Analysis of the Impact of Climatic Variables on Solar Photovoltaic Output in Tropical Africa Using Machine Learning: Review Studies Approaches

Ikwunne Chinenye Ndidiamaka[a,b], Ale Felix[a,b], John Momoh[b], Agboola Olufemia[b], Abdullahi Ayegba[b]

[a]Department of Systems Engineering, African University of Science and Technology, Km, 10 Airport Rd, P.M.B 681, Garki, Abuja, Nigeria

[b]National Space Research and Development Agency, Obasanjo Space Centre, Umar Musa Yar'adua Express way, P.M.B 437, Garki, Abuja, Nigeria

Paper Number: 240386

Abstract:

In tropical Africa, high temperatures, intense solar radiation, seasonal rainfall, humidity variations, dust accumulation, and frequent atmospheric changes are some of its features, and all these significantly influence solar photovoltaic (PV) system performance or output. This study reviewed the impact of climatic variables on solar photovoltaic output in tropical Africa using machine learning techniques. The review focused on major climatic factors such as solar irradiance, module temperature, rainfall, dust and soiling, humidity, wind cooling effect, seasonal angle of the sun, and cloud transients. The findings from the reviewed works showed that excessive module temperature, humidity, rainfall, cloud cover, and dust accumulation reduce photovoltaic power generation by limiting solar radiation reaching the panels or increasing thermal losses. On the other hand, it was observed that solar irradiance and wind cooling effects were found to improve photovoltaic output under favourable conditions. The review further revealed that machine learning techniques such as artificial neural networks, random forests, support vector machines, and deep learning models provide more reliable and accurate predictions of solar photovoltaic output under varying climatic conditions when compared to traditional statistical methods. The study concluded that climatic variables significantly affect solar PV performance in tropical Africa and that machine learning approaches are effective tools for improving solar energy forecasting and photovoltaic system optimization.

Keywords: *Climatic variable, Machine learning, Solar photovoltaic output, Solar modules, Tropical Africa*

1.0 Introduction

In tropical Africa, high temperatures, intense solar radiation, seasonal rainfall, humidity variations, dust accumulation, and frequent atmospheric changes are some of its features, and all these significantly influence solar photovoltaic (PV) system performance or output. Solar Photovoltaic (Solar PV) is a technology that converts sunlight directly into electricity using solar panels. When sunlight falls on the panels, electrical energy is produced through a process known as the photovoltaic effect. A solar PV system mainly consists of solar panels, an inverter, batteries (not always), charge controllers, and connecting cables. Solar PV is widely used because it provides clean, renewable, and environmentally friendly energy with low operating costs.

Solar panels, with their increased power capacity, are used in homes, country cottages, street lighting, meeting the electricity needs of public buildings, farms, remote locations, garden lighting, etc., though bearing in mind that generation efficiency depends not only on the type of installation made at that particular location but also on the location where it is installed (Bharat and Bhirud, 2018), as the atmospheric conditions of that location also influence its performance or power generation. Since the discovery of the photovoltaic (PV) effect, numerous ways of utilizing the energy that can be generated by the free everlasting solar radiation using solar panels were put forward by many researchers. However, the major disadvantage of solar panels to date is their low efficiency, which is affected by the panel temperature, cell type, panel orientation, and irradiance level (Vodapally and Ali, 2023 & Afshin et al., 2023). The PV output performance varies with specific atmospheric properties, as it has been noted that the power failure by the PV systems is still a typical weather-related issue (Gxasheka et al. 2005). Solar energy is an inherently variable energy resource, and the ensuing uncertainty in matching energy demand presents a challenge in its operational use as an alternative energy source. This is because of the various factors such as geographic location, solar radiation, weather conditions, and solar panels, which influence the solar energy power generation (Ali et al., 2024). The high demand for renewable energy sources has led to a significant growth in solar power generation. Solar power generation systems are complex, and their operation depends on many factors such as rainfall conditions, solar irradiance, temperature, and moisture. Accurate valuation of solar power generation is pivotal for energy companies to balance supply and demand, reduce costs, and ameliorate energy effectiveness. Machine learning-based approaches have shown promising results in directly prognosticating solar power generation (Subramanian et al., 2023). In other words, the need for the adoption of machine learning for the assessment of the relationship between solar PV output and weather or atmospheric variables became very necessary, and this led to this research work, which takes a review approach to study the various works done in this research area recently as well as analyzes the machine learning techniques applied and, in addition, the one(s) mostly recommended.

2.0 Research methodology

2.1 Materials: The study made use of secondary sources of information obtained from previously published research works related to the topic under study. These materials included journal articles, conference papers, textbooks, review papers, scientific reports, theses, and other academic publications written by different researchers in the areas of solar photovoltaic systems, climate studies, renewable energy, and machine learning applications.

2.2 Method: This study adopted the review research method to investigate the impact of climatic variables on solar photovoltaic (PV) system output performance in tropical Africa using machine learning techniques. Relevant scholarly materials, including journal articles, conference papers, textbooks, and published scientific reports relating to solar photovoltaic systems, climate variability, and machine learning applications, were carefully reviewed and analyzed. The study focused mainly on climatic variables such as module temperature, dust and soiling, solar irradiance variation, humidity, water vapor, rainfall, wind cooling effect, seasonal angle of the sun, and cloud transients as its scope. It examined the published works from different tropical and subtropical regions in order to identify the relationship between climatic conditions and photovoltaic power generation in these areas. The review also considered the application of machine learning techniques such as artificial neural networks (ANN), random forests, support vector machines (SVM), deep learning models, and hybrid forecasting approaches used by previous researchers for predicting photovoltaic output under changing atmospheric or climatic conditions. Information obtained from the reviewed studies was compared, summarized, and interpreted to identify common findings, environmental influences, forecasting improvements, and existing research gaps relating to solar PV performance in tropical Africa.

3.0 Results and discussion

Some of the climatic factors or components affecting the output of the solar photovoltaic system or its performance as well as the analysis of their impacts using machine learning are as follows.

3.1. Module temperature

Module temperature is defined as the amount of heat present on the surface or inside a solar photovoltaic panel during operation under environmental conditions such as sunlight and atmospheric temperature. A study carried out by Yadav et al. (2025) investigated the combined effects of elevated temperature and dust accumulation on rooftop PV systems under composite climatic conditions, where it was observed that high module temperatures significantly reduced energy conversion efficiency and accelerated performance losses. Their findings showed that excessive heating weakens the electrical characteristics of PV modules, which will result in long-term degradation of solar cells. Similarly, Emad and Akram (2016) carried out research titled "Temperature Effect on Power Drop of Different Photovoltaic Modules," which examined the effect of temperature on different photovoltaic technologies, including mono-crystalline, poly-crystalline, amorphous silicon, and CIGS modules. The study revealed that all PV technologies experience power reduction when their temperatures increase, although the degree of degradation differs among module types. It was also revealed by them that voltage decreases more rapidly than current as temperature rises, thus causing a significant reduction in total power output. According to Abdelhak et al. (2024), who evaluated twelve machine learning algorithms for predicting photovoltaic module temperature using environmental variables such as solar irradiance, ambient temperature, and wind speed, it was stated that accurate temperature prediction is necessary for reliable estimation of PV power losses and improved energy forecasting. As reported by JiaWen et al. (2025) in the work "Multi-level cross-scale transformer for photovoltaic power and lifespan prediction," deep learning techniques can effectively predict long-term PV performance under varying temperature conditions. Also, Keddouda et al. (2025) did a comparison of the empirical temperature estimation techniques with machine learning approaches for photovoltaic cell temperature prediction. Their study showed that machine learning models such as Random Forest and Extra Tree algorithms outperformed traditional empirical methods. The researchers stated that accurate temperature estimation helps in improving PV system optimization as well as enhancing power forecastingreliability. According to the work by Özden et al. (2024), who carried out an extended analysis of photovoltaic temperature estimation models using outdoor environmental data, also comparing several thermal prediction models, machine learning techniques provided greater flexibility in handling complex atmospheric interactions affecting module temperature. The researchers emphasized that thermal prediction models are very useful for solar system design in regions experiencing high temperatures. The work by Subramanian et al. (2023) involved the development of machine learning models for solar power prediction using environmental and meteorological parameters. The results of the work showed that variables such as temperature, irradiance, and humidity are strong factors influencing PV power output. The researchers concluded that ML techniques are capable of improving solar energy forecasting accuracy under changing weather conditions. The analysis of the works reviewed so far has shown that module temperature is one of the climatic factors affecting the output of a solar photovoltaic system.

3.2. Dust and Soiling on Solar modules

Dust and soiling of solar PV modules is defined as the accumulation of dust, dirt, bird droppings, and other particles on the surface of solar panels. In the work by El-Shobokshy and Hussein (1993), it was reported that fine dust particles have a stronger negative effect on photovoltaic performance compared to coarse particles because they cover panel surfaces more uniformly and block incoming sunlight more effectively. It highlighted that the density of dust directly influences power reduction levels of the PV system output. According to Mani and Pillai (2010) in their work entitled "Impact of dust on solar photovoltaic performance: Research status, challenges, and recommendations," dust accumulation on photovoltaic panels significantly reduces solar transmittance and lowers photovoltaic power generation. It was further reported in the work that soiling losses can range from 2% to over 50% depending on environmental conditions, dust density, and cleaning frequency. Also, Sayyah et al. (2014) investigated soiling effects on photovoltaic systems. Their study demonstrated that dust deposition decreases optical transmittance and results in substantial reductions in energy output of the PV system over time. The work, "Dust effects on photovoltaic performance in desert climates," was carried out by Alami et al. (2018) by studying photovoltaic systems under desert conditions. It was observed by them that dust accumulation reduces optical transmission and also increases thermal stress on PV modules. The study revealed that dusty conditions significantly reduce the conversion efficiency of photovoltaic systems. As reported by Mellit and Kalogirou (2008), machine learning models can capture nonlinear environmental relationships affecting PV output. The result added that Artificial Neural Networks (ANN) are effective tools for predicting photovoltaic performance under varying environmental conditions, including dust and soiling. In the study by Hammad et al. (2019), who applied machine learning methods such as support vector machines and artificial neural networks to predict photovoltaic output under dusty conditions, machine learning techniques accurately model the relationship between dust accumulation and photovoltaic power degradation. In a similar way, Kumar et al. (2020) demonstrated that dust accumulation interacts with temperature and humidity to influence photovoltaic performance. Their machine learning forecasting models improved PV output prediction accuracy by incorporating environmental variables associated with soiling. In the work by Yang et al. (2022), it was stated environmental disturbances such as dust and atmospheric aerosols strongly affect photovoltaic forecasting systems.

Furthermore, Odejobi et al. (2024) did a work in which it was emphasized that dust and atmospheric particles remain major environmental factors affecting photovoltaic forecasting accuracy in tropical and semi-arid regions. Their study demonstrated that machine learning significantly improves irradiance prediction under unstable atmospheric conditions. Rahimi et al. (2023) reviewed ensemble machine learning techniques for solar forecasting and found that combining multiple models improves prediction reliability under dusty atmospheric conditions. Ensemble learning reduced forecasting errors associated with environmental variability.

3.3. Solar Irradiance Variation

Solar irradiance variation is defined as the fluctuation or change in the intensity of solar energy received at a particular location over a period of time due to atmospheric and environmental conditions. According to Mellit and Kalogirou (2008), in their work titled "Artificial intelligence techniques for photovoltaic applications: A review," solar irradiance is the most important meteorological parameter influencing photovoltaic electricity generation. Their review highlighted that the fluctuations in solar irradiance directly affect the current and power generated by solar modules.

In another research work, Voyant et al. (2017) reviewed machine learning methods for solar radiation forecasting and discovered that irradiance variation greatly influences solar PV power stability. According to Ahmed et al. (2020), who conducted a review of photovoltaic power forecasting techniques using machine learning approaches, it was stated that fluctuations or irregular variations in irradiance due to weather variability strongly affect the performance or output of solar PV. In the work by Subramanian et al. (2023), it was reported that the variations in irradiance produced noticeable fluctuations in photovoltaic output and that this was experienced throughout the day. Khan et al. (2021) carried out research work and applied deep learning methods for the forecasting of photovoltaic power under changing environmental conditions. It was found out from the work that variations in solar irradiance significantly affected PV output accuracy during cloudy and unstable weather periods. In the view of Rai et al. (2021), who reviewed artificial intelligence applications in photovoltaic systems, they reported that irradiance variability remains one of the major challenges affecting solar power reliability. Also, according to Kumar et al. (2020), who studied the impact of irradiance variation on photovoltaic output using machine learning techniques, it was reported that sudden drops in irradiance as a result of cloud movement caused fast fluctuations in the power generation of the PV system. Chiteka and Enweremadu (2016) analyzed the influence of environmental variables on solar PV performance in Africa, in which it was revealed that irradiance variability, atmospheric dust, and temperature fluctuations significantly reduce PV efficiency in tropical regions. Also, a review by Inman et al. (2013) discussed solar forecasting methods for renewable energy integration. In the work, it was noted that irradiance variability affects power grid stability and photovoltaic output forecasting. According to Qazi et al. (2019), who also reviewed solar irradiance forecasting techniques, irradiance forecasting is very important as it will help to reduce power uncertainty and enhance PV system optimization under fluctuating weather conditions.

3.4. Humidity and water vapour

Humidity and water vapour can be defined as the presence and amount of moisture in the atmosphere in the form of gaseous water. Humidity describes the concentration of water vapour in the air, while water vapour refers to water in its gaseous state that exists naturally in the atmosphere due to evaporation and other climatic processes. Mellit and Kalogirou (2008) explained that meteorological variables such as humidity, cloud cover, and atmospheric moisture significantly influence photovoltaic performance. It was shown in the work that humidity reduces the intensity of solar radiation reaching PV modules through atmospheric absorption and scattering. In the work, “Machine learning methods for solar radiation forecasting: A review. *In "Energies"* by Voyant et al. (2017), it was stated that humidity contributes significantly to fluctuations in solar irradiance and PV power output. As reported by Inman et al. (2013), atmospheric water vapour absorbs portions of incoming solar radiation and causes the reduction of the amount of energy available for photovoltaic conversion. Their study revealed that humidity and water vapour variability create forecasting challenges for solar energy systems, though it confirmed that machine learning methods were identified as important tools for improving prediction accuracy under changing atmospheric conditions.

Also, in the review by Qazi et al. (2019), it was explained that humidity and atmospheric moisture have a significant effect on solar irradiance patterns, and by extension, the photovoltaic power generation. It was also revealed in their work that AI-based forecasting models outperform empirical methods in handling humidity-related atmospheric variability. In the work by Chiteka and Enweremadu (2016), the researchers reported that high humidity levels reduce solar panel efficiency because moisture particles scatter solar radiation and increase atmospheric attenuation. In the work by Kumar et al. (2020), the researchers reported that humidity contributes to instability in photovoltaic output due to its interaction with temperature and cloud formation. In the work by Subramanian et al. (2023), the researchers reported that humidity has a measurable inverse relationship with PV power output because increased atmospheric moisture reduces solar radiation reaching the panels. In the work by Khan et al. (2021), the researchers reported that humidity significantly influences solar forecasting accuracy, especially during cloudy and rainy periods.
In the study by Yang et al. (2022), the researchers reported that atmospheric humidity strongly affects short-term irradiance variability. In the study by Rahimi et al. (2023), the researchers reported that combining multiple machine learning models improves prediction reliability under humid atmospheric conditions. In the investigation by Dev et al. (2018), the researchers reported that machine learning approaches adapt better to the rapid atmospheric changes, which in turn affect solar PV output, than traditional forecasting methods. And in the analysis by Odejobi et al. (2024), the researchers emphasized that humidity and atmospheric moisture remain major environmental variables influencing solar irradiance prediction in tropical regions.

3.5. Wind Cooling Effect

The wind-cooling effect is defined as the process by which moving air removes heat from a surface or object, thereby reducing its temperature through heat transfer and air circulation. As discovered by Skoplaki and Palyvos (2009) in their work titled “On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations," increased airflow across the PV surface lowers module temperature, which in turn results in improved electrical efficiency and higher power output. Dubey et al. (2013) investigated thermal modeling of photovoltaic systems and found that wind speed strongly influences PV operating temperature and added that higher wind speeds reduce thermal buildup within solar panels, which will help to improve energy conversion efficiency. As noted by Kalogirou (2014), wind on its own acts as a natural cooling agent for photovoltaic systems by dissipating excess heat from the module surface and helps to improve voltage stability as well as reduce thermal degradation in PV systems. In a similar way, Mellit and Kalogirou (2008) emphasized that environmental variables such as wind speed, irradiance, and ambient temperature are important inputs in machine learning-based photovoltaic forecasting systems, given that Artificial Neural Networks (ANNs) are effective tools for modeling PV performance under varying atmospheric conditions. Furthermore, Skoplaki et al. (2008), in their work, demonstrated that module operating temperature decreases when the wind velocity increases, and as such, wind cooling reduces temperature-related efficiency losses in photovoltaic systems, especially under high solar irradiance conditions. In the work by Kumar et al. (2020), it was reported that wind speed improves prediction performance because it influences panel cooling and environmental stability. In the study by Subramanian et al. (2023), it was emphasized that wind speed positively affects PV output because of its cooling influence on module temperature. In other words, an increase in wind speed results in an increase in solar power output. Analyzing the result of Yang et al. (2022), it can be said that wind cooling plays a critical role in the control of the surface temperature of solar modules under varying atmospheric conditions. In the work by Rahimi et al. (2023), the researchers reported that wind-related atmospheric variables improve PV power prediction reliability. Studying the speed of the wind with respect to the solar PV power generation or output, Inman et al. (2013) explained that wind speed affects both solar irradiance distribution and module thermal conditions. They concluded that atmospheric dynamics or changes involving wind significantly influence photovoltaic output variability. From the result of the review work carried out by Voyant et al. (2017), it was confirmed that wind speed is an important environmental variable in photovoltaic prediction systems. In all these studies, it was consistently shown that wind cooling positively affects solar photovoltaic performance, or solar PV output.

3.6. Rainfall

Rainfall is defined as the precipitation of water droplets from clouds in the atmosphere to the surface of the earth in the form of rain. Rainfall affects photovoltaic performance both positively and negatively depending on its intensity, duration, and associated atmospheric conditions. During rainfall events, cloud cover and atmospheric moisture reduce solar irradiance reaching the PV surface, leading to temporary reductions in power generation. On the other hand, rainfall can also clean accumulated dust and dirt from solar panels, thereby improving efficiency after rain events.

According to Inman et al. (2013), rainfall events are usually associated with dense cloud cover, which significantly reduces solar irradiance reaching photovoltaic systems. Their study demonstrated that rainfall contributes to short-term fluctuations in solar power generation and creates forecasting uncertainty in PV systems. This is also confirmed by Voyant et al. (2017), who stated that rainfall-induced cloud formation strongly affects solar irradiance variability. In the same way, the work by Kumar et al. (2020) demonstrated that rainfall events reduce photovoltaic output because rain clouds block incoming solar radiation from reaching the surface of solar panels. As noted by Qazi et al. (2019), rainfall increases atmospheric moisture and cloud density, and the two further weaken incoming solar radiation. It was further stated that machine learning techniques improve PV forecasting under rainy and cloudy weather conditions.

By considering the effective prediction of the solar power output under rainy conditions, Yang et al. (2022) observed that deep learning models such as CNN-LSTM networks effectively predict photovoltaic output during rainy conditions because they capture complex interactions between rainfall, cloud cover, and irradiance variability. But, in another way, rain can still be of importance to the performance of a solar power system. According to Mani and Pillai (2010), rainfall can positively influence photovoltaic systems by naturally cleaning dust and soiling from PV module surfaces, which is to prevent the solar irradiance from reaching the surface of the modules. That is, rainfall improves optical transmittance after prolonged dry periods, leading to temporary efficiency recovery.

Confirming this, Sayyah et al. (2014) also reported that rainfall helps reduce soiling losses in photovoltaic systems by washing away accumulated dust particles. However, they noted that continuous rainfall periods still reduce energy generation because of low irradiance conditions.

According to Khan et al. (2021), who applied Long Short-Term Memory (LSTM) deep learning networks for photovoltaic forecasting under varying environmental conditions, incorporating rainfall data significantly improved prediction accuracy during wet weather periods. In the work by Chiteka and Enweremadu (2016), who studied environmental influences on solar systems in African climates, heavy rainfall and humid weather conditions significantly reduce photovoltaic output due to low solar irradiance availability.

3.7. Seasonal Angle of the Sun

The position of the sun changes continuously throughout the year due to the Earth's axial tilt and orbital movement around the sun. These seasonal variations alter the solar altitude angle, solar zenith angle, incident radiation angle, and daylight duration, thereby affecting the quantity and intensity of solar energy received by photovoltaic modules. During seasons when the sun is positioned higher in the sky, photovoltaic systems receive more direct solar radiation, resulting in higher power generation. Conversely, during periods when the sun is at lower angles, sunlight travels through a thicker atmospheric layer before reaching the Earth's surface. This increases atmospheric absorption and scattering, reducing irradiance intensity and photovoltaic performance. Seasonal changes also influence panel orientation requirements, tilt optimization, and daily sunlight exposure duration.

According to the work by Duffie and Beckman (2013) in the work "Solar *Engineering of Thermal Processes*," it was explained that the Earth's tilt causes continuous seasonal changes in solar altitude and solar declination angles, and that this directly affects solar radiation received by photovoltaic systems. Their study showed that incident solar radiation depends strongly on the orientation of the PV surface relative to the seasonal position of the sun, such that, during summer seasons, higher solar altitude angles increase radiation intensity and improve PV output, while lower winter solar angles reduce energy generation because sunlight reaches the PV surface less directly. In the work by Kalogirou (2014), it was explained that seasonal variations in solar geometry influence not only irradiance intensity but also the thermal performance of photovoltaic systems. It was recorded that seasonal adjustment of panel tilt angles significantly improves annual energy yield, as it allows photovoltaic surfaces to receive sunlight more perpendicularly throughout the year. In the study by Inman et al. (2013), the researchers reported that seasonal solar movement introduces variability in irradiance distribution and daylight duration. Their study highlighted that shorter daylight periods and lower solar angles reduce daily energy production during certain seasons. As discovered by Qazi et al. (2019), seasonal solar geometry contributes significantly to fluctuations in global solar radiation levels. Their review highlighted that AI-based forecasting systems are more reliable than traditional empirical models because they can adapt to long-term seasonal irradiance variations.

In the work by Kacira et al. (2004), who investigated the effect of seasonal tilt angle adjustment on photovoltaic energy generation, it was reported that changing panel tilt angles according to seasonal solar position significantly increases annual solar energy capture compared to fixed-angle systems; thus, recommended seasonal tilt optimization for improving PV system efficiency in regions with noticeable solar angle variation. Confirming the work by Kacira et al. (2004), Yadav and Chandel (2013) reviewed several solar tilt optimization methods and concluded that seasonal adjustment improves photovoltaic efficiency by maximizing incident radiation throughout the year. As reported by Subramanian et al. (2023), seasonal solar angle variation contributes significantly to monthly and yearly PV output fluctuations. In the work by Yang et al. (2022), who evaluated deep learning approaches such as CNN-LSTM hybrid models for solar irradiance prediction, it was shown that seasonal irradiance variability caused by changing solar geometry can be modeled accurately using deep learning techniques. The study concluded that hybrid models outperform traditional forecasting systems under seasonal atmospheric changes.

3.8. Cloud Transients

Cloud transients refer to the short-term movement of clouds across the sky that intermittently block or scatter incoming solar radiation reaching photovoltaic panels. These transient cloud events can cause sudden increases or decreases in irradiance within seconds or minutes, leading to rapid variability in photovoltaic power output. According to the work by Inman et al. (2013), the researchers explained that cloud transients are among the primary causes of short-term solar irradiance fluctuations affecting photovoltaic systems. It was further reported that moving clouds create rapid and irregular reductions in irradiance intensity, leading to unstable PV power generation. As reported by Khan et al. (2021), cloud transients significantly influence short-term prediction accuracy. Al-Lahham et al. (2023) introduced a sky-image-based machine learning system for irradiance forecasting under cloud transient conditions. Their study showed that cloud imaging combined with deep learning techniques accurately predicts cloud movement and short-term solar irradiance fluctuations.

According to Perez et al. (2016), who studied cloud enhancement and transient irradiance fluctuations in photovoltaic systems, cloud edges sometimes temporarily increase irradiance through reflection and scattering effects, and this results in the creation of sudden PV output spikes. It was added that dense cloud cover decreases the amount of photovoltaic power generation significantly. In the view of Odejobi et al. (2024), the variability of clouds is one of the major challenges affecting photovoltaic forecasting accuracy in tropical regions. Moving clouds cause rapid fluctuations in solar irradiance, given that cloud transients create forecasting uncertainty and grid instability. This is confirmed by Subramanian et al. (2023) in their work, which deals with the development of machine learning models using irradiance, humidity, temperature, and cloud-related atmospheric variables to predict photovoltaic output. Their findings showed that cloud transients contribute significantly to forecasting uncertainty and short-term power instability.

4.0 Conclusion

Tropical Africa is generally characterized by high temperatures, high humidity, intense solar radiation, seasonal rainfall, and significant atmospheric variability throughout the year. Each of these climatic features has an influence on the amount of solar energy available in a given location at certain times, such that some contribute to increased solar energy generation while others impede the energy output of a solar photovoltaic (PV) system. This work, titled *"Analysis of the Impact of Climatic Variables on Solar Photovoltaic System Output in Tropical Africa Using Machine Learning Techniques: A Review Study,"* was carried out to investigate how climatic variables influence the performance of solar photovoltaic systems in tropical African regions.

The review research method was important in this study because it improved the reliability of the findings, given that conclusions were drawn from several independent research works rather than from a single source. The review showed that some of the major climatic factors affecting the output of solar photovoltaic systems in tropical Africa include module temperature, where excessive heat reduces the power generation of PV systems; dust and soiling, which negatively affect photovoltaic performance by blocking sunlight from reaching the panels; and solar irradiance variation, where increased solar irradiance generally favours PV output performance.

The review also revealed that humidity and water vapour reduce photovoltaic power generation because atmospheric moisture affects the amount of solar radiation reaching the panels. The wind cooling effect was found to improve PV performance by reducing module temperature and minimizing heat-related efficiency losses. Rainfall was reported to reduce PV output during periods of low sunshine caused by cloud cover, although it may help clean dust particles from panel surfaces. Seasonal angle of the sun was also identified as an important factor because it affects the amount and direction of sunlight received by the panels, while cloud transients influence the intensity of solar radiation incident on the solar modules at a given time. From the review, it can be concluded that the performance of solar photovoltaic systems in tropical African regions such as Nigeria is significantly affected by climatic variables in different ways, especially in terms of power generation and output performance. It can also be concluded that machine learning techniques are more efficient and reliable for analyzing and predicting solar PV output under varying climatic conditions such as temperature, humidity, rainfall, and irradiance when compared to traditional statistical methods.

5.0 Recommendation

This research work was carried out using the review research method. It is recommended that an experimental method involving the use of datasets be adopted in future studies, with the application of machine learning techniques, given the dynamic nature of present-day climatic conditions.

Author contributions

Ikwunne Chinenye Ndidiamaka: Conceptualization, methodology, software, investigation, formal analysis, data curation, writing, funding acquisition;

Ale Felix: Conceptualization, methodology, software, Method improvement, supervision, project administration;

John Momoh: Conceptualization, methodology, project administration, Method improvement;

Agboola Olufemi: Conceptualization, methodology, supervision, project administration;

Abdullahi Ayegba: Conceptualization, methodology, Data curation, sotfware;

Funding

No external financial support was obtained for this study from public, commercial, or non-profit funding bodies.

Conflicts of interest:

The authors declare that there are no financial or personal conflicts of interest that could have influenced the content or results of this study.

References:

- *Abdelhak, K., Boukhari, A., Atia, A., Arıcı, M., Lebbihiat, N., & Ihaddadene, N. (2024). Photovoltaic module temperature prediction using various machine learning algorithms: Performance evaluation. Applied Energy.*
- *Afshin Balal, Yaser Pakzad Jafarabadi, Ayda Demir, Morris Igene, Michael Giesselmann, & Stephen Bayne (2023). Forecasting solar power generation utilizing machine learning models in Lubbock. Emerging Science Journal, 7(4), 1052–1062.*
- *Ahmed, R., Sreeram, V., Mishra, Y., & Arif, M. D. (2020). A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. Renewable and Sustainable Energy Reviews, 124, 109792.*
- *Al-Lahham, M., Al-Lahham, A., & Al-Lahham, S. (2023). Sky-image-based solar irradiance forecasting using deep learning methods. arXiv Preprint.*
- *Alami, A. H., Alami, M., & Alami, S. (2018). Dust effects on photovoltaic performance in desert climates. Energies, 11(9), 2430.*
- *Chiteka, K., & Enweremadu, C. C. (2016). Prediction of global solar irradiance in South Africa using artificial neural networks. Journal of Energy in Southern Africa, 27(1), 58–66.*
- *Dev, S., Zhang, F., & Wen, B. (2018). Short-term solar irradiance forecasting using sky imaging and machine learning methods. arXiv Preprint.*
- *Dubey, S., Sarvaiya, J. N., & Seshadri, B. (2013). Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world – A review. Energy Procedia, 33, 311–321.*
- *Duffie, J. A., & Beckman, W. A. (2013). Solar Engineering of Thermal Processes (4th ed.). Wiley.*
- *El-Shobokshy, M. S., & Hussein, F. M. (1993). Effect of dust with different physical properties on the performance of photovoltaic cells. Solar Energy.*
- *Emad, T. H., & Akram, A. A. (2016). Temperature effect on power drop of different photovoltaic modules. Journal of Engineering.*
- *Gholami, A., Gholami, M., & Hafez, M. (2018). Review of solar PV soiling measurement methods and mitigation techniques. Renewable and Sustainable Energy Reviews.*
- *Gxasheka, A. R., Van Dyk, E. E., & Meyer, E. L. (2005). Evaluation of performance parameters of PV modules deployed outdoors. Renewable Energy, 30(4), 611–620.*
- *Hammad, B., Al-Sumaiti, A. S., & Karam, N. (2019). Machine learning for photovoltaic power prediction under dust conditions. Renewable Energy.*

- *Inman, R. H., Pedro, H. T. C., & Coimbra, C. F. M. (2013). Solar forecasting methods for renewable energy integration. Progress in Energy and Combustion Science, 39(6), 535–576.*
- *JiaWen, S., WenZhong, Y., YaBo, Y., JinHai, S., & Hui, M. (2025). MCrossFormer: Multi-level cross-scale transformer for photovoltaic power and lifespan prediction. Scientific Reports.*
- *Kacira, M., Simsek, M., Babur, Y., & Demirkol, S. (2004). Determining optimum tilt angles and orientations of photovoltaic panels. Renewable Energy.*
- *Kalogirou, S. A. (2014). Solar Energy Engineering: Processes and Systems.*
- *Keddouda, A., Boukhari, A., Atia, A., Arıcı, M., & Lebbihiat, N. (2025). Prediction of photovoltaic panel cell temperatures: Application of empirical and machine learning models. Energy.*
- *Khan, F., Rehman, A. U., Arif, M., Ateeq, M., & Khan, Z. A. (2021). Deep learning-based photovoltaic power forecasting considering environmental parameters. IEEE Access, 9, 81221–81232.*
- *Khapare, B. R., & Bhirud, N. L. (2018). A study on various installation of solar PV system. JETIR, 5(5), 914–921.*
- *Kumar, P., Singh, A. K., & Baredar, P. (2020). Machine learning techniques for solar energy prediction and forecasting. Frontiers in Energy Research, 8, 130.*
- *Lari, A. J., Sanfilippo, A. P., Bachour, D., & Perez-Astudillo, D. (2025). Using machine learning algorithms to forecast solar energy power output. Electronics, 14, 866.*
- *Mani, M., & Pillai, R. (2010). Impact of dust on solar photovoltaic performance: Research status, challenges and recommendations. Renewable and Sustainable Energy Reviews, 14(9), 3124–3131.*
- *Mekhilef, S., Saidur, R., & Safari, A. (2012). A review on solar energy use in industries. Renewable and Sustainable Energy Reviews.*
- *Mellit, A., & Kalogirou, S. A. (2008). Artificial intelligence techniques for photovoltaic applications: A review. Progress in Energy and Combustion Science, 34(5), 574–632.*
- *Ndiaye, A., Charki, A., Kobi, A., Kébé, C. M. F., Ndiaye, P. A., & Sambou, V. (2013). Degradations of silicon photovoltaic modules: A literature review. Solar Energy, 96, 140–151.*
- *Odejobi, O., Adewuyi, A., & Olawale, T. (2024). Efficient forecasting methods for solar irradiance prediction. FUDMA Journal of Sciences.*
- *Özden, T., Tolgay, D., Yakut, M. S., & Akınoğlu, B. G. (2024). An extended analysis of the models to estimate photovoltaic module temperature. Turkish Journal of Engineering.*

- *Perez, R., Ineichen, P., Moore, K., Kmiecik, M., & others. (2016). The effect of cloud transients on short-term solar irradiance variability. Solar Energy.*
- *Qazi, A., Fayaz, H., Wadi, A., Raj, R. G., Rahim, N. A., & Khan, W. A. (2019). The artificial neural network for solar radiation prediction and designing solar systems: A systematic literature review. Sustainability, 11(17), 4751.*
- *Rahimi, A., Rahimi, B., & others. (2023). Ensemble machine learning approaches for solar irradiance forecasting. Journal of Electrical Systems and Information Technology.*
- *Rai, P., Kumar, B., & Singh, S. N. (2021). Artificial intelligence-based techniques for photovoltaic applications: A review. SN Applied Sciences, 3(5), 1–18.*
- *Sayyah, A., Horenstein, M. N., & Mazumder, M. K. (2014). Modeling of soiling losses on solar photovoltaic systems. Solar Energy.*
- *Skoplaki, E., & Palyvos, J. A. (2009). On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations. Solar Energy, 83(5), 614–624.*
- *Skoplaki, E., Boudouvis, A. G., & Palyvos, J. A. (2008). A simple correlation for the operating temperature of photovoltaic modules of arbitrary mounting. Solar Energy Materials and Solar Cells.*
- *Subramanian, E., Mithun, K., Krishna, G. P., Prasath, D. V., & Kumar, V. S. (2023). Solar power prediction using machine learning. arXiv Preprint.*
- *Vodapally, S. N., & Ali, M. H. (2023). A comprehensive review of solar photovoltaic (PV) technologies, architecture, and its applications to improved efficiency. Energies, 16, 319.*
- *Voyant, C., Notton, G., Kalogirou, S., Nivet, M. L., Paoli, C., Motte, F., & Fouilloy, A. (2017). Machine learning methods for solar radiation forecasting: A review. Energies, 10(8), 1140.*
- *Yadav, A. K., & Chandel, S. S. (2013). Tilt angle optimization to maximize incident solar radiation: A review. Renewable and Sustainable Energy Reviews.*
- *Yadav, D., Yadav, S. K., & Singh, R. B. (2025). Experimental analysis of elevated temperature and soiling loss on rooftop PV modules performance under composite climatic conditions. Scientific Reports.*
- *Yagli, G. M., Yang, D., & Srinivasan, D. (2019). Automatic hourly solar forecasting using machine learning models. Energies, 12(3), 557.*
- *Yang, D., Li, X., Wang, J., & others. (2022). Deep learning methods for solar irradiance prediction under varying atmospheric conditions. Scientific Reports.*