e-palli

AMERICAN JOURNAL OF
ENERGY AND NATURAL RESOURCES (AJENR)

ISSN: 2835-9186 (ONLINE)

VOLUME 3 ISSUE 1 (2024)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Energy and Natural Resources (AJENR)
Volume 3 Issue 1, Year 2024
ISSN: 2835-9186 (Online)
DOI: https://doi.org/10.54536/ajenr.v3i1.2430
https://journals.e-palli.com/home/index.php/ajenr

A Systematic Review on the Accessibility of Spatial and Temporal Variability of Solar Energy Availability on a Short Scale Measurement

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Article Information

Received: August 01, 2024

Accepted: August 30, 2024

Published: September 05, 2024

Keywords

Accessibility, Solar, Spatio-Temporal, Mid-West, Variability, Mozambique

ABSTRACT

The difficult access to energy in rural communities make up 80% of the world's population, without access to electricity, strongly impels the need to establish the metric for access to this resource, to respond to the demand for inefficiency, fluctuations and instability that reduces output efficiency of a photovoltaic (PV) solar generator plant. The analysis of around 123 bibliographical sources accessed through the ePPI reviewer platform, focusing on the last 20 years, shows the majority to be applied to studies of small resolutions (one second) for hundreds of kilometers. One minute added to ten minutes of annual measurements is applied for thousands of interprovincial kilometers throughout Mid-western Mozambique. The potential is concluded as a source of spatial and temporal accessibility to the availability of solar energy is created.

INTRODUCTION

The global rate of access to electricity has increased in recent years (Yu *et al.*, 2021; Mucomole *et al.*, 2023), it is estimated that the number of unserved people is 733 million (IEA *et al.*, 2023), representing an annual access growth rate of 0.5 percentage points of the total of the population worldwide (IFC, 2015), around 80% of the world's population without access to electricity lives in rural areas (IEA *et al.*,, 2023), that are more deficient compared to urbanized areas, at this rate, the world will only reach 92% electrification by 2030 (energypedia, 2023). Fossil energy is still the most used (Sha & Aiello, 2018), although it contributes to climate change (Adib, 2015). Increase the use of renewable and clean energy, which needs to reach more than 30% of the total electrification contribution by 2030 (IEA *et al.*,, 2023), to achieve net–zero energy emissions by 2050 (X. Zhou *et al.*, 2023; IEA *et al.*, 2023; energypedia, 2023), focusing on solar PV technology (Mucomole *et al.*, 2023) which is clean (Vijayakumar, 2004), solar–powered and efficient and long–term is an added value (Sengupta *et al.*, 2015; Mucomole *et al.*, 2023; IEA *et al.*, 2023). Around 20 million people not served by electricity are equivalent to Mozambique (IEA *et al.*, 2023), ranking sixth in the range of nations with the largest unserved populations (energypedia, 2023), with the need to make the deadline for the projects to harness solar energy, focusing on micro, mini and macro PV plant plants, sizing (Come Zebra *et al.*, 2021; Roversi & Rampinelli, 2020) of: yield estimation (Klein, 1977), storage, balancing generation and load (Roversi & Rampinelli, 2020), and support for energy quality, originating from the variability of solar energy induced in the region (Perez *et al.*, 2018). The metric of behavior in space of variability in solar energy is interesting as the variability in irradiance increments on spatial and temporal scales, from small temporal order to large kilometers and several days (Ciampi *et al.*, 2013; Litjens *et al.*, 2018). Analyzes have characterized the irradiance of a single location on time scales ranging from hours to months, while later studies have often been aimed at increasing temporal resolutions of, for example, 10s to as little as 0.001s (Mucomole *et al.*, 2023; Jerez *et al.*, 2019; Lucaciu *et al.*, 2016). The spatial coverage of many of these data remained very limited (small number of simultaneous pyranometers), satellite data were additionally used to augment terrestrial measurements and extend analysis (15 min and 1 hour), employment of empirical data (does not always reveal the reality) (Mazumdar *et al.*, 2014; Amillo *et al.*, 2018; Ayet & Tandeo, 2018; Lave & Kleissl, 2013). Knowing these scales of predominance of energy access, it will be possible to better proceed with analysis based on localized data, with global solar radiation (GHI) data from the Mid-western region of Mozambique being implemented here, corresponding to the accessibility metric of variability in space and over time, which are essential for the successful design and stable operation of future electrical networks that have massified and increased the use of clean energy and access to efficient technology, with the same energy being able to be used autonomously (small plants) injected into convectional electrical network (small or large plants). In view of summarizing 123 bibliographic sources presented in Table 1., accessed on the 25th and 26th of December 2023, through the ePPI reviewer

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platform, assisted by data collection in free access sources at: Web of Science/ of knowledge, Science Direct, IEEE Xplore and SCOPUS that cover everything from the development of anisotropic solar models of ramp rate correlation and characterization to the impact of the distributed solar energy transition, power and energy. Given that the study region has limited access to infrastructure as well as similar studies, in addition to the fact that part of the population lacks energy and guides for designing energy use projects (IEA *et al.*, 2023). In order to answer the question, What is the availability of access to solar energy in space and time throughout the Mid-west region of Mozambique?, The daily GHI population was defined, the actors that are the stations throughout the region Mid-west; the comparisons made between the spatial and temporal variability of the availability of solar energy throughout the region and the outcome, which is the clear–sky index K^*_t, were validated with the sample of GHI data collected, through the ePPI reviewer platform that shows some considerations of the analysis goals with the comparison to the STATA Software statistical package platform with a transversal focus on percentage accessibility of energy variation to the area of the action line. However, in this systematic review research we approach a scale of 10 minutes of measurement interval at a long distance of interprovincial separation of internal measurement stations of 10^3 km validated, and summarize the other bibliographical sources of the genre, listed in literature that characterizes relative changes in variability of solar energy in space and time, as well as showing accessibility in average space and time of the variability of solar energy. The research complements other types of research on the variability of solar energy, the use of different methods associated with machine learning to study the accessibility of the variability of solar energy.

MATERIALS AND METHODS

Data Collection and Processing

Around 123 sources of the most recent research were accessed and classified in spatio-temporal descriptive terms based on titles and specific keywords when subscribing to abstracts, with the following search keywords "variability, spatio-temporal and solar energy" being adopted, and a combination of the aforementioned keywords, accessed from the ePPI reviewer platform (https://eppi.ioe.ac.uk/eppireviewer-web/home) assisted by data collection in access sources such as: Web of Science/ Knowledge (https://www.webofscience.com/wos/alldb/basic-search), SCOPUS (https://www.scopus.com/search/form.uri?display=basic#basic), IEEE Xplore (https://ieeexplore.ieee.org/xpl/RecentIssue.jsp?punumber=6287639), and Science Direct (https://www.sciencedirect.com/), accessed on December 25,2023.

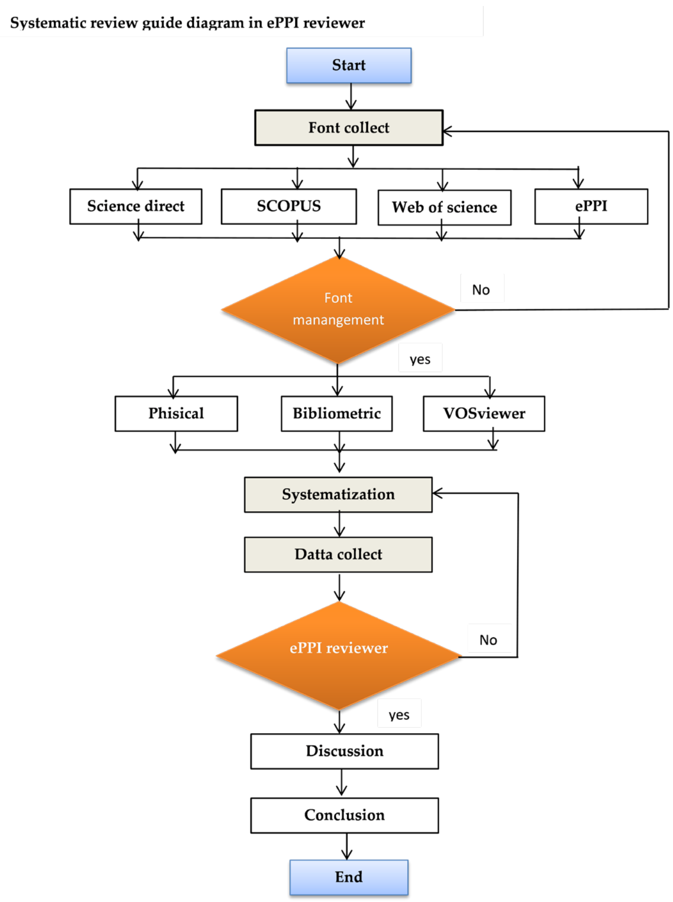


Figure 1: Exploratory data collection design

In order to obtain greater clarity in the research, research from 2003 to 2023 was explored, combined with the limited existence of studies combined with search keywords.

Materials

The articles linked to literature were carefully chosen and analyzed covering a spectrum of twenty years, analyzed based on the ePPI review. The selected terms were then entered into a reference management system, which produced a research information system file format for keyword analysis. The VOS viewer program (https://app.vosviewer.com/) was used to create networks of scientific keywords connected by a co-occurrence link, which is a connection between two terms. The size of the word determined the magnitude and strength of the co-occurrence, which depicts the perspectives and trends of keywords such as temporal, spatio-temporal, variability, quantification, irradiance and assessment.

Method Used

The systematic scope analysis review adopted to manage all collected data was associated with the Bibliometrics method in reference management.

METHODOLOGY

To carry out the systematic review, data were collected consisting of bibliographic sources, extracted through the ePPI reviewer database, assisted by collection from sources such as: Web of Science/ Knowledge, Science Direct, IEEE Xplore and SCOPUS.

The sample of bibliographic sources was collected using the key words "variability, spatio–temporal, solar energy", which in turn generated numerous sub–key words from the approximately 123 bibliographic sources accessed.

The minimum number of occurrences of a keyword was defined as the main qualitative factor and as one of the parameters, which describes the interconnection of the keywords present in the post–selected bibliographic sources. Thus, the highest total link strength of 428 relevant keywords were established over the previous decade.

Due to the poor production seen in post–processing in the last 20 years, the eligibility criterion was selected to consider bibliographic sources in the period from 2003 to 2023 to obtain greater clarity of the systematic review. The number of bibliographic sources, combined with numerous key words, adopted a strategy of analyzing the scope collected. For better management of all collected data, the Bibliometrics method in program reference management was associated with the research development method in the information system, which develops the review, focusing on the co–occurrence of keywords, which helped to improve contributions to the search and analysis of bibliographic sources within the ePPI reviewer 6 platform, for a detailed analysis of the context of each source accessed, and a description.

The bibliographic sources collected have transversal elements that are the use of data samples, develop the study and analyze results based on GHI measured in situ or by satellite, cloud speed and/or series of measured data, analyzing spatial and temporal variability, however without describing how to access it.

Having the scope of selected sources, the review was guided by the research question: What is the availability of access to solar energy in space and time throughout the Mid–west region of Mozambique?

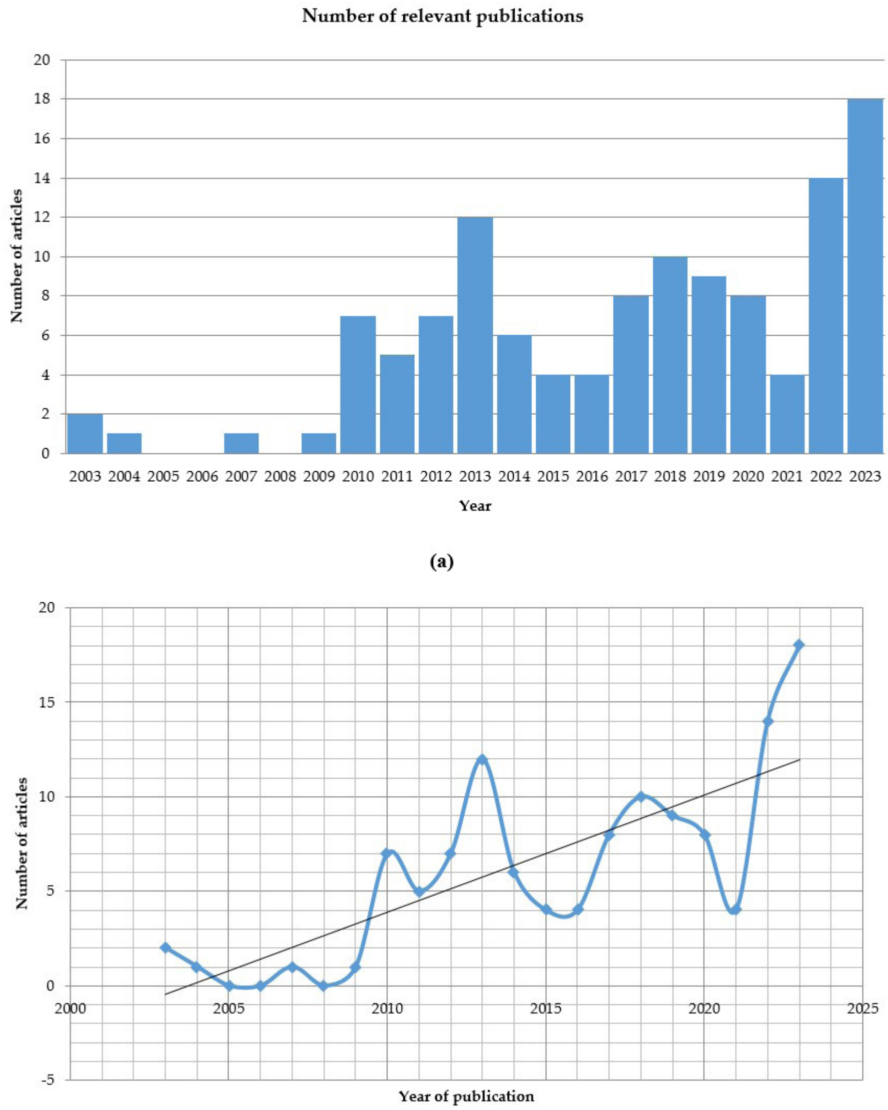
At this stage, the Population was defined: daily GHI, the Stakeholders: the stations of Nhangau (Sofala), Nhapassa–1 and Nhapassa–2 (Manica) and Maravia (Tete) throughout the Mid–western region of Mozambique; Comparisons: made between the spatial and temporal variability of the availability of solar energy throughout the region and the Outcome: the K^*_t that hypothetically describes the sky without any interference with the real behavior of solar energy on the horizontal surface of the earth.

Around 96% of the selected sources obtain the results of their analyzes from GHI processing in situ or extracted by satellite, for various analyzes with emphasis on regression and spatial/temporal correlation using various methods, other sources use irradiance data and cloud speed for similar studies.

The sample proposed for analysis was collected within the scope of the FUNAE (Mozambique National Energy Fund) campaign, between the period 2012–2014, totaling three years of full measurements throughout the Mid-western region of Mozambique, along the section which starts in Sofala (Nhangau), passing through Manica (Nhapassa–1 and Nhapassa–2) and culminating in Tete (Maravia). Due to the fact that the GHI inferred by a pyranometer is full at the surface of the earth, the sample was selected in order to validate the range of full measurements from sunrise to sunset (Figure 4(a), 4(b) and 4(c)).

The sample of bibliographic sources collected was registered on the ePPI Reviewer 6 platform, version 6.15, on December 13th, under ID: 44675. This sample generated a consultation register for this review for future related studies. Of the approximately 123 sources, the highest relative production (based on the analysis of Table 1.) was in the year 2023 (Figure 2(a)), and a positive correlation (Figure 2(b)) of knowledge production from 2003 to 2023, with around 428 of the keywords collected that interconnect from the interconnection diagram built in VOS exploer.

The collected GHI sample was submitted to the ePPI reviewer platform and validated, the system showed a set of meta analyzes namely: the determination of K_t, determination of K^*_t as the selected method, and with the randomized values of this the evaluation of the daily course of a day, its temporal deviation during one year, temporal analysis using histograms, analysis of the K^*_t variability index as a function of the time of day, the rate of variability using various methods, the adjustment of K^*_t normalized, study of the effects of K^*_t, the temporal



(a)

(b)

Figure 2: Analysis of article repetition: (a) Temporal and (b) spatial

variability of a singular measurement point and the spatial-temporal variability between two points.

Additionally, the data was dragged to observe possible analyzes in the STATA Software. It was possible to observe similarity in some meta–analyses (ID: 26939), highlighting energy accessibility proposals in the different stations along the chosen section.

From the sources, some cross–sectional descriptions already listed in paragraphs 2.1 and 2.2 were summarized, however paragraphs 3, 4 and 5 are presented due to new results that must be analyzed with the entire validated GHI sample. In section 6, the discussion presented reports the set of bibliographies discussed that, together with the decisions in the ePPI reviewer, assisted with observations in STATA software, dictated in paragraph 7, the conclusions of the systematic review that describe limitations and the entire scope analyzed and led to the choice of the theme of this research as a proposal for "Accessibility of the variability of spatial and temporal availability of solar energy in the Mid–western region of Mozambique.

Clear-Sky Radiation Estimation

A good estimate of solar energy consists of collecting solar radiation under previously standardized conditions. If the intention is to evaluate the horizontal surface (Nam & Hur, 2019; Mucomole *et al.*, 2023) the radiometers must be placed along the surface of the earth (Perez *et al.*, 2012, Kumar, 2021), but an inclination angle can be established to measure GHI, DNI and DHI (Yang *et al.*, 2017; Mazumdar *et al.*, 2014; Habte *et al.*, 2020; Dambreville *et al.*, 2014). The passage of the solar radiation beam is reduced (Zervos & Lins, 2016; Zhang *et al.*,2017) due to several factors that disturb and disperse the radiation beam, such as: presence of aerosols (Yu *et al.*, 2021; Lohmann & Monahan, 2018), gases (Anenberg *et al.*, 2017), micro particles (Mucomole *et al.*, 2023) among others. The atmospheric transmittance for the incident radiation τ_b is the ratio between the incoming radiation and the extraterrestrial radiation G_{bn}/G_{on} (or G_{bT}/G_{oT}), (Lohmann *et al.*, 2016; Duffie & Beckman, 1991), however due to several factors, the solar declination is lowest at sunrise and sunset (Charabi & Gastli, 2012; Sha & Aiello, 2018) recording high values close to 0.65 on March 6,2012, this is maximum at noon, and may vary from each type of day on which the radiation is more intense or not (Hummon *et al.*, 2012; Mucomole *et al.*, 2023). For days with much higher radiation where the radiation is close to the theoretical radiation Figure 2(a), it is greater, contrary to other days it is given by (eq. 1) (Tovar *et al.*, 2001; Yu *et al.*, 2009),

$$\tau_b = a_0 + a_1 \exp((-k)/(\cos\theta_z)) \quad \text{(eq. 1)}$$

The constants a_0, a_1 and k for a standard atmosphere are defined at 23 km visibility and for altitudes below 2.5 km. The empirical relationship between the transmission coefficients for diffuse radiation beams on clear days is shown by the expression below (Duffie & Beckman, 1991; Mucomole *et al.*, 2023):

$$\tau_d = 0.271 - 0.294\,\tau_b \quad \text{(eq. 2)}$$

where τ_d is G_d/G_0 (I_d/I_0), the relationship between the DHI and the extraterrestrial DHI in the horizontal plane. A practical way of perceiving the real metric of daily solar radiation transcription is the relationship between experimental radiation and extraterrestrial radiation H_0 (G. M. Lohmann *et al.*, 2016; Liu *et al.*, 2013; Mucomole *et al.*, 2023 and R. Perez, David, *et al.*, 2016), another hypothetically discovered radiation accuracy of clouds among other radiation beam inhibitors (Lohmann, 2018) that aids the investigation of clear–sky index that is best described for intervals infinitely small time periods and for studies applied to the surface of the earth or along the internal layers of the earth (Hoff & Perez, 2010; Hoff & Perez, 2010; Gueymard & Ruiz-Arias, 2015; Mucomole *et al.*, 2023).

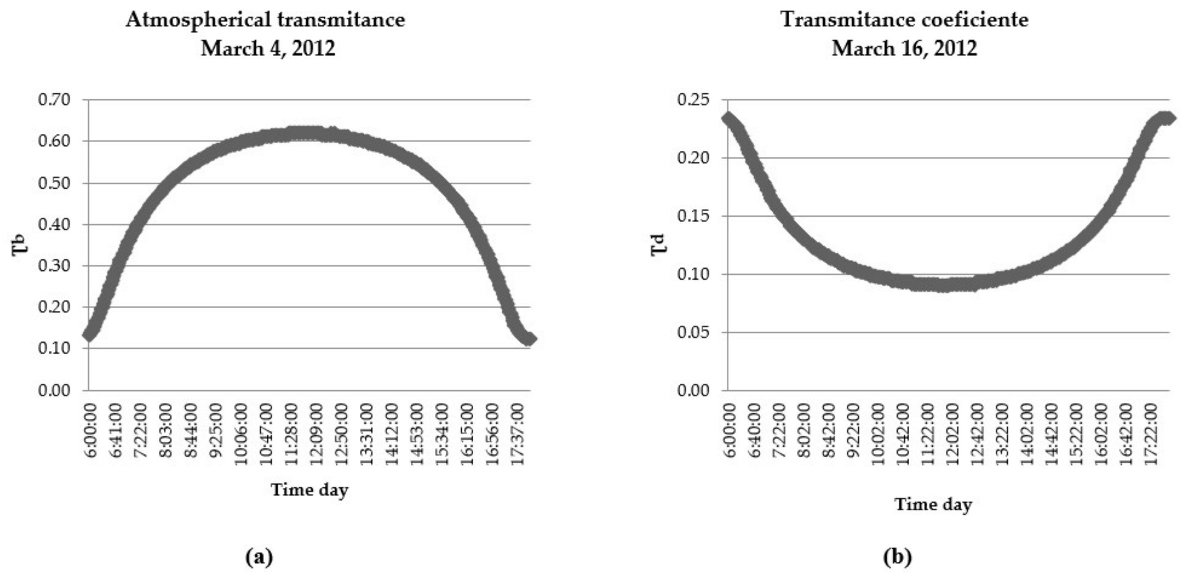


Figure 3: Behavior of: (a) Atmospheric transmittance and (b) Transmittance coefficient

Several methods have been tested and developed, some for analyzing samples from small measurement intervals and on a kilometer scale (Litjens *et al.*, 2018; Kreuwel *et al.*, 2020; Barry *et al.*, 2017; Wilcox *et al.*, 2016), others for spatial and spatio–temporal analysis of large–scale samples using satellite or empirically generated data (Verbois *et al.*, 2023; Kühnert *et al.*, 2013; Wenham *et al.*,2007). For the determination of normal direct horizontal radiation from clear–skies, the description in Mucomole *et al.* (2023), which determines the clear–sky radiation from the input variables and the output relates to the experimental global radiation measured by radiometers to obtain randomized values. The analyzes show, on most days, normalized values whose spectra are close to extraterrestrial radiation (Lohmann & Monahan, 2017, Uti *et al.*, 2023, Mazumdar *et al.*, 2014, Habte *et al.*, 2020, Dambreville *et al.*, 2014, Aryaputera *et al.*, 2015, Vindel *et al.*, 2020, Wilcox *et al.*, 2017, M. J. R. Perez & Fthenakis, 2015, Hoff & Perez, 2011, Hoff & Perez, 2010, Lucaciu *et al.*, 2016) this contributes to the correct establishment of classes of day types (cloudy, clear and intermediate, upper or lower), and in proposing more accurate analyzes of reality as well as machining the tested model and comparison with empirical models that describe most stations with solar radiation values close to theoretical radiation, written in (eq. 3) (Duffie & Beckman, 1991).

$$G_{cb} = G_{on}\,\tau_b\,\cos\theta_z \quad \text{(eq. 3)}$$

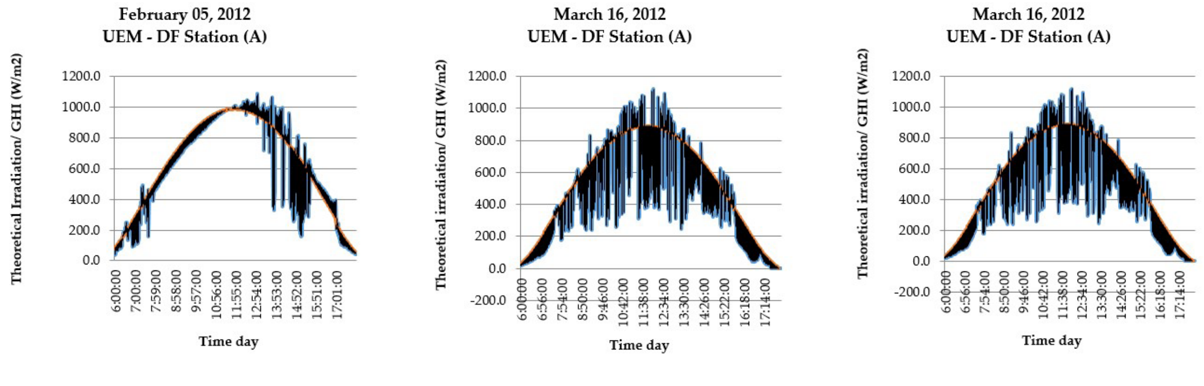


Figure 4: Theoretical irradiation in clear–skies: (a) Δt=1 minutes on February 5th, 2012, (b) Δt=10 minutes on November 14th, 2012 and (c) Δt=10 minutes on the 30th June 2012

Clear–Sky Index Assessment

To remove the variability due to the reduction of solar radiation arriving at the horizontal surface, a normalized quantity is introduced, the clearness–index, K_t or the clear–sky index K^*_t (Nwokolo *et al.*, 2022, Keeratimahat, 2020, Vijayakumar, 2018). The latter more effectively removes the effects of solar geometry on elevations and has a more intuitive scope (Mucomole *et al.*, 2023; Rapti, 2000; R. Perez, David, *et al.*, 2016). The clearness–index K^*_t is defined as the ratio of GHI to daily extraterrestrial radiation (Monjoly *et al.*, 2019),

$K_t = GHI/H_0$ (eq. 4)

We can also define the clear–sky index K^*_t as the relationship between GHI and clear-sky radiation (Perez *et al.*, 2016) that is, irradiation of the Earth's atmosphere with clear–skies (Keeratimahat, 2020; Perez *et al.*, 2016), for a good estimate, has values that do not exceed 1, otherwise, this is due to various atmospheric factors, reflection by clouds, measurements (calibration of the environment and equipment), validation of the model used, among others.

$K^*_t = GHI/G_{Clear}$ (eq. 5)

where $G_{Clearis}$ the total radiation on the horizontal surface, that is, the sum between the direct radiation on the horizontal surface that arrives at a given time and the diffuse radiation on the horizontal surface (Iqbal, 1983; Duffie & Beckman, 1990).

Considering the measurement interval of solar radiation on the horizontal surface of one day (amplitude). To access the character of the irradiance variability conditioned on the type of skies for N iterations, the simple arithmetic mean can be written,

$$\overline{K_t^*} = \frac{1}{N}\sum_{t=1}^{N} K_t^*(t) \qquad \text{(eq. 6)}$$

A reliable precision interval is adopted that separates two consecutive measurements of one minute (time interval), for the temporal accessibility of variability.

$\Delta K^*_t = K^*_{(t+1)} - K^*_t$ (eq. 7)

This accumulation has a standard deviation that will be $\sigma^{(K^*t)} = \sqrt{(1/(T-1)\ \sum^{T}_{(t=1)}(K^*_t\ (t)-(\overline{K^*_t}))^2)}$. The variation in the daily course of K^*_t is shown below.

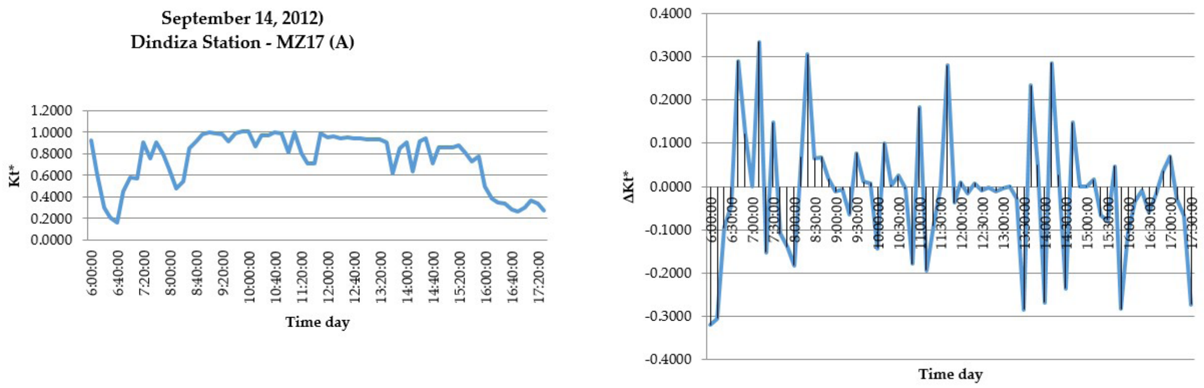


Figure 5: Distribution of K^*_t and ΔK^*_t as a function of the time of day, for a time interval of one minute and an amplitude of one day, throughout the 14th of September 2012

Results validation tests from recent studies investigate the global radiation frequency distribution using different probability density functions (Chen *et al.*, 2022, Liu *et al.*, 2013, Tovar *et al.*, 2001, Lohmann & Monahan, 2018). The transcription of the course of a day observed in the interval from sunrise to sunset presents high and low values of K^*_t, however it is within the interval within the theoretical irradiation, thus making a normal distribution. For better clarity in the classification of days, the probability density function of the Kernel Density estimate is calculated, which best explains the classes of membership of each day (M. J. R. Perez & Fthenakis, 2015; Habte *et al.*, 2020), although there is previous practice to establish the classification by daily or monthly averages of K^*_t. The days treated were modeled to belong to each quartile, with the designation of first quartile (T_1) being the portion of 75% of data>T_1 or 25%<T_1; the middle or second quartile (T_2) the 50% of data>T_2 or 50<T_2; the third quartile (T_3) the 25% portion of 25% of data>T_3 ,or 75<T_3 (Wilson & Tanaka, 2018); the interquartile ranking (ITR) is the portion of the interval containing half of the data that can be calculated by T_3-T_1 (Wilson & Tanaka, 2018; Voyant *et al.*, 2015 and Evrendilek & Ertekin, 2007). Additionally, the edge of the lower whisker (w_{low}) is defined, the portion of low data values that can be calculated by T_1-1.5.ITR; the Upper whisker (w_{up}) the portion of high T_1-1.5.ITR data values and the outliers that represent any data points <w_{low} or>w_{up} (Verbois *et al.*, 2023; Amjad *et al.*, 2023 and Wilson & Tanaka, 2018).

Statistical Measure of Spatio–Temporal Variability

Spatial Variability Measure

Based on K^*_t values and their averages calculated for the temporal variation at a certain period of time at a given spatially located measuring station, a spatial correlation will be made between two stations i and j, in order to determine the magnitude of probability density or Kernel Density Probability $\chi^{(\Delta k^*\tau)}_{ij}$, which statistically and spatially classifies the days of each year, for a subspace station between two stations y and x, of randomized values that relate to y+x, we write the correlation coefficient,

$$\chi_{ij}^{K_t^*} = \frac{\sum_{\tau=1}^{\tau}\left(\Delta K_{t,i}^*(t) - \overline{\Delta K_{t,\iota}^*(t)}\right)\left(\Delta K_{t,j}^*(t) - \overline{\Delta K_{t,J}^*(t)}\right)}{\sigma_{\Delta K_{t,i}^*(t)}\sigma_{\Delta k_{t,j}^*}} \quad \text{(eq. 8)}$$

where $\Delta K^*_{(t,i)}$ (t), $\Delta K^*_{(t,j)}$ (t) and ($\overline{\Delta K^*}_{(t,i)}$) e ($\overline{\Delta K^*}_{(t,j)}$) are the increments and the corresponding artimetric averages, individual in the time series between two locations i and j, and T is the number of points between two series of measurements. Furthermore, comparable correlation curves can be derived by employing analogous models mentioned in the works of Marcos *et al.*, (2011), Lave *et al.*, (2012) and Lohmann, (2018), in addition to eq. 9. A fascinating instance can be seen in the discovery of decorrelation patterns in the Mid–western of Mozambique. These patterns were observed for clear–sky days (Figure 6(a)), cloudy–sky days (Figure 6(b)), intermediate– sky conditions (Figure 6(c)), and all types of days (Figure 6(d)). The discreet model, represented by eq. 9, and the model proposed by R. Perez, David, *et al.*, (2016) as $\chi^{(\Delta K^*\tau)}_{ij}$ =1/(1+l_{ij}/tv), were utilized to achieve this understanding of solar energy behavior.

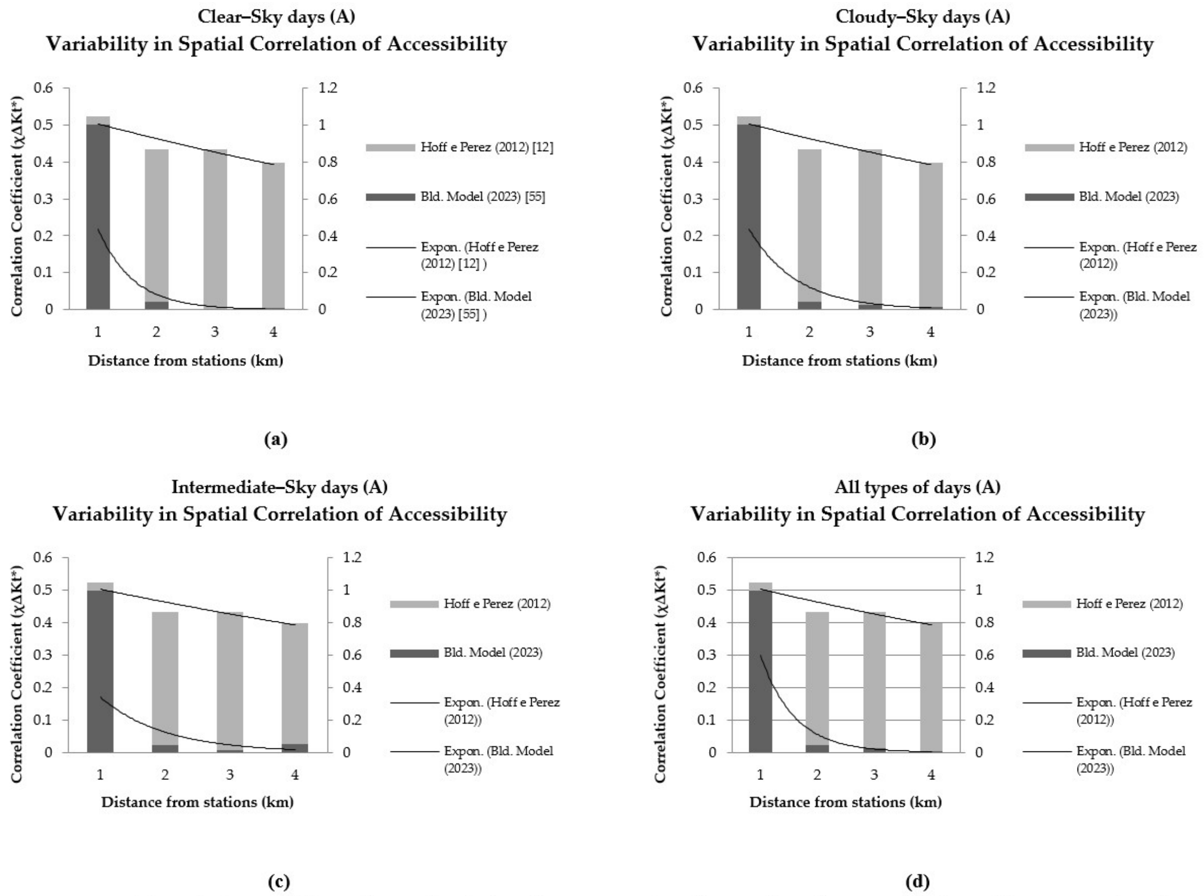


Figure 6: Spatial correlation coefficients of two points in the Mid–western region of Mozambique for acceptable days of the type: (a) clear–sky, (b) cloudy–sky, (c) intermediate–sky and (d) all sky types of days.

The figure reveals a decorrelation of the K^*_t coefficient index as a function of distance, for thousands of kilometers, however the same was obtained for 10 km$<l_{ij}\leq$300Km (Marcos *et al.*, 2011; R. Perez, David, *et al.*, 2016, Rábago, *et al.*, 2016 and Lohmann, 2018).

Measure of Temporal Variability

Temporal and spatio–temporal studies mostly describe: the development of anisotropic solar models of ramp rates correlation and characterization (Gutiérrez *et al.*, 2017; Tapia *et al.*, 2022; Bailek *et al.*, 2020; Lave *et al.*, 2012 and Arias-Castro *et al.*, 2014); analysis of the temporal variability of solar irradiation in a short measuring range and definition of calculation of K^*_t or K_t (Mucomole *et al.*, 2023, Belúcio, L. P. *et al.*, 2014; Fernando, D. M. Z., 2018; Macedo, Al. S. and Fisch, G., 20115); analysis of long–and short–term spatio–temporal variability fluctuations on small and large measurement scales (Hoff & Perez, 2010, Lohmann *et al.*, 2018, Marcos *et al.*, 2011, Hassan *et al.*, 2022, Mills, 2010, Lorenzo, 2016, Ohtake *et al.*, 2013, Zhu *et al.*, 2019).

The fluctuations (sometimes a slight variation) of K^*_t and ΔK^*_t (Figure 7(a)), are related to the cloudiness that the sky presents which impedes the trajectory of solar radiation, other studies show the spectrum clearly shows that from 8:00 AM until 3:00 PM, solar radiation varies abruptly, registering a complicated variation and then begins to increase from 5 pm onwards, this is due to the strong amount of annual cloudiness observed on the order of 14.0% (Figure 7(b)).

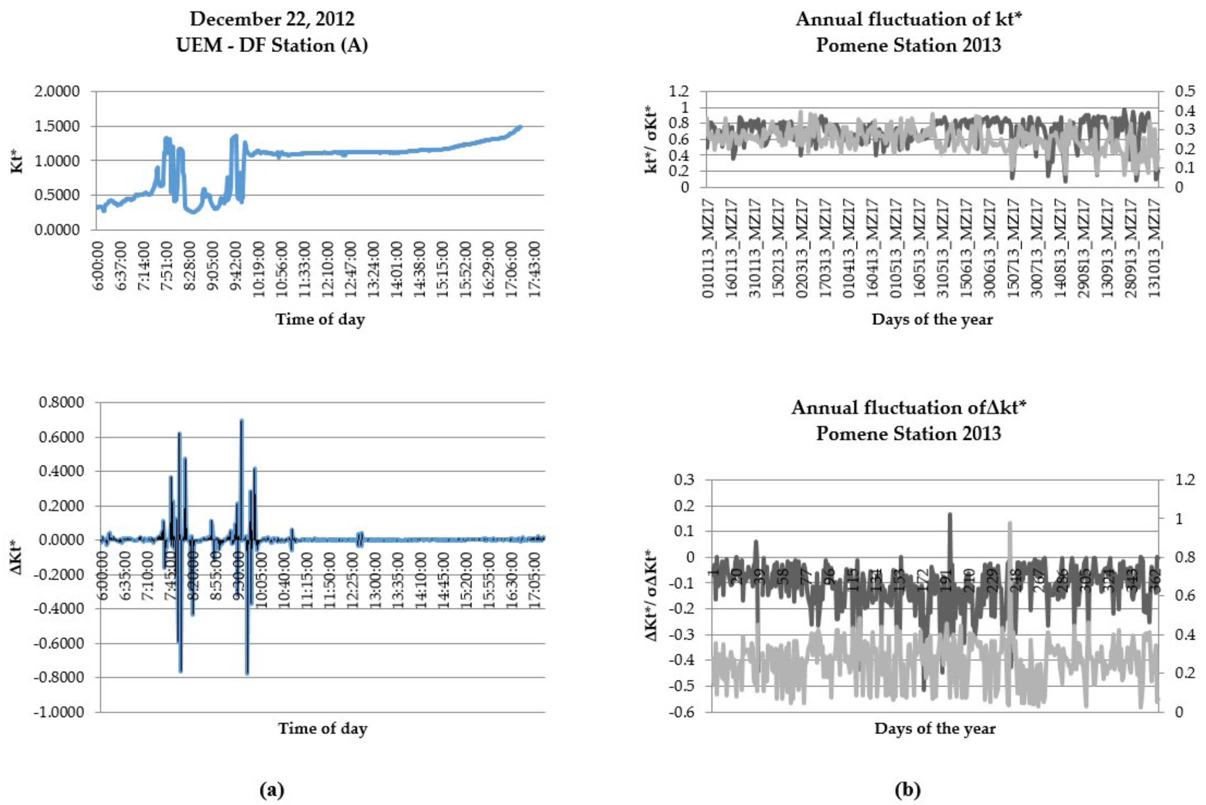


Figure 7: Distribution of K^*_t and ΔK^*_t as a function of the time of day, for: (a) A time interval of one minute and an amplitude of one day (December 22, 2012); (b) A time interval of one minute and an amplitude of one year

The intermittent behavior of PV arrays plays a role in the spatial and temporal variability of K^*_t (Lave & Kleissl, 2013, Marcos *et al.*, 2011). For detailed studies on cloud–enhanced sunlight, it is important to consider the optimal temporal resolution (de Souza *et al.*, 2012, D. Yang *et al.*, 2017). Additionally, the impact of transitioning to distributed solar energy, as well as power and energy considerations, should be taken into account (Neggers *et al.*, 2003, Suri *et al.*, 2010, Almorox *et al.*, 2021). Modeling and machine learning techniques can also contribute to understanding the spatio–temporal variability of solar energy (Nwokolo *et al.*, 2022, Nwokolo *et al.*, 2023, Obiwulu *et al.*, 2022).

These frequent fluctuations align with the adopted model for calculating global irradiation under clear skies, as they fall within the appropriate time interval and amplitude for studying variations.

Accessibility of the Spatial and Temporal Availability of Solar Energy

The Earth's surface receives the highest amount of solar radiation with a peak flux density (Duffie & Beckman, 1991) within a specific wavelength range (Iqbal, 1983). This radiation can be accurately described using the Planck distribution function (Wenham *et al.*, 2007; Mucomole *et al.*, 2023; Duffie & Beckman, 1991).

$$B_\lambda(T) = \frac{2\pi hc^2}{\lambda^5\left[exp\left(\frac{hc}{\lambda kT}\right) - 1\right]} \qquad \text{(eq. 9)}$$

where The spectral emissivity of a black body at temperature T is denoted as B_λ (T), h is Planck's constant (h=6,625×10$^{(-34)}$ J.s), c is the speed of light (c=3×10^8 m/s), k is the Boltzman constant (k=1,38×10$^{(-23)}$ J.K$^{(-1)}$) (Duffie & Beckman, 1991; Mucomole *et al*., 2023).

At altitudes above 60 m of GHI inference, greater clarity of fluctuations is shown compared to lower altitudes. Studies inferred on the surface for different latitudes infer greater large–scale fluctuations in evaluated days.

$$K_t^* = \frac{1}{G_{clear_i}}\left(\sum_{i=1}^{n} DNI_i + \sum_{i=1}^{n} DHI_i\right) \qquad \text{(eq. 10)}$$

The K^*_t ranges for the sky coverage classification in the southern zone sample region vary from the cloudy–sky classes: 0.3896 ≤ K^*_t< 0.7344, lower intermediate–sky: 0.7344 ≤ K^*_t< 0.7818, upper intermediate–sky: 0.0.7818≤K^*_t<0.8599 and clear–skies: 0,8599 ≤ K^*_t< 0,9347, however optimal values also close to 1 can be found in estimating the availability of solar energy, some studies estimate values close to 1.011; 1.23 and 1.4 the majority causes are in the applied model and sometimes due to an increase in cloudiness that contributes to the increase (Uti *et al*., 2023, Lan *et al*., 2018).

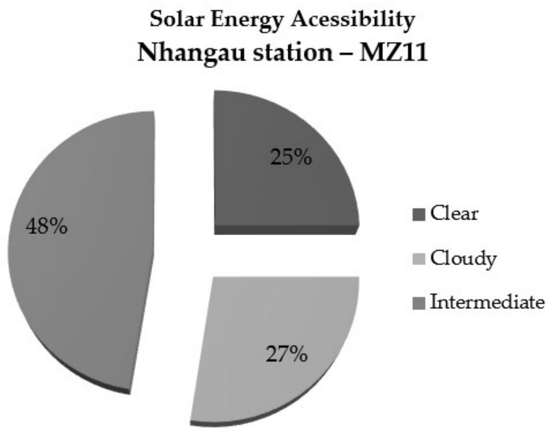


Figure 8: Solar energy accessibility diagram in terms of types of days

Comparative estimate between theoretical clear–sky radiation and terrestrial experimental GHI over the Mid–western region of Mozambique, under annual observations in 2012 with greater uniformity of measurements (Figure 8) reveals the Nhangau and Maravia stations with the greatest potential for full availability of solar radiation around 68.0% and 67.0% of acceptable days, followed by the Nhapassa–2 and Nhapassa–1 stations with around 57.0% and 55.0%. Below is a summary of the sources lit.

Table 1: Assessment of spatio–temporal variability on a short measurement scale

Type	Source	Data source	Interval	Contributions	Model	Year	Location
In sitio	(Mucomole *et al*., 2023)	GHI	1 –10 min.	Temporal variability in the South	Analytical	2023	Mozambique
	(R. Perez *et al*., 2016)	GHI	0,01s	Spatial and Temporal Variability of GHI	Correlative	2016	USA
	(Stetz *et al*., 2015)	GHI	1 Hour	The Impact of Solar on Germany's Energy	Analytical	2015	Germany
	(Suri *et al*., 2007)	GHI	1 Hour	Solar electricity GHI prediction fluctuation	Analytical	2007	France
	(Hoff & Perez, 2010)	GHI	1, 2, 3, 4 Hours	Modeling PV fleet output variability	PV fleet	2010	USA
	(Elsinga, B. and van Sark, W., 2014)	GHI	1 min.	Urban rooftop PV systems &fluctuation	Correlative	2014	Netherlands

(Lonij V. P. *et al.*, 2013)	(de Souza *et al.*, 2019)	(Fernando, D. M. Z, 2018)	(Lohmann & Monahan, 2017)	(Lohmann & Monahan, 2018)	(Lohmann *et al.*, 2016)	(Klima & Apt, 2015)	(Almorox *et al.*, 2021)	(Nwokolo *et al.*, 2023)	(Nwokolo *et al.*, 2022)	(Lave *et al.*, 2013)	(Calif *et al.*, 2013)
GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI
1–24 Hours	1 Hour	1–24 Hours	15 min., 1 s, 0,01s	15 min., 1 s, 0,01s	15 min., 1 s, 0,01s	0,01 s	1 Hour	1 Hour	1 Hour	20 s	0,01 s
Forecasts of solar power production	GHI Vale do Rio Doce estimate	Mozambique K_t behavior	Quantification of the intermediate–sky	Quantifying GHI in the short term	Day type behavior	Geographic solar PV smoothing	Extraterrestrial/ clear–sky radiation	Impact of Climate Change on Solar PV	Methods/ formulas of K_t for regions	Calibration of K^*_t as a function of distance	Intermittency of GHI in a tropical climate
Correlative	Analytical	Analytical	Correlative	Correlative	Correlative	Correlative	Analytical	Physical models	Gumbel probabilistic	Correlative	Correlative
2013	2019	2018	2017	2018	2016	2015	2021	2023	2022	2013	2013
Canada	Brasil	Brazil	Germany	Germany	Germany	USA	Spain	Africa	Africa	USA	France

(Toufik Arrif, *et al.*, 2022)	(Takilalte, A., *et al.*, 2020)	(Rodriguez-Abreo, O., *et al.*, 20221)	(Guermoui M. *et al.*, 2022)	(Bailek *et al.*, 2020)	(Van Haaren *et al.*, 2014)	(Hinkelman, L. M., 2011)	(Inman, R. H. *et al.*, 2013)	(Mills, 2011)	(Marcos *et al.*, 2011)	(Madhavan, B. L. *et al.*, 2016)	(Luoma, J. *et al.*, 2012)
GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI
1–24 Hours	5 min.	1 min.	1 s, 1 min.	1 min.	1 min.	1 min.	0,01 s; 1 min.	1 min.	1 s	0,01 s	0,01 s
Potential assessment of GHI	Estimate GHI data on tilted from horizontal	Climate classification by neural irradiance	New temperature–based predicting GHI	New model of GHI in Algeria	Assessment of short–term PV variability	Characteristics of GHI Variability	Renewable energy integration	Variability GHI Wide–Area Geographic	Power fluctuations: the PV plant/ filter	Observe small–scale cloud inhomogeneity	K_t evaluation and correlation
TVF-EMD	New approach	Irradiance models	Vector regression	New prediction	Empirical	Correlative	Forecasting	Correlative	Correlative	Correlative	Correlative
2022	2020	2022	2022	2020	2012	2011	2013	2011	2022	2016	2012
Algeria	Algeria	Mexico	France	Algeria	USA	USA	UK	USA	Spain	Mexico	Canada

(Sha & Aiello, 2020)	(Roversi, K., & Rampinelli, G. A., 2020)	(Tovar *et al.*, 2001)	(Vijayakumar, 2004)	(Wilcox *et al.*, 2010)	(D. Yang *et al.*, 2017)	(C. Yang & Xie, 2012)	(Assuno, H. F., *et al.*, 2003)	(Aryaputera *et al.*, 2015)	(Arias-Castro *et al.*, 2014)	(Y. Zhang *et al.*, 2018)	(Hassan *et al.*, 2022)	(Obiwulu *et al.*, 2022)
GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI
1 min.	1–24 Hours	1 min.	1, 3 min., 1 Hour	1 Hour	5 min.	1 min.	10 min.	50 s	1 min.	1 min.	1 Hour	1 Hour
Decentralised, Energy Exchange Smart Grid	Grid connected inverter analysis	Dependence of one–minute GHI PDF	Assessment of GHI in solar energy systems	Variability of the GHI in the united states.	Forecasting by covariance structures	A ARX–based multi–scale PV forecast	Frequency of 5 min. GHI indexes by Beta.	Very short–term irradiance forecasting	Anisotropic solar ramp rate correlations	Validation of GFS day–ahead solar China	Forecasting of PV power production	Modeling optimal tilt angle GHI of PV
Monte Carlo method	On grid	HELIOSAT and GISTEL	HDKR model	SUNY model	Kriking	ARX	Probabilities	Kriking	Poisson	Correlative	Non-linear regressive	Modeling correlate
2018	2020	2011	2004	2010	2014	2012	2003	2015	2014	2018	2022	2022
Netherlands	Brazil	Spain	USA	USA	Singapore	USA	Brasil	Singapore	USA	China	Egypt	Africa

	(Come Zebra *et al.*, 2021)	GHI	1 Hour	Renewable Energy Tariff in Mozambique	Analytical	2021	Mozambique
	(Nam, S., & Hur, J., 2019)	GHI	1 min.	A hybrid spatio–temporal forecasting	Physical	2019	Korea
	(Monjoly *et al.*, 2019)	GHI	1 min.	Forecast Horizon and Solar Variability	MHFM	2019	France
	(Mills, 2011)	GHI	1 min.	PV variability for Integrate Electric	Correlative	2011	USA
	(M. J. R. Perez & Fthenakis, 2015)	GHI	>1Hour	On the spatial decorrelation	Correlative	2015	USA
	(Ohtake *et al.*, 2013)	GHI	1 Hour	Accuracy of the solar irradiance in Japan	Analytical	2013	Japan
	(Hoff & Perez, 2010)	GHI	20 s	Quantifying PV power Output Variability.	Novel	2010	USA
	(Haegel *et al.*, 2017)	GHI	1 Hour	Terawatt–scale photovoltaics	Correlative	2017	USA
	(Habte *et al.*, 2020)	GHI	1 Hour	Variability over America (1998–2017)	Correlative	2020	USA
	(Kreuwel *et al.*, 2020)	GHI	15 min.	High frequency PV energy fluctuations	Analytical	2020	Netherlands
	(Koudouris *et al.*, 2018)	GHI	1 Hour	GHI process for renewable manage	Stochastic	2018	Greece
	(Keeratimahat *et al.*, 2017)	GHI	5 min.	short-term variability, renewables penetrate	Analytical	2017	Australia

	(R. Perez, Rábago *et al.*, 2016)	(R. Perez *et al.*, 2018)	(Lan, H. et al, 2018)	(Barry *et al.*, 2017)	(Litjens *et al.*, 2018)	(Lefèvre *et al.*, 2013)	(Lave *et al.*, 2012)	(Ibanez *et al.*, 2002)	(Hummon *et al.*, 2012)	(Keeratimahat *et al.*, 2017)	(Dantas, 2018)	(Dambreville, R. *et al.*, 2014)
	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI	GHI
	0,01 s; 1s	1 s	1 Hour	5 s	1 min.	1 min.	0.01s, 1 min.	1 Hour	>1 Hour	5 min.	1 Hour	15 min.
	High PV penetration for effective electricity	Solar Resource Variability	Forecasting GHI along a navigation route	Power fluctuations in solar–storage clusters	Assessment of residential PV power	Estimating ground GHI in clear–sky	High-frequency GHI fluctuations geo	Frequency Hourly and Daily K_t	Sub-Hour Solar Data for Power System	Variability of utility–scale PV Australian	Sizing a PV system	Forecasting GHI by autoregressive model
	Grig, correlate	Different methods	Correlative	Correlative	Analytical	New model	Correlational	Correlational	Static Spatial	Correlative	Physical	Autoregressive
	2016	2018	2018	2017	2018	2013	2012	2022	2012	2017	2018	2014
	USA	USA	China	Germany	Netherlands	France	India	Madison	USA	Australia	Brazil	France

(Yordanov, G. *et al.*, 2013)	(Hassan *et al.*, 2022)	(Belúcio, L. P. et. al., 2022)	(Lozano *et al.*, 2022)	(Qiu, R. *et al.*, 2022)	(C. A. Gueymard & Wilcox, 2011)	(Jerez *et al.*, 2019)	(Ciampi *et al.*, 2013)	(Liu *et al.*, 2013)	(Lucaciu *et al.*, 2016)	(Shakirov, 2019)	(Y. Zhou *et al.*, 2019)
Cloud speed	PV systems	Insolation	GHI and DNI	GHI hist.	GHI and DNI	GHI and wind	GHI and Thermal	GHI and wind	GHI and irradiative	GHI and wind	GHI
15 min.	1 min.	1 min.	1 Hour	1 min.	1 Hour	1 Hour	1 min.	1 Hour	0,01s, 1 min.	1 min.	1 Hour
Temporal cloud–enhanced sunlight	Energy affected by environmental factors	GHI of Heatstroke	Analysis of cloud effects Mediterranean	Boosting model predicting daily GHI	Variability in direct irradiance (Sahara)	Future temporal variability PV Europe	Energy efficiency in buildings: for thermal	China's solar and wind in a wide area	Variability based on the clearness Index	Wind and solar power variability	Assessment of the zero energy potential
Clod enhanced	Physical models	Estimative	Analytical	Boosting	Correlative	Analytical	Thermal	Correlational	Correlative	Anisotropic model	Correlative
2013	2022	2014	2022	2022	2010	2019	2013	2013	2016	2019	2019
Bulgaria	Egypt	Brasil	Spain	China	USA	Spain	Netherlands	China	Romania	Russia	USA

(Xia *et al.*, 2023)	(Neggers *et al.*, 2003)	(Obiwulu *et al.*, 2020)	(Anenberg *et al.*, 2017)	(Salmanoğlu & ÇetiN, 2022)	(Rapti, 2000)	(Perpiñán & Lorenzo, 2011)	(Mazumdar *et al.*, 2014)	(Charabi & Gastli, 2012)	(Gallego, C. *et al.*, 2013)	(Lave & Kleissl, 2013)	(Uti, M. N. *et al.*, 2023)
GHI	Clouds speed	PV datta	Air pollution	Wind	Climate	PV output	PV power	Solar energy	Wind power	Cloud speed	Ocean speed
1 Hour	1 min.	1 Hour	1 Hour	1–24 Hours	1 Hour	1 min.	0,01 s	1 Hour	0,1 s, 1 min.	1 min.	5 min.
Non–iterative decentralization in multi-micro grid systems	Size cumulus cloud populations	Modeling of back temperature by PV	Air pollution–related in Mozambique	Harvest wind-Solar PV for Production	Atmospheric climatic turbidity, transparency	Variability of GHI, PV power time vs. wavelet	Analysis of utility-scale solar PV power	Assessment of dust risk by proxy data.	large wind power ramp characterisation	Impact cloud speed solar variability	Ocean renewable energy
Non–iterative decentralized	large-eddy SIM.	Temperature model	Analytical	Wind	Atmospherical	WVM	Empirical model	MISR	WVM based	WVM	K–means
2023	2003	2020	2017	2022	2010	2011	2014	2012	2013	2013	2023
China	USA	Africa	Mozambique	Harvest	Greece	Spain	India	Oman	USA	USA	Malaysia

	(Xu *et al.*, 2023)	GHI	1 Hour	Environmental regulation	GTWR	2023	China
	(Sørensen *et al.*, 2023)	GHI	1 Hour	Multivariate wind and solar power forecast	State– of– the art	2023	Denmark
	(Kong *et al.*, 2023)	GHI, thermal	1 Hour	solar radiation for space heating	Convolutional network	2023	China
	(Shen *et al.*, 2023)	GHI, thermal	1 Hour	Spatiotemporal analysis of surface energy change and heating	Long–wave	2023	China
	(Zheng *et al.*, 2023)	PV, thermal, wind	1 Hour	Power generation from multiple hybrid sources	Auto – Regression	2023	China
	(Mol *et al.*, 2023)	GHI, images	1 Hour	Observation of the variability of solar irradiation with cloud	Large eddy	2023	Netherlands
	(Wu *et al.*, 2023)	PV power	1 Hour	Analysis of energy consumption at various scales	Different methods	2023	China
	(Z. Liu *et al.*, 2013)	PV power	1 Hour	Spatial and temporal assessment of the PV potential of urban buildings	anisotropic sky diffuse	2023	China
	(Jain *et al.*, 2023)	GHI, PV power	1 Hour	System planning, variability and operational constraints	Different RES	2023	India
	(Di Fonzo & Girolimetto, 2023)	PV power	1 Hour	Description of solar forecast rate reconciliation	NWP	2023	Italy

Satellite											
(Hoff & Perez, 2011)	(Hoff & Perez, 2010)	(Lorenzo, 2017)	(R. Perez *et al.*, 2012)	(Q., & Xu, J., 2019)	(Zhu *et al.*, 2019)	(Tapia *et al.*, 2022)	(Vindel *et al.*, 2020)	(Chen *et al.*, 2022)	(Alharkan *et al.*, 2023)	(Yan *et al.*, 2020)	(S. Zhang & Yan, 2022)
Insolation	Insolation	GHI	GHI	Cloud	Cloud	GHI	GHI	GHI and PV	Power energy	GHI	GHI
1 Hour	0,01s; 1 s	1 min., 1 Hour	20s, 15 min.	1 Hour	1 Hour	1 Hour	1 Hour	20 s, 1min.	1 Hour	1 Hour	1 Hour
PV Power Output Variability	Changes K_t two locations/ distance	Forecasting network, satellite imagery	Short-term irradiance variability estimation	Estimating Sunshine from a Geostationary	Estimating sunshine duration cloud amount	Variability of GHI in Ecuador	Variability analysis of the GHI intertropical	PV power by NARX, Density Peak e cluster	Solar energy using architecture	Optimization of the energy distribution network between multimicrogrids	State representation and identification for the structure of cavitation flow
Correlative	Correlative	Interpolation	Correlative	Correlative	New Physical model	SFDA	REST2 model	Novel	CNN, LSTM, DSCLANet	MISOCP	CFD
2011	2010	2017	2012	2019	2020	2022	2019	2022	2023	2023	2023
USA	USA	USA	USA	China	China	Ecuador	Spain	China	Saudi Arabia	China	China

(Gutiérrez, C *et al.*, 2017)	(Alharkan *et al.*, 2023)	(L. Yu *et al.*, 2021)	(Kühnert *et al.*, 2013)	(Kumar, 2021)	(Ayet & Tandeo, 2018)	(Amillo *et al.*, 2018)	(Verbois *et al.*, 2023)	(Miller *et al.*, 2018)	(L. Yu *et al.*, 2021)
GHI	GHI	Aerosol,water & vapors	GHI	GHI	GHI	GHI	GHI	GHI	Aerosol,water & vapors
1 Hour	1 min.	1 Hour	1 Hour	1 Hour	6 Hours	1 Hour	1 min.	0,01 s; 1 min.	1 Hour
A multi–step PV production variability	Improvement of satellite–derived GHI	Effects of aerosols and water vapor in China	German Satellite PV Forecasting	Variability using Meteosat satellite	Now casting solar irradiance	Satellite high GHI in South Africa	Improvement of satellite–derived GHI	Short-term solar irradiance forecasting	Effects of aerosols and water vapors in China
Multi–Correlational	Extrapolation/ statist	SSR	Analytical	Derived datasets	NWP	Correlative	Extrapolation/ statist	Coupling	SSR
2017	2023	2020	2013	2021	2018	2018	2023	2021	2020
Spain	France	China	Germany	India	France	South Africa	France	Germany	China

where: WVM – Wavelet variability model; NWM – Numerical weather model; NWP – Numerical Weather Prediction; HDKR – Hay, Davies, Klucher and Reindl model; MHFM – Multiscale hybrid forecast model; USA – United States of America; UK – United Kingdom; RES – Renewable Energy Sources; GTWR – Geographically and Temporally Weighted Regression; CFD – Computational Fluid Dynamics; MISOCP – mixed–integer second–order cone programming; CNN – convolutional neural network; LSTM – long short–term memory and DSCLANet – network followed by a self–attention mechanism network.

Discussion on Assessing the Spatial and Temporal Accessibility of Solar Energy

Throughout the systematic evaluation of recent sources, it is shown that several methods have been proposed for low–resolution analysis of smaller scale data (Assuno *et al.*, 2003), but few with focus on K^*_t, which better reduces the variability due to the geometry of the sun and space, as in R. Perez *et al.*, (2011), G. Lohmann, (2018), G. M. Lohmann & Monahan, (2017), Mucomole *et al.*, (2023), Ibanez *et al.*, (2002), Z. Zhang & Spiegel, (2017), G. M. Lohmann *et al.*, (2018), Assuno *et al.*, (2003), i.e. most focuses on K_t. To simulate variability on temporal scales below the input data, the methodological description adopted takes into account local variables and can be adopted at any point in the world to access the temporal and/or spatio–temporal variability of the availability of solar energy, simply by entering data characteristics of each location, such as: daily measurements that define declination (Mucomole *et al.*, 2023), hour angle, atmospheric transmittance, correction factors for each type of climate to measure clear–sky radiation and output, one can observe the behavior of the clear–sky index over up to years (Duffie & Beckman, 1991, Iqbal, 1983).

Studies from the last twenty years show a greater tendency to analyze samples of small–scale GHI data measuring ~0.0005s to improve real perception of the variability of solar energy, which affects the yield of a PV system (Lohlman *et al.*, 2016; Mucomole et. al., 2023).

The design and monitoring of larger PV plants, connected to the conventional electrical grid, also require highly resolved measurements (Dantas, 2015) to analyze the resourcefulness and output in the PV generator, due to the current dynamics of particles induced in the atmosphere that block the passage of the radiation beam (G. Lohmann, 2018 and G. Lohmann, 2018) as well as cloud dynamics (Shakirov, 2019; Lave & Kleissl, 2013 and Haegel *et al.*, 2017), this also helps in classifying the brightest day and cloudier (Mucomole *et al.*, 2023), to size the PV system according to daily needs, taking into account the availability of local solar energy (Dantas, 2015; Roversi & Rampinelli, 2020).

The methodological description applied here can be inferred for any measurement interval by simply inputting and evaluating the input data by observing the comparison between experimental radiation and clear–sky radiation (Mucomole *et al.*, 2023), however, the other various methods proposed impute data in time and/or space, but without conditioning for large–scale information, which would limit the future machinization of generated model knowledge, and the reduction of coarse–resolution real–world measurements, they can also be adapted for this purpose.

Comparisons with other sources regarding temporal intervals constitute a tool for representative samples of solar energy resources through the use of high–resolution global solar radiation as well as simulations of changes in the clear–sky index of classes of days in different ways and analysis of its variability (Duffie & Beckman, 1991; Iqbal, 1983; G. Lohmann, 2018 and G. Lohmann, 2018).

Large–scale resolutions of measurement intervals are more conducive to evaluating K^*_t (Mucomole *et al.*, 2023; G. M. Lohmann *et al.*, 2018) as a smaller measurement interval would apparently be more suitable for defining the passage of a cloud on a smaller metric scale that translates greater perception of the ray of sunlight measured at closest approximation (Hoff & Perez, 2010; R. Perez, David, *et al.*, 2016; Mucomole *et al.*, 2023), and some research reveals results from studies at approximately 0.0005s measurement interval and show the spatial and temporal variability as well as in the precision of a 0.05 correlation coefficient metric (R. Perez, Rábago, *et al.*, 2016; Perpiñán & Lorenzo, 2011; Sengupta *et al.*, 2015; Marcos *et al.*, 2011; G. M. Lohmann, 2018 and G. M. Lohmann & Monahan, 2018) and present a spatial decorrelation (Hoff & Perez, 2010; Hoff & Perez, 2011 and G. M. Lohmann , 2018). A measurement range for the sample from the Mid-west region largely contributes to the establishment of solar energy accessibility metrics over long distances and in a short measurement interval using data measured in situ with traditional sources such as epply pyranometers, other studies of the same kind even infer on a large scale but using satellite inferred data as in (Amillo *et al.*, 201 and Kühnert *et al.*, 2013, Miller *et al.*, 2018) introduces an error of 0.64 compared to 0.5 traditional pyranometer stations (Mucomole *et al.*, 2023) or empirically generated by numerical models (Mazumdar *et al.*, 2014 and Lefèvre *et al.*, 2013), the majority of research accessed evaluates using mostly in sitio sources rather than campaigns that infer data in a short spatial tuning fork of kilometer sentences in the case of Lohlman *et al.*, (2018) and Perez *et al.*, (2016).

The observation clarity of solar energy variability that is closest to the real has not yet been standardized (Salmanoğlu & ÇetiN, 2022; Hoff & Perez, 2011; Koudouris *et al.*, 2018 and Van Haaren *et al.*, 2014).

Optimal values of K^*_t for optimal analyzes vary up to unity, some studies present a marked value of 1.4, although this value is close to 1; This considerably introduces values outside the defined ones into the temporal assessment of the clear–sky index and induces non–real spatial assessment metrics.

CONCLUSION

With the systematization of the revised sources on spatial and temporal variability on a medium and small scale, it can be concluded that their real prior knowledge helps in managing the output of a solar plant and expands the use of clean energy and better use, contributed to establish a source of summative consultation of the 123 scarce sources in a span of 20 years (listed in the bibliographic references), additionally with this systematization of the literature it is concluded that:

Until now there is no agreement on the temporal resolution and inference of real variability, thus contributing here to a future idealization with the methodology and analysis used for the metric of long distances and in a short analysis time interval (IEA at al., 2023; G. M. Lohmann & Monahan, 2017; Uti *et al.*, 2023; Mazumdar *et al.*, 2014; Habte *et al.*, 2020; Dambreville *et al.*, 2014).

There is a need to apply it to greater distances and to emphasize the interprovincial variability highlighted here, which considerably transcribes the potential along the route as well as the evaluation in terms of temporal intermittence of the energy resource in the section under analysis compared to the evaluation of hundreds of kilometers for small projects, however, this greatly contributes to meeting the goals of sustainable energy access objectives that are taxed until the end of 2030 and assisting in the use of clean energy that is expected to be taxed until the end of the 2050s (M. J. R. Perez & Fthenakis, 2015; Hoff & Perez, 2010; Hoff & Perez, 2018 and Lucaciu *et al.*, 2016)

The spatial behavior of solar energy variation here is quantified in a decorrelation, the same found in Lohlman *et al.*, (2018), Lohlman *et al.*, (2016), Marcos *et al.*, (2015), although the sample has different characteristics, here 1 min is adopted aggregated to 10 min, and in the remaining surveys 1s aggregated to 15 min of measurement intervals. Due to the dynamics to which it is subject, such as atmospheric pollution that emits harmful gases into the Earth's atmosphere, aerosols emitted by gases and solid particles that concentrate near the ozone layer, and other phenomena (Twidell & Weir, 1999) as in the case of atmospheric absorption, scattering, also largely interfere with the fluctuations and variability of solar energy on the Earth's surface (Perpiñán & Lorenzo, 2011; Sengupta *et al.*, 2015; Marcos *et al.*, 2011; G. M. Lohmann , 2018 and G. M. Lohmann & Monahan, 2018)

The temporal behavior of the study area presents a temporal tuning fork of the index with the majority of measurements with the methodological description present in the graphic representations with a maximum normalized to 1 for all data due to there being some values that were not adopted normalized to around up to around of 1.011 admissible for approximation to 1, every day has the spectrum within the theoretical irradiation in clear–skies which classifies the model as ideal for processing studies on small measurement scales, large scales as well as for long or infinitely reduced distances for any part of the world, simply adopt the local characteristic variables described in the previous section (Mucomole *et al.*, 2023; Marcos *et al.*, 2011).

Source of Funding

This research is funded by CS–OGET (Center of Excellence of Studies in Oil and Gas Engineering and Technology), from the Faculty of Engineering of Eduardo Mondlane University.

Acknowledgments

The findings of this study are not yet published, but they can be obtained from INAM, FUNAE, UEM, or by contacting the corresponding author and making a reasonable request.

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