald, L. (2005). Integration of HelioClim-1 database into PV-GIS to estimate solar electricity potential in Africa. *20th European Photovoltaic Solar Energy Conference and Exhibition*, Bacelona, Spain., p 23-25

Hussein, T.A.T. (2012). Estimation of Hourly Global Solar Radiation in Egypt Using Mathematical Model. *International Journal of Latest Trends in Agricultural Food Science.*, 2(2), 74-82.

Höfer, Sunak, Y., Siddique, H. & Madlener, R. (2014). *Wind Farm Siting Using a Spatial Analytic Hierarchy Process Approach: A Case Study of the Städteregion Aachen*. FCN Working Paper No. 16/2014: 1-52. Director, Institute for Future Energy Consumer Needs and Behavior (FCN): Aachen University, Germany.

Ibeh, G.F., Agbo, G.A., Ekpe, J.E. & Isikwue, B.C. (2012). Estimation of global solar radiation at Calabar using two models. *Journal of Natural Sciences Research*, 2(5), 17-25.

Isikwue, B.C., Amah, A.N. & Agada, P.O. (2012). Empirical Model for the Estimation of Global Solar Radiation in Makurdi, Nigeria. *Global Journal of Science Frontier Research Physics and Space Science*, 12(1), 58-61.

Janjai, S. (2013). A method for estimating direct normal solar irradiation from satellite data for a tropical environment. *Solar Energy*, 84 (1), 1685-1695.

Journee, M. & Bertrand, C. (2010). Improving the spatio-temporal distribution of surface solar radiation data by merging ground and satellite measurements. *Remote Sensing of Environment*, 114(1), 2692-2704.

Journee, M., Müller, R. & Bertrand, C. (2011). Towards a climatology of surface incoming Solar radiation over the Benelux by merging long time- series of Meteosat-derived estimations and ground-based measurements. Royal Meteorological Institute Belgium (RMIB): Brussels, Belgium, p 35-38

Kalidindi, S., Bala, G., Modak, A., Modak, A. & Caldeira, K. (2014). Modelling of solar radiation management: a comparison of simulations using reduced solar constant and stratospheric sulphate aerosols. *Climate Dynamics*, 44(9), 2909-2925.

Lawin, A.E., Afouda, A., Gosset, M. & Lebel, T. (2019). Variabilité comparée du régime pluviométrique aux échellesrégionales et locales sur la Haute Vallée de l’Ouémé au Bénin. IAHS Publ., 340, 61–68.

Lealea, T. & Tchinda, R. (2013). Estimation of diffuse solar radiation in the north and far north of Cameroon. *European Scientific Journal*, 9(18), 370-381.

Li, D. (2013). *Using GIS and Remote Sensing Techniques for Solar Panel Installation Site Selection.* University of Waterloo, Waterloo, Ontario, Canada.

Madlener, R., Antunes, C. H., & Dias, L. C. (2009). Assessing the performance of biogas plants with multi-criteria and data envelopment analysis. *European Journal of Operational Research*, 197, 1084–1094.

Maleki, S. A. M., Hizam, H. & Gomes, C. (2017). Estimation of Hourly, Daily and Monthly Global Solar Radiation on Inclined Surfaces: *Models Re-visited. Energies*, 10(134), 1-28.

Medugu, D. W., Adisa, A.B., Burari, F. W. & Abdul'Azeez, M. A. (2013). Solar radiation: Correlation between measured and predicted values in Mubi, Nigeria *International Journal of Science and Technology Education Research*, 4(1), 11-17.

Monedero, J., García, J., Dobon, F., Yanes, M.A. & Hernandez, F. (2007). *Calculation of PV potential maps in the Canary Islands.* A Project funded by Spanish Ministry of Industry, Tourism and Commerce and the European Regional Development Fund.

Monforti-Ferrario F., Jager-Waldu, A., Szabo, M. (2011). Renewable Electricity in Europe. *Energy Policy*, 7(2), 45-48

Muneer, T., Asif, M. & Munawar, S. (2005). Sustainable production of solar electricity with particular reference to the Indian economy. *Renewable Sustainable Energy Review*, 9(2), 44-73.

Mohammed, G., Abubakar, A. G., Umar, B. A., Mustapha, A. & Manga, P. J. (2015). Modelling of Cloudiness Index with Maximum Temperature and Relative Humidity of Sokoto Northwestern, Nigeria. *International Journal of Marine, Atmospheric & Earth Sciences*, 3(1), 28-46.

Muhammad, A. & Dama, T. H. (2014). Estimation of Global Solar Radiation for Kano State Nigeria Based on Meteorological Data. *IOSR Journal of Applied Physics,* 6(6), 19-23.

Musa, B., Zangina, U. & Aminu, M. (2012). Estimation of global solar radiation in Maiduguri, Nigeria using angstrom model. *ARPN Journal of Engineering and Applied Science*, 7(12), 1623-1627.

McKee, T.B. Doesken, N. J. & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology, Anaheim*, CA, USA, 17–22 January; pp. 179–183.

Muzathik, A. M., Nik, W. B. W., Ibrahim, M. Z., Samo, K. B., Sopian, K. and Alghoul, M. A. (2011). Daily global solar radiation estimate based on Sunshine hours. *International Journal of Mechanical and Materials Engineering (IJMME)*,6(1): 75-80.

NASA (2016). *A renewable energy resource web site (release 6.0)* sponsored by NASA's Applied Science Program in the Science Mission Directorate developed by POWER: Prediction of Worldwide Energy Resource Project. http://eosweb.larc.nasa.gov/sse

Natural Resources Canada (2015). *Fundamentals of Remote Sensing: A Canada Centre for Remote Sensing Remote Sensing Tutorial*. Government of Canada. Retrieved from http://www.nrcan.gc.ca/Earth-sciences/geomatics/satellite-imagery-air-photos/satellite-imagery-products/educational-resources/9309

National Aeronautics and Space Administration, Science Mission Directorate, NASA (2010). The Earth's Radiation Budget. Retrieved [insert date - e.g. August 10, 2021], from NASA Science website: http://science.nasa.gov/ems/13_radiationbudget.

Oberschmidt, J., Geldermann, J., Ludwig, J., & Schmehl, M. (2010). Modified PROMETHEE approach for assessing energy technologies. *International Journal of Energy Sector Management*, 4, 183–212.

Ogbaka, D.T. & Silikwa, N.W. (2016).The Use of Sunshine Based Models to Estimate Global Solar Radiation in Yola, Nigeria. *Journal of Scientific and Engineering Research*, 3(4), 334-338.

Okundamiya, M.S. and Nzeako, A.N. (2011). Empirical Model for Estimating Global Solar Radiation on Horizontal Surfaces for Selected Cities in the Six Geopolitical Zones in Nigeria. *Journal of Control Science and Engineering,* 2(1), 1-7.

Ojosu, J. O. (1990). Theiso-radiation map for Nigeria. *Solar and Wind Technology*, 7(5), 563-575.

Oloo, F., Olang, L. & Strobl, J. (2016). Spatial Modelling of Solar Energy Potential in Kenya. *International Journal of Sustainable Energy Planning and Management*, 06, 17-30.

Omitaomu, O. A., Singh, N. & Bhaduri, B. L. (2015). Mapping suitability areas for concentrated solar power plants using remote sensing data. *Journal of Applied Remote Sensing*, 9(9), 1-14.

Osueke, C. O., Uzendu, P. & Ogbonna I. D. (2013). Study and Evaluation of Solar Energy Variation in Nigeria. *International Journal of Emerging Technology and Advanced Engineering*, 3(6), 78-79.

Pettazzi, A. & Salsón, S. (2012). Merging remote sensing data with in-situ measurements of global solar radiation: the right path to estimate the solar resource in Galicia. *International Conference on Renewable Energies and Power Quality* (ICREPQ'12). Santiago de Compostela (Spain).

Perez, R., Seals, R., Stewart, R., Zelenka, A. & Estrada-Cajigal V. (1994). Supplementing radiation network data by cokriging with satellite images s. *Solar Energy*, 53(6), 491-495.

Pinker, R. T., Frouin, R. and Li, Z. (1995). A Review of Satellite Methods to Derive Surface Shortwave Irradiance. *Remote Sens. Environ*., 51 (2), 108-124.

Pohekar, S., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews*, 8(2), 365–381.

PVGIS (2016). *Photovoltaic Geographical Information System*. European Commission, Joint Research Centre, Institute for Energy, Renewable Energy Unit. Available at http://re.jrc.ec.europa.eu/pvgis/index.htm

Rajan, D. (2017). *What are the factors affecting the distribution of insolation?* Retrieved on 14/04/2017 from http://www.preservearticles.com/2011111217104/what-are-the-factors-affecting-the-distribution-of-insolation.html

Ramanathan, R., & Ganesch, L. S. (1993). A multiobjective programming approach to energy resource allocation problems. *International Journal of Energy Research*, 17(2), 105-119.

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

Rehman, S. & Ghori, S.G. (2000). Spatial estimation of global solar radiation using geostatistics. *Renewable Energy*, 21, 583-605.

Safari, B. (2012). Trend analysis of mean annual temperature conduct in Rwanda during fifty two years. *Journal of Environmental Protection*, 3(2), 538–551.

Saaty, T. L. (1980). The analytic hierarchy process: planning, priority setting, resources allocation. New York: McGraw

Saaty, T. L. (1996). Decision making with dependence and feedback: The analytic network process. Pittsburgh: RSW publications.

Sambo, A. S. (1988). The measurement and prediction of global and diffuse component of solar radiation for Kano in Northern Nigeria. *Solar and Wind Technology,* 5(1), 1-5.

Sanusi, Y.K. & Abisoye, S.G. (2011). Estimation of Solar Radiation at Ibadan, Nigeria. *Journal of Emerging Trends in Engineering and Applied Sciences*, 2(4), 701-705.

Shukla, K.N., Rangnekar, S. & Sudhakar, K. (2015). Comparative study of isotropiuc and anisotropic sky models to estimate solar radiation incident on tilted surface: A case study of Bhopal, India. *Energy Reports*, 1(2), 11-21.

Stanhill, G. & Cohen, S. (2001). Global dimming: Areview of the evidence for a widespread and significant reduction inglobal radiation with discussion of its probable causes and possible agricultural consequences. Agric. *Meteorology*. 107(5), 255–278.

Šúri, M., Huld, T. A., Dunlop, E. D., Albuisson, M. & Wald, L. (2006). Online data and tools for estimation of solar electricity in Africa: the PVGIS approach. Proceedings from 21st European Photovoltaic Solar Energy Conference and Exhibition, 4-8 October, 2006. Dresden, Germany.

Udo, S.O. (2002). Contribution to the Relationship between Solar Radiation and Sunshine Duration in the Tropics: A Case Study of Experimental Data at Ilorin, Nigeria. *Turkish Journal of Physics*, 26(2), 229-236.

United States Department of Agriculture, Forest Service (USFS) (2005). *Assessing the Potential for Renewable Energy on National Forest System Lands*,USDA Forest Service and NREL, United States.

Uyan, M. (2013). GIS-based solar farms site selection using analytic hierarchy process (AHP) in Karapinar region, Konya/Turkey. *Renewable and Sustainable Energy Reviews*, 28, 11-17.

Wang, J.-J., Jing, Y.-Y., Zhang, C.-F., & Zhao, J.-H. (2009). Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews*, 13(3), 2263–2278.

Wang, M., Lin, S. J., & Lo, Y. C. (2010). The comparison between MAUT and PROMETHEE. In Industrial Engineering and Engineering Management (IEEM), *IEEE International Conference*, p. 753-757

Wikipedia, (2019). https://en.m.wikipedia.org

Zadeh, L. A. (1965). Fuzzy sets. Information and control, 8(3), 338-353.

APPENDIX A: Mean daily temperature data (^{O}c) For Kogi State

Years	January	February	March	April	May	June	July	August	September	October	November	December	Mean
1988	25.77	27.30	28.11	28.09	26.96	25.46	24.36	24.27	24.78	25.58	25.31	24.33	25.85
1989	21.40	24.38	27.43	27.63	26.26	25.14	24.45	24.29	24.52	24.99	25.15	23.76	24.95
1990	25.25	26.13	27.38	27.91	26.37	26.06	24.62	24.88	25.16	25.57	26.00	26.19	25.96
1991	25.52	28.70	29.18	27.60	26.62	26.04	24.62	24.22	25.15	24.77	25.63	23.51	25.94
1992	23.94	26.57	29.00	28.14	26.63	25.65	24.24	23.94	24.42	25.09	24.03	23.35	25.41
1993	23.05	26.08	27.29	27.74	26.88	25.59	24.48	24.35	24.75	25.33	25.67	23.94	25.42
1994	24.77	25.89	27.60	27.23	26.32	25.64	24.62	24.27	24.57	24.86	24.14	21.67	25.12
1995	24.00	25.61	27.32	27.35	26.31	25.68	24.49	24.52	25.02	25.40	24.04	24.00	25.31
1996	25.14	27.13	27.28	27.24	26.73	25.59	24.55	24.46	24.67	24.83	23.75	23.93	25.43
1997	24.67	23.88	26.86	26.60	26.06	25.43	24.71	24.79	25.56	26.11	26.14	24.22	25.43
1998	24.04	27.69	28.98	28.76	27.67	26.16	25.20	24.74	25.09	25.90	25.96	24.72	26.23
1999	25.72	27.77	29.62	29.38	28.60	27.24	26.18	26.19	26.19	26.34	28.06	27.08	27.36
2000	28.51	28.49	29.59	29.42	28.77	25.24	24.43	24.42	24.87	25.27	25.04	22.65	26.38
2001	22.69	24.40	27.94	27.56	27.01	25.61	25.02	25.02	25.00	25.69	26.00	25.80	25.65
2002	24.59	27.84	28.95	27.79	27.25	26.04	25.44	25.04	25.37	25.36	25.77	24.64	26.16
2003	25.58	27.93	28.06	27.80	27.20	26.04	25.21	25.36	25.30	26.07	26.04	24.76	26.26
2004	26.00	27.43	29.42	28.30	26.73	25.63	24.87	25.23	25.40	25.95	26.54	26.41	26.49
2005	25.77	29.60	29.34	29.68	28.59	27.24	26.19	26.89	25.98	26.01	26.63	27.36	27.42
2006	28.50	29.50	29.25	29.48	27.60	26.94	26.26	25.15	25.03	26.34	25.11	24.42	26.95
2007	24.18	27.81	29.28	29.33	27.70	25.80	25.07	24.60	25.09	25.24	25.69	23.85	26.12
2008	23.26	24.72	27.54	27.46	27.35	26.17	25.00	24.65	25.14	25.90	25.95	25.49	25.72

2009	26.24	28.01	28.66	27.55	26.69	25.86	25.49	25.09	25.46	25.59	25.22	24.96	26.22
2010	26.45	28.68	29.24	28.77	27.65	26.15	25.07	25.03	25.02	25.54	26.15	24.49	26.50
2011	24.08	27.41	28.69	28.15	27.09	25.92	25.28	24.97	25.05	25.41	25.70	23.87	25.95
2012	25.80	28.42	28.70	28.08	26.80	25.91	24.90	24.63	24.79	25.48	26.04	24.51	26.16
2013	25.79	27.38	28.44	28.47	27.06	25.99	24.99	24.96	25.32	26.10	27.03	26.08	26.46
2014	27.44	28.61	28.88	28.21	27.78	27.21	26.20	25.20	25.22	26.02	26.93	27.25	27.07
2015	26.22	29.70	29.10	29.22	28.52	26.90	25.86	25.50	25.57	26.22	26.92	24.59	27.00
2016	26.71	29.71	30.06	29.66	27.50	25.97	25.22	25.13	25.28	25.96	26.62	25.68	26.94
2017	26.85	27.96	29.65	28.46	27.13	26.33	25.31	25.12	25.32	26.18	26.11	25.87	26.68
2018	24.14	27.82	28.42	28.23	27.15	25.70	25.22	25.04	25.27	25.97	26.71	25.26	26.23
MEAN	**25.23**	**27.37**	**28.56**	**28.23**	**27.19**	**26.01**	**25.08**	**24.90**	**25.14**	**25.65**	**25.81**	**24.79**	**26.15**

APPENDIX B: Mean daily solar radiation (kwh/m^2/day) for Kogi state

Years	January	February	March	April	May	June	July	August	September	October	November	December	Mean
1988	5.61	5.71	5.65	5.48	5.20	5.02	4.46	3.77	4.16	4.71	5.28	5.37	**5.03**
1989	6.30	6.02	5.74	5.65	5.00	4.66	4.54	3.99	4.27	4.57	5.77	5.97	**5.20**
1990	5.70	6.04	6.68	5.42	5.26	4.72	4.06	4.12	4.43	4.80	5.20	4.93	**5.11**
1991	5.73	5.55	5.48	5.11	4.76	4.97	4.08	3.92	4.59	4.76	5.66	5.67	**5.02**
1992	5.82	6.28	5.51	5.42	5.04	4.59	4.32	4.14	4.04	5.15	5.46	5.94	**5.14**
1993	5.85	5.92	5.78	5.55	5.25	4.89	4.48	4.41	4.82	5.01	5.14	5.69	**5.23**
1994	5.85	5.98	6.03	5.27	5.40	4.92	4.32	4.14	4.81	4.85	5.80	6.07	**5.28**
1995	6.06	6.12	5.53	5.33	5.16	4.62	4.14	3.84	4.42	4.78	5.65	5.45	**5.08**
1996	5.75	5.47	5.55	5.40	5.16	4.66	4.29	4.06	4.00	4.55	5.93	5.45	**5.02**
1997	5.45	6.27	5.27	5.02	5.28	4.41	4.12	4.06	4.43	4.70	5.02	5.42	**4.94**
1998	5.78	5.69	5.92	5.66	5.28	4.71	4.38	4.22	4.10	4.58	5.46	5.43	**5.10**
1999	5.57	5.57	5.66	5.51	5.17	4.39	4.41	4.52	3.93	4.42	5.14	5.74	**5.00**
2000	5.76	6.04	6.26	4.97	5.38	4.44	4.39	3.98	4.32	4.37	5.49	5.73	**5.09**
2001	5.87	5.83	5.87	5.26	5.28	4.97	4.16	4.31	3.95	4.81	5.28	5.50	**5.09**
2002	6.00	5.75	5.53	4.86	4.79	4.67	4.27	3.54	4.14	4.42	5.33	5.66	**4.91**
2003	5.73	5.72	5.62	5.30	5.01	4.35	4.41	4.27	4.11	5.03	5.23	5.73	**5.04**
2004	5.63	5.77	5.69	5.20	4.74	4.73	4.48	3.87	4.49	4.67	5.02	5.56	**4.98**
2005	5.53	5.41	5.55	5.55	5.08	4.35	4.02	4.00	4.36	4.58	5.55	5.45	**4.95**
2006	5.27	5.46	5.55	5.88	4.61	4.79	4.23	3.66	4.31	4.77	5.85	5.46	**4.98**
2007	5.77	5.69	5.58	5.33	5.32	4.58	4.29	3.64	4.22	4.82	5.32	5.48	**5.00**
2008	5.51	6.21	5.89	5.26	4.85	4.73	4.25	4.29	4.32	5.31	5.43	5.22	**5.10**

2009	5.37	5.52	5.84	5.21	5.21	4.82	4.36	4.10	4.46	4.49	5.31	5.43	**5.01**
2010	5.56	5.67	5.72	5.59	4.95	4.48	4.30	4.13	4.25	4.72	5.15	5.40	**4.99**
2011	5.65	5.78	5.94	4.94	5.07	4.58	4.31	3.93	4.26	4.77	5.47	5.56	**5.02**
2012	5.78	5.56	6.06	5.26	4.94	4.54	4.13	3.83	4.06	4.64	5.30	5.33	**4.95**
2013	4.74	4.74	4.79	4.55	4.30	4.47	3.58	3.81	3.96	4.76	4.91	4.77	**4.45**
2014	4.78	4.72	4.77	4.92	4.64	4.50	4.19	3.65	4.04	4.65	5.00	4.86	**4.56**
2015	4.89	4.57	4.79	5.15	5.09	3.97	3.95	3.67	4.03	4.49	5.20	5.11	**4.58**
2016	4.94	4.83	4.48	5.30	4.85	4.11	3.92	3.54	4.11	4.91	5.20	4.73	**4.57**
2017	4.82	5.26	4.73	5.03	4.30	4.48	3.83	3.52	3.93	5.01	5.10	4.75	**4.56**

APPENDIX D: Mean daily solar radiation (kwh/m^2/day) for Niger state

Years	January	February	March	April	May	June	July	August	September	October	November	December	Mean
1988	5.41	5.76	6.26	6.13	5.71	5.43	4.70	3.79	4.49	5.67	5.60	5.40	**5.36**
1989	5.78	5.88	6.27	6.35	5.73	5.01	4.85	4.24	4.46	5.48	6.11	6.02	**5.51**
1990	5.69	6.09	6.44	6.16	5.62	5.20	4.26	4.35	5.24	5.47	5.82	5.63	**5.49**
1991	5.84	5.98	6.02	6.00	5.28	5.40	4.53	4.15	5.38	5.21	5.99	5.60	**5.44**
1992	5.53	6.16	5.73	6.09	5.78	4.96	4.65	4.32	4.78	5.63	5.87	5.93	**5.45**
1993	5.71	6.28	6.11	6.56	6.03	5.15	4.75	4.67	5.46	5.55	5.87	5.76	**5.65**
1994	5.66	6.01	6.75	6.07	5.57	5.45	4.85	4.03	4.63	5.41	6.24	5.87	**5.54**
1995	5.74	6.05	6.40	5.96	5.72	5.16	4.83	4.03	4.77	5.42	5.75	5.87	**5.47**
1996	5.92	6.00	6.22	6.09	5.72	4.85	4.64	4.03	4.64	5.43	6.17	5.87	**5.46**
1997	5.83	6.10	5.90	6.01	5.58	5.08	4.65	4.79	5.05	5.12	5.71	5.77	**5.46**
1998	5.69	5.97	6.28	6.15	5.51	5.17	4.40	4.12	4.47	5.12	6.01	5.55	**5.36**
1999	5.89	6.25	6.37	6.13	5.82	5.21	4.51	4.21	4.39	5.07	5.78	5.83	**5.45**
2000	5.82	6.13	6.66	6.16	5.83	5.03	4.48	4.56	4.54	5.27	5.94	5.90	**5.52**
2001	6.00	5.92	6.78	6.25	5.65	5.15	4.07	4.24	4.29	5.78	6.31	5.86	**5.52**
2002	5.52	5.97	6.20	5.95	5.82	5.33	4.36	4.39	4.81	4.89	5.60	5.78	**5.38**
2003	5.61	6.09	6.34	5.99	5.91	4.90	4.63	4.35	4.65	5.50	5.82	5.90	**5.47**
2004	5.67	5.63	6.13	5.86	5.37	5.30	4.72	4.12	5.14	5.51	5.45	5.97	**5.40**
2005	5.49	5.80	6.43	6.31	5.76	4.84	4.08	4.23	4.92	5.02	5.96	5.96	**5.40**
2006	5.74	5.88	6.14	6.56	5.30	5.27	4.60	3.88	4.62	5.44	5.75	5.47	**5.38**
2007	5.52	5.97	6.00	5.84	5.73	5.08	4.57	3.92	4.95	5.60	5.77	5.66	**5.38**
2008	6.04	6.73	6.80	6.24	5.60	5.57	4.73	4.33	5.33	5.86	5.92	5.50	**5.72**

2009	5.88	6.32	6.70	6.15	5.93	5.18	5.05	4.72	5.18	5.57	5.79	5.74	**5.68**
2010	6.01	6.52	6.55	6.36	5.51	5.30	4.52	4.45	4.66	5.22	5.83	5.54	**5.53**
2011	6.02	6.27	6.75	6.18	5.62	5.11	5.18	4.34	5.14	5.43	5.90	5.84	**5.64**
2012	5.98	6.28	6.79	6.27	5.49	5.12	4.57	4.10	4.65	5.49	5.76	5.69	**5.51**
2013	5.19	5.39	5.60	5.59	5.49	4.68	3.92	4.12	4.98	5.43	5.77	5.38	**5.13**
2014	5.24	5.57	5.42	5.90	4.88	5.05	4.56	4.04	4.81	5.43	5.65	5.42	**5.16**
2015	5.35	5.13	5.49	6.17	5.45	4.59	4.72	3.74	4.59	5.04	5.75	5.47	**5.12**
2016	5.31	5.44	5.20	6.19	5.38	4.67	4.66	4.00	4.90	5.84	5.75	5.25	**5.21**
2017	5.21	5.63	5.70	5.80	5.00	5.00	4.60	3.91	5.00	5.83	5.78	4.99	**5.20**
2018	5.37	5.02	5.45	5.67	5.17	4.73	4.52	3.95	5.03	5.53	5.47	5.19	**5.09**
Mean	**5.67**	**5.94**	**6.19**	**6.10**	**5.58**	**5.10**	**4.59**	**4.20**	**4.84**	**5.43**	**5.84**	**5.66**	**5.42**

APPENDIX E: Mean daily temperature data (^oc) for Nasarawa state

Years	January	February	March	April	May	June	July	August	September	October	November	December	Mean
1988	25.38	27.20	28.50	27.65	26.25	24.78	23.57	23.13	24.13	24.43	23.68	23.64	**25.19**
1989	22.22	25.41	28.08	27.92	25.33	24.27	23.61	23.29	23.88	24.04	23.29	22.56	**24.48**
1990	24.67	26.01	28.18	27.98	25.42	24.85	23.80	23.97	24.13	24.40	24.48	24.93	**25.23**
1991	24.95	28.00	28.81	26.62	25.80	25.05	23.69	23.08	24.33	24.03	24.10	23.07	**25.11**
1992	24.45	26.97	28.76	27.13	25.70	24.52	23.43	23.01	23.59	24.29	22.78	22.26	**24.73**
1993	22.65	25.99	27.16	27.53	26.05	24.84	23.79	23.50	24.11	24.56	24.68	23.18	**24.82**
1994	24.49	25.89	28.76	27.16	25.70	24.78	23.60	23.12	23.57	24.07	22.72	21.12	**24.57**
1995	23.52	25.05	27.70	27.43	25.75	24.88	23.72	23.68	24.28	24.52	22.56	22.50	**24.63**
1996	23.89	26.38	27.23	27.01	25.93	24.59	23.71	23.53	23.81	24.05	21.90	22.33	**24.52**
1997	23.88	24.69	26.60	26.08	25.42	24.53	23.92	23.92	24.65	25.12	24.62	23.01	**24.70**
1998	24.22	27.41	29.39	28.64	26.60	25.32	24.23	23.96	24.36	24.88	24.42	24.02	**25.61**
1999	25.18	27.78	29.34	28.77	27.39	26.06	24.82	24.39	25.51	25.14	26.49	26.14	**26.40**
2000	27.77	28.10	29.66	28.66	27.87	24.53	23.72	23.69	24.13	24.27	23.30	21.79	**25.62**
2001	22.30	24.91	28.08	26.82	26.76	24.88	24.32	24.14	24.10	24.86	25.19	25.73	**25.18**
2002	25.50	27.91	29.45	27.28	26.31	25.38	24.74	24.09	24.50	24.47	24.41	24.56	**25.70**
2003	25.63	28.12	29.00	27.54	27.39	25.50	25.24	24.64	24.74	25.20	25.47	25.40	**26.14**
2004	26.80	28.36	29.92	28.58	26.10	25.23	24.87	24.69	25.63	26.60	27.50	27.38	**26.80**
2005	26.56	30.34	30.10	29.33	27.29	26.31	25.54	25.46	24.90	25.13	25.72	26.75	**26.93**
2006	27.94	28.67	29.63	29.19	26.57	26.69	25.80	24.15	24.26	25.41	23.56	23.79	**26.29**
2007	24.72	27.86	29.60	28.47	27.28	25.03	24.09	23.58	24.22	24.57	24.42	22.49	**25.51**
2008	23.31	25.63	28.30	27.73	26.96	25.45	24.18	23.70	24.41	25.05	24.61	25.24	**25.38**
2009	26.84	28.52	29.72	28.05	26.46	25.21	24.72	24.20	24.59	24.65	24.76	25.23	**26.06**

2010	26.84	29.43	29.57	28.99	26.60	25.58	24.00	23.98	24.00	24.76	25.13	23.81	**26.03**
2011	25.06	28.05	29.37	29.27	26.48	25.42	24.83	24.15	24.15	24.79	25.09	24.76	**25.93**
2012	26.53	28.97	29.80	28.88	26.78	25.05	23.96	23.63	23.90	24.82	24.85	23.36	**25.86**
2013	25.64	27.76	28.56	28.31	26.93	25.93	25.02	24.31	25.23	26.30	27.89	27.15	**26.57**
2014	27.97	29.56	29.18	28.02	27.20	25.81	25.01	24.07	24.43	25.35	26.71	26.53	**26.63**
2015	25.63	29.62	29.46	29.53	29.63	27.07	25.38	24.61	24.80	25.63	26.41	24.58	**26.84**
2016	26.59	29.40	30.34	28.72	26.98	25.15	24.35	24.17	24.35	25.04	24.93	24.82	**26.22**
2017	26.51	27.76	29.85	28.63	26.55	25.81	24.89	24.22	24.62	25.51	26.29	26.74	**26.44**
2018	25.55	29.22	29.89	29.74	27.43	25.62	24.53	24.30	24.70	25.56	26.86	26.45	**26.63**
Mean	**25.26**	**27.58**	**28.97**	**28.12**	**26.61**	**25.29**	**24.36**	**23.95**	**24.39**	**24.89**	**24.80**	**24.36**	**25.70**

APPENDIX F: Mean daily solar radiation (kwh/m^2/day) for Nasarawa state

Years	January	February	March	April	May	June	July	August	September	October	November	December	Mean
1988	5.64	6.15	6.12	5.73	5.43	5.38	4.30	3.88	4.48	5.05	5.76	5.53	**5.28**
1989	6.19	6.23	6.39	6.06	5.19	4.88	4.72	4.14	4.56	5.23	6.30	6.25	**5.51**
1990	5.84	6.26	6.74	5.94	5.38	4.85	4.40	4.42	4.68	5.20	5.51	5.30	**5.37**
1991	6.04	6.00	5.89	5.56	5.02	5.08	4.65	4.02	5.10	4.91	6.07	5.94	**5.35**
1992	5.61	6.44	6.05	5.65	5.32	4.61	4.49	4.05	4.41	5.28	5.94	6.19	**5.33**
1993	5.87	6.25	6.03	5.84	5.34	4.80	4.44	4.64	5.12	5.22	5.86	5.84	**5.43**
1994	5.81	6.24	6.60	5.33	5.49	5.08	4.76	3.85	4.51	4.97	6.24	6.14	**5.41**
1995	6.11	6.40	6.05	5.80	5.14	4.91	4.39	4.25	4.72	5.21	5.89	5.95	**5.40**
1996	6.11	5.88	5.96	5.72	5.22	4.56	4.38	3.91	4.17	5.15	6.21	6.10	**5.28**
1997	5.82	6.36	5.83	5.44	5.33	4.72	4.45	4.44	4.97	5.12	5.59	5.88	**5.32**
1998	5.85	6.06	6.42	5.79	5.41	4.91	4.33	4.08	4.24	4.83	5.84	5.73	**5.29**
1999	5.96	6.12	5.96	5.87	5.31	4.94	4.56	4.31	4.29	4.85	5.80	5.95	**5.32**
2000	5.89	6.36	6.67	5.52	5.42	4.44	4.35	4.20	4.38	4.85	5.95	6.02	**5.33**
2001	6.19	6.02	6.51	5.73	5.52	4.98	4.12	4.47	3.80	5.37	6.17	6.03	**5.41**
2002	5.90	6.22	6.13	5.40	5.43	5.00	4.23	4.05	4.18	4.73	5.71	5.88	**5.23**
2003	5.92	6.02	6.07	5.51	5.58	4.62	4.69	4.16	4.48	5.04	5.77	5.91	**5.31**
2004	6.01	6.10	6.16	5.62	5.01	5.00	4.43	3.98	4.71	5.23	5.37	5.99	**5.30**
2005	5.56	5.92	6.13	5.89	5.36	4.58	4.23	3.99	4.62	5.26	6.07	6.07	**5.30**
2006	5.86	5.66	5.89	6.13	5.08	5.08	4.50	3.86	4.31	5.15	6.03	5.62	**5.26**
2007	6.02	6.13	6.05	5.62	5.29	4.57	4.43	3.45	4.66	5.33	5.77	5.89	**5.26**
2008	5.97	6.84	6.50	5.88	5.85	5.01	4.79	4.55	4.85	5.84	5.74	5.63	**5.62**

2009	5.65	6.13	6.49	5.85	5.67	5.11	4.73	4.63	4.94	5.29	5.76	5.73	**5.49**
2010	6.09	6.48	6.50	5.97	5.36	5.03	4.44	4.54	4.66	5.25	5.74	5.83	**5.48**
2011	6.11	6.16	6.67	5.85	5.55	4.56	4.90	4.21	4.81	5.19	6.08	5.98	**5.50**
2012	6.09	6.09	6.64	5.95	5.73	5.16	4.59	4.39	4.42	5.47	5.65	5.83	**5.50**
2013	5.24	5.44	5.36	5.27	5.08	4.53	4.46	3.95	4.55	5.25	5.65	5.21	**5.00**
2014	5.29	5.38	5.40	5.49	5.21	4.85	4.15	3.96	4.22	5.32	5.63	5.46	**5.03**
2015	5.49	5.14	5.31	6.17	5.54	4.35	4.47	4.15	4.50	5.18	5.80	5.59	**5.14**
2016	5.50	5.72	4.93	5.48	5.27	4.66	4.20	4.29	4.47	5.44	5.81	5.41	**5.10**
2017	5.30	5.73	5.58	5.41	5.28	4.55	4.17	4.01	4.65	5.79	5.55	5.25	**5.10**
2018	5.55	5.02	5.42	5.45	4.86	4.35	4.38	4.17	4.62	5.50	5.46	5.46	**5.02**
Mean	5.82	6.03	6.08	5.71	5.34	4.81	4.46	4.16	4.55	5.21	5.83	5.79	**5.31**