

Classification and Dynamics of Solar Radiation Regimes Using Multi-State Hidden Markov Models

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One of the key climatic factors affecting the production of renewable energy, especially photovoltaic (PV) power, is solar radiation. Using Multi-State Hidden Markov Models (HMMs), the classification and dynamics of solar radiation regimes are examined in this work. Hidden solar radiation states belonging to low, moderate, and high energy regimes were identified and their transition dynamics across time were analysed using the HMM framework. The results revealed that solar radiation dynamics in the study region are better represented by a three-regime structure rather than a two-regime classification. The shifts between the states highlight the dynamic nature of renewable energy sources. Low and moderate radiation states were more common than high-radiation regimes, according to frequency distribution analysis. State 1 exhibits the highest energy potential (ranging between 0.70 and 0.90) in Niger, Kwara, Nasarawa, and FCT, but the lowest in Benue and Kogi. These results demonstrate the value of Hidden Markov Models in comprehending the stochastic dynamics of solar radiation and enhancing grid integration, renewable energy forecasting, and sustainable energy management. The study confirms that the region possesses significant renewable energy potential despite observed atmospheric inconsistency and recommends the incorporation of hybrid renewable systems and energy storage technologies to improve energy reliability.

Keywords: Solar radiation; Renewable energy; Hidden Markov Models; Stochastic; Middle belt states

Introduction

Research on renewable energy sources, especially solar energy, has increased due to the growing demand for sustainable and clean energy on a global scale. The depletion of non-renewable energy resources, climate change, and environmental concerns have made the switch from fossil fuel dependence to renewable energy systems imperative [1]. Long-term energy security, reduced greenhouse gas emissions, and environmental sustainability are just a few benefits of solar energy. Because solar radiation is affected by meteorological factors such as cloud cover, rainfall, atmospheric particles, humidity, and seasonal climatic variations, it shows significant temporal and spatial variability [2]. These variations make photovoltaic power generation unreliable and present serious difficulties for energy storage design, smart grid management, and forecasting renewable energy [3]. For the purpose of improving renewable energy systems and guaranteeing a

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steady supply of electricity, accurate characterization of solar radiation regimes is consequently crucial.

Several researchers have used diverse statistical methods to analyse solar radiation variability in Nigeria [4-14]. The latent stochastic dynamics and temporal dependencies connected to solar irradiance fluctuation are frequently not captured by these conventional statistical methods [15]. Markov Chain Model and Hidden Markov Model (HMM) have become a potent probabilistic tool in recent years for modelling complex time series with dynamic transitions and hidden states [15-19]. Frimane *et al.*, [15] demonstrated that HMM-based models successfully capture solar radiation dynamics and state persistence by introducing an infinite Hidden Markov Model for short-term solar irradiance forecasting. Hou *et al.* [19] created a Markov chain multi-model technique for solar radiation forecasting and showed how it may be used for photovoltaic integration and renewable energy forecasting. [20] highlighted the significance of hidden-state modelling in renewable energy management by proposing a non-homogeneous multi-observation Hidden Markov Model for probabilistic solar power forecasting. HMMs offer a greater knowledge of atmospheric dynamics, intermittency of renewable energy, and persistence of solar resources by dividing solar radiation into several hidden states. It can also categorize atmospheric conditions into discrete radiation regimes and calculate the likelihood of transitions between these regimes over time.

This study therefore focuses on the classification and dynamics of solar radiation regimes using Multi-State Hidden Markov Models. Identifying different solar radiation states, analysing their transition dynamics, assessing their energy potential characteristics, and evaluating their significance for the production of renewable energy are the goals of this study. In order to comprehend the unpredictability and sustainability of solar energy resources within the study area, the study additionally looks at the frequency distribution of the discovered states. Not much work has been done on the Middle Belt states of Nigeria using Hidden Markov Models to analyse solar radiation, despite the fact that several studies have utilized stochastic models to analyse solar radiation worldwide.

Methodology

Study Area and Data Source

The Middle Belt of Nigeria is a transitional area between latitudes 6°N and 11°30'N and longitudes 2°42'E and 15°E. Its tropical wet (April–October) and dry (November–March) seasons vary from the south to the north, with regions such as the Jos Plateau experiencing cooler temperatures. The North Central geopolitical zone, which comprises the Plateau, Nasarawa, Niger, Kogi, Kwara, Benue states, and the Federal Capital Territory (FCT), makes up the majority of Nigeria's Middle Belt (Figure 1). It is well-known for its numerous ethnic groups and cultural diversity between the largely Hausa-Fulani North and the Yoruba/Igbo South. It also extends to the southern regions of other northern states of Kaduna, Adamawa, Taraba, Bauchi, Kebbi, Gombe, and Yobe [18]. Daily Solar radiation data for the Middle Belt States (Abuja, Benue, Kogi, Kwara, Nasarawa, Niger, and Plateau) in Nigeria from January 1, 1991 to December 31, 2020 (30 years) was obtained from National Aeronautic and Space Administration (NASA) meteorological center.



Figure 1. Map of the middle belt states in Nigeria

Hidden Markov Model

The Hidden Markov Model consists of a discrete hidden state process that evolves according to a Markov chain model. A Markov chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event (Markovian property). A first-order Hidden Markov model instantiates two simplifying assumptions. First, as with a first-order Markov chain, the probability of a particular state depends only on the previous state [17]:

$$\text{Markov Assumption: } P(q_i/q_1 \dots q_{i-1}) = P(q_i/q_{i-1}) \quad (1)$$

Secondly, the probability of an output observation o_i depends only on the state that produced the observation q_i and not on any other states or any other observations:

$$\text{Output Independence: } P(o_i/q_1 \dots q_i \dots q_T, o_1 \dots o_i \dots o_T) = P(o_i/q_i) \quad (2)$$

The Hidden Markov Model consists of a finite number of hidden states represented as:

$$Q = q_1, q_2, \dots, q_N \quad (3)$$

where N is the number of hidden states and q_i is the hidden solar radiation regime (Low, moderate and high radiation states).

A two and three-state model was adopted based on climatological interpretation: the two states are Low and high solar radiation; the three hidden states are Low, Moderate and high solar radiation regime. Let $q_i \in \{1,2\}$ represent the two state HMM and $q_i \in \{1,2,3\}$ represent the three state HMM as shown below:

$$2 - \text{States} = \begin{cases} 1: \text{Low solar radiation regime} \\ 2: \text{High solar radiation regime} \end{cases} \quad (4)$$

$$3 - \text{States} = \begin{cases} 1: \text{Low solar radiation regime} \\ 2: \text{Moderate solar radiation regime} \\ 3: \text{High solar radiation regime} \end{cases} \quad (5)$$

AIC and BIC statistical criteria were used to select the best model among competing models by balancing the goodness of fit and model simplicity. AIC minimizes information loss and is often preferred for prediction, while BIC imposes a stronger penalty on complexity and tends to select simpler, more stable models [21]. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is given as:

$$AIC = 2k - 2\ln(L), \quad BIC = k \ln(n) - 2 \ln(L) \quad (6)$$

where k = number of parameters, n = sample size, L = maximum likelihood.

The transition probability P_{ij} describes the probability of moving from one solar radiation regime to another regime and is governed by a 3x3 matrix [22]:

$$P_{ij} = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \quad (7)$$

where $p_{ij} = P(q_i = j/q_{i-1} = i)$, each row sums to unity. High diagonal values indicate persistence of solar radiation regimes.

The initial state probability over hidden states is given as:

$$\pi = \{\pi_k\}, \quad \pi_k = P(q_1 = k) \quad \sum_{k=1}^K \pi_k = 1 \quad (8)$$

The initial state probabilities describe the likelihood of observing a particular solar radiation regime at the beginning of the observation period [23].

For continuous solar radiation data, the observation probability density is modelled using the Gaussian distribution [24]:

$$b_j(o_t) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{(o_t - \mu_j)^2}{2\sigma_j^2}\right) \quad (9)$$

where o_t, μ_j, σ_j^2 are the observed solar radiation at time t , mean solar radiation for state j and variance of state j , respectively.

The likelihood of the HMM is expressed as [24]:

$$P(O/\lambda) = \sum_Q P(O, Q/\lambda) \quad (10)$$

where O is the observed solar radiation sequence, Q is the hidden state sequence and λ is the HMM parameter (A, B, π). The likelihood function measures how well the HMM explains the observed solar radiation data.

The forward probability equation is used to compute the probability of the observed solar radiation sequence and is defined as [24]:

$$\alpha_t(i) = P(O_1, O_2, \dots, O_t, q_t = S_i/\lambda) \quad (11)$$

The recursive relation is given as:

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^N \alpha_t(i) a_{ij} \right] b_j(O_{t+1}) \quad (12)$$

The Viterbi algorithm identifies the most likely sequence of solar radiation states responsible for the observed renewable energy variations. The most probable hidden state sequence is obtained using [25]:

$$Q^* = \operatorname{argmax}_Q P(Q | O, \lambda) \quad (13)$$

The photovoltaic energy output is directly proportional to solar radiation as given by [26]:

$$E = \eta AH \quad (14)$$

where E, η, A, H is the electrical energy generated, efficiency of the photovoltaic system, area of the solar panel and solar radiation intensity respectively. This equation explains why higher solar radiation states correspond to higher renewable energy generation potential.

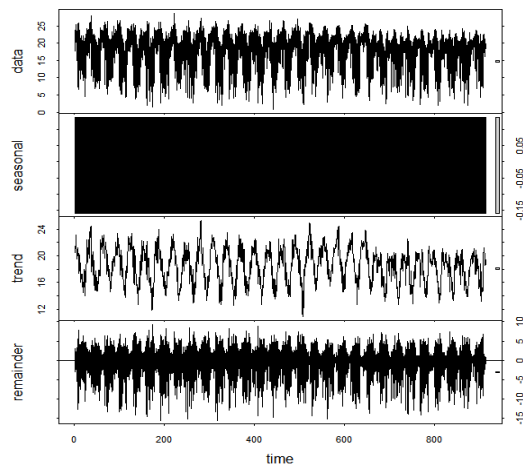
This methodology offers a systematic context for the classification and analysis of solar radiation regimes using Multi-State Hidden Markov Models (HMMs). The Hidden Markov Model approach was implemented because of its capability to capture hidden atmospheric states and probabilistic transitions connected with solar radiation variability [24]. The methodology involved data preprocessing, model estimation, state classification, transition probability analysis, and model validation using statistical

criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The identified hidden states were interpreted as low, moderate, and high solar radiation regimes, corresponding to different renewable energy potential conditions.

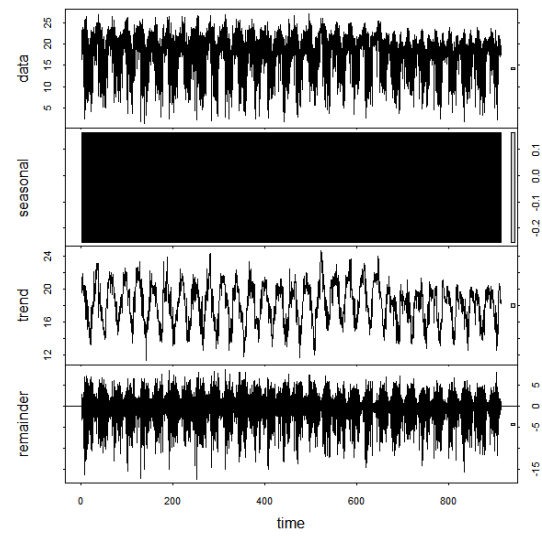
Results and Discussion

The decomposition study of the solar radiation series for Nigeria's middle belt state sheds important light on how solar radiation behaves over time and how it relates to Hidden Markov Models (HMMs). The observed data, seasonal component, trend component, and remaining component are the four primary components that the decomposition divides the solar radiation data into (Figure 2 (a-g)). These elements show the underlying atmospheric processes affecting the fluctuation of solar radiation in the study region. Over time, the recorded solar radiation series show recurring oscillatory patterns with alternating peaks and troughs. These variations show that shifting atmospheric conditions, not only random processes, control the behaviour of solar radiation. This result is consistent with other research showing that solar radiation over Nigeria exhibits significant seasonal and interannual fluctuation regulated by air circulation, cloud cover, and climatic oscillations [25]. The Middle Belt region's alternating rainy and dry seasons are linked to the seasonal variations (Figure 2 (a-g)). Higher solar irradiance can reach the earth's surface during the dry season due to less cloud cover and lower atmospheric moisture, while higher cloudiness and humidity during the rainy season diminish incoming solar energy. Similar seasonal patterns of solar radiation have been documented in tropical Nigerian settings, where the intensity of solar radiation is greatly reduced by wet-season cloud cover [26].

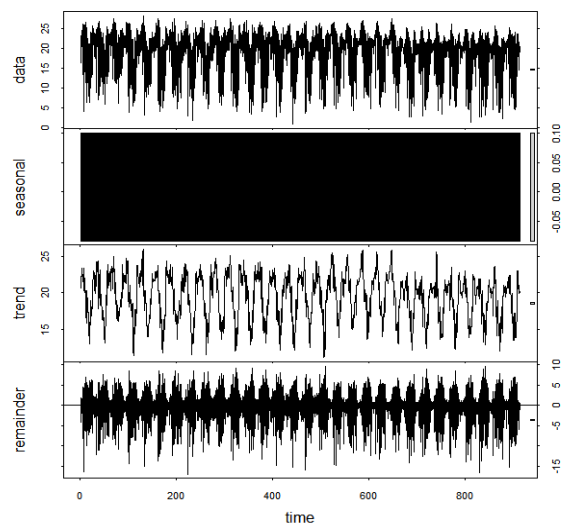
The trend component shows long-wave oscillations that are smooth and lack a noticeable long-term rise or fall (Figure 2 (a-g)). This implies that while there are short-term variations in solar radiation, the long-term solar radiation in the Middle Belt is generally steady. The Markovian premise that atmospheric conditions stay in particular states for a certain amount of time before changing into other states is supported by the persistence shown in the trend component as supported by [17]. Additionally, after trend and seasonal influences are eliminated, the remaining components show erratic spikes and residual swings (Figure 2 (a-g)). Short-term meteorological events including thunderstorms, abrupt cloud formation, atmospheric instability, and Harmattan dust incursion can cause these stochastic disturbances. Thus, the decomposition analysis offers compelling support for using HMM in sun radiation research across Nigeria's middle belt states.



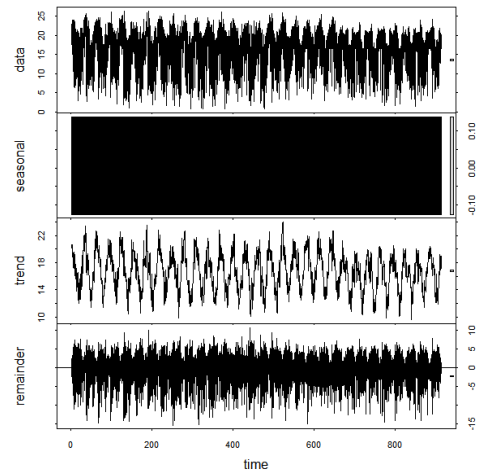
a) Benue



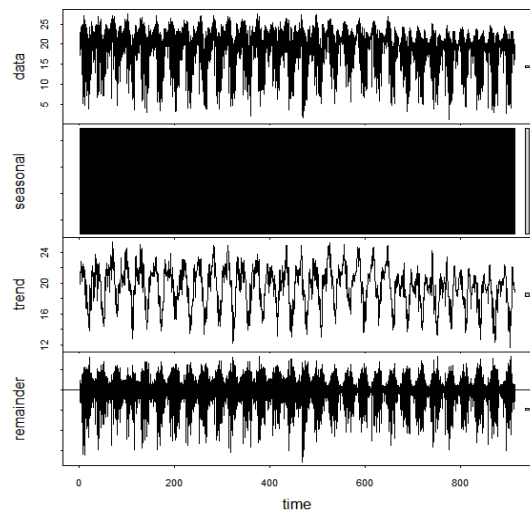
d) Kogi



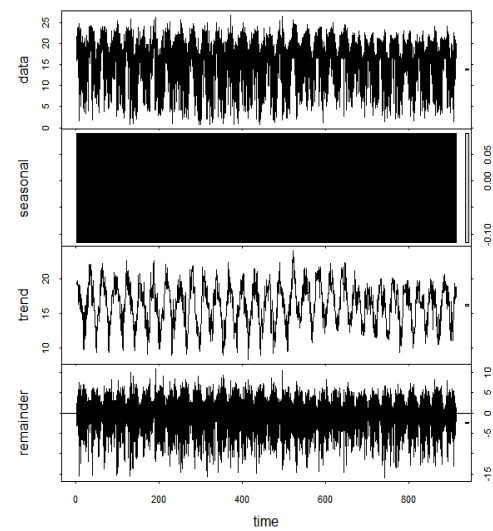
b) Plateau



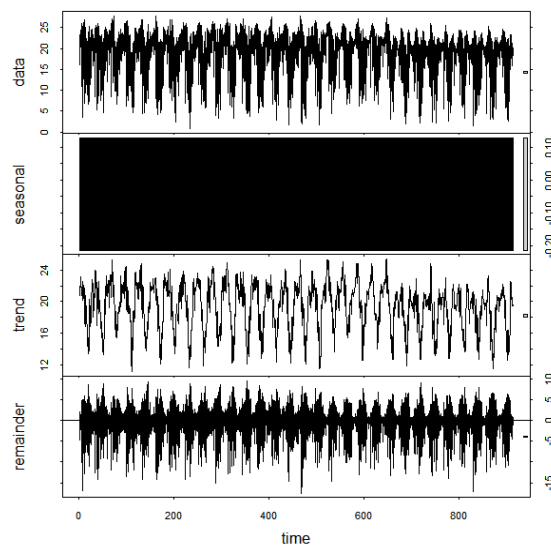
e) Kwara



c) Niger



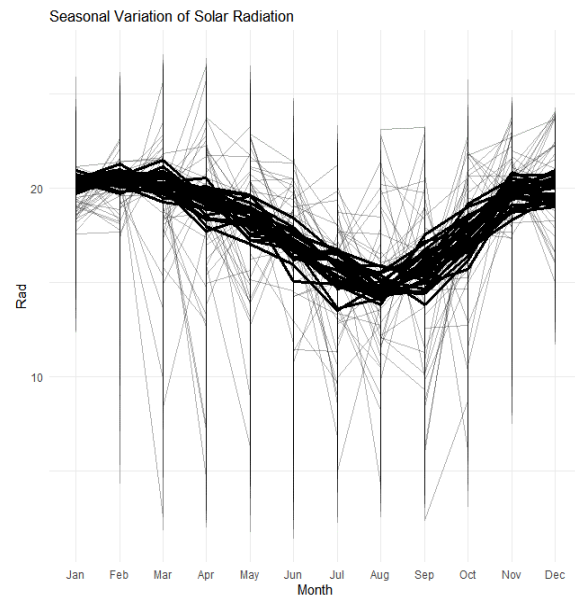
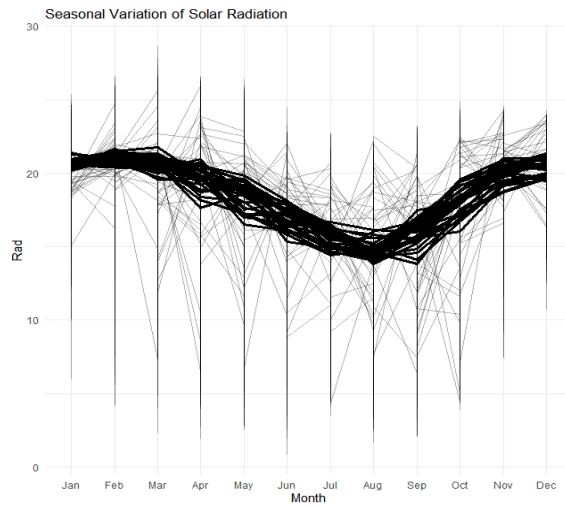
f) Nasarawa



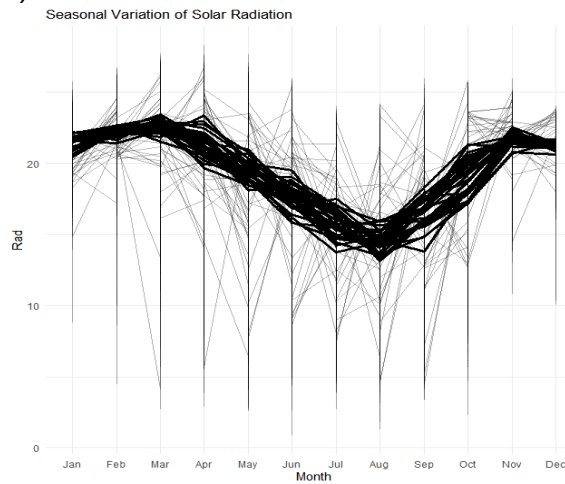
g) FCT

Figure 2. Time-series decomposition of daily solar radiation across Middle Belt states, Nigeria.

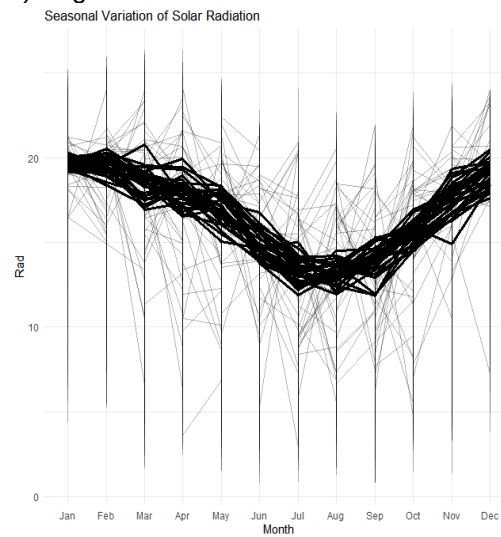
a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT



a) Benue



d) Kogi



b) Plateau

e) Kwara

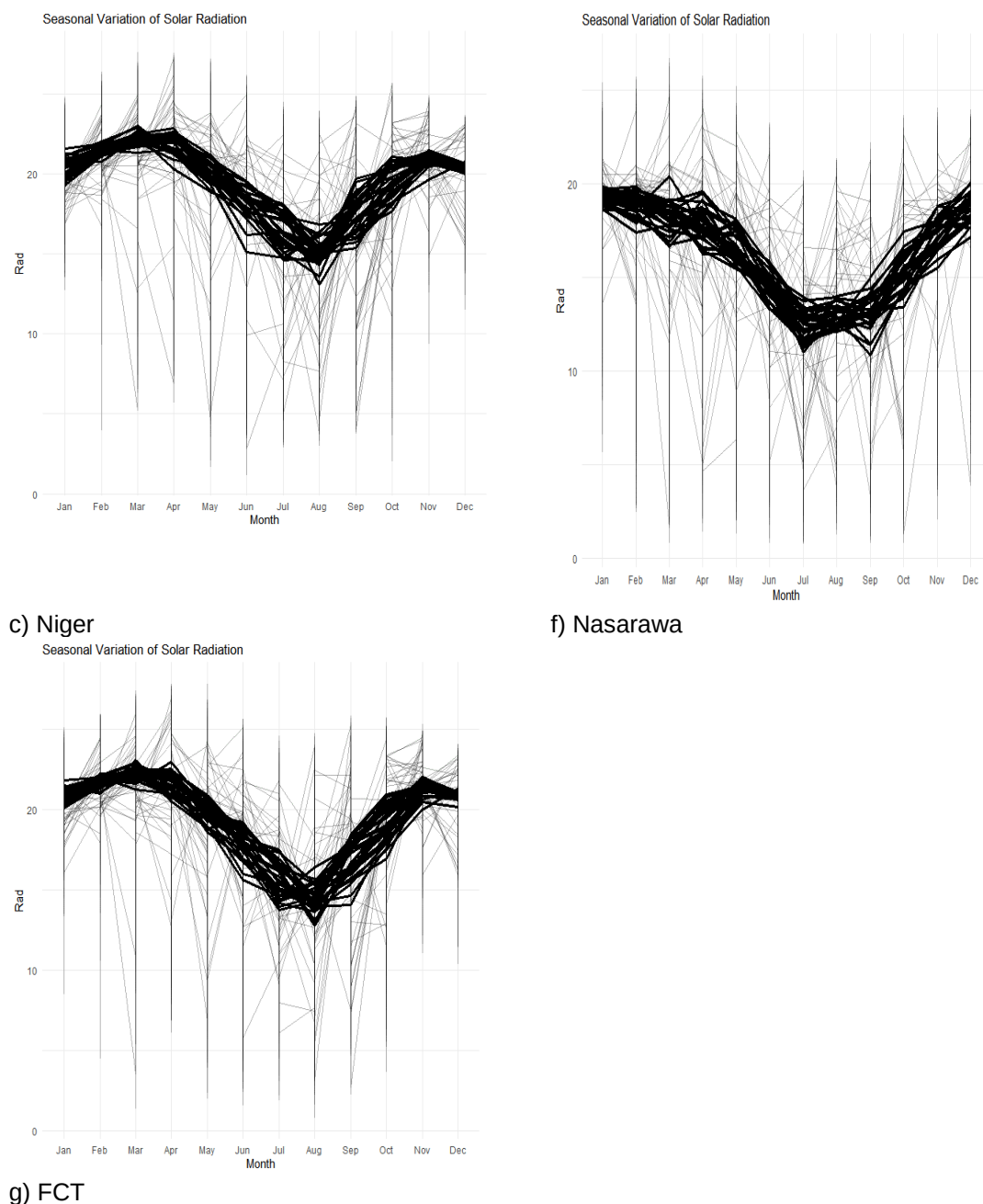


Figure 3. Seasonal variation of solar radiation
a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT

Solar radiation is the main energy source for photovoltaic systems, the seasonal fluctuations shown in Figure 3 (a-g) directly affect the availability, efficiency, and sustainability of renewable energy within the study area. The high solar radiation values recorded between January and April indicate periods of enhanced renewable energy potential. These favourable atmospheric conditions allow more solar irradiance to reach the Earth's surface, increasing the efficiency of photovoltaic panels. The dry season is therefore ideal for large-scale solar energy harvesting, rural electrification initiatives, and decentralized renewable energy deployment because solar renewable energy systems are anticipated to operate at their best during this time [16]. The rainy season, which is

characterized by cloud cover, rainfall, and atmospheric moisture, is represented by the slow decrease in solar energy seen from May to August. Because photovoltaic systems depend on constant sun irradiation for effective functioning, this decline directly affects the production of renewable energy. Reduced power output, energy instability, and intermittency issues in solar renewable energy systems may arise from lower solar radiation during these months [26]. As meteorological conditions improve and rainfall diminishes, the potential for renewable energy is gradually restored, as evidenced by the recovery in solar radiation from September to December. As the year draws to a close, this rise in solar irradiance improves photovoltaic efficiency and helps provide more reliable renewable energy. The cyclical structure of the radiation pattern indicates that seasonal climate dynamics have a significant influence on the production of renewable energy in the study area.

The contrast between 2-state and 3-state HMM models show a significant reduction in both AIC and BIC values across all datasets, indicating an improved model fit when the number of hidden states is increased (Table 1). This shows that solar radiation dynamics in the study region are better represented by a three-regime structure rather than a two-regime classification. The third state captures important transitional atmospheric conditions that are crucial for modelling solar energy variability in the Middle Belt region of Nigeria.

According to Table 2, State 1 has comparatively high mean solar radiation values across locations except Benue and Kogi state. Radiation readings above 21.0 are observed in Plateau, Niger, Kwara, Nasarawa and FCT. These high values imply that State 1 in these areas corresponds to a high-radiation or clear-sky regime, which is marked by increased atmospheric transparency and decreased cloud cover. Higher incoming solar radiation directly boosts energy yield, making these conditions ideal for photovoltaic (PV) energy generation. On the other hand, Benue (15.5) and Kogi (15.8) have lower mean values, indicating weaker sun radiation conditions. These lower values could be linked to localized weather variability, increased cloud activity, or higher atmospheric humidity [27].

Table 1. AIC and BIC of Model Selection

Locations	State	AIC	BIC
Benue	2	55676.78	55727.90
	3	54121.05	54223.28
Plateau	2	55345.77	55396.88
	3	53628.61	53730.83
Niger	2	55238.48	55289.59
	3	53345.09	53447.32
Kogi	2	55469.78	55520.89
	3	53989.58	54091.80
Kwara	2	58670.37	58721.49
	3	57654.59	57756.82
Nasarawa	2	59626.99	59678.11
	3	58776.47	58878.69
FCT	2	55017.73	55058.85
	3	53166.16	53268.39

The spatial layout in State 2 is noticeably different (Table 2). Niger (20.3) and Benue (22.1) have the highest mean values. On the other hand, Nasarawa (13.3) and Kwara (14.0) have exceptionally low values. While the low values in Nasarawa and Kwara suggest considerable air attenuation because of cloudiness or moisture content, the relatively high averages in Benue and Niger indicate stronger sun conditions. State 2's high degree of variability suggests that this regime might be associated with times when atmospheric conditions are unstable and solar radiation alternates between low and high intensity levels. From an energy standpoint, places with lower State 2 means would see sporadic energy output and decreased solar reliability, whereas those with higher means might still be able to maintain moderate PV power generation. In State 3, Plateau has the highest overall mean value (23.7), followed by Kogi (21.9) and the Federal Capital Territory (20.5). The Plateau's high value could be attributed to its higher topography and comparatively reduced atmospheric turbidity, which improve the penetration of solar radiation [28]. This implies that a severe high-radiation regime with significant solar energy potential is associated with State 3 in the Plateau. Niger, on the other hand, has lower values (16.4), suggesting a lower radiation intensity under this regime. This fluctuation demonstrates that the hidden states found by HMM are location-dependent and represent variations in regional climate. Plateau, Kogi, and FCT may have greater long-term solar energy chances because to their high State 3 means, especially when it comes to the deployment of photovoltaic systems and hybrid renewable energy systems.

Table 2. Hidden Markov State mean across locations

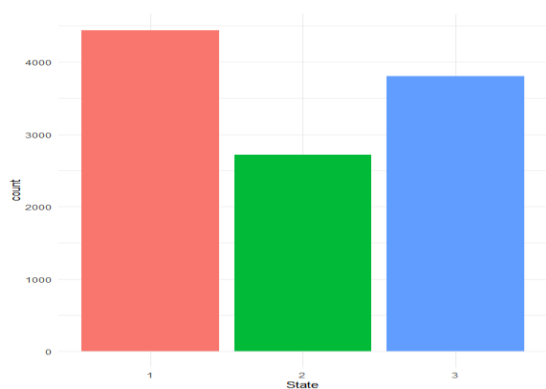
State	Benue	Plateau	Niger	Kogi	Kwara	Nasarawa	FCT
1	15.5	21.2	23.1	15.8	21.3	21.0	23.1
2	22.1	16.6	20.3	19.4	14.0	13.3	16.0
3	19.5	23.7	16.4	21.9	18.6	18.5	20.5

Each solar radiation state is quite stable over time and likely to continue once it occurs, as seen by the transition probabilities (Table 3). This shows great persistence and gradual movement between solar radiation regimes where the diagonal probabilities are high. The most stable regime is the moderate state (regime 2), indicating that middle belt region often has intermediate atmospheric conditions that predominate yearly. The high solar radiation (regime 3) rarely collapses directly to low solar radiation and vice versa, indicating gradual rather than abrupt changes in the atmosphere. The frequency distribution of the three hidden states found in the Hidden Markov Model analysis of solar radiation energy potential is presented in Figure 4 (a-g). State 1 (Low solar radiation) has the highest frequency in Benue and Kogi, indicating that low-energy atmospheric conditions dominate the solar radiation dynamics of the study area. In Niger, Plateau, Kwara, Nasarawa, and FCT, State 2 (moderate sun radiation) is associated with the highest energy potential regime. It implies that these regions experience extended periods of moderate solar irradiance capable of supporting continuous photovoltaic power generation. The second most common state in Benue, Niger, Kwara, Nasarawa, and the Federal Capital Territory is State 3 (strong sun radiation). Its occurrence attests to the presence of extremely favourable air conditions that are ideal for maximizing solar energy collecting. Photovoltaic systems can reach maximum operating efficiency and

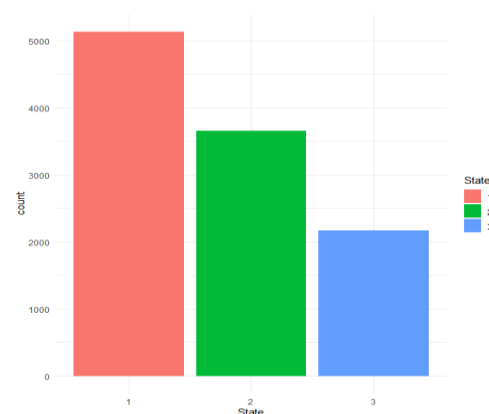
increased electricity generation during these periods [15]. The uneven frequency distribution illustrates how solar radiation systems behave in a stochastic and dynamic manner. From the standpoint of renewable energy planning, the study area's solar power generation may vary considerably over time because to the predominance of low and moderate states. In order to increase energy reliability and reduce power outages, battery storage systems, hybrid renewable systems, and smart grid technologies must be integrated [29].

Table 3. Transition probabilities for the three-state Hidden Markov Model

Locations	States	High	Moderate	Low
Benue	High	0.890	0.020	0.090
	Moderate	0.013	0.920	0.067
	Low	0.120	0.040	0.840
Plateau	High	0.900	0.020	0.080
	Moderate	0.010	0.960	0.030
	Low	0.050	0.050	0.900
Niger	High	0.890	0.040	0.070
	Moderate	0.020	0.900	0.080
	Low	0.040	0.070	0.890
Kogi	High	0.900	0.010	0.090
	Moderate	0.010	0.910	0.080
	Low	0.040	0.110	0.850
Kwara	High	0.820	0.040	0.140
	Moderate	0.090	0.900	0.010
	Low	0.090	0.010	0.900
Nasarawa	High	0.810	0.030	0.160
	Moderate	0.110	0.880	0.010
	Low	0.100	0.010	0.890
FCT	High	0.890	0.060	0.050
	Moderate	0.060	0.930	0.010
	Low	0.070	0.030	0.900



a) Benue



d) Kogi

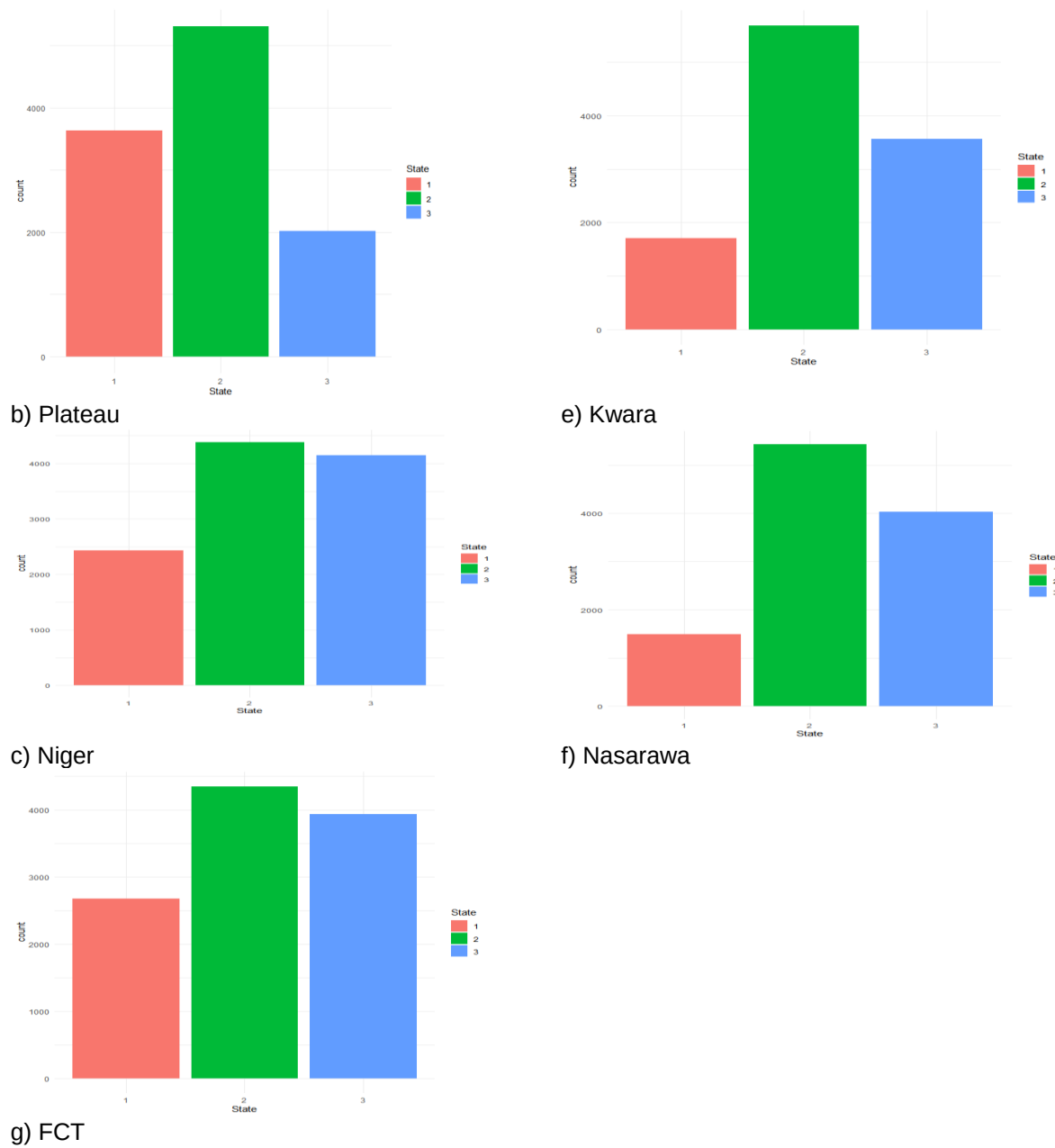
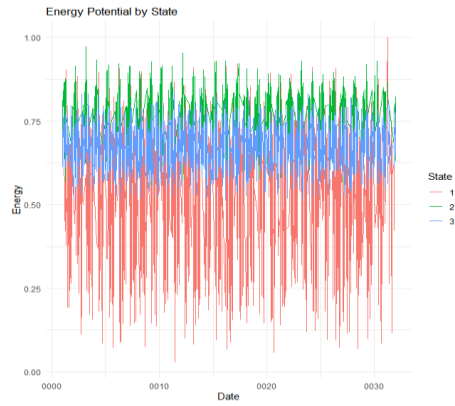
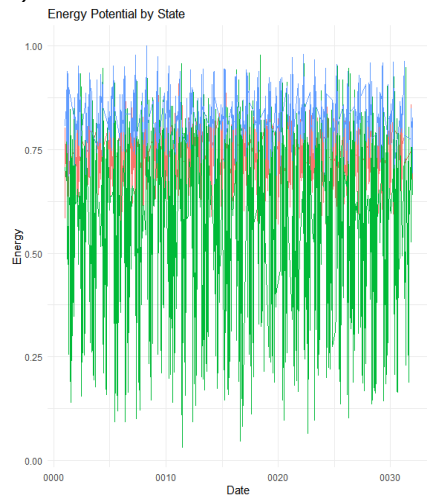


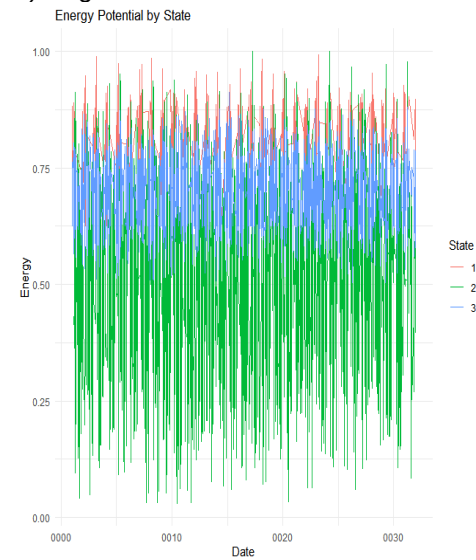
Figure 4. Frequency distribution of the hidden state
a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT



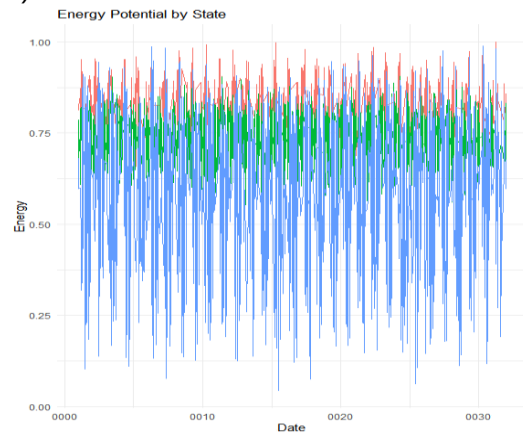
a) Benue



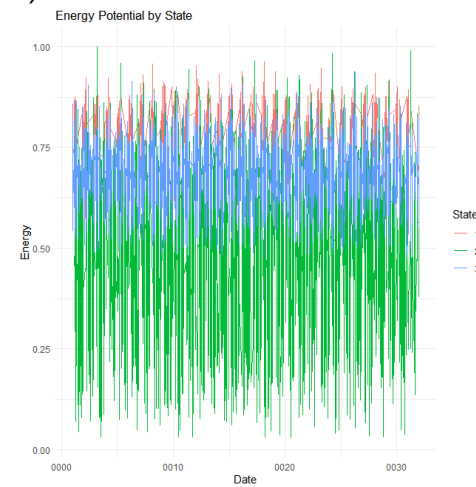
d) Kogi



b) Plateau

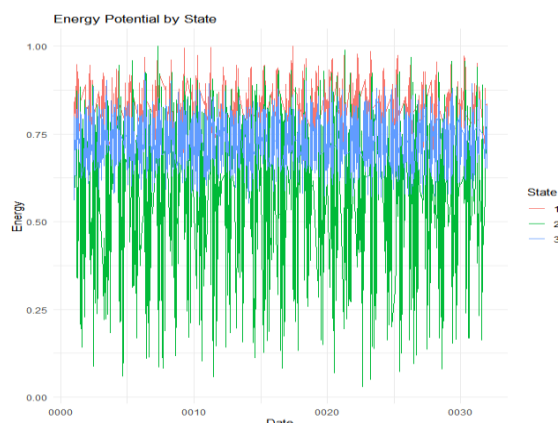


e) Kwara



c) Niger

f) Nasarawa



g) FCT

Figure 5. Energy potential by state across regions

a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT

The temporal change of normalized energy potential across three hidden is shown in Figure 5 (a-g). The three states show different energy potential characteristics, which is also a significant finding from Figure 5 (a-g). State 2 records the highest energy potential values, mostly changing between 0.70 and 0.90 in Benue. This state reflects moderate energy conditions where solar radiation remains reasonably strong but experiences occasional fluctuations. This could be indicative of transitional atmospheric conditions, where seasonal fluctuations or mild cloudiness marginally lower incoming solar radiation without resulting in significant energy loss. State 3 holds an intermediate position with energy potential values between 0.60 and 0.80 in Benue, Kwara, Nasarawa, and FCT. This suggests that State 3 represents periods of highly favourable atmospheric conditions for solar energy generation. The relatively stable and elevated energy values specify strong solar radiation intensity with less atmospheric interference such as cloud cover, haze, or moisture variability. Such situations are typically connected with clear-sky periods and enhanced solar availability. State 1 exhibits the highest energy potential in Niger, Kwara, Nasarawa, and FCT, but the most variability and lowest energy potential values in Benue and Kogi. This suggests periods of low solar radiation availability and unstable atmospheric conditions. The stochastic nature of solar energy variability is further revealed by the overlap between the three stages. In genuine atmospheric systems, where changes between energy regimes happen gradually rather than abruptly, the states are recognizable but not entirely separated. The fact that HMMs can capture hidden transitions between various atmospheric states lends credence to the Hidden Markov Model's applicability for modelling solar radiation dynamics. The predominance of moderate and high-energy states in the image suggests that the region has significant potential for solar renewable energy from the standpoint of energy planning. The viability of growing solar-based renewable energy infrastructure is supported by the availability of consistent moderate-to-high radiation levels.

CONCLUSIONS

Using Hidden Markov Model state classification, solar radiation data was converted into useful energy regimes representing the temporal dynamics of solar

resource availability. The decomposition analysis of radiation in the Middle Belt region displays stochastic regime-switching behaviour, temporal dependency, and high seasonal periodicity. These features confirm that HMM provide a reliable statistical framework for analysing solar radiation variability, transitions, and assisting with sustainable renewable energy planning in the Middle Belt region of Nigeria. This method promotes better planning and optimization of photovoltaic systems in the middle belt region of Nigeria and offers a solid statistical basis for assessing solar energy potential. Future research should combine Hidden Markov Models with Artificial Neural Networks (ANN) to advance solar radiation forecasting precision and renewable energy prediction performance.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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