Analysis Of Solar Radiation Data From Satellite And Nigeria Meteorological Station

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Abstract- Life largely depends on the radiation from the sun. This is mainly because virtually all physical, chemical and biological processes occurring near the ground or in the atmosphere involves energy transformation. The solar radiation data at ground level and in the atmosphere are an important feature in solar energy applications such as photovoltaic systems for electricity generation, solar collectors for heating and passive solar devices. In this paper a comparison of solar radiation data measured with the satellite and the ground measurement radiation was analyse. The Kolmogorov-Smirnov test which is use in assessing statistical similarity between the two sets of data was applied to global horizontal daily radiation data value from Gun-Bellani Pyranometer collected at Nigeria Meteorological Agency Oshodi, Lagos and Satellite data from National Aeronautics and Space Administration (NASA). The result affirm that the new parameters contribute valuable information to the comparison of the data sets complimenting those that are found with Mean Bias and Root Mean Square difference.

Keywords- Mean Bias difference, Root Mean Square difference, solar radiation, Kolmogorov-Smirnov test.

1. Introduction

Solar radiation is a major requirement in our environmental processes for example, in evaporation and transpiration, rock weathering and the development of landforms. It is also significant for other processes related to water, land, soil, vegetation, and animals. Although so important, only a very small fraction of solar energy poured out into the space by the sun is intercepted by the earth. Most of the energy is lost in space. It is therefore not surprising that the study of solar radiation is fundamental in all studies related to energy balance in any area. Researchers used data from meteorological Stations and Satellite to predict weather and to broadcast storm warning when necessary. Various authors have used different methods of estimating irradiation on earth surface, Perez. et al (1997); Zelenka et al..(1999), use geostationary satellite data for the estimation irradiation on earth surface against interpolation method applied to measurement data from a metrological network. Satellite data are instantaneous measurements over a small solid viewing angle, while ground measurements are integrated over a time and solid angle of 2π, Noia .M et al., (1993).

The solar radiation data at ground level is an important feature in solar energy application. This information can be obtained from difference data source. This information can be derived from the ground measurement by Pyranometer, reference cell or derived from satellite data. When data are measure, strict quality controls are mandatory in order to build a confidence data base.

The model accuracy is determined by validation or comparison of modeled data series against measured or other reference data series. Hence it is important to quantify the similarities or the differences between the two series. Usually graphics and correlation are most commonly used method for this task.

The validation of modeled radiation value against measurement focuses usually on the root mean square differences (RMS) and mean bias difference (MB) as shown in the studies of Davies et al. (1996), Djemaa and Delorme (1992), Pereira et al (1996), Perez et al. (1997), Argirion et al.(1999), Schillings et al. (2003), and Lefevre et al. (2007). Other parameters are the determination coefficient by illera et al., (1995), lopez et al., (2001), Gueymard et al,(2003), standard deviation Lopez and Batlles, (2004), Kudish et al., (2005) and, in a less number of cases, the variation coefficient, and difference between the mean and the median Kudish et al.(2005) and the analysis of the residuals Rubio et al., (2005), Gueymard, et al (2003) are widely used as well. Subsequent validation studies introduce higher moments of distribution, skewness and Kurtosis, as validation benchmarks Perez et al., (1992), De Miguel et al., (2001). However this parameter are often insufficient to establish a complete coherent comparison for benchmarking, due to the additional measures for model quality based on the analysis of cumulative distribution function (CDF) have been introduced e.g. Pereira at al (2003) who introduced a sort of root mean square (RMS) for the difference cumulative distribution function, since all the cumulative distribution function (CDF) begin at zero and raise to one, it is the behavior between these two values that distinguishes distribution, thus, the series.

In this paper several statistical measure are introduce for quantification of numerically comparable result from different sets of data obtain from ground measure at metrological station in Nigeria through out the south west and satellite measure from national aeronautic and space (NASA) .The new parameter, based on the Kolmogorov-Smirnov (KS) test Messay, Jr., F.J., (1951) are proposed to assess two similarity of two data sets, Although there are several statistical test and ways of evaluating the goodness of fit, KS test has an advantage of making no assumption about the data distribution and is thus a non parametric, distribution free test.

2. Data

The data used throughout this study are the measured average daily solar radiation (mm) ground data taken for five cities located in south-west of Nigeria and collected from Nigeria Metrological Agency, Oshodi over the time period of 1986 to1990. The satellite data are retrieved from image data of the geostationary metrological satellites measured by National Aeronautics and Space Administration (NASA) ($MJ/m^2/day$). The daily average radiation derived from satellite image cover the same period and has been calculated for each of the above mention locations in mega joule per meter square per day .The ground data, average daily solar radiation and the daily average data derived from satellite are all converted to $KWh/m^2/day$. Fig.1 shows the geographical location of each station.

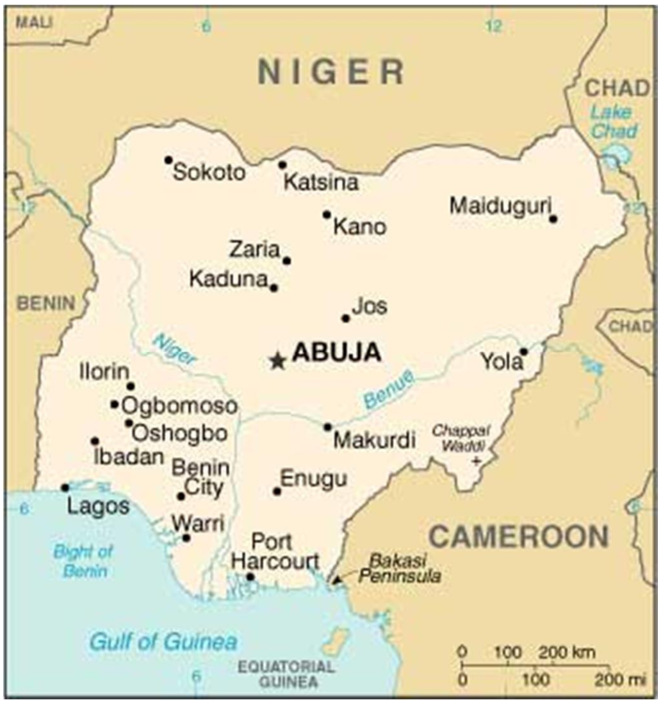

Fig. 1. The geographical location of each station

3. Methodology

The Kolmogorov-Smirnov (KS) test determine if two data set differ significantly with this test, the distribution of a data sets is compare to a reference distribution and the difference are accessed. This is done by converting the least of data points to an unbiased estimator S (x_i) of the cumulative distribution function,

i= 1, 2, 3……n where n is the size of data.

The Kolmogorov-Smirnov (KS) test, statistic D is defined as the maximum value of the absolute difference between the two cumulative distribution functions.

$$D=max/S(xi)–R(xi) \qquad (1)$$

R (x_i) is the cumulative distribution function (CDF) of the reference set, the belonging null hypothesis can be formulated as follow: If the D statistic characterizing the difference between one and the reference distribution is lower than the threshold value Vc, the two data set have a very similar distribution one could be statistically be the same in this case, the null hypothesis is accepted. The critical value Vc depend in on N and its calculated for a 5% level of confidence as Messey et al (1951).

$$V_c = \frac{1\cdot 360}{\sqrt{n}}, N \geq 21 \quad (2)$$

This test detects smaller deviations in cumulative distribution than the x^2 test does Messy et al (1951). However, instead of using the original one, an extended KS test is used here, in the maximum differences between the cumulative distributions functions (CDFs) are calculated over the whole range of the variable x: In this case, daily solar irradiation data are tested. A discretisation in n = 1,…,m levels is applied. In the following m = 100 intervals are used. Greater order of magnitude for m is not recommended since it implies more computational power for no accuracy improvement in the result. e.g., for m = 1200, the greatest variation for the KS test parameters is around 2%, but the time computation increases greatly.

The interval distance p is defined as

$$P = \frac{X_{max} - X_{min}}{M} \quad (3)$$

Where X_{min} and X_{max}, are the extreme values of independent variable. Then, the difference between the cumulative distributions functions (CDFs) are defined for each interval as

$$Dn=max/S(x_i)–R(x_i)/,x_i \quad (4)$$

$$\in [x_{max} + (n – 1) p, x_{min} + np$$

The representation of the values D_n, along with the critical value V_c show the complete testing behavior of the cumulative distribution functions (CDFs) with respect to the reference cumulative distribution functions (CDFs) over the whole range. Thus, the extended Kolmogorov-Smirnov (KS) test is very useful for model response assessments. It has been used before Ramirez et al, (2000), Zarzalejo et al, (2006), Polo et al, (2006). However, although the application of Kolmogorov-Smirnov (KS) test contributes valuable information, it only materializes in the acceptance or rejection of Null hypothesis. in this work, the calculation of parameter is proposed, which, based on the estimation of the differences between the two compared cumulative distribution functions (CDFs), by allowing a quantification of the difference distribution functions over the whole range in a single number.

4. Description Of The Parameters

4.1. Root Mean Square (Rms)

Root Mean Square is the square root of the mean square value of a random variable based on the Kolmogorov-Smirnov. It is a statistical measure of the magnitude of a varying quantity. It can be calculated for discrete values or for a continuously varying fraction. This can be expressed as equation (5) and the result is shown in Table 1.

Table 1. The Kolmogorov-Smirnov test integral for the cities are as follow

Location	KSI	R^2	RMS
Ikeja	137.18%	1.07	0.23
Ondo	58.6%	0.38	0.02
Akure	105.8%	0.91	0.21
Abeokuta	108.9%	0.77	0.17
Ibadan	109.3%	0.82	0.18

4.2. Root Square (R2)

Root Square is the square root of the square value of a random variable based on the Kolmogorov-Smirnov. It scan be used to calculate a discrete values. This is expressed by “equation (6)” and the result of the root square based on Kolmogorov-Smirnov can be shown in Table 1.

$$R^2 = \sqrt{x_1^2 + x_2^2 + x_3^2 \ldots\ldots\ldots . x_n^2} \quad (6)$$

4.3. Kolmogorov-Smirnov Integral, Parameter Ksi

The Kolmogorov-Smirnov test integral (KSI) parameter is defined as the integrated differences between the cumulative distribution functions of the two data sets.

The unit of this index is the same for the corresponding magnitude. The value of which depends on it. The graph in figure 2 to 6 show the cumulative distribution functions for the data of the cities.

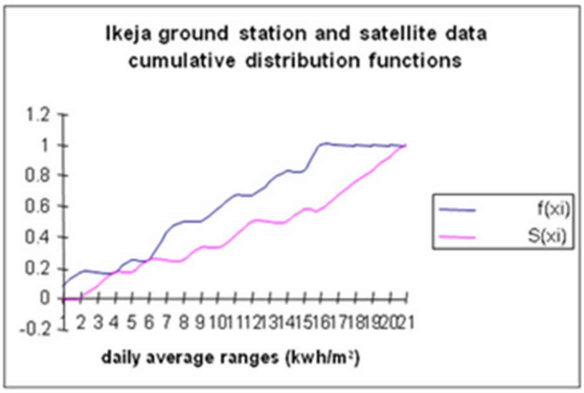

Fig. 2. Ikeja ground station and satellite data cumulative distribution functions

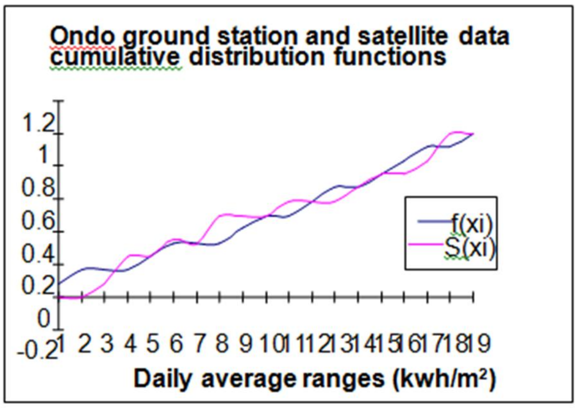

Fig. 3. Ondo ground station and satellite data cumulative distribution functions

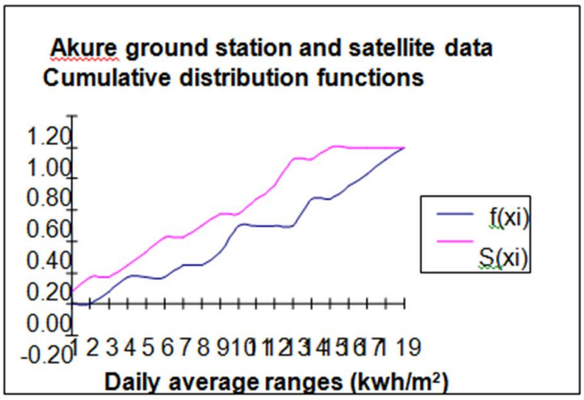

Fig. 4. Akure ground station and satellite data cumulative distribution functions

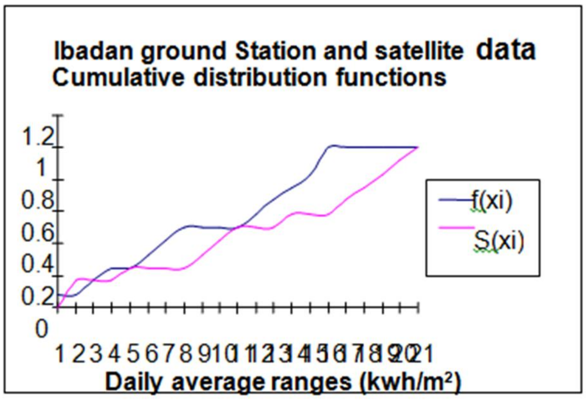

Fig. 5. Ibadan ground station and satellite data cumulative distribution functions

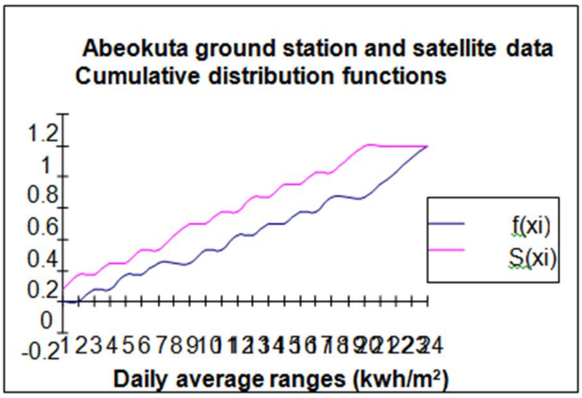

Fig. 6. Abeokuta ground station and satellite data cumulative distribution functions

The differences in Kolmogorov-Smirnov Dn between the cumulative distribution functions are shown in Figure 7 to 11.

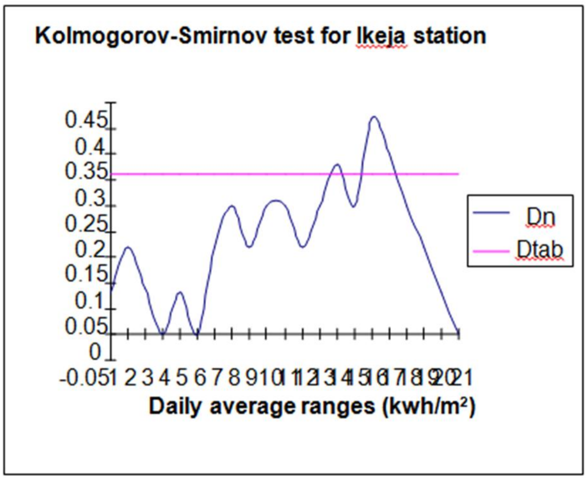

Fig. 7. Kolmogorov smirnov test for ikeja station

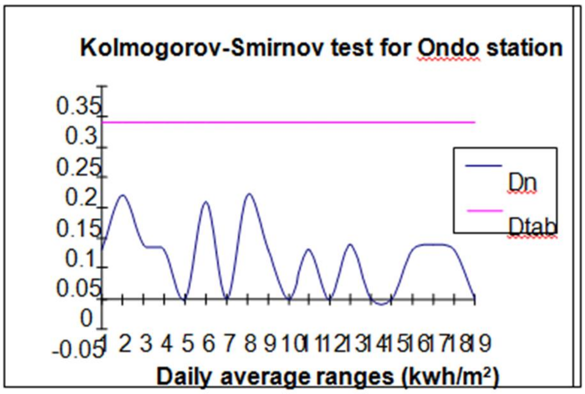

Fig. 8. Kolmogorov smirnov test for Ondo station

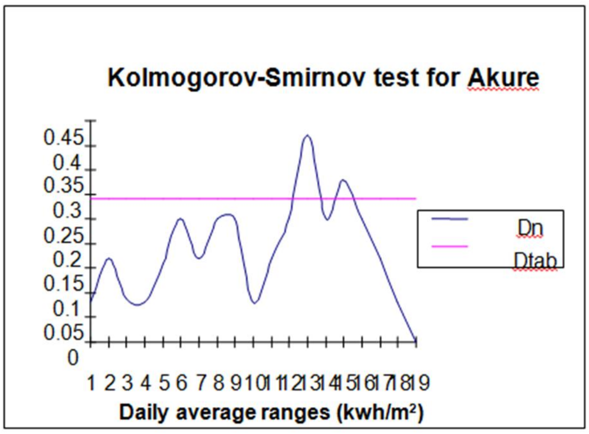

Fig. 9. Kolmogorov smirnov test for Akure station

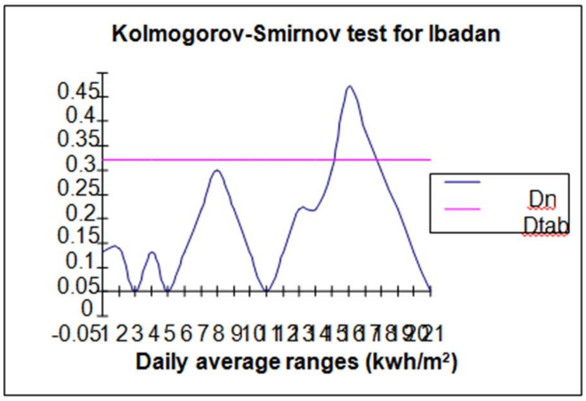

Fig. 10. Kolmogorov smirnov test for Ibadan station

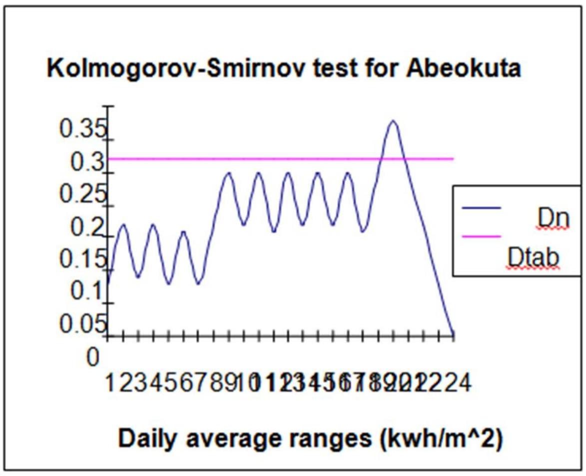

Fig. 11. Kolmogorov smirnov test for Abeokuta station

The dotted line represents the critical limit V_c, which is calculated for the number of available date.

The KSI is therefore defined as the integral.

$$KSI = \int_{xmin}^{xmax} Dn \cdot dx \quad (7)$$

As D_n is a discrete variable and the number of integration interval x is identical in all cases, trapezoidal integration is used over the whole range of the independent variable x. a relative value of KSI integral is obtained by normalizing the critical area, a critical.

$$KSI(\%) = 100 \int_{xmin}^{xmax} Dn \cdot dx \quad (8)$$

a critical

$$\text{a critical} = V_c \text{ x } (X_{max} – X_{min}) \quad (9)$$

The normalization to the critical area allows the comparison of different KSI (%) values from different test. The minimum value of the KSI index is zero, which means that the cumulative distribution functions of the two data set compared are equal.

4.4. Parameter Over

In definition of this parameter the critical limit from the original Kolmogorov-Smirnov (KS) test is applied and calculated according to the number of data N in the set. For its determination, the integration is calculated only for those differences between the cumulative distribution function (CDFs) that exceed the critical limit Vc_c. Figure 7 to 11 shows the results of plotting the CDF for the five stations.

To calculate the OVER, the auxiliary vector for the values that exceed the critical value aux is generated at first. If any of the components does not exceed the critical value vc, it's corresponding in the auxiliary vector is zero.

$$Aux = \begin{cases} Dn - Vc \; if \; Dn > Vc \\ 0 - \quad\quad if \; Dn < Vc \end{cases} \quad (10)$$

The OVER parameter and its relative value are then calculated as the trapezoidal integral of that auxiliary vector and normalized to the critical area.

$$Over = \int_{xmin}^{xmax} Aux \cdot dx \quad (11)$$

$$Over(\%) = 100 \int_{xmin}^{xmax} Dn \cdot dx \quad (12)$$

4.5. Evaluation Parameter Based On Ks Test, Kse(F)

When the KSI and the OVER indexes have been defined, the need raised to combine the information for both parameters in one. This allows to generate a continuous series of parameters, but also maintaining the cutoff point estimated by the OVER index. Therefore, the following linear combination is proposed.

$$KSE = KSI + (OVER \times F) \quad (13)$$

Where F is an empirical weight, which is multiplied with the OVER value. OVER and KSI expressed as relative values. In the definition, more weight has been given to the OVER, because this index is considered to be the most determining in the classification of the results. Thus, for an OVER equal to zero, the KSE(F) value is those of the KSI, but for an OVER greater than zero, the KSE(F) grows constantly. KSE for f=100 and f =500 are shown in Table 3.

4.6. Proposal for a general parameter: RIO

In continuation a classification base on the use of the parameter, the parameter RIO is proposed. It combine the three most representative parameter: OVER(%), KSI(%), and RMS(%) (Thus, it name: RMS, KSI, OVER). Base on KSE(F) it seems pertinent to combine the information from the cumulative distribution functions (CDFs) with the information supplied by the root mean square (RMS). This is done as follows:

$$RIO = (KSE(F) + RMS)/2 \quad (14)$$

Root mean square RMS expressed as its relative value. A RIO greater than 100 means a poor similarity of the data series for the weight F. values are sorted as ascending from the lowest to the highest .The highest RIO to classify the results according to their statistical similarity with respect to the unit line and to the regression line. The root mean square RMS(%) and KSI(%) keep within the range of reference values. This contribution to the RIO is defined when the OVER(%) is null.

5. Result And Discussion

The measured data and the estimated sets have been transform to daily averages in the same unit (kwh/m^2/day) in Table 2, the correlation is calculated and the differences between the cumulative distribution functions (CDFs) are plotted for the data of each station.

Table 2. Converted Data From Mlimeter (Mm) To Kilowatts Hour Per Meter Squre Per Day For The Daily Global Horizontal Radiation (1986-1990)Unit: (kwh/m^2/day)

Ref/stn	Lagos	Ondo	Akure	Abeokuta	Ibadan
Jan	5.24	5.10	5.17	4.12	4.09
Feb	5.32	5.64	5.56	5.06	5.68
Mar	5.32	5.41	5.76	5.25	5.80
April	5.21	5.48	5.99	5.17	6.15
May	4.75	4.71	5.60	4.98	5.64
June	4.16	4.20	5.13	4.36	5.06
July	3.70	3.11	4.05	3.19	3.85
Aug	3.67	3.23	4.08	3.15	3.85
Sep	4.73	4.16	4.89	3.89	4.55
Oct	5.00	4.62	5.56	4.55	5.37
Nov	4.37	5.32	5.91	4.71	5.76
Dec	4.79	5.66	5.17	4.01	5.02

Table 3 show the value of the usual statistic (RMS(%), MB(%), and R2) along with the result of the parameters, Kolmogorov-Smirnov (KS) test quantifiers (KSI(%) OVER(%) and KSE(F)).

Table 3. Results sorted from the lowest to the highest RIO_500 values

Station	Ikeja	Ondo	Akure	Abeokuta	Ibadan
Num	20	19	19	20	21
RMS (%)	23.30	2.00	21.00	16.70	17.80
MB (%)	-18.00	3.00	18.00	17.00	-13.00
R^2	1.07	0.38	0.94	0.77	0.82
KSI (%)	137.2	58.6	105.74	108.86	109.33
OVER(%)	36.70	0.00	5.73	10.13	10.53
KSE_100	30.07	0.43	5.09	8.86	8.72
KSE_500	146.07	0.43	22.29	40.86	40.32
RIO_100	15.15	0.25	2.65	4.52	4.45
RIO_500	73.15	0.23	20.27	20.51	11.25

Finally, the RIO(F) parameters, calculated as the linear combination described above, are also given in Table 3. The result are shown sorted according to RIO_500 parameters, as in this case, the use of the factor F = 100 does not give enough weight to the over index compared to the Kolmogorov-Smirnov integral (KSI). Example, the station Abeokuta would not be classified properly. Here, it is very important to notice that station classification results using usual parameters are not the same. Therefore, in a preliminary analysis as shown in Table 4, the extreme values from the RMS(%), MB(%), KSI(%), and OVER(%) parameters extracted.

Table 4. Extreme value of main evaluation parameters and there means. In parenthesis 0f the station that reach each of these values

	Rms	Mb(%)	Ksi(%)	Over(%)
Best result	2.00 Ondo	3.00 Ondo	58.6 Ondo	0.00
Worst result	23.30 Ikeja	-18.00 IKeja	137.2 Ikeja	36.70
Mean result	16.16	1.40	103.946	12.62

The graph result sorted from the lowest to the highest RIO_500 values against the stations through out the south-west in Nigeria.

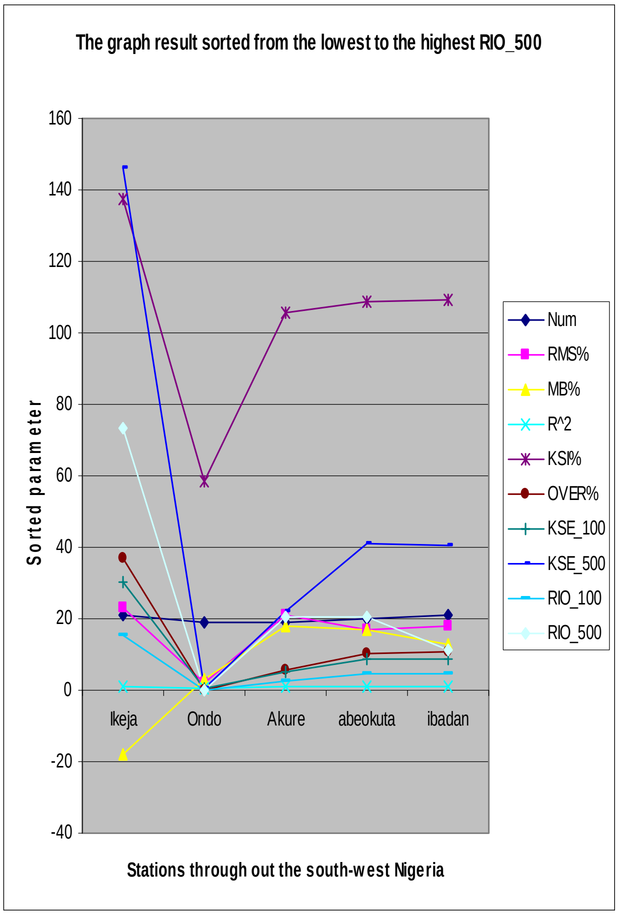

Fig. 12. The graph result sorted from the lowest to the highest RIO_500

The definition of the KSE and RIO parameters reflects the effect of the weight factor (F = 100, 500) at the stations in a Abeokuta and Ibadan. Although before these, the values coincide with those of the Kolmogorov-Smirnov integral. As the over is recorded with non-null values, here the weight factor that shows its effect. The better positioning of the result is observed for F = 500. The symmetry between RMS and KSE is noteworthy, while OVER remain null and RIO shows a quasi- linear increase. This symmetry disappear for non-zero value of OVER, when the KSE increase greatly. The importance of incorporating the new information on the cumulative distribution function CDF allows distinguishing the behavior of stations with similar Root mean square RMS value. It may be observed that by using the RIO_500 index, a single complete classification of all of the stations is achieved.

The best results in RMS (%) are found at the station in Ondo (KS), Ondo has the best MB (%) and best KSI (%). All the parameters coincide in the worst result of comparing the measured and estimated data is found at the Ikeja station .Here, it is important to point out that the values of the various parameters describe different characteristics of the behaviour of the data. The RMS and the R2 show how the points are clustered around a regression, so, the closer the points are to the line, the better are the results, and worse if they are more scattered. On the other hand, the results of the KSI and the MB show the distribution of the points around a unit line, but the KSI also provides information on the behaviour of the CDF. Thus, in Table 4 it is displayed that the RMS (%) indicates that the Ikeja station has the worst fit to the regression line; the MB (%) and the KSI (%) also show that the station in ikeja fits worst to the unit line.

After studying the results, it can be stated that the development of the RMS and the new index KSE are complementary. Thus the RMS informs on the statistical comparison of distribution functions. The generation of a single parameter (RIO) that accounts for all of these aspects is therefore considered as pertinent for more complete information on the comparison of data sets.

6. Conclusion

The basis for the proposal of the new parameters is the KS test Massey (1951). But in this case the aim is the quantification of numerically comparable results from the different sets. Therefore, the parameters KSI and OVER are introduced. The KSI is the integration of differences between the CDF for the two sets. The OVER is also the integrated differences between the CDFs, but only for the ones where the critical value Vc is exceeded. In addition, its relative value provides a value comparable between different data sets.

A third parameter, the KSE has been developed to combine the KSI (%) and the OVER (%). The purpose is to generate a single value accounting for the OVER cut-off point above or below zero, thus, to enable a continuous classification of the results.

From the analysis of the results in Table 3, several conclusions may be derived. In the first place, it is clear that a classification of stations from the best to the worst behaviour varies quite a lot depending on the used parameters.

The OVER is the only one that allows the observing of a significant difference in the behaviour of the comparison. It shows whether the critical value is passed or not. So the classification has to account for this value first, classifying those stations as the best that had an OVER equal to zero. That means that the compared data sets are statistically so similar that they could be the same.

The differences found in the comparison of the data may in turn have different explanations. Thus, they may originate both in the behaviour of the measured data at a specific station, such as recording errors, and in the behaviour of the estimates made from the satellite images in the pixels for complex topographies.The RIO (F) parameters enable a single classification of the stations considering the results of the most significant evaluation indicators and, therefore, clearer and balanced conclusions concerning the behaviour of the data sets. We conclude with reference to our findings that there is a discrepancy between satellite estimations and ground stations measurements at this specified location. The Data delivered by each system mainly differ due to the sensor and due to the way of collection of the data itself. Typically, the instrument ,use for ground measurements is the pyranometer, which measures all the radiation coming from the sun and from the sky or clouds The Ground radiation measurement are much localized in space (i.e. depending on the region), whereas the Sattelite integrates the radiation over its pixels, the satellites measure the light (visible or infrared) coming from the Earth. This light is mainly the light reflected from the ground or from clouds.Also satellites do not measure temperature. They measure radiances in various wavelength bands, which must then be mathematically inverted to obtain indirect inferences of temperature. The resulting temperature profiles depend on details of the methods that are used to obtain temperatures from radiances. The effect of the analysis on photovoltaic application in terms of temperature is that bad radiation estimation generates an error in the electricity produce. But underestimating is also very dangerous since the system can be over dimensioned and slightly underestimate the electricity produce. We need the most accurate sizing of the photovoltaic plant. For settling solar power plant purposes, it is interesting to use time series of irradiation values over the longer period of time available and localize precisely on the region of interest. This long period of time enables us to see if there is any global trend of irradiation along the years, as well as analyzing the different scenarios, worst or best year. When you want to know the solar radiation at a specific place, ground station measurements give the best results.

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