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# Interannual and spatial variability of solar radiation energy potential in Kenya using Meteosat satellite

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ABSTRACT

Kenya is faced with a rising demand in electricity resulting from a rapidly growing economy and an increasing population. Being a tropical country, lying astride the equator, solar energy is one of the readily available renewable energy resource options to meet this need. Unfortunately, there is still very low adoption of solar systems in the country which could be majorly attributed to lack of adequate solar resource assessment. Besides, past studies on this area in Kenya only focused on the available amount of solar resource leaving out the issue of variability. To bridge this gap, the temporal and spatial variability of global horizontal irradiance (GHI) and direct normal Irradiance (DNI) is analyzed using 19-year long (1995–2013) Meteosat satellite dataset. GHI interannual variability is low in most parts of the country but DNI has a clearly higher variability except a few locations in the East and Northern desert. Low spatial variability for GHI was recorded for locations within 1225 $km^2$ while DNI variability was double that of GHI. The results offer readers a quick reference of variability of solar resource at different locations in Kenya which is useful in guiding measurement requirements and consequently in promoting deployment of solar systems.

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## 1. Introduction

Governments all over the world have an obligation to ensure that their citizens have access to energy which is vital for social and economic stability and growth. However, provision of energy services must be done in a sustainable and environmentally benign way. One of the most agreeable ways to strike a balance between energy service delivery and a clean environment is by utilization of renewable energy (RE) sources. Besides the fact that they are sustainable, being replenished freely by nature, their greater advantage is that they produce little or no by-products like the carbon emission. In the light of global warming and climate change which is attributed to anthropogenic greenhouse gases emissions, RE sources have received a global attention especially in electricity generation [1–3].

Kenya, a study area here, is a developing country with a fast growing economy at a current GDP annual growth rate of 5.7%. Additionally, according to the recent census of 2009, the population of Kenya which currently stands at approximately 45 million people is also growing at an estimated rate of 3% per annum. Less than 50% of this population has access to electricity with only 5% of the rural population being electrified [5]. It is therefore apparent that, the electricity sector in Kenya is facing a sharp increase in its demand, a factor which is accelerated by current development strategies in place e.g., the vision 2030 economic blue print of 2012, which comes with huge industrial projects and consequently, heavy energy obligations [6].

To address the electricity and energy problem in Kenya, solar systems including photovoltaic (PV) systems, Solar thermal and building thermal systems are suitable RE options, considering that the country is favorably located astride the equator and therefore, has high insolation rates at an average of 5 peak sunshine hours (The equivalent number of hours per day when solar irradiance averages 1000 W $m^{-2}$). However, an addition of solar systems to local electricity mix requires means of handling challenges that arise from cloud induced fluctuations of generated power output, which are a major concern to utilities and grid operators. These fluctuations result from variation of solar radiation incident on the PV cell, and therefore, solar radiation variability studies could give grid operators a prior knowledge of their characteristics at specific

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locations of PV systems' deployment [7].

The radiation reaching the earth's surface can be represented in a number of different ways. Global horizontal irradiance (GHI) is the total amount of shortwave radiation received from above by a surface horizontal to the surface of the earth. This value is of particular interest to flat plate PV installations and includes both direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI). DNI is the solar radiation that comes in a straight line from the direction of the sun at its current position in the sky falling on a surface held at normal to the sun rays. It is relevant for application in solar concentrating technologies including, concentrating solar power and concentrating solar PV [8,9]. In this study, focus is given to the PV technology i.e. flat plate and concentrating PV.

In the Kenya's electricity mix, by August 2014, hydro power generation controlled the largest share at 37.2%. Thermal power plants (medium and high speed diesel power plants) were in the second place providing 30.7% of electricity but these includes emergency power plants which are mainly reserves for drought periods when the hydro power is not sufficient. Geothermal power installed capacity accounting for 27% of Kenya's total electricity production is the third source of electricity [10]. This mix is, however, changing dramatically with accelerated efforts by the government to reduce over-dependency on hydropower to avoid the effects of climate change including shifting rainfall patterns and chronic droughts which threatens the viability of big hydro projects in this region. To shift from the hydro power, while maintaining renewable sourced electricity in Kenya, the government has increased generation from geothermal and wind, and has also indicated interest in nuclear and coal based generation in the future. According to [10]; the electricity production in Kenya by the year 2014 stood at 2,205 MW but has a projected growth of over 500% translating to 21,620 MW of installed capacity by the year 2030 [6,10]. The government has not considered solar PV as a candidate technology in the most recent long-term power system plan towards 2030. In spite of this, Solar PV home systems installed in Kenya have increased rapidly with recent statistics indicating that the country is a leader in the African continent in the number of small scale PV installations. Further, studies show that building water heaters application has increased rapidly in the recent years [17]. Recently, research and development efforts have improved the conversion efficiency of PV cells to as good as 15% by 2014, while laboratory prototypes -not commercialized yet, can give efficiencies up to 30%. Additionally, solar PV plants requires short construction time, very little maintenance costs, and can be built near the consumption, thereby reducing the cost of transmission and distribution losses [8,9,11]. Besides, the costs of solar energy technologies, and most importantly solar PV, have continued to decline rapidly [8,11] and there is therefore the need for system planners to consider these recent developments. Most importantly, solar generated electricity has no greenhouse gases emission during electricity generation, no fuel costs, and no risks of fuel price spikes [2,8], and has therefore the potential to help move the country towards cleaner, reliable, and affordable sources of electricity.

Solar resource assessment conducted in Kenya includes [12] who were among the first to characterize solar irradiation from satellite observation in the region. The study utilized data from METEOSAT 2 limited to a period of two years (1985–1986). This study has vital information on the available amount of global horizontal radiation reaching the earth's surface in three regions namely, Europe, Asia Minor, African continent and parts of Atlantic Ocean. The study further details the annual and temporal variability of solar radiation in the wide study area. [13] also provided solar radiation data in Kenya by mapping annual and monthly potentials of GHI and DNI by using satellite data for a period of three years (2000–2002). In another study [5], reported that Kenya has an average of 5 kWh $m^{-2}$ $day^{-1}$ of solar radiation potential. [14] utilized a digital elevation model to characterize solar energy potential and its spatial distribution and similarly concluded that, Kenya has high radiation energy potential. The study indicated that 34% of the total land of Kenya receives between 5 and 5.5 kWh $m^{-2}$ $day^{-1}$ with another significantly large area covering 26.5% of the total land receiving between 5.5 and 6 kWh $m^{-2}$ $day^{-1}$ while 10.1% of the land receives 6.0–6.5 kWh $m^{-2}$ $day^{-1}$. While the previous studies have given vital information on the available amount of radiation over Kenya, a complete characterization of solar radiation is one which includes variability of this resource. This issue of variability has not been adequately addressed in the previous studies. Variability may be explained in terms of space, that is, how the solar radiation varies with distance or in temporal, how it changes with time, which is normally in different time scales that is, small time steps from seconds to minutes or longer time scales, running from hours, days or even years [7,9,15]. Variability at these different time steps has different impacts to the grid and causes unexpected sudden changes in power output which is a major concern to grid and utility operators. The knowledge on temporal variability informs the system designers about the quality of solar radiation for the intricate design of solar systems for instance, in the sizing of storage systems. Prior knowledge of variability is also useful in relating statistics of short term measurements to long term ones [7,9,16]. For instance, although a single year of data cannot be used to represent a long term measurement, if low interannual variability for a certain place is recorded, it can be assumed that measurement for a short period could be used to explain long term characteristic of solar radiation. Similarly, low spatial variability can be used to conclude that measurement in one place could represent the characteristic of solar radiation in nearby locations [7].

Studies aimed at determining the effects of solar resource variability on solar PV output and its potential impacts to the systems operators begun in the 1980s [17–20]. There have been increased efforts to conduct solar resource variability analysis globally but such studies have not been conducted in Kenya. [7] characterized the interannual and spatial variability of GHI over US and found out that the consistency of solar resource in that country varies widely in both time and space. They mapped the analyzed results over US and provided the data to the national renewable energy laboratory (NREL) where the data is provided free of charge becoming a very useful reference for investors and policy makers in the solar energy industry of that country. [16] conducted similar analysis for Benelux and characterized solar radiation at the different climatic regions in Benelux based on the available amount and the year-to-year variation of solar radiation over Benelux. However, recent study by Ref. [21] in the European Union (EU) concluded that there is a limited understanding of the variability characteristics of future power system. The study reveals that, even though the EU is aiming to develop a future power system with very high contributions from wind and solar production, only a few studies have analyzed the variability characteristics of such a system, whose primary cause is variability of output from the weather dependent generation options like solar and wind. Similar observations had long been made by Ref. [7] who reported that research on solar resource variability is limited globally.

The purpose of this study is to conduct solar resource assessment to determine not only the available amount but also the temporal and spatial variability of GHI and DNI potential over Kenya. With a focus on variability, this study is expected to fill in the gap in previous similar studies in Kenya. This study is expected to deliver useful solar resource information on suitable locations, as well as the best technologies of deployment for these locations in Kenya. Additionally, the findings in this study are expected to

provide guidance on solar radiation measurement requirements in Kenya.

## 2. Study area

Kenya is located in East Africa and lies approximately between 5°S and 5°N in latitudes and 34°E and 42°E in longitudes (Fig. 1). Kenya's terrain is quite diverse, ranging from 0° latitude at the Indian Ocean coast to sandy arid areas, forested uplands, to the highest point at 5,199 m on the perpetually snow-covered Mount Kenya. Particularly striking feature is the Great Rift Valley of East Africa that runs through Kenya. Additionally, a climate contrast exists between the central and southwestern highlands and the low plateaus and plains of the eastern region and desert in northern Kenya. The latter two occupies approximately two thirds of Kenya. The total spatial area of the country is approximately 580,300 $km^2$ and the population was approximated at 40 million people in the latest census of 2009 [22].

## 3. Data and method

### 3.1. Satellite derived surface incoming solar radiation

Satellite derived radiation data has extensively been applied in many studies to characterize solar resource potential owing to the fact that, ground measurements, even though more accurate, has limited spatial coverage [7,9,16]. To utilize this gain, we used surface incoming solar radiation data from the Meteosat first generation (Meteosat-1 to −7) and second generation (MSG-1 to −3) satellites. The particular data sets utilized in this study are called Surface Solar Radiation Data records −Heliosat (SARAH) [23] whose spatial resolution is 0.05° × 0.05° grids in longitudes and latitudes and temporal resolution is hourly. The GHI and DNI dataset was downloaded from the European organization for the exploitation of meteorological satellites (EUMETSAT) website. To characterize the climatology of this resource we took advantage of the available 19 year (1995–2013) long term data for both components because previous studies have indicated that an artificial artifact exist in the 1983–1994 data [16,23]. The Meteosat data product must fulfill very specific accuracy requirements that have been determined by CMSAF. The determination of this accuracy is based on validation performed against ground measured data of the baseline surface radiation network (BSRN). The measurement in the BSRN started in 1993 and the density of this network is very poor for Africa [16,23]. Consequently, the validation fails to capture all the climate regions in Africa including the current study area. Therefore, validation of the satellite data against available ground measured data is conducted in Section 3.2.

### 3.2. Ground measured data

For validation of satellite dataset, four years (2010–2013) ground measured monthly means of GHI for 6 stations were sourced from the meteorological department of Kenya. The

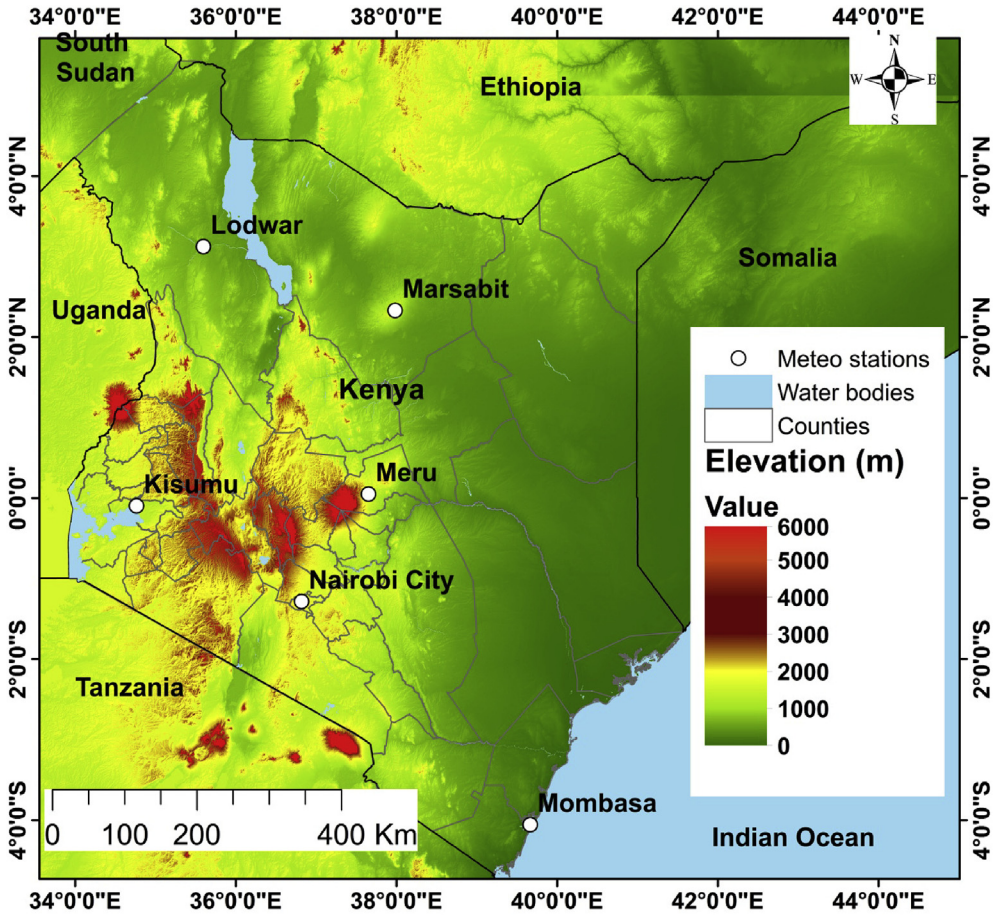


**Fig. 1.** Map of the study area. Thick black lines indicate the international boundary faint black lines indicate the county boundaries and the white dots are the meteorological stations measuring solar radiation in Kenya. Color shading represents topography. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

measurement stations considered are Dagorreti, Lowdwar, Mombasa, Kisumu, Marsabit, and Nyeri (Fig. 1). The choice of these stations was based on the availability of solar radiation data, but fortunately, they also have a good climate representation for Kenya.

Mean bias error (MBE), mean absolute error (MAE), relative mean bias error (rMBE) and the relative mean absolute error (rMAE) are statistical metrics that have been used to quantify the accuracy of satellite derived or modeled radiation data [9,14,16]. Their computation is described in the following equations.

$$\mathrm{MBE} = \frac{1}{N}\sum_{m=1}^{N}[g_d(m) - G_d(m)]$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{m=1}^{N}|g_d(m) - G_d(m)|$$

$$\mathrm{rMBE} = \frac{1}{N}\sum_{m=1}^{N}\left(\frac{g_d(m) - G_d(m)}{G_d(m)}\right)$$

$$\mathrm{rMAE} = \frac{1}{N}\sum_{m=1}^{N}\left|\frac{g_d(m) - G_d(m)}{G_d(m)}\right|$$

where $g_d(m)$ is the satellite derived data, $G_d(m)$ is the ground measured counterpart for each month m, and $N = 216$ is the total number of data points (3 years by 12 months at 6 stations).

The results as summarized in Table 1, shows that, positive MBE of 25 Wh $m^{-2}$ on average over all stations was recorded. The positive MBE values at five out of the six stations indicate that the satellite overestimates solar radiation in the study area. The correlation coefficient between the monthly-mean ground measured and satellite derived solar radiation data combined in all stations was approximately 0.5 indicating a moderate agreement. A scatter plot of the monthly averaged ground measured GHI against satellite derived monthly means for the individual 6 stations for the three years (2010–2013) is shown in Fig. 2a–f. The only negative MBE value obtained in Lodwar is likely due to its location in a desert where the high clear-sky reflection over bright desert surfaces is associated with the underestimation of GHI in such regions [23]. The reflectance from such surfaces reduces the contrast between cloud and ground reflectance, resulting in underestimations of GHI. The highest positive MBE was observed in Meru which is located on the windward side and at the foot of Mt. Kenya. This location is associated with a high amount of cloud cover over the mountains. Since retrieval of SARAH data (i.e. the Heliosat method) relies on the accuracy of retrieval of cloud reflection and clear sky reflection to calculate the effective cloud albedo (CAL), the calculation of CAL can only be determined accurately if a certain amount of clear sky cases are present within each month. In some regions and months this is not the case. In regions like Meru and periods with long-lasting clouds where clear sky does not occur, higher uncertainties are likely to occur [23,24]. In Mombasa, which is located next to the Indian Ocean, difference between land and water surfaces could be responsible for high MBE values. Similar high MBE values were obtained in a study for the Benelux at a similar location near a water body [16]. In that study, this kind of result was associated with estimation by satellite being taken as a grid average while the ground measurement is taken from a pin-point location on the land. The heterogeneous land and sea surfaces within the same grid would therefore result into reflectance error. However, the results further revealed a good correlation of approximately 0.5 on average between the ground measured GHI and satellite derived counterparts. The low correlation in Turkana and Marsabit could be assumed to result from the low quality of ground measurements as these locations, especially Marsabit, with the lowest correlation, are in very remote locations. Therefore, it is likely that the measurement instruments in these stations lack routine maintenance and necessary calibration. Nevertheless, for the intended purpose in the current study, the satellite data was found acceptable because of the wide coverage over the study area and also for the length of measurement of 19 years (1995–2013).

## 4. Results

### 4.1. Available amount of solar energy potential

Fig. 3 displays annual GHI and DNI energy potential averaged for the 19 years (1995–2013). The annual potential of GHI is above 6 kWh $m^{-2}$ $day^{-1}$ over most parts of the country, with some exceptions in the highlands regions of central and western Kenya. The highest potential between 6 and 7.5 kWh $m^{-2}$ $day^{-1}$ is observed over the desert and over the Indian Ocean (Fig. 3a). On the flipside, DNI indicated lower amounts but quite a similar spatial distribution as GHI. In most parts of the country, the average annual DNI is lower than 6 kWh $m^{-2}$ $day^{-1}$ (Fig. 3b).

Area averaged seasonal climatology and each of the 19 years monthly means of GHI and DNI radiation energy potential are presented in Figs. 4 and 5, respectively. The average GHI radiation energy potential is above 6 kWh $m^{-2}$ $day^{-1}$ in 8 months of the year namely, January–April and September–December. In the months of May–July the amount of GHI potential reduces marginally to about 5.5 kW $m^{-2}$ $day^{-1}$. These are good results considering that, the conventional flat plate PV systems have no set threshold amount of GHI as opposed to the concentrating PV which only perform optimally with DNI above 6 kWh $m^{-2}$ $day^{-1}$ [25]. Notably, DNI amount is only recorded in 4 months, i.e. December–March placing the deployment of concentrating PV in Kenya at a disadvantage, considering that the minimum potential for these systems to perform optimally is 6 kWh $m^{-2}$ $day^{-1}$ [25]. This amount of DNI potential over Kenya is only a reserve of a few months and furthermore, these locations with high DNI potential include the less populated Chalbi desert in northern Kenya with majority of people practicing nomadic pastoralism, which therefore makes it

**Table 1**
Validation of the Meteosat derived GHI dataset against ground measurements from 6 stations in Kenya for three years (2010–2013).

| Measurement Station | Mean (W $m^{-2}$) | | MBE (Wh $m^{-2}$) | rMBE (%) | MAE (Wh $m^{-2}$) | rMAE (%) |
|---|---|---|---|---|---|---|
| | Satellite | Ground measurement | | | | |
| Turkana | 248.80 | 260.40 | −11.93 | −0.04 | 19.20 | 0.07 |
| Marsabit | 256.21 | 242.85 | 13.74 | 0.07 | 23.50 | 0.13 |
| Kisumu | 252.21 | 224.12 | 28.89 | 0.14 | 34.32 | 0.16 |
| Mombasa | 233.95 | 206.66 | 28.08 | 0.13 | 35.53 | 0.17 |
| Nairobi | 251.21 | 211.02 | 41.34 | 0.23 | 41.61 | 0.23 |
| Meru | 252.64 | 200.15 | 51.88 | 0.30 | 52.28 | 0.29 |

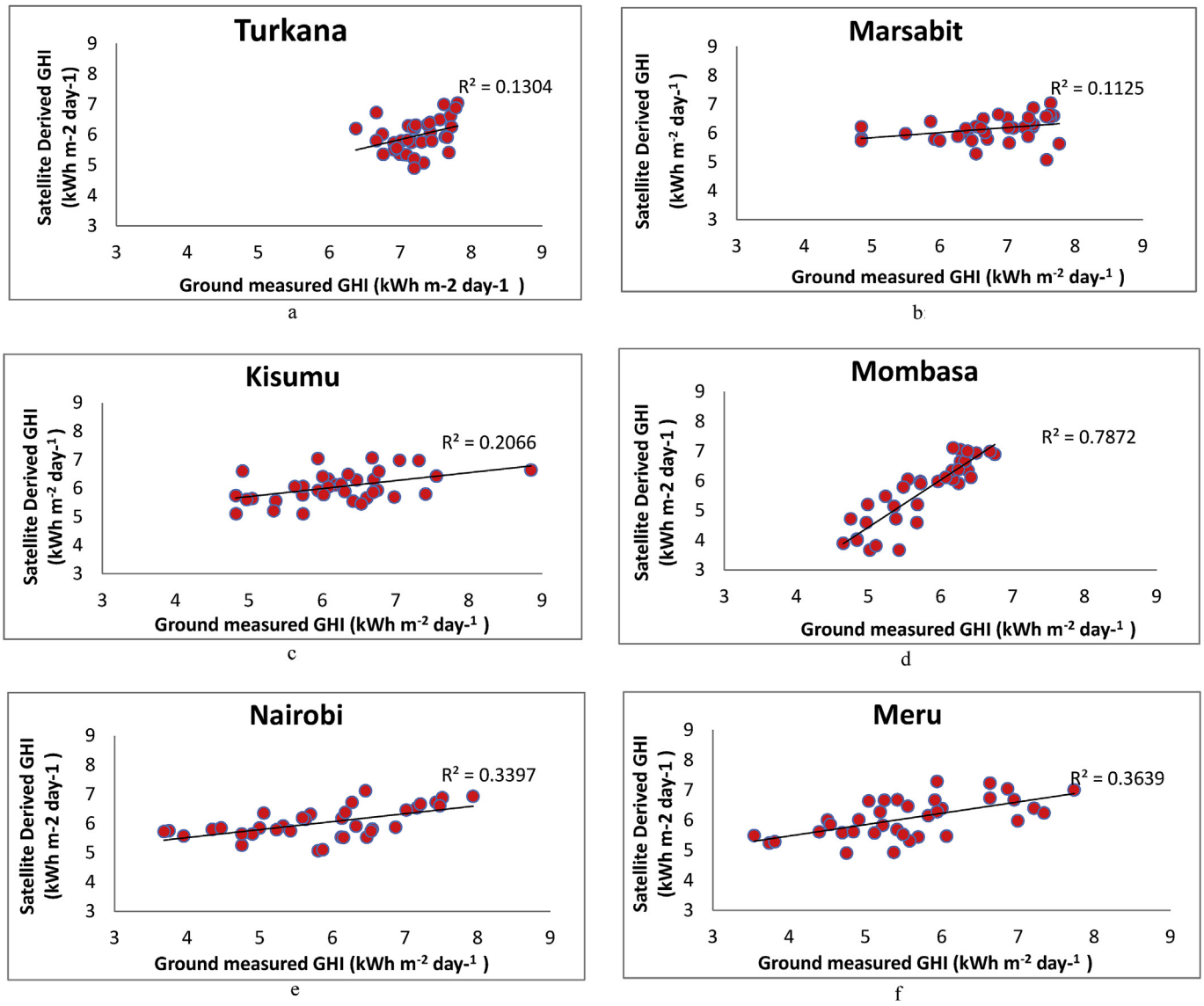


**Fig. 2.** a: Scatter plot of the ground measured and satellite derived monthly mean GHI during 2010–2013 for Turkana station. b: Same as 2a above but for Marsabit station. c: Same as 2a above but for Kisumu station. d: Same as 2a but for Mombasa station. e: Same as 2a but for Nairobi station. f: Same as 2a but for Meru station.

even harder for deployment of solar systems. Therefore, as far as the available amounts of GHI and DNI radiation energy potential is concerned, flat plate PV systems are more suitable for deployment in Kenya as compared to concentrated PV. Additionally, the high amounts of radiation places the country at an advantage in as far as installation of solar systems is concerned. Therefore, the building industry could ride upon this advantage and install solar water heaters, whereas the government could also explore various options of solar systems including solar thermal and concentrated solar power systems for electricity generation.

### 4.2. Variability of solar energy potential

In this subsection, we address some questions that arise from the variable nature of solar radiation which impacts the integration of solar systems into the electricity generation mix and which also ultimately becomes a concern to the grid and utilities operators. The analysis here is organized by trying to address the following questions [7,16].

i. How many years of measurement of solar radiation components are enough to produce an average value that is close to a long term measured average?
ii. Is there significant difference in the annual mean irradiance from one location to other surrounding locations?

To answer these two questions, we conducted two kinds of analysis, namely the interannual and spatial GHI and DNI variability analysis which are provided in detail in sections 4.2.1 and 4.2.2 for the first and second questions, respectively.

#### 4.2.1. Interannual variability

To characterize the horizontal distribution of inter-annual variability, coefficient of variability (COV) of annual GHI and DNI was computed. The COV is defined as the percentage of standard deviation of the annual mean relative to the 19 years average of the annual means as below.

$$COV_{time} = \sigma_t / E_T \times 100$$

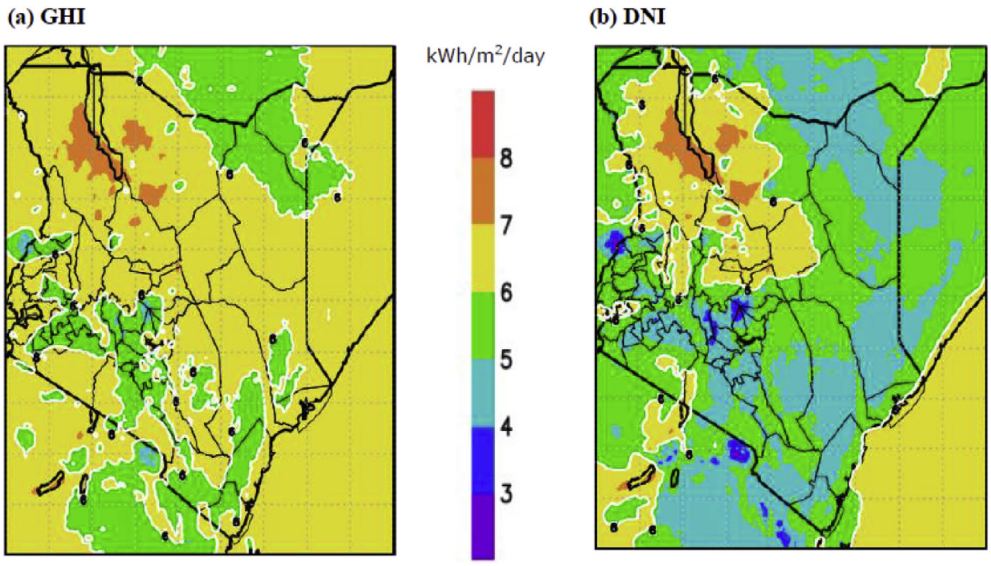


**Fig. 3.** Spatial distribution of the annual mean (a) GHI and (b) DNI averaged over 19 years (1995–2013).

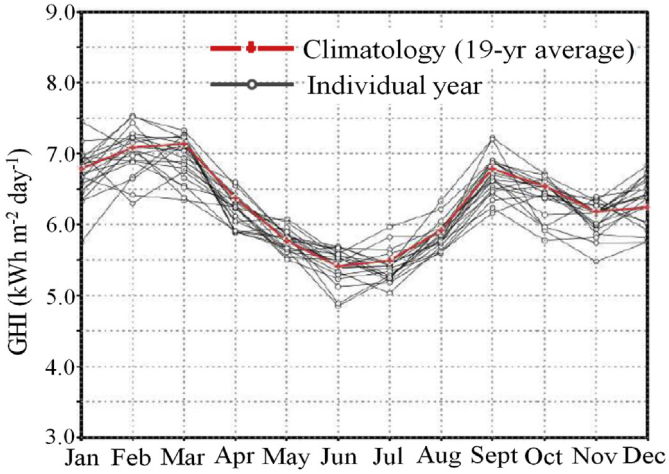


**Fig. 4.** Seasonal variation of GHI based on 19 years (1995–2013) satellite derived radiation data. Red line and black lines indicate climatology and each individual year, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

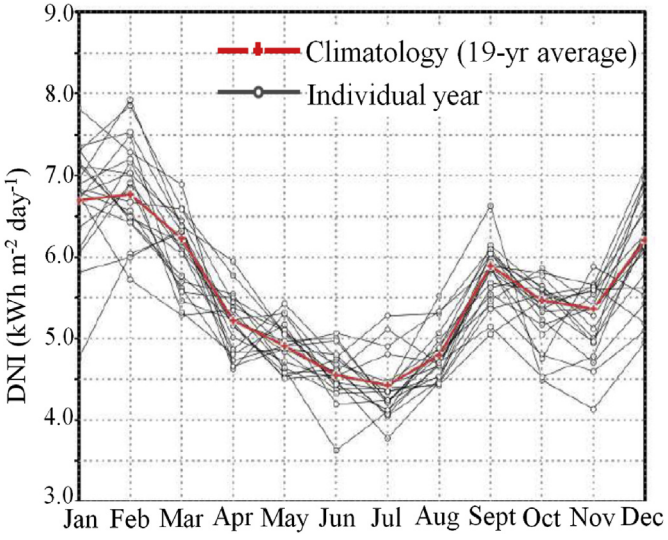


**Fig. 5.** Same as Fig. 4 but for DNI.

$$\sigma_t = \sqrt{\sum_{t=1}^{k} (E(t) - E_T)^2 \Big/ k}$$

where $\sigma_t$ is the standard deviation for interannual variation, $E_T$ is the 19 years average of annual mean, $E(t)$ is the annual mean for each individual year t, and k is the total number of years ($k = 19$).

Fig. 6 shows that interannual variability of GHI is low as indicated by low $COV_{time}$ values between 1% and 5% recorded over the country. The lowest variability is found on the low lying eastern Kenya and some parts of the northern Kenya mostly near Lake Turkana with $COV_{time}$ ranging between 1 and 4%. The highest variability is found in the central and western Kenya, which are high topography areas especially near Mt. Kenya, Mt. Kilimanjaro and Mt. Elgon, where $COV_{time}$ ranges between 5 and 6%.

A similar spatial pattern but higher variability is seen for DNI with $COV_{time}$ values almost double that of GHI in most parts of the country ranging between 3 and 10% over Kenya. This makes short-term measurement of DNI less reliable as solar potential since each year's measurement in a specific location would differ greatly. On the flipside, GHI measurement in one year over most parts of the country can be assumed to represent consequent years and thereby greatly reducing the cost of measurement and placing utilization of GHI in fixed flat plate PV at an advantage over the concentrating PV.

#### 4.2.2. Spatial variability

It has long been observed that, variability of solar radiation and consequently power generation from a solar plant in one particular location would be higher than for multiple locations within the same region [7,9]. Therefore, it is necessary to characterize solar radiation variability in spatial realms. In this study, the consideration for such analysis was conducted based on the annual mean over 19 years (1995–2013) for both GHI and DNI. The long term mean for each of the $0.05^\circ \times 0.05^\circ$ (approximately 5 km × 5 km) grid cells was compared with those of the surrounding grid cells. These surrounding cells were determined as illustrated in Fig. 7.

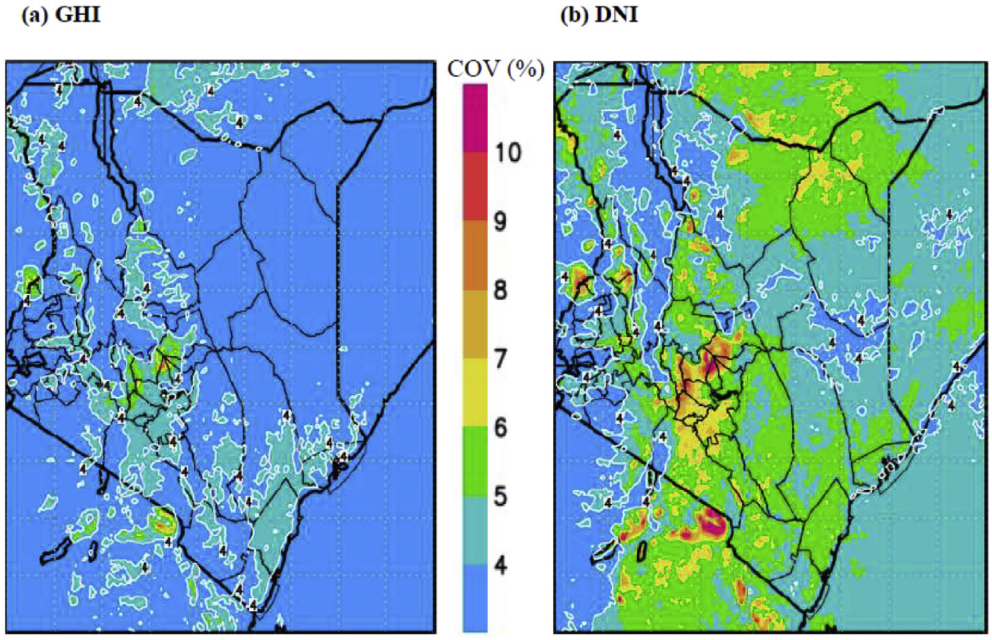


**Fig. 6.** Spatial distributions of $COV_{time}$ for (a) GHI and (b) DNI.

Similar to the temporal variability analysis, the spatial variability was also expressed in terms of coefficient of variability (COV) calculated as follows.

$$COV_{space} = \sigma_s / E_A \times 100$$

$$\sigma_s = \sqrt{\sum_{i=1}^{X}\sum_{j=1}^{Y}(E(i,j) - E_A)^2 \Big/ (XY)}$$

where $\sigma_s$ is the standard deviation for horizontal variability surrounding the central grid in the matrix, XY is the total number of the surrounding cells, $E_A$ and $E(i,j)$ is the solar radiation energy potential of the central grid and that at each particular grid point within the matrix, respectively.

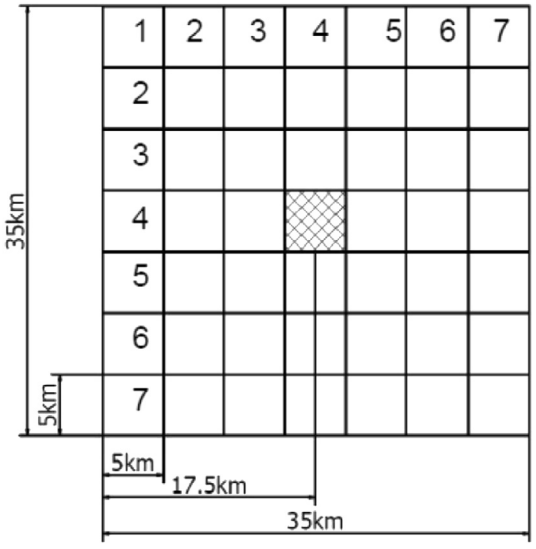


**Fig. 7.** Illustration of the spatial variability grid arrangement into 7 × 7 grid matrix (central grid surrounded by 48 cells).

As shown in Fig. 8, the $COV_{space}$ for GHI at 7 × 7 matrix by setting X = 7 and Y = 7 (corresponding to 1,225 $km^2$ coverage) in most locations of Kenya is below 6% with a large portion of the east recording $COV_{space}$ between 0% and 2%. Higher variability is found in the mountainous regions and along the coast where $COV_{space}$ values range between 6% and 14%. For DNI, the magnitude of $COV_{space}$ is almost twice that of GHI in almost all regions and especially in Western and Southwestern Kenya which is dominated by highlands. A similar pattern of spatial variability is seen at the 15 × 15 matrix (i.e., X = 15 and Y = 15, correspondingly 5,625 $km^2$ coverage; not shown here) where higher $COV_{space}$ are recorded at the western region as compared to the eastern region. However, at this matrix, the magnitude of spatial variability for both GHI and DNI increases in all places and attains a range of 2–18% and 2–40%, respectively.

## 5. Discussions

The knowledge of spatial and temporal variability of solar radiation potential obtained in Section 4.2 is useful to guide the policymakers as well as investors on where and how to conduct measurement of solar radiation in Kenya. In the deployment stages of these systems, the knowledge of variability is very important in guiding the measurements of irradiance location which is normally done to determine the viability of deploying solar systems. For instance, it has long been found through statistical autocorrelation methods that, solar irradiance received cumulatively in one year at a certain location is independent of that of previous year(s) [7,9,16].

As an application of the temporal variability of solar radiation, it is possible to suggest minimal period of data needed to estimate a mean solar radiation potential that is close to the climatology [7,16]. For the purpose of such analysis, satellite derived GHI and DNI annual mean anomalies from the 19 years (1995–2013) long term means were area-averaged over Kenya and analyzed here. These anomalies were sorted out for the negative and the positive values, and then the positive anomalies are arranged in an increasing order from the smallest to the largest values while the negative

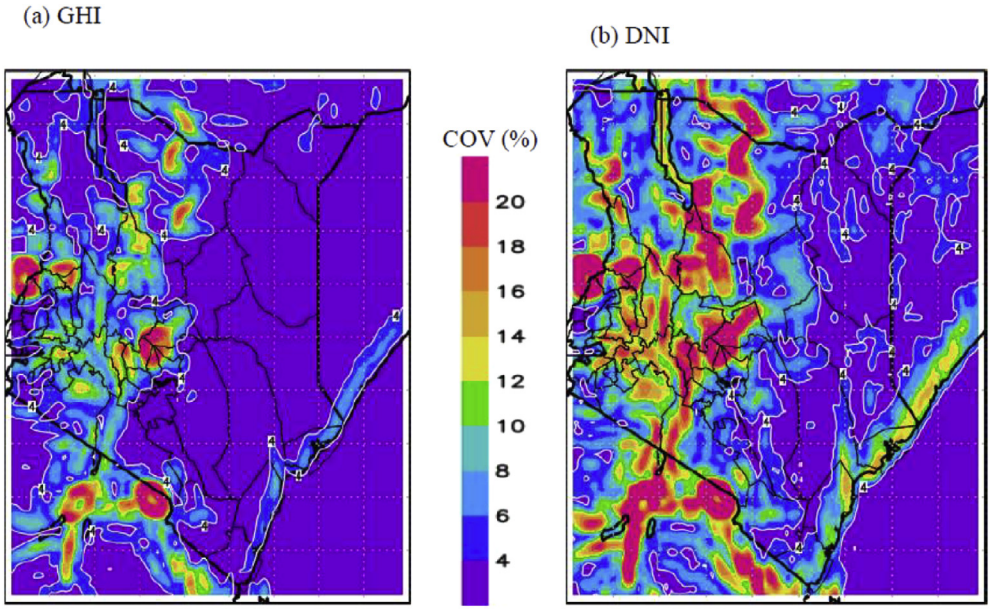


**Fig. 8.** Spatial distributions of $COV_{space}$ for (a) GHI and (b) DNI.

anomalies are arranged in a decreasing order from the largest to smallest value (Fig. 9). This typifies hypothetic situations of solar radiation measurement commencing at either better years (positive anomaly) or worse years (negative anomaly) relative to the climatological mean. Fig. 9 indicates that deviations of more than 20% are expected if just 1 year of GHI and DNI measurements were to be relied upon. It is however clear that, it would take 5.5 years and 7 years of GHI and DNI measurements in Kenya respectively for the deviations to converge to ±5% anomaly (black dotted lines in Fig. 9) from the long term mean. This indicates that measurement of GHI and DNI for 5.5 and 7 years respectively in Kenya can describe climatology. This is an important finding as it reduces the need to carry out long term measurement to characterize climatology of solar radiation in Kenya which consequently reduces the cost and time of measurements. The number of data years considered for this analysis is 19 years (1995–2013) due to the fact that METEOSAT data in this period has been proven to be stable than the one between 1983 and 1994 by Ref. [16]. The result indicated that we had more negative than positive anomalies in GHI and vice versa for DNI and thus, for GHI it would take 9 years of measurement to converge to near 0 deviation from climatology, if measurement was started from worse years. On the other hand, it would take 10 years for GHI measurement convergence to near 0 deviation from climatology, if measurement commenced from better years. For DNI it would take 10 and 9 years for convergence to near zero deviation from climatology with measurements commencing from a better and worse years respectively. This is quite different from the United states and Benelux where similar studies revealed that it would take just 1 year and 4 years respectively for convergence to the ±5% level [7,16] and about 15 years and 10 years for convergence of GHI and DNI to near 0 deviation from climatology in U.S and Benelux respectively for both the worse and better years scenarios. This could be associated with the climate difference between mid-latitude and tropical zone and also the diverse terrain characteristics in the current study area resulting in very different local climate conditions in regions within Kenya.

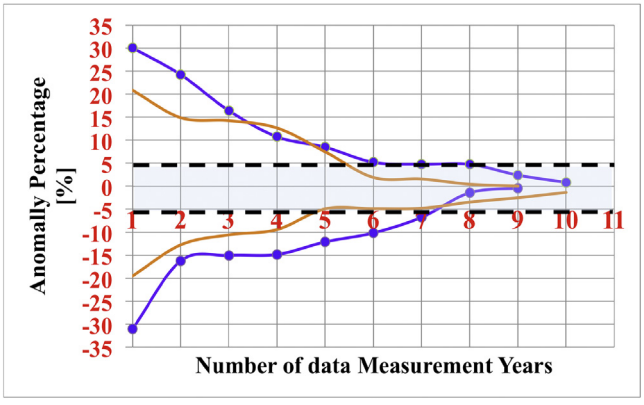


**Fig. 9.** A relationship between annual solar radiation anomaly with respect to 1995–2013 and the number of measurement years.

Fig. 6 reveals that, DNI interannual variability is twice as much as that of GHI. For GHI, $COV_{time}$ values ranging 1–5% indicates a low interannual variation in the entire study domain. The topography influence on interannual variability is quite evident with the low lying eastern plains, north and northeastern regions showing lower $COV_{time}$ values than the central and south western highlands possibly because of the local climate effects of topography that is known to affect cloud frequency (e.g. Ref. [26]). GHI, which is normally utilized in flat plate PV, has therefore shown a much lower interannual variability as compared to DNI, utilized in concentrating PV, which continues to limit the deployment of the latter technology in Kenya.

The spatial variability is dependent on distance from a central location assumed in this study as a measurement station. The low variability for GHI at $7 \times 7$ matrix indicates that if a measurement of the solar radiation component was to be taken at a location in Kenya, it would most likely represent other locations within an area of 1,225 $km^2$ and consequently this would reduce the cost of measurement. Most importantly, all locations that indicate $COV_{space}$ below 3% which is considered a nominal uncertainty for high quality measurement should be expected to yield similar results and it can therefore be assumed that measurement at one such location can represent others within the given area where this low variability is recorded [25].

## 6. Conclusion

The Meteosat satellite derived solar radiation (GHI and DNI) data was utilized to characterize solar radiation energy potential over Kenya with a focus on spatial and temporal variabilities. The strength of the satellite data is exhibited in the wide coverage over the study area where ground measurement of solar radiation has a coarse spatial distribution. The satellite data was validated using 6 ground measured data. From the validation results, Meteosat satellite data was found to be good enough to characterize solar radiation over the study area with a moderate correlation of approximately 0.5 between the satellite and the ground measured data. It is also found that solar radiation is overestimated at five out of the six stations in Kenya as indicated by the positive MBE.

The analysis of the available amount of GHI and DNI radiation energy potential over Kenya revealed that the annual GHI potential ranges between 5 and 7 kW hh $m^{-2}$ $day^{-1}$ with most parts recording over 6 kWh $m^{-2}$ $day^{-1}$. DNI potential is lower with most parts recording below 6 kWh $m^{-2}$ $day^{-1}$. This limits the possibilities of deploying solar concentrating PV in Kenya which utilizes DNI and whose threshold for these systems to operate optimally is set at 6 kWh $m^{-2}$ $day^{-1}$.

GHI interannual variability is significantly low ($COV_{time}$ is 2–4%) in most parts of the country with an exception of the mountainous regions which could be expected because of the topographic effect on cloud frequency. This is a good indication that one year measurement of GHI in the regions that have low $COV_{time}$ can be used to represent consequent years. However, measurement of solar radiation in one year would be different from a long term "climatology" mean and it is therefore established that, measurement of solar radiation in Kenya for 5.5 and 7 years for GHI and DNI respectively would be enough to explain the climatology mean. On the other hand, DNI interannual variability is almost two times higher ($COV_{time}$ is 3%–30%) than GHI in most parts of the country which further limits the deployment of concentrating PV in the study area.

As indicated by the spatial variability analysis, this study has established that measurement of GHI in a location can be representative of others within an area of 1,225 $km^2$ in Kenya, with an exception of the central and western highlands where higher $COV_{space}$ was recorded. As expected, when the area was increased to 5,625 $km^2$ the variation between locations increased significantly indicating that measurement of radiation within such an area cannot be representative of other locations in Kenya except some parts of eastern regions which maintains low$COV_{space}$. Similar to interannual variability, DNI spatial variability is twice that of GHI. For deployment of solar systems as far as the amount and variability are concerned, the best results are seen in the Eastern and Northern Kenya and flat plate solar systems including flat plate PV are more favorable to deploy than concentrated solar systems like the concentrated solar PV systems.

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