AMERICAN JOURNAL OF SCIENTIFIC AND INDUSTRIAL RESEARCH

ISSN: 2153-649X doi:10.5251/ajsir.2010.1.2.144.157

Modeling of solar energy potential in Africa using an artificial neural network

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ABSTRACT

In this study, the feasibility of an artificial neural network (ANN) based model for the prediction of solar energy potential in Africa was investigated. Standard multilayered, feed-forward, back-propagation neural networks with different architecture were designed using NeuroSolutions®. Geographical and meteorological data of 172 locations in Africa for the period of 22 years (1983-2005) were obtained from NASA geo-satellite database. The input data (geographical and meteorological parameters) to the network includes: latitude, longitude, altitude, month, mean sunshine duration, mean temperature, and relative humidity while the solar radiation intensity was used as the output of the network. The results showed that after sufficient training sessions, the predicted and the actual values of solar energy potential had Mean Square Errors (MSE) that ranged between 0.002 - 0.004, thus suggesting a high reliability of the model for evaluation of solar radiation in locations where solar radiation data are not available in Africa. The predicted and actual values of solar energy potential were given in form of monthly maps. The solar radiation potential (actual and ANN predicted) in northern Africa (region above the equator) and the southern Africa (region below the equator) for the period of April – September ranged respectively from 5.0 - 7.5 and 3.5 - 5.5 kW h/m^2/day while for the period of October – March ranged respectively from 2.5 – 5.5 and 5.5 - 7.5 kW h/m^2/day. This study has shown that ANN-based model can accurately predict solar radiation potential in Africa.

Keywords: Artificial neural network, solar radiation, modeling, renewable energy, Africa

INTRODUCTION

Many countries in Africa are faced with immense energy challenges, characterized by low rates of access to electricity, irregularities and a general shortage in electricity supply. Solar energy provides African governments with the opportunity to address these challenges. Africa is endowed with sufficient solar radiation potential that can be effectively harnessed as renewable energy resource. Consequently, this is favoured by her location which is within 37°21'N and 34°51'15"S latitudes. Many African countries have most of its land mass exposed to an average of 325 days per year of bright sunlight (Yansane *et al*, 2007), thus suggesting a clear indication of the potential usage of solar energy resource in Africa. Reports have shown that the usage of solar energy radiation in Africa is now receiving the attention it has always deserves (Irimisose, 2009; REMP, 2007). The global energy crisis has prompted the need to proffer effective and efficient ways of harnessing solar energy resources. At present, many of the African countries are embarking on exploration of solar energy resources for power supply. Thus, country like Nigeria seeks a long–term solution to the energy crisis through the Renewable Energy Master Plan (REMP, 2007). Currently, the Libyan government seeks the application of solar energy to household appliance with the aim of minimizing cost of electrical appliances at household level. The governments of Germany and South Africa provided joint support to a solar stove pilot program that included a comparative field test under real-life conditions to determine the social acceptance of solar stoves, as well as testing the commercial dissemination of solar stoves (Erica and Marlett, 2002). Furthermore, Europe, Germany and China proposed partnership between some Africa countries with the plan to build solar panel factories with a positive step towards addressing energy challenges. Under these circumstances, it is highly desirable that detailed information about the availability of solar radiation on horizontal surface is essential for the optimum design and study of solar energy conversion systems. Solar radiation data are available for most part of the world, but is not available for many countries in Africa which cannot afford the measurement equipment and techniques involved (Ahmad *et al*, 2004).

Solar resources are known to exhibit a high variability in space and time due to the influence of other climatic factors such as cloud cover. Therefore, solar resource modeling or mapping is one of the essential management tools for proper development, planning, maintenance scheduling and pricing of solar energy systems. For efficient conversion and utilization of solar energy, the solar engineer designing solar energy systems require an accurate and detailed short term and long-term knowledge of the solar radiation characteristics of the location in various forms such as models or maps for proper sizing of the solar energy systems (Sozen *et al*, 2004; Chendo, 2001; Oparaku, 2003). Solar radiation models or maps are therefore essential design-input parameter in the assessment of solar energy systems (Fadare, 2009). The unavailability of solar radiation measuring equipment and techniques in many African countries has limited the development of solar energy applications in the continent.

Therefore, it is rather important to develop method to estimate the global and diffuse solar radiation based on other climatological parameters that are easily measured with more available equipment. To this effect, several empirical formulas have been developed to calculate the global solar radiation using various parameters. Previous studies in this area have been focused on the development of empirical models based parameters which include: sunshine hours (Glover and McCulloch, 1958), declination angle and latitude (Liu and Jordan, 1960), number of rainy days, sunshine hours, latitude and locations (Reddy, 1971), sunshine duration, relative humidity, maximum temperature, latitude, altitude and location (Sabbagh *et al*, 1977). Other studies in this area include the works of Ahmad *et al*, 2004; Abdullah and Farugh 1988; Chandal *et al*, 2005; Udo, 2002; Togrul and Onat, 2002. All these developed empirical models are location specific and hence are limited in scope and application.

Artificial neural network (ANN) modeling technique offers a better solution for developing a more generalized model for prediction of solar radiation data using climatological parameters. ANN is a modeling and prediction tool, widely accepted as a technique offering an alternative way to tackle complex and ill-defined problems (Kalogirou, 2001). They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, to deal with non-linear problems and, once trained, can perform prediction and generalization at high speed. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing and social/ psychological sciences. They are particularly useful in system modeling such as in implementing complex mappings and system identification (Kalogirou, 2000). ANN has been applied to modeling of complex systems such as meteorological parameters (Kalogirou, 2001; Kalogirou *et al*, 1998). Jiya and Alfa (2002) and Fadare (2009) have applied ANN model to model and predict solar radiation in Nigeria while Sozen *et al*. (2004) used the technique for mapping solar potential in Turkey. ANN models are efficient and less time consuming in modeling of complex systems compared to other mathematical models such as regression (Lin *et al*, 2003). ANN with different topologies has been developed for spatial prediction of wind speed in different parts of the world (Cellura *et al*, 2008, Kariniotakis *et al*, 1996; Fadare, 2010). Comprehensive reviews on ANN applications in renewable energy systems have been reported by Kalogirou, (2000; 2001). Basic theory and application of ANN can be found in generic text like (Picton, 2000). ANN models are known to be efficient and less time-consuming in modeling of complex systems compared to other mathematical models such as multiple regression (Kaldellis *et al*, 2009 and Adekoya and Adewale, 1992; Agbaka, 1987).

The aim of this study was to develop forward, back-propagation, multilayer preceptor neural network to predict the mean monthly global solar radiation in Africa. The essence of the study was to develop a cheap alternative model that can predict the monthly mean solar radiation potential for specific locations in Africa where there are no records of solar radiation.

MATERIALS AND METHOD

Model description: ANN is a branch of artificial intelligence (AI), which belongs to the group of computational algorithms called connectionist models (Ojosu *et al*, 1990). ANN models are inspired by the biological neural system, with capability to learn, store and recall information based on a given training dataset. They are 'black-box' modeling technique capable of performing non-linear mapping of a multidimensional input space onto another multidimensional output space without the knowledge of the dynamics of the relationship between the input and output spaces. ANN-based models have been successfully employed in solving complex problems in various fields of application including pattern recognition, identification, classification, speech, vision, and control systems. In recent times, application of ANN models is becoming increasingly popular in many fields of engineering.

Basically, ANN models consist of multiple connected processing elements (PE), which are called nodes or neurons. They consist generally of five basic components: (1) input, (2) weight and biases, (3) summing junction, (4) transfer function, and (5) output. The neurons are arranged in three multiple layers known as input, hidden, and output layer. In neural networks, knowledge is acquired during the training or learning process by updating or adjusting the weights in the network through different algorithms. The network weights are upgraded literarily until the network reproduces the desired output or target from a given set of input. The network is trained with either supervised learning (when both input and the desired targets are presented to the network) or unsupervised learning (when the expected targets are not used in the training). The back-propagation algorithm is a supervised training rule with multiple-layer networks, in which the network weights are moved along the negative of the gradient of the mean squared error (MSE) so as to minimize the difference between the network's output and the desired target. There are generally four steps in the training process: (1) assembling the training data, (2) designing the network object, (3) training the network, and (4) simulating the network response with new input data sets. After a sufficient training session, which may require considerable computational resources such as memory and time of the computer, the trained network has adequate capabilities to perform non-linear pattern association between input and output variables and can easily predict the output when a new input data set that is not used in the training is presented to the network.

Data Collection: Geographical and meteorological data of 172 locations in Africa for the period of 22 years (1983-2005) were obtained from NASA geo-satellite database. The data includes geographical parameters: latitude (positive symbol [+] indicates Northern region and negative symbol [-] indicates Southern region), longitude (positive symbol [+] indicates Eastern region and negative symbol [-] indicates Western region), altitude, month of the year, and mean monthly meteorological parameters (sunshine duration, temperature, and relative humidity, and solar radiation intensity). Figure 1shows the geographical locations of the 172 locations in Africa used for the training (114 locations) and testing (58 locations) of the model. Tables 1 and 2 show the detailed geographical parameters of 114 locations used for training and 58 locations used for testing the model, respectively.

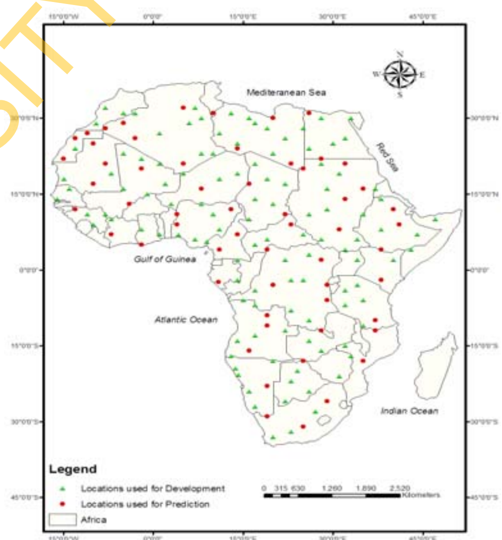


Fig 1: Geographical locations used for the development of the model

Table 1: Geographical location of the 114 sites within Africa used for training, validation and testing of the neural network model

S/No	LAT	LONG	ELVN		S/No	LAT	LONG	ELVN		S/No	LAT	LONG	ELVN
1	21	1	412		39	18	19	374		77	4	32	936
2	22	-2	333		40	17	22	896		78	1.5	34	1515
3	23	-5	301		41	16	29	424		79	2	40	411
4	24	-13	355		42	18.5	31	311		80	4	43	465
5	25	14	516		43	16	36.5	489		81	-2	14	576
6	25	30	229		44	14	-15.5	36		82	-4	17	334
7	26	22	184		45	11	-11	466		83	-1.5	22.5	448
8	26	31.5	258		46	10.5	-8	398		84	-1.5	25	481
9	26.5	1	18.5		47	14.5	-1	278		85	-4	31.5	1227
10	27	11	531		48	12.5	2.5	241		86	-3	34	1425
11	27.5	19	228		49	13	8	436		87	-6	15	684
12	28	25	123		50	10.5	10	447		88	-7	17	820
13	28.5	17	285		51	14	17	292		89	-8	23	891
14	29	6	292		52	12.5	20	461		90	-9.5	26	1126
15	29.5	8	347		53	10.5	26	459		91	-7	32	1162
16	30	16	186		54	12	29	622		92	-6	35	1153
17	30	28	58		55	11	35	744		93	-14	14	1356
18	30	33	312		56	14	38	1629		94	-13	16.5	1682
19	30.5	13	465		57	9	-10	550		95	-12	22	1160
20	30.5	-3	576		58	10	-7	366		96	-14	26	1239
21	32	-8	438		59	8	-2	140		97	-14.5	32	857
22	32	7	134		60	7	1	174		98	-10.5	35	972
23	31	-5	953		61	6	7	186		99	-19	11	2
24	31	-10	344		62	8	11	568		100	-17	13	1105
25	23	7.5	1261		63	9.5	16	369		101	-18	20	1089
26	22.5	9.5	707		64	5.5	19	453		102	-19.5	23.5	937
27	20.5	17	1460		65	7	25	732		103	-16	27.5	1031
28	23	19.5	708		66	6	28	499		104	-17	32.5	563
29	24	26	660		67	5.5	34	700		105	-21	13.5	233
30	20.5	28	390		68	8	38	2221		106	-24	16	1557
31	18	-15.5	19		69	7	44	884		107	-22	23	972
32	16	-14	54		70	9.5	47	883		108	-24	26	977
33	19	-7	314		71	4	4	0		109	-20.5	30.5	859
34	15.5	-5	269		72	4	8	55		110	-27	17	1020
35	17	2	469		73	2	13.5	584		111	-26	22	1004
36	18.5	5	453		74	4.5	16.5	575		112	-28	26.5	1368
37	17.5	11	461		75	1.5	22	422		113	-33	20	1135
38	19	14	443		76	3	26	621		114	-32	23	1307

Table 2: The 58 geographical locations in Africa used for prediction of solar energy potential

S/No	LAT	LONG	ELVN	S/No	LAT	LONG	ELVN
1	20.5	-8.0	313	30	7.0	-7.0	366
2	22.0	-15.0	301	31	9.0	4.0	192
3	24.5	-10.0	277	32	7.0	13.5	932
4	25.5	-3.0	313	33	8.5	23.0	849
5	26.0	-13.0	222	34	7.5	31.0	402
6	27.0	-11.0	414	35	9.0	41.0	1433
7	28.0	-8.0	492	36	5.0	-2.0	111
8	29.0	-5.0	568	37	4.0	10.5	241
9	30.0	20.0	40	38	4.0	19.0	539
10	30.5	10.0	452	39	2.0	28.0	859
11	32.0	5.0	197	40	3.5	38.0	835
12	31.0	26.0	75	41	-3.0	10.0	100
13	21.0	5.0	677	42	-2.5	20.0	424
14	24.0	13.5	642	43	-3.0	29.0	1722
15	21.0	23.0	559	44	-2.0	38.0	630
16	20.5	32.0	439	45	-9.0	19.0	1091
17	17.0	-10.0	221	46	-5.5	29.0	902
18	19.5	-2.0	283	47	-9.5	36.5.0	616
19	16.0	7.5.0	456	48	-11.0	19.0	1265
20	16.5	16.0	258	49	-11.5	28.0	1162
21	19.5	25.0	585	50	-12.0	37.0	458
22	15.5	35.0	454	51	-16.0	16.0	1304
23	12.0	-13.0	233	52	-17.5	25.0	977
24	13.0	-4.0	278	53	-18.0	35.0	153
25	11.0	4.0	220	54	-23.0	19.0	1401
26	12.0	13.0	287	55	21.5	28.0	840
27	11.0	22.0	573	56	-29.0	19.0	755
28	13.5	32.0	390	57	-25.5	29.0	1469
29	11.5	40.0	720	58	-31.0	25.0	1397

Design of the artificial neural network model: Multi-layer feed-forward back-propagation hierarchical networks with different architecture were designed using the NeuroSolutions® version 5.0. The networks consist of three layers: input layer; hidden layer; and output layer. A typical three layered ANN is shown in Figure 2. There were seven input parameters into the network, which consisted of the geographical and meteorological parameters of the locations and one output parameter corresponding to the global solar radiation intensity. Different networks with single or double hidden layer topologies were used and the number of neurons was varied from 5 to 15, at interval of five neurons. No transfer function was used in the neurons in the input layer, while neurons with tangent sigmoid (tansig) and linear (purelin) transfer functions were used in the hidden layer(s) and output layer, respectively.

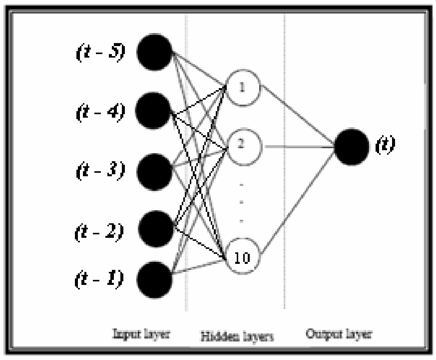


Fig. 2: Typical structure of a MLP neural network

Training and testing of the model: Prior to the training process, both input and target data sets were normalized to range -1 and +1. Scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) learning algorithms were used for the training of the networks. In order to avoid 'over fitting' of the data and hence improve generalization of the network the *'early stopping'* technique was used in conjunction with the training algorithms. The input/target dataset was divided randomly into three subsets: training; validation; and testing datasets. The training set, which consists of 50% of the dataset, was used for computing the gradient and updating the network weights and biases, while 25% of the dataset was used as validation and test dataset respectively for each network. The maximum number of 3000 epochs was used in the training process. The networks were tested 35 times using different randomly selected weights and biases. The different network structures were trained using dataset of the 114 locations and their predictive performance were evaluated based on the Mean Square Error (MSE) and Cross Validation Mean Square Error (CV MSE) between the predicted and the actual values in order to determine the network optimum structure required for best predictive performance.

RESULTS AND DISCUSSION

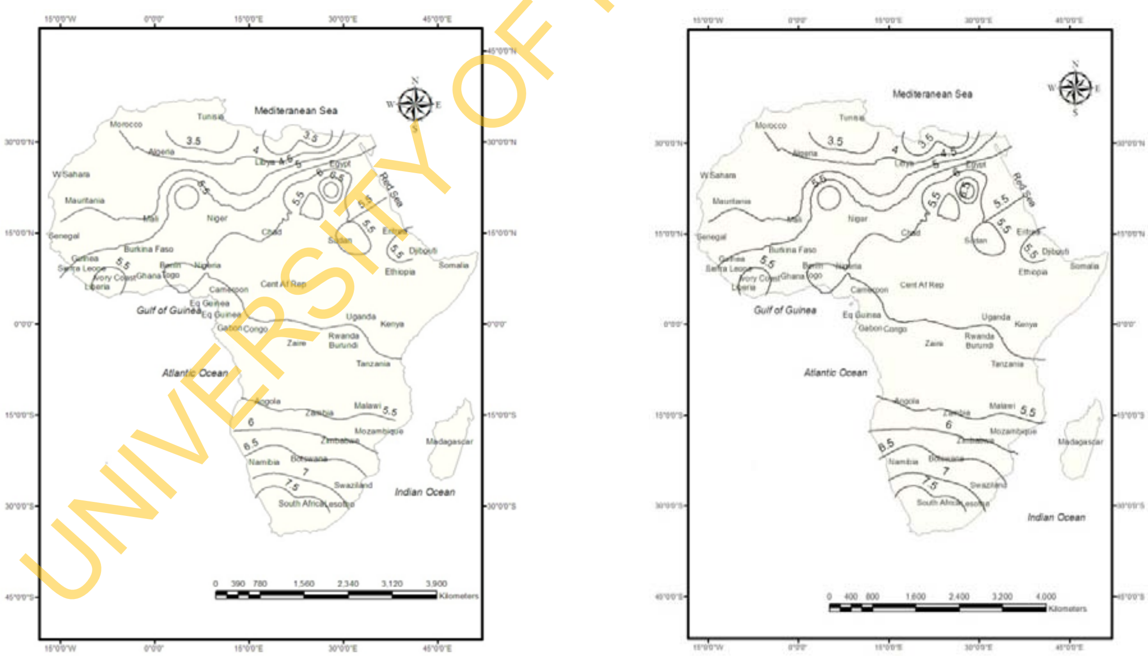
Network optimization: After sufficient training sessions, which required considerable computational resources in terms of memory and time of the computer, the networks were found to have considerable capabilities to perform non-linear pattern association between the input (geographical and meteorological parameters) and output (solar radiation). The network with single hidden layer of five neurons trained with Levenberg Marquardt learning algorithm was found to be the optimum network structure required for the model. Using the optimum network structure, the correlation between the predicted and the actual values of monthly mean solar radiation for January is shown graphically in Figure 3, while Table 3 shows the results of values of mean square error (MSE) and cross validation mean square error (CV MSE) obtained for the months of January to December. As shown in Table 3 the MSE values ranged between 0.002 and 0.004, while CV MSE ranged between 0.03 and 0.053, which implies that the ANN predicted solar radiation values are very close to the actual values.

Table 3: Values of MSE and CV MSE for each network model

MONTH	MSE	CV MSE
JANUARY	0.002	0.045
FEBRUARY	0.002	0.05
MARCH	0.004	0.05
APRIL	0.003	0.03
MAY	0.003	0.043
JUNE	0.002	0.04
JULY	0.003	0.04
AUGUST	0.003	0.053
SEPTEMBER	0.003	0.035
OCTOBER	0.002	0.04
NOVEMBER	0.004	0.054
DECEMBER	0.003	0.039

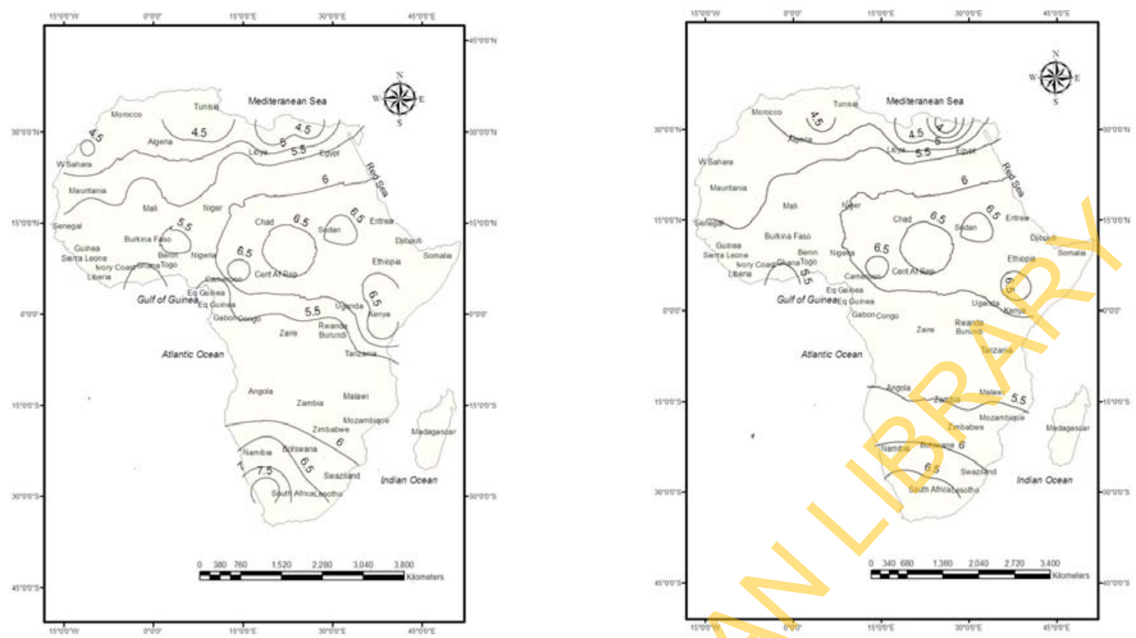
Fig. 3: Comparison between the ANN predicted and actual solar radiation for the month of January in Africa

Prediction of solar radiation potential in Africa: After the network has been trained with sufficient accuracy, the model was used to predict the monthly mean solar radiation potential for other 58 locations spread over Africa that were not used in the training of the model. The actual and the ANN predicted monthly mean solar radiation values for the 58 locations for the months of January to December were presented in the form of monthly maps in Figures 4 to 15 using the Geographical Information System (GIS) software ArcVeiw® 3.2. Figures 4 – 15 (a) show the actual solar radiation maps, Figures 4 - 15 (b) show the ANN predicted solar radiation maps. It can be seen that the ANN predictions are very close to the actual solar radiation values. It can also be observed that the trend of the contour lines showed that from April – September the solar energy potential was higher in the northern hemisphere, which is the region of Africa above the equator. The solar energy potential over Northern Africa within these periods ranged between 5.0 and 7.5 kW h/m^2/day (Figures 7 – 12). These periods correspond to the wet season when the sun is directly overhead the northern region of Africa, thus, causing intense solar radiation. The Sahara desert is also located in this area, the low amount of cloud-cover over the desert also make the condition of higher solar energy potential for the desert region possible. Southern Africa, which is the region below the equator, showed lower solar energy potential for the same period. The sun is at an oblique angle during this period and is never directly overhead the southern region of Africa. This relative inclination of the southern region to sun radiation during this period thus affects the amount of solar energy reaching the region. Hence, lower values of solar radiation were observed in the southern region for these periods, which varied between 3.5 and 5.5 kW h/m^2/day (Figures 7 - 12). However, the trend was reversed for the months of October to March. The solar energy potential for these periods was higher in the southern hemisphere of Africa compared to the north hemisphere. This corresponds to the period when the sun is almost directly overhead in southern region. For these periods, the solar energy potential for the southern region of Africa ranged between 5.5 and 7.5 kW h/m^2/day (see Figures 4 - 6, 13 and 15). The Kalahari Desert, which covers most of Botswana and portions of northern South Africa and eastern Namibia and the Namib Desert, which stretches along the southwestern coast of Africa, from southern Angola along the entire length of Namibia, and into western South Africa, are typical areas with the highest solar radiation (7.0 – 7.5 kW h/m^2/day) for these periods. The solar radiation potential for the same period in the northern region of Africa were lower and ranged between 2.5 and 5.5 kW h/m^2/day.



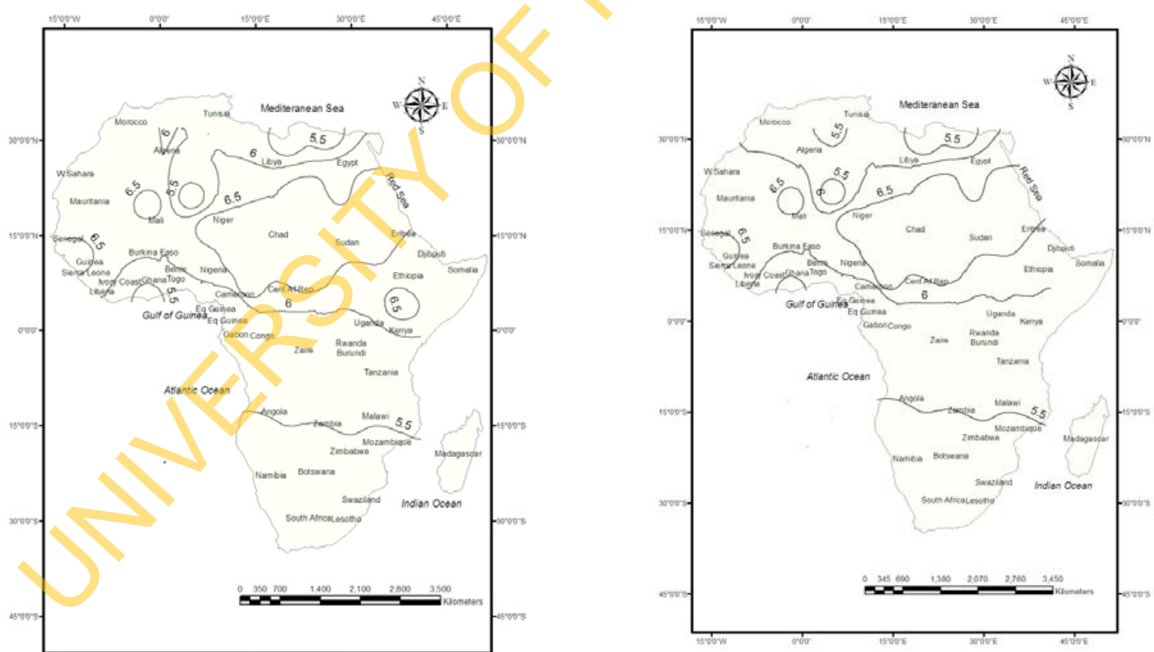
(a) (b)

Fig.4: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of January in Africa



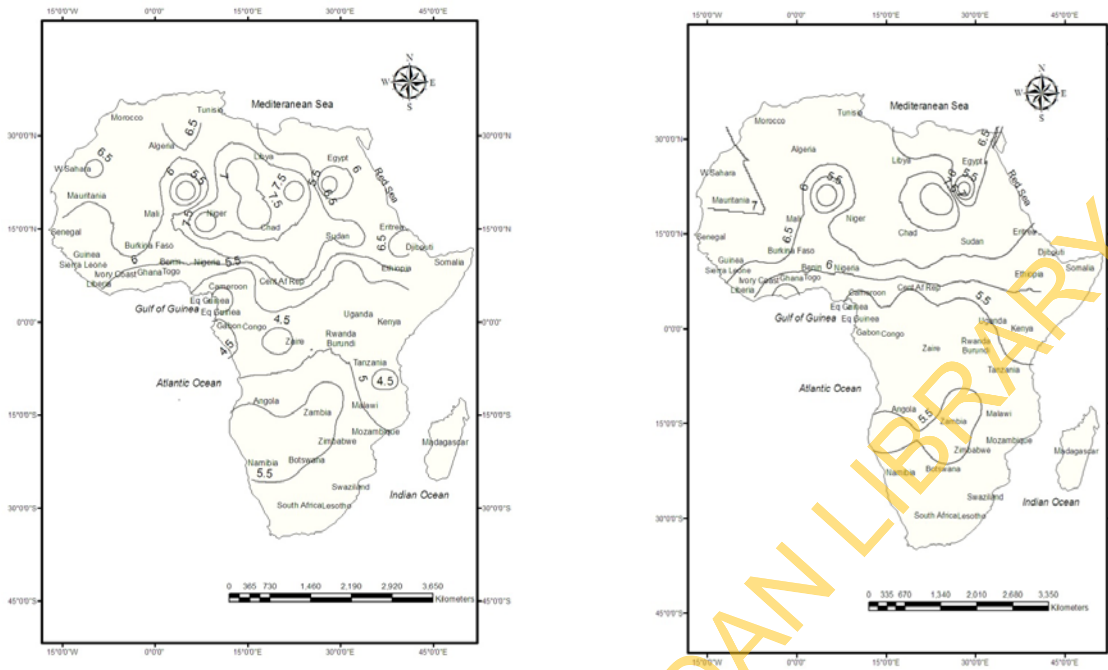
(a) (b)

Fig. 5: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of February in Africa



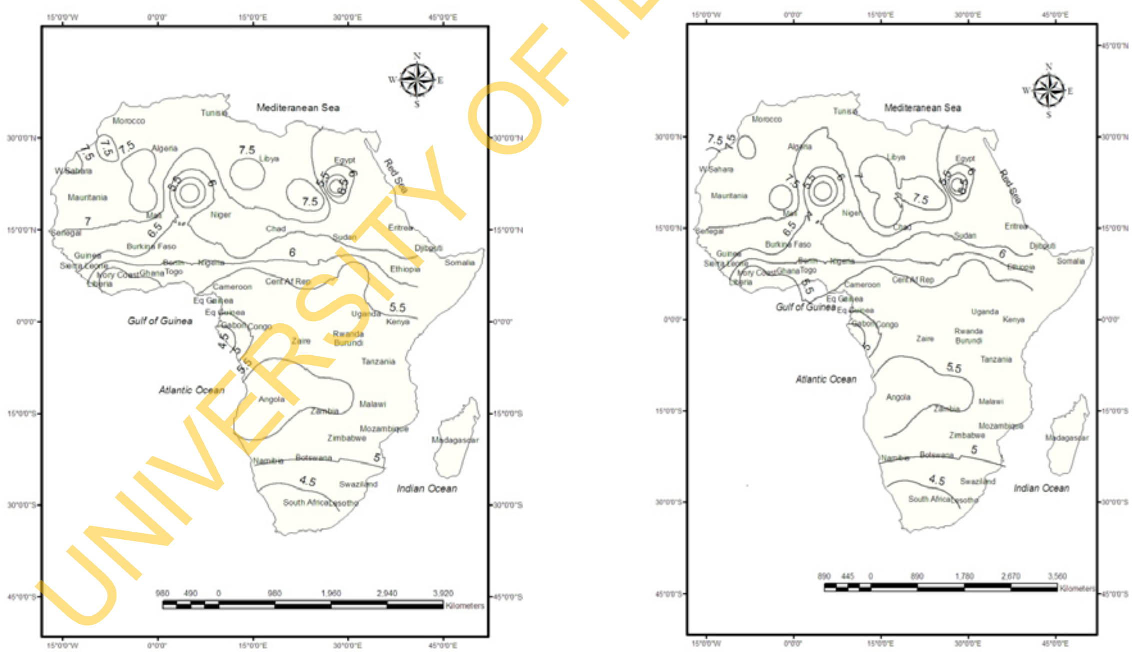
(a) (b)

Fig. 6: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of March in Africa



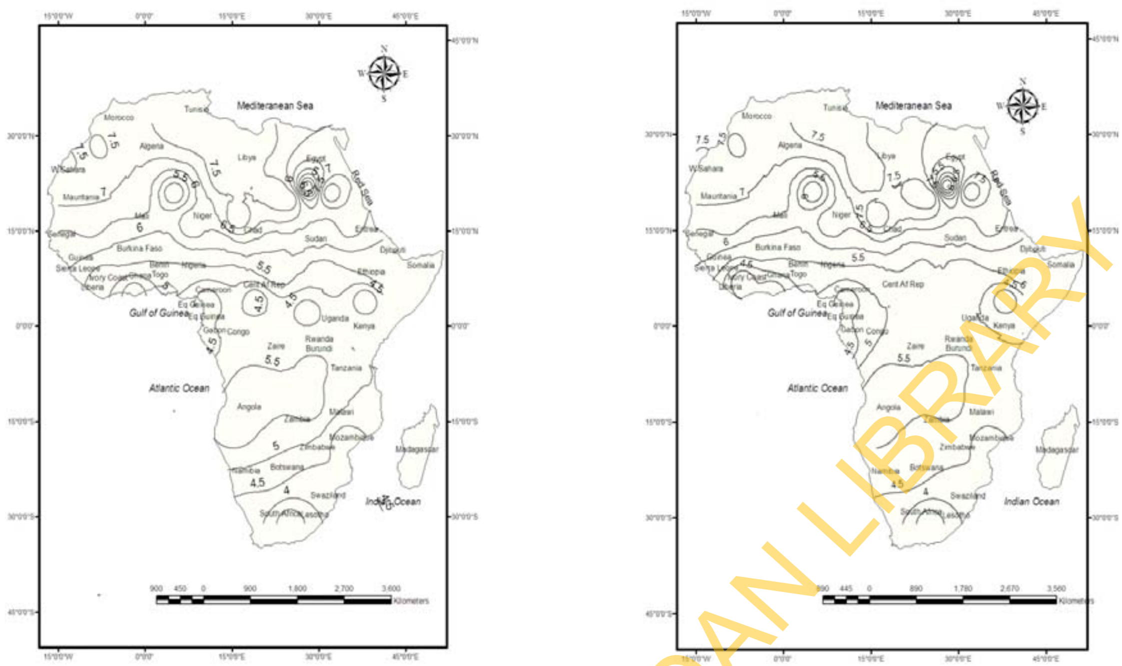
(a) (b)

Fig. 7: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of April in Africa



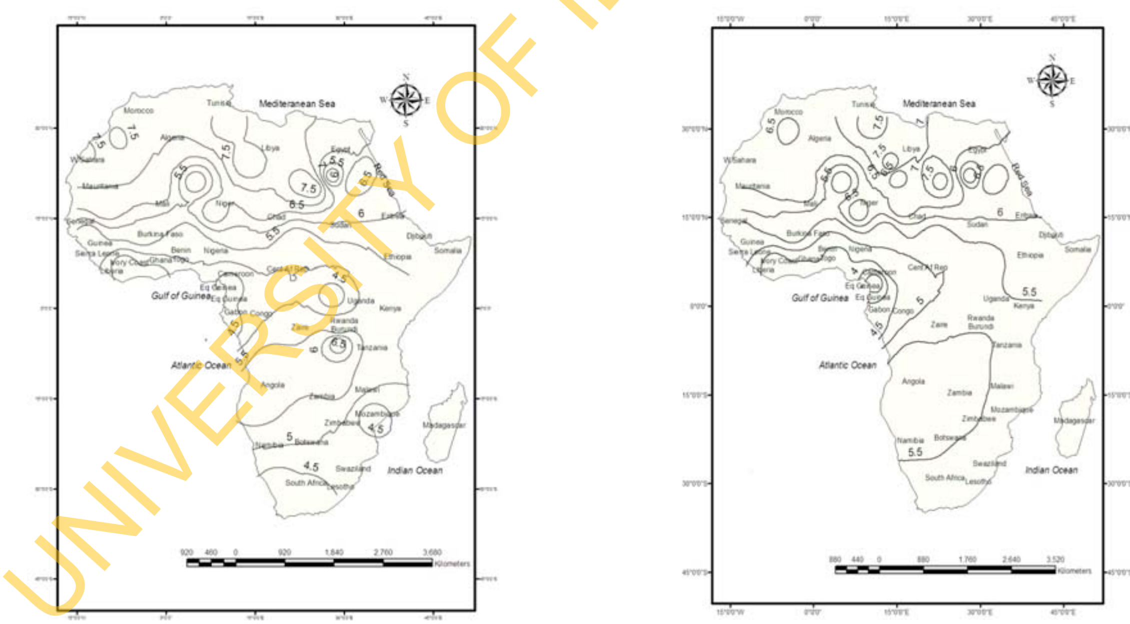
(a) (b)

Fig. 8: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of May in Africa



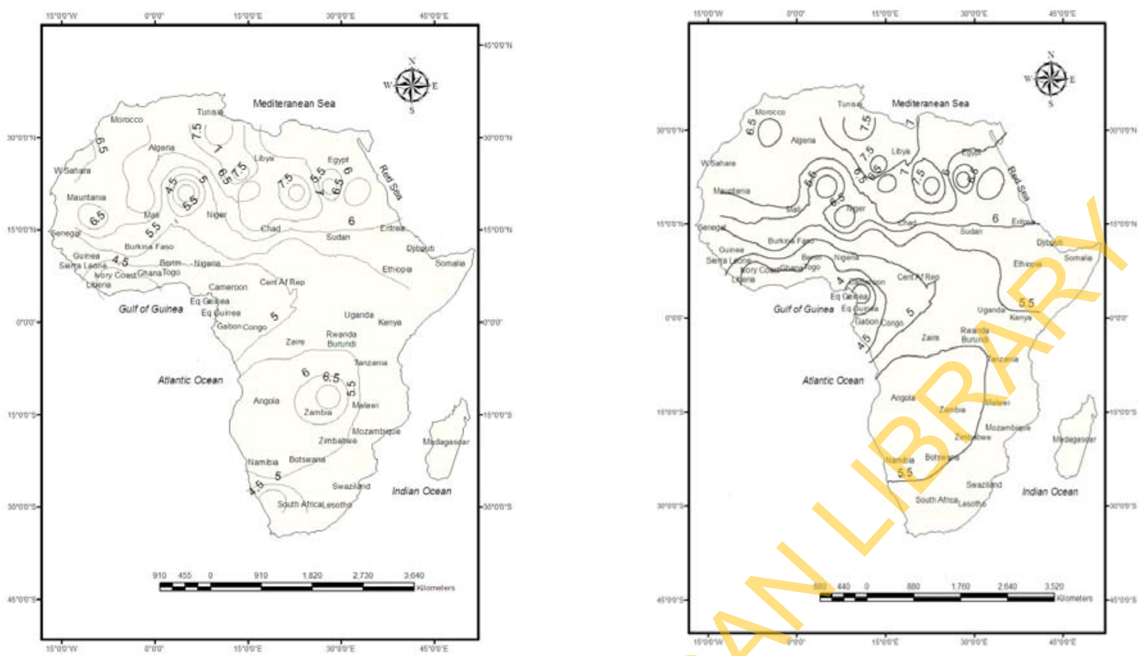
(a) (b)

Fig. 9: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of June in Africa



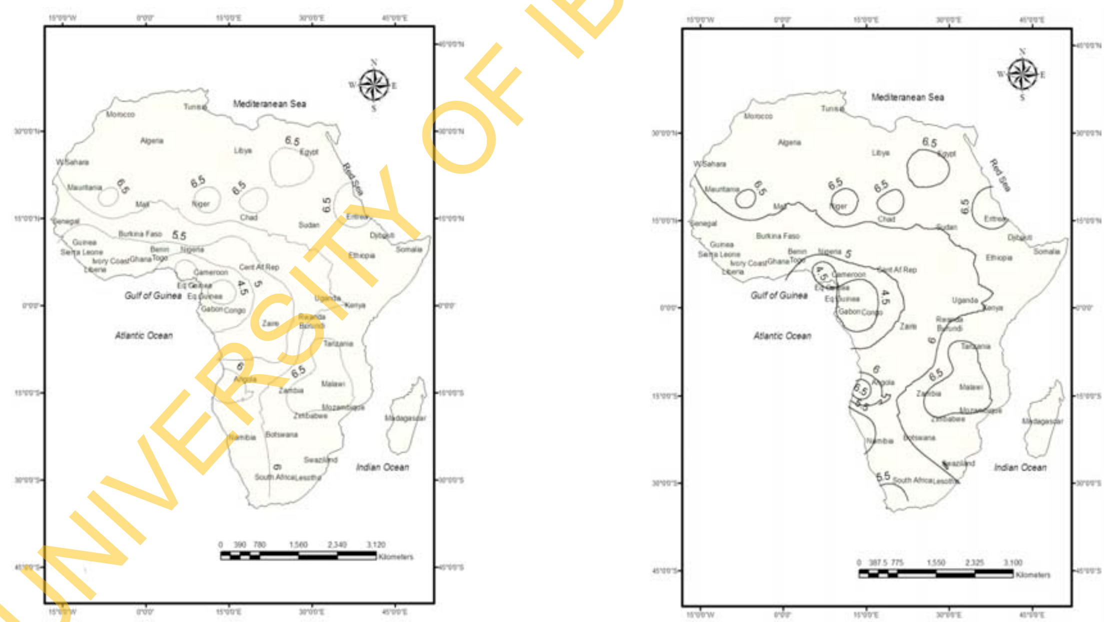
(a) (b)

Fig. 10: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of July in Africa



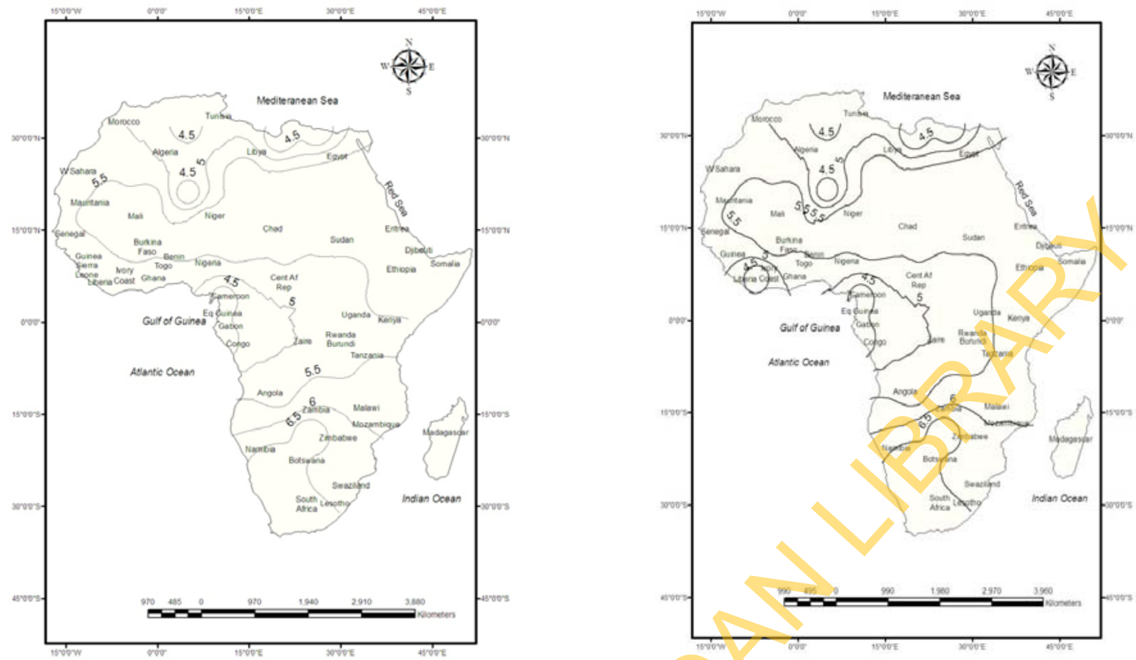
(a) (b)

Fig. 11: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of August in Africa



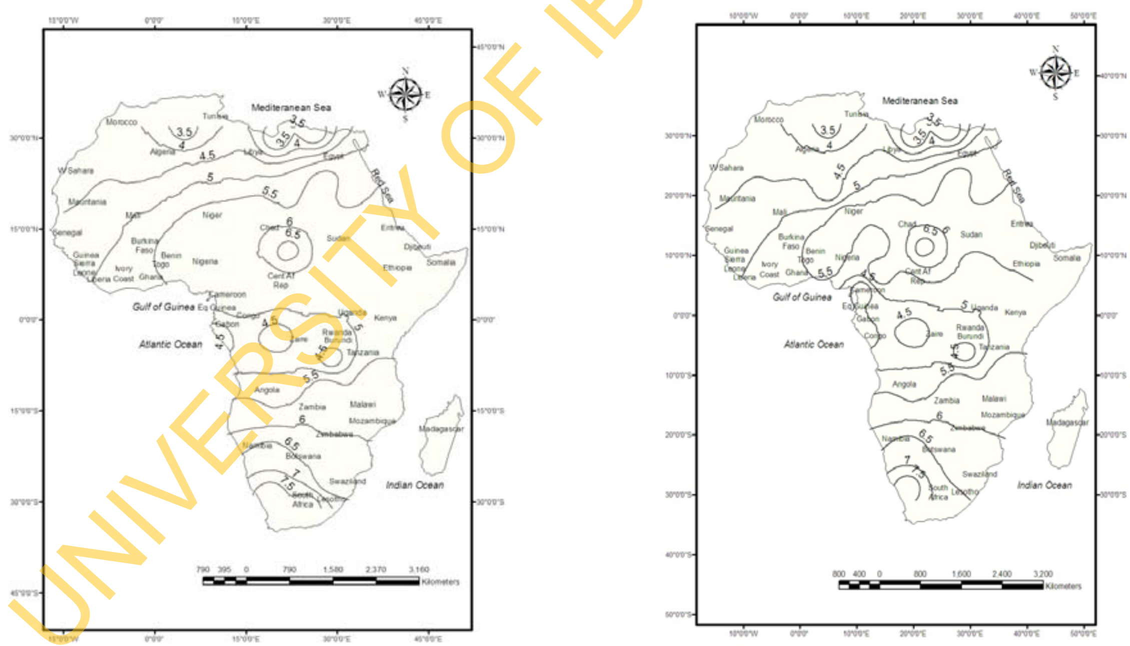
(a) (b)

Fig. 12: Actual (a) and ANN (b) predicted solar energy potential (KWh/m^2/day) for the month of September in Africa



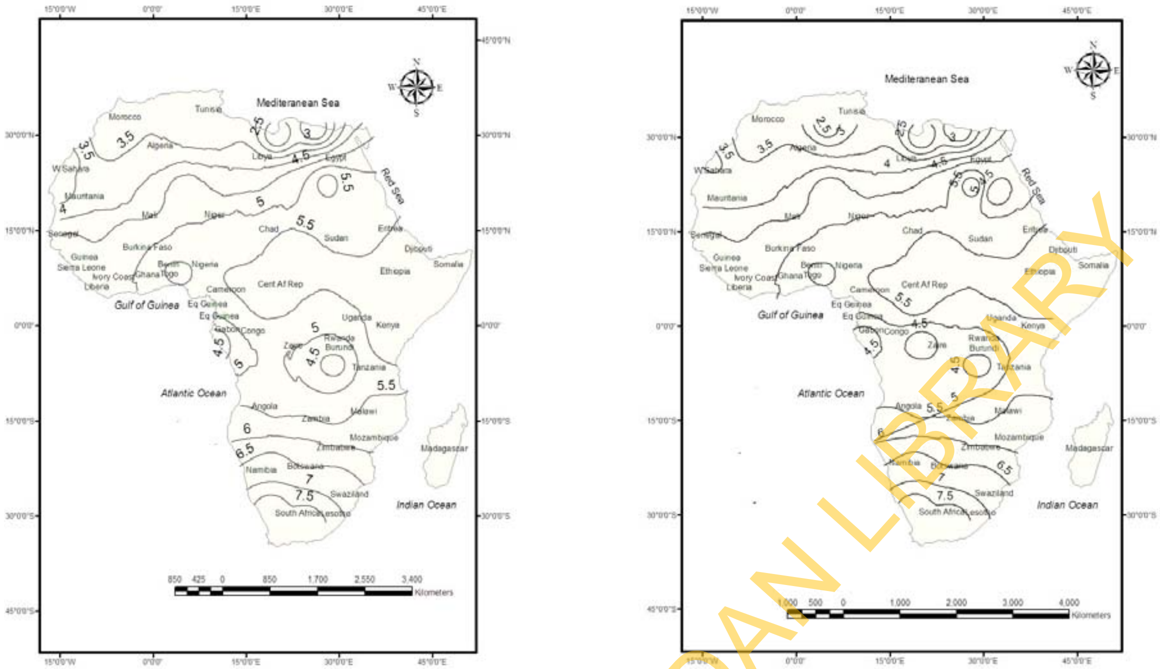
(a) (b)

Fig.13: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of October in Africa



(a) (b)

Fig. 14: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of November in Africa



(a) (b)

Fig 15: Actual (a) and ANN (b) predicted solar energy potential (kW h/m^2/day) for the month of December in Africa

CONCLUSION

The comparison of the ANN predicted solar energy potential compared with the actual values showed negligible difference. Hence, the study confirms the ability of the ANN- based model for accurate modeling and prediction solar radiation data. The ANN model was capable of predicting accurately and therefore, can be used to predict solar radiation for any location without solar radiation data but provided that comprehensive meteorological data are available.

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