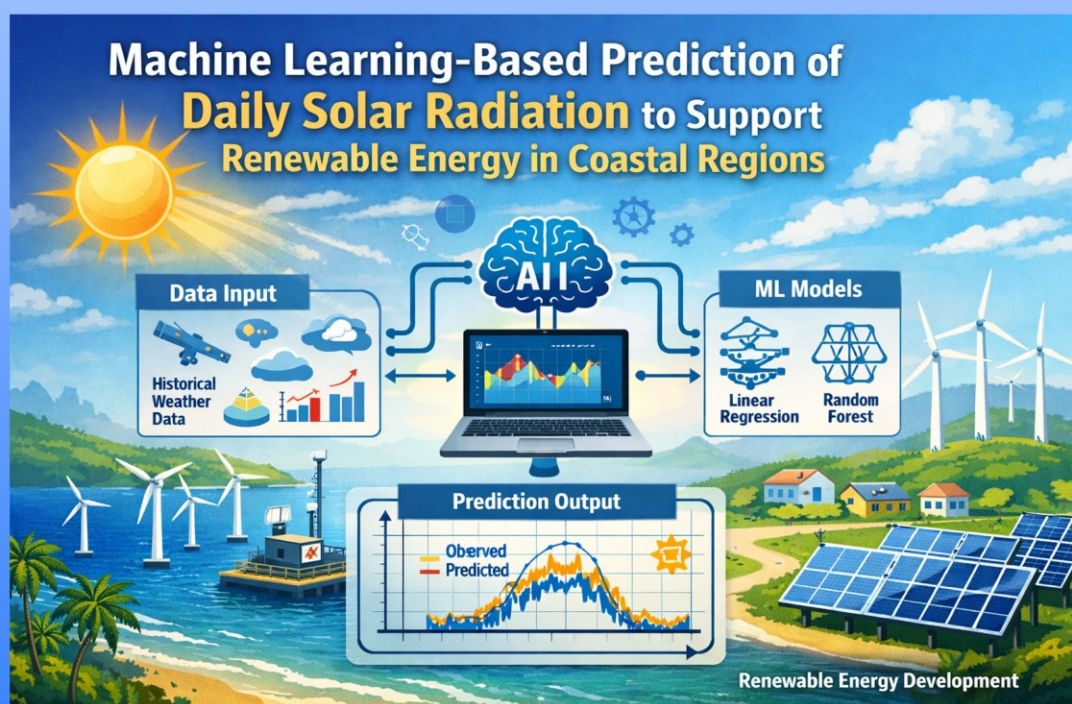


Trends in Renewable Energy

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Cover image: Machine Learning–Based Prediction of Daily Solar Radiation Article by Umoh et al.



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Performance Variability of Polycrystalline Photovoltaic Modules under Monthly Climatic Fluctuations in Calabar, Nigeria

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This study presents a high-resolution, in-situ analysis of the monthly performance of a domestic polycrystalline photovoltaic (PV) module operating within Calabar's humid monsoon climate, translating empirical field observations into practical design thresholds for residential applications and system installers. Using a digital plane-of-array solar irradiance meter in conjunction with an intelligent MPPT tracker, voltage, current, and power were monitored at 30-minute intervals between 06:00 and 18:00 from July to September. The analysis reveals a stable voltage plateau once plane-of-array solar irradiance exceeds approximately 200 W m^{-2} , corresponding to near-standard test condition (STC) voltages across all months. In contrast, achieving manufacturer-rated current during August–September would require irradiance levels exceeding 1000 W m^{-2} , which are seldom observed under real outdoor conditions. July exhibited the highest output current and power, while September recorded the lowest, despite August having the fewest sunshine hours. Notably, output power remained approximately uniform across the $0\text{--}450 \text{ W m}^{-2}$ irradiance range, irrespective of month. At irradiance levels above approximately 400 W m^{-2} , conversion efficiency follows the order July > August > September, with the module's rated maximum power appearing unattainable in September under the observed operating conditions.

Significance/Novelty: (i) Provides location-specific, month-resolved operating thresholds ($\geq 200 \text{ W m}^{-2}$ for voltage stability; $>1000 \text{ W m}^{-2}$ required to approach rated current in wetter months), bridging the gap between laboratory specifications and real-world tropical performance; (ii) identifies counterintuitive seasonal behavior, wherein greater sunshine duration does not necessarily yield higher output, thereby informing climate-responsive sizing of storage and inverter systems; and (iii) establishes actionable heuristics—uniform power response under low-to-moderate irradiance and month-dependent efficiency—that reduce performance uncertainty, mitigate premature system abandonment, and promote reliable PV deployment for energy access and net-zero transitions in southern Nigeria.

Keywords: Solar irradiance (plane-of-array); Month; Polycrystalline PV module; Maximum power point; Efficiency

Introduction

Renewable energy is an inexhaustible resource that is clean, quiet, and minimally polluting. Photovoltaic technology represents one of the most efficient and accessible means of electricity generation, offering a low-maintenance solution powered by a free and abundant energy source available in many countries [1]. Photovoltaic technology enables electricity generation with minimal technical expertise, as users are primarily required to install the modules in unobstructed areas and maintain clean, dust-free surfaces for optimal performance [2].

It is well established that fossil fuel reserves are finite [3], and their continued use poses severe environmental risks. The combustion of fossil fuels significantly contributes to climate change, global warming, air pollution, and acid rain, underscoring the urgency of transitioning to sustainable energy sources [4-6]. Therefore, there is an urgent need to advance renewable energy technologies to address the political, economic, and environmental challenges associated with electricity generation [7]. It is therefore essential to evaluate the most suitable renewable options for specific locations to reduce the global carbon footprint. The anticipated depletion of fossil fuel reserves has further accelerated technological progress in the renewable energy sector, particularly in photovoltaics [8].

The Russia–Ukraine conflict has resulted in a significant global shortage of fossil fuel products, leading to unprecedented price increases [9]. Despite Nigeria's position as a major fossil fuel exporter, domestic prices have continued to surge. This surge prompted President Tinubu in 2025 to adopt photovoltaic systems for powering the Presidential Villa and Aso Rock. Similarly, communities in rural areas without grid access now face increasing difficulties in generating electricity due to the escalating cost of fossil fuels [10]. In 2018, the Indonesian government introduced the Rooftop Photovoltaic Solar Systems (RPVSS) policy, enabling customers of the State Electricity Company to generate electricity through solar PV systems and export surplus power to the national grid at 65% of the retail tariff. This initiative aimed to increase the share of renewable energy in the national energy mix to 23% by 2025 [11]. Photovoltaic technology offers a practical solution to the rising costs of fossil fuels and the global challenges of climate change [12]. Owing to its advantages over conventional power generation systems, demand for PV continues to grow in the renewable energy market, positioning it as a key contributor to future energy sustainability [13].

Global energy demand has increased substantially from 8,588 million tonnes of oil equivalent (Mtoe) in 1995 to 13,147 Mtoe in 2015, with emerging economies such as India and China emerging as the leading consumers by Kapilan *et al.* [14]. Energy performance is a core component of energy policy and a critical enabler of sustainable global economic growth [14]. Climate change and rapid population growth are among the top global drivers of energy demand. Energy efficiency, consumer behaviour, infrastructure investment, and financial shocks influence national economies, while governance and international relations shape the global energy market. Advancements in renewable energy technologies, alongside innovations in the oil and gas sector, are significant drivers of global energy dynamics [15]. Global energy consumption is

projected to increase by up to 50% between 2005 and 2030, with developing countries such as India and China emerging as the leading consumers [16].

In Nigeria, many individuals adopt photovoltaic (PV) systems as an alternative to fossil fuel-based electricity due to rising fuel costs. However, expectations of consistent optimal performance throughout the day, months, and seasons often lead to disappointment. Users commonly assume that PV systems will deliver outputs identical to those stated in manufacturer specification sheets, which are determined under standard test conditions in controlled environments. In reality, outdoor performance is influenced by variable meteorological factors and therefore deviates from laboratory specifications [17]. Unrealistic expectations have caused some users to abandon PV systems in frustration, reverting to fossil fuel generators, while others persist with dissatisfaction. This challenge arises largely from the absence of localized performance data to guide realistic expectations. Consequently, this research seeks to provide empirical insights into the monthly performance of PV systems for electricity generation in Calabar.

With the rapid expansion of solar PV applications, understanding their operational performance has become a critical area of research. Reliable knowledge of PV output under real weather conditions is essential for system design, configuration, and product selection [18]. Similarly, engineers must evaluate PV performance in actual operating environments, as manufacturer specifications alone cannot provide accurate data for general conditions.

The performance of a PV system is influenced not only by its inherent features—such as solar cell technology, charge controller design, battery type, and inverter configuration—but also by the climatic conditions at the installation site [19]. Among these factors, solar irradiance plays a particularly significant role, as its continuous variation directly affects electricity generation. Thus, the energy output of PV systems at any given moment remains strongly dependent on prevailing climatic conditions [20].

Numerous studies exist that explore the performance of photovoltaics in various locations. Takyi and Laryea [21] compared different PV technologies in Kumasi, Ghana. The findings indicated that the degradation rates of polycrystalline PV modules in Ghana range from 1.6% to 1.75% per year, leading to total power losses of between 15% and 21%. These exceed the typical benchmark of 1% per year for 25-year warranties. A performance evaluation of various crystalline silicon photovoltaic technologies was conducted by Yu *et al.* [22] in Pingshan, China. The results indicated that the silicon heterojunction (SHJ) PV module achieved the highest energy yield, averaging approximately 6% more than monocrystalline and polycrystalline PV modules. The researchers attributed the superior performance of the SHJ module to its lower temperature coefficient (0.29%/°C compared to 0.41%/°C), which effectively minimized midday summer thermal losses—less than 10% for SHJ versus roughly 14% for traditional crystalline silicon modules. A study conducted by Khanam *et al.* [23] examined the performance efficiency of monocrystalline silicon, polycrystalline silicon, and thin-film photovoltaic (PV) modules across four distinct climatic zones in India: New Delhi, Srinagar, Bangalore, and Jodhpur. These cities were chosen to represent a range of climates—from hot and humid to high-altitude cold—allowing for an analysis of performance variations influenced by regional environmental conditions. The results demonstrated that thin-film PV modules consistently exhibited superior annual energy output compared to monocrystalline and polycrystalline modules across all four climatic zones. The researchers concluded that the selection of PV technology should be tailored to the specific climate of the location. A comparative analysis was conducted by Ma *et al.*

[24] on multi-crystalline silicon (m-Si), Heterojunction with Intrinsic Thin-layer (HIT), and Cadmium Telluride (CdTe) photovoltaic modules placed on floating platforms over water bodies. The objective was to evaluate their degradation and efficiency in aquatic environments compared to traditional land-based installations. This research was carried out at Tianjin University in China. The findings indicated that HIT modules exhibited the least degradation, with a rate of approximately 0.50% per year, closely matching their performance on land. In contrast, m-Si modules experienced a higher degradation rate of about 1.32% per year on water, surpassing the land installation rate of approximately 0.93%. CdTe modules showed a degradation rate of 1.68% per year in aquatic settings, slightly higher than the land-based degradation rate of around 1.41%. The authors determined that the selection of photovoltaic technology should consider the environmental context. For floating applications, they recommended utilizing HIT modules due to their exceptional durability and minimal degradation rates. A study conducted by Schweiger *et al.* [25] over two years across multiple sites monitored the performance of 15 different photovoltaic (PV) module technologies in four distinct climate zones: temperate Germany, the alpine region of northern Italy, hot-humid India, and hot-dry Arizona (USA). The findings revealed significant variations in degradation rates, influenced by climate and module type. Modules in hot-humid and hot-dry climates experienced more rapid performance declines than temperate and alpine environments. In Germany and the Alps, degradation rates were relatively modest, whereas in India and Arizona, the steeper declines indicated stronger effects from elevated temperatures, humidity, and irradiance stress. The study concluded that cooler climates are associated with more stable output over time, while hot and humid environments accelerate degradation—highlighting the importance of aligning PV technology with local climate resilience. Atia *et al.* [26] conducted a detailed field-based evaluation of 24 monocrystalline photovoltaic (PV) modules that had been running on rooftops in Cairo, Egypt for 25 years. The study aimed to evaluate long-term degradation by analyzing variations in electrical performance parameters and energy yield over time. The results demonstrated a 23.3% decline in the maximum power ($P_{\max}$) of the modules. Additionally, the maximum voltage ($V_{\max}$) and maximum current ($I_{\max}$) experienced degradation of 12.16% and 7.2%, respectively. The open-circuit voltage and short-circuit current (I_{sc}) showed degradation of 2.28% and 12.16%, respectively. Furthermore, the fill factor (FF) and performance ratio (PR) diminished by 15.3% and 85.9%, respectively.

A three-year field study was conducted by Femin *et al.* [27] to evaluate the performance of six photovoltaic (PV) technologies in a tropical environment. The technologies assessed included monocrystalline silicon, polycrystalline silicon, amorphous silicon, copper indium selenium (CIS), heterojunction intrinsic thin-layer, and microcrystalline silicon. The findings indicated that the CIS technology achieved the highest annual energy output, with a performance ratio of 86.1%. In contrast, monocrystalline silicon technology experienced the most significant temperature-related energy loss, approximately 14.4%. A study by Islam *et al.* [28] examined the long-term electrical performance and ageing of field-deployed photovoltaic (PV) modules in the tropical climate of Malaysia. The research focused on modules operational for 8 years at Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) and 10 years at Pasir Mas. The findings indicated that the average annual degradation rates at UMPSA were 0.3% for open-circuit voltage, 0.23% for short-circuit current (I_{sc}), 0.81% for maximum power output ($P_{\max}$), and 0.35% for fill factor (FF). In contrast, at Pasir Mas, the average annual degradation rates were 1.124% for V_{oc} , 0.166% for I_{sc} , 1.276% for $P_{\max}$, and 0.43% for

FF. Additionally, the study revealed that monocrystalline silicon modules experienced an average power degradation of 6.48%, whereas polycrystalline silicon modules faced a higher degradation of 12.76%. A study by Adouane *et al.* [29] examined the performance of eight photovoltaic (PV) technologies in Kuwait's harsh desert climate, characterized by high irradiance, extreme temperatures, and significant dust accumulation. The experiments were conducted on a raised test facility (3 meters above ground) at the Kuwait Institute for Scientific Research (KISR), near the seashore, over 12 months. The results indicated that monocrystalline, polycrystalline, and HIT PV modules performed exceptionally well under intense sunlight but experienced a rapid decline in efficiency under low irradiance conditions. In contrast, the cylindrical copper indium gallium diselenide (CIGS) module performed relatively better at low light levels. Akonjom and Njok [30] conducted an experimental evaluation to determine how key meteorological factors, such as relative humidity, panel temperature and irradiance, affect the electrical performance of photovoltaic (PV) modules in the Guinea Savannah climate of Ogoja, Nigeria. The findings indicated that voltage output remains stable when relative humidity is between 47% and 67%. However, when relative humidity falls below 47%, the voltage output becomes erratic, hindering the module's ability to reach its full efficiency. Additionally, the average panel temperature rarely exceeds 40°C, except during January, suggesting that PV modules in this location can achieve an efficiency of approximately 90%. Njok *et al.* [31] explored the influence of solar irradiance (plane-of-array) and variations in solar flux on the efficiency of polycrystalline photovoltaic (PV) modules installed near a river. The authors found that proximity to water bodies can impact module performance due to enhanced reflection, increased diffuse irradiance, and microclimatic factors, including humidity and temperature fluctuations. The results indicated that both solar flux intensity and river-related environmental conditions significantly affected energy yield and overall module efficiency. This research underscores the necessity of considering site-specific ecological factors, particularly in riverine areas, when designing and deploying PV systems.

Several studies have examined the performance of photovoltaic systems under varying climatic conditions; however, much of the available data remains region-specific. There is limited information on the monthly variations in the output electrical performance of polycrystalline photovoltaic modules for household applications in Calabar, which is essential for effective system design and sizing [32]. While different PV modules and systems have been investigated across diverse climatic and geographical settings, this study considers solar irradiance, month of the year, and time of day.

Manufacturer specifications of PV modules often deviate from actual outdoor performance, making it necessary to account for local climatic conditions at the installation site [33, 34]. In southern Cross River State, Nigeria, limited research exists on the monthly variations in the electrical output of polycrystalline PV systems for household applications, particularly concerning manufacturer specifications. In practice, system monitoring after installation is challenging, yet climatic factors strongly influence performance at any given time. To address this gap, monthly performance analyses have been undertaken [35, 36]. Without knowledge of seasonal efficiency patterns, users may experience unmet expectations. This study provides insights to help identify the monthly performance of PV systems.

Throughout this paper, “solar irradiance” denotes the optical input at the module plane, expressed as power per area (W m^{-2}) and measured by the irradiance meter; it is the independent driver for performance plots and thresholds (*e.g.*, ≈ 200 and $>1000 \text{ W m}^{-2}$).

m^{-2}). “PV output power” denotes the electrical response of the module (W), computed from the measured current and voltage at the maximum power point. This distinction avoids conflating the optical resource with the electrical output and ensures unit consistency in figures and equations, where H represents incident irradiance.

Materials and Methods

This section outlines the materials employed in the study, the setup configuration, and the procedures adopted for measurement and data acquisition.

Materials Employed in the Study

The study utilized a polycrystalline photovoltaic module (model: AF-130W) manufactured by Africell Solar, with a rated maximum power of 130 W. The module’s output electrical characteristics are shown in Table 1. A high-precision digital maximum power point (MPP) tracker (model: WS400A) was employed to measure and record the maximum power, voltage, and current generated by the module. In addition, a digital solar irradiance (plane-of-array) meter (model: SM206) was used to monitor and ascertain the solar irradiance incident on the PV module surface.

Table 1. PV Module Technical/Electrical Characteristics

Electrical Specification	Value
Maximum Power	130 W
Current at Maximum Power	7.18 A
Voltage at Maximum Power	18.10 V
Short Circuit Current	7.91 A
Open-circuit Voltage	21.72 V
Number of cells	36
Module dimension	1480mm*670mm*35mm
Model	AF-130 zW
Manufacturer	Africell Solar

Experimental Setup

The PV module was installed horizontally with its surface facing the sun on a platform one metre above ground level, as shown in Fig. 1. Output cables from the module were connected to a two-way switch. One output of the switch was linked to the MPP tracker to monitor maximum power points (Fig. 2), while the other was connected to the input of a solar charge controller. The controller’s output was directed to a solar gel battery to facilitate stable charging, and the stored energy was subsequently used to power loads through an inverter.

Measurement Procedure

Measurements were conducted over three months, from July to September, at 30-minute intervals between 06:00 and 18:00. During the data collection, the time of day was also recorded. The output power, current, and voltage from the PV module were measured using an intelligent maximum power point (MPP) tracker. The solar irradiance



Figure 1. Photovoltaic module on a platform 1 metre high

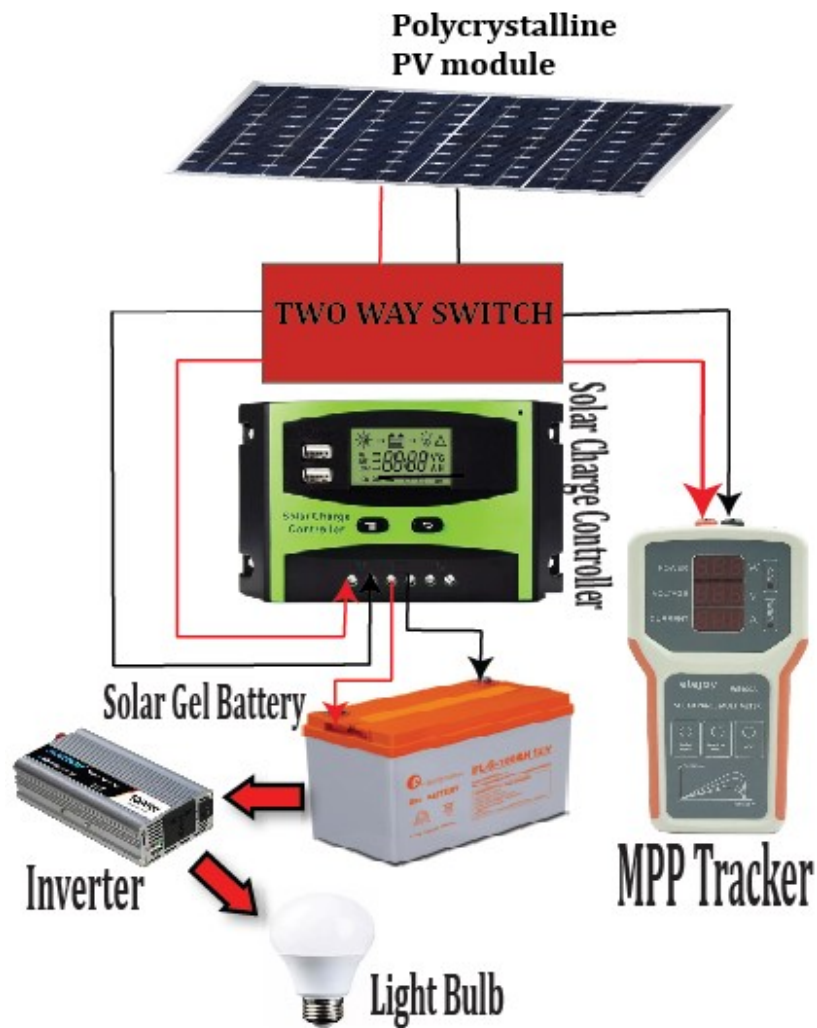


Figure 2. The Experimental Setup

(plane-of-array) level at the surface of the PV technology was measured via the digital solar irradiance (plane-of-array) meter.

The optical input used in this study is plane-of-array irradiance, expressed in W m^{-2} . Irradiance was measured at the module surface using a digital solar power meter (SM206) positioned co-planar with the PV module and sampled every 30 minutes in tandem with MPP-tracker electrical readings ($V_{MP}I_{MP}P_{MP}$). Throughout the manuscript this quantity is denoted as G_{POA} (also H in the governing equations) and represents the instantaneous radiant power per unit area incident on the module. Electrical output (power in W, energy in Wh/kWh) is reported separately.

Data Processing

In this study, the phrase “solar irradiance (plane-of-array)” (W m^{-2}) refers to plane-of-array solar irradiance—the instantaneous radiant power per unit area incident on the module surface (hereafter irradiance, G_{POA}). Electrical quantities from the PV module are denoted separately: output power $P_{out} = V_{MP}I_{MP}$ in watts (W), energy in watt-hours (Wh) or kilowatt-hours (kWh), current (A), and voltage (V). Unless otherwise stated, thresholds reported as “ 200 W m^{-2} ” or “ $>1000 \text{ W m}^{-2}$ ” pertain to irradiance at the module plane, measured by the hand-held irradiance meter. H in the equations denotes incident irradiance (W m^{-2}). The study was conducted under real outdoor conditions with fluctuating solar irradiance (plane-of-array). The instantaneous voltage (V_{MP}), current (I_{MP}), and maximum power (P_{MP}) at maximum power, at specific solar irradiance (plane-of-array) levels, were measured directly using the intelligent PV module MPP tracker. The efficiency of a PV system is strongly influenced by its voltage and current output, which are in turn affected by climatic factors such as solar irradiance (plane-of-array) and maintenance. Both the current at maximum power (I_{MP}) and the voltage at maximum power (V_{MP}) are significantly determined by system design, maintenance practices, and solar irradiance (plane-of-array) (H), as expressed in equations (1) and (2) [37].

Load Current:

$$I_{MP} = I_{PH} - I_0 \left[e^{\frac{q V_{MP}}{K_B T}} - 1 \right] \quad (1)$$

Load Voltage:

$$V_{MP} = \frac{K_B T}{q} \ln \left[\frac{I_{PH} + I_0 - I_{MP}}{I_0} \right] \quad (2)$$

Short Circuit Current:

$$I_{PH} = I_{SC} = bH \quad (3)$$

where I_{PH} is the photogenerated current, which is the short circuit current I_{SC} as expressed in equation (3) also by [37]. b is a constant that is determined by the junction properties of the semiconductor, and H is the incident solar irradiance (plane-of-array) reaching the PV module. I_0 is the diode reverse saturated current, K_B is the Boltzmann constant, T is the absolute temperature, q is the electronic charge, and e is the exponential symbol. From the data obtained, the dynamic efficiency of the PV modules was computed with (4), while the PV module efficiency at standard test conditions [1] was confirmed via (5) as shown by [37].

Dynamic Efficiency:

$$\eta_P = \frac{P_{MEA}}{P_{MAX}} \times 100\% \quad (4)$$

where P_{MEA} and P_{MAX} are the measured power and the maximum power of the PV module at STC respectively.

Module efficiency at standard test conditions (STC: 1000 W m⁻², 25°C cell temperature, AM 1.5G spectrum) was confirmed via (5):

$$\eta_{MOD} = \frac{\text{Power of photovoltaic module} \times 100\%}{\text{Area of photovoltaic module} \times 1000 \text{ W/m}^2} \quad (5)$$

Study Area

The study was conducted in Calabar, the capital of Cross River State in southern Nigeria, located at 4°57'06" N latitude and 8°19'19" E longitude, with an elevation of 32 meters above sea level. The region is characterised by a tropical monsoon climate, marked by heavy rainfall for most of the year and two short dry seasons, typically from January to March and October to December [37]. Overall, Calabar remains hot and humid year-round, with overcast conditions prevailing during the wet season and predominantly cloudy skies during the dry season. Sunshine duration also varies seasonally, with December recording the highest average of 9.5 hours per day, while August receives the lowest, at approximately 4 hours daily [38].

Results and Discussion

This section explains data from in-situ measurements and analysis, structured into two parts. The first part examines the monthly fluctuations in the level of solar irradiance (plane-of-array) diurnally, as illustrated in Fig. 3. The second part provides an analysis of the results, focusing on the monthly output electrical performance of the PV module with varying solar irradiance (plane-of-array), as shown in Fig. 4.

Table 2 displays the monthly descriptive analysis of the amount of solar irradiance (plane-of-array) reaching the PV module surface. Tables 3, 4 and 5 show the monthly descriptive analysis of the output electrical parameters from the PV module.

It is pertinent to understand that the output electrical parameters (V_{MP} , I_{MP} , P_{MP} , and η_P) used in the analysis of the results are the maximum voltage, current, power, and efficiency, respectively, that the PV module produces instantly under a particular level of solar irradiance (plane-of-array) (atmospheric condition).

Table 2. Descriptive analysis of monthly plane-of-array irradiance, G_{POA} (W m⁻²) at PV modules surface

Statistics	Solar irradiance (plane-of-array) (W/m ²)	Solar irradiance (plane-of-array) (W/m ²)	Solar irradiance (plane-of-array) (W/m ²)
Month	July	August	September
Minimum	0	0	0
Maximum	930.3	625.9	783.5
Range	930.3	625.9	783.5
Mean	301.7	274.7	328.8
Median	300	259.4	299.2
Variance	57000.4	38090.3	60775.4
Standard Deviation	238.8	195.2	246.5
Standard Error	47.8	39	49.3

Descriptive statistics of plane-of-array irradiance, G_{POA} (W m^{-2}) measured on the PV module surface with a digital solar power meter (SM206). Values are the instantaneous irradiance readings taken at 30-minute intervals (06:00–18:00) during July–September, concurrent with electrical measurements from the MPP tracker.

Table 3. Descriptive analysis of output electrical parameters from PV module in July

Statistics	V_{MP} (V)	I_{MP} (A)	P_{MP} (W)	η_P (%)
Minimum	0.79	0	0	0%
Maximum	18.46	6.14	112.57	87%
Range	17.67	6.14	112.57	87%
Mean	16.81	1.97	36.92	28%
Median	18.04	1.9	41.23	32%
Variance	15.63	2.46	824.52	5%
Standard Deviation	3.95	1.57	28.71	22%
Standard Error	0.86	0.33	5.99	5%

Table 4. Descriptive analysis of output electrical parameters from PV module in August

Statistics	V_{MP} (V)	I_{MP} (A)	P_{MP} (W)	η_P (%)
Minimum	2.4	0	0	0%
Maximum	18.4	4.44	82.36	63%
Range	16	4.44	82.36	63%
Mean	16.3	1.91	34.66	27%
Median	18.04	1.89	34.6	27%
Variance	17.71	1.92	652.18	4%
Standard Deviation	4.21	1.39	25.54	20%
Standard Error	1.09	0.29	5.32	4%

Table 5. Descriptive analysis of output electrical parameters from PV module in September

Statistics	V_{MP} (V)	I_{MP} (A)	P_{MP} (W)	η_P (%)
Minimum	2.43	0	0	0%
Maximum	18.35	5.05	92.02	71%
Range	15.92	5.05	92.02	71%
Mean	16.71	2.17	41.23	32%
Median	18.03	2.11	39.23	30%
Variance	15.05	2.98	948.8	6%
Standard Deviation	3.88	1.73	30.8	24%
Standard Error	0.94	0.37	6.29	5%

Diurnal and Monthly Variations in the Level of Solar Irradiance (plane-of-array)

Figure 3 shows how the level of solar irradiance (plane-of-array) varies daily for each month. The figure reveals an almost linear increase in solar irradiance (plane-of-array) between 06:00 and 12:00. Also, the figure reveals peaks in the level of solar irradiance (plane-of-array). These are periods when solar irradiance (plane-of-array) is at its highest. In July, the peak in solar irradiance (plane-of-array) is observed at 12:00. In August, the peak is observed at 12:30. In September, double peaks in solar irradiance (plane-of-array) are at 11:00 and 14:00.

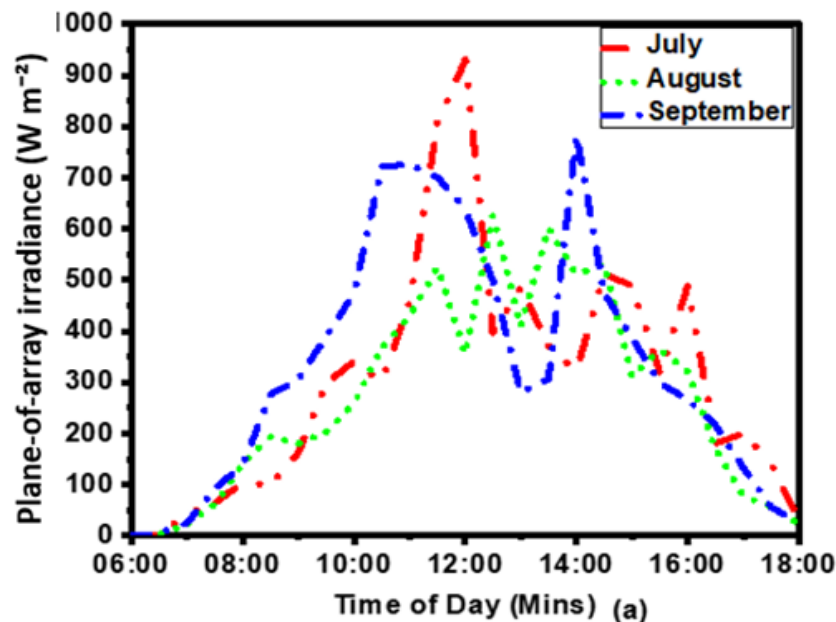


Figure 3. Daily energy variations in solar irradiance levels (plane-of-array).

Monthly Performance in PV Module Output Electrical Parameters under Varying Solar Irradiance (plane-of-array)

Figure 4a depicts the monthly voltage performance from the PV module with solar irradiance (plane-of-array). The figure reveals some interesting trends as it shows that, regardless of the month, voltage increases between 0 and 200 W/m^2 of solar irradiance (plane-of-array) before attaining stability close to the voltage at STC, which agrees with earlier studies by [31]. Still, in Figure 3, a slight ripple trend is visible as solar irradiance (plane-of-array) increases. This ripple as solar irradiance (plane-of-array) increases is due to the fluctuations in panel temperature with varying solar irradiance (plane-of-array), which conforms to earlier studies by [34], which reveal that about 0.5 V is lost or gained for every degree rise or drop in temperature, respectively. Furthermore, the figure demonstrates that harvesting maximum voltage from a polycrystalline PV module is possible regardless of the month as long as the solar irradiance (plane-of-array) level does not drop below 200 W/m^2 .

Figure 4b portrays the monthly output-current performance from the PV module with solar irradiance (plane-of-array). The figure shows that regardless of the month, a linear positive trend is observed as solar irradiance (plane-of-array) increases, confirming that a linear relationship exists between solar irradiance (plane-of-array) and current, which also agrees with earlier work by [31]. The figure interestingly reveals the PV module having the highest output-current performance in July, and the least performance in September, despite August having the fewest sunshine hours. Furthermore, Figure 3 shows that harvesting maximum current from the PV module, as specified in the manufacturer's technical data (Table 1), is possible in July. In August and September, harvesting maximum current from the PV module will be difficult because the level of solar irradiance (plane-of-array) at the module surface has to be in excess of 1000 W/m^2 .

Figure 4c illustrates the monthly output power performance of the PV module as a function of solar irradiance (plane-of-array). The results indicate that, irrespective of the

month, the output power exhibits a linear positive trend with increasing solar irradiance (plane-of-array), consistent with the findings of [37], which confirm the existence of a linear relationship between solar irradiance (plane-of-array) and PV output power. Notably, the module demonstrates its highest output performance in July and its lowest in September, despite August recording the fewest sunshine hours. Furthermore, Figure 3 highlights that achieving the maximum power output specified in the manufacturer's technical data (Table 1) is unattainable in September, as the incident solar irradiance (plane-of-array) on the module surface would need to exceed 1000 W/m^2 . A closer inspection of the figure reveals that the module delivers approximately the same output power within the solar irradiance (plane-of-array) range of 0 to 450 W/m^2 , regardless of the month.

Figure 4d unravels how efficient the PV module is monthly as solar irradiance (plane-of-array) varies. The figure reveals that between 0 and 400 W/m^2 , the monthly PV module efficiency is the same regardless of the month. Above 400 W/m^2 , the module is most efficient in July and least efficient in September. Interestingly, the PV module is more efficient in August than in September despite August having fewer sunshine hours. Furthermore, Figure 4d highlights that achieving 100% efficiency from the PV module is unattainable in September, as the incident solar irradiance (plane-of-array) on the module surface would need to exceed 1000 W/m^2 , even though September has more sunshine hours than August.

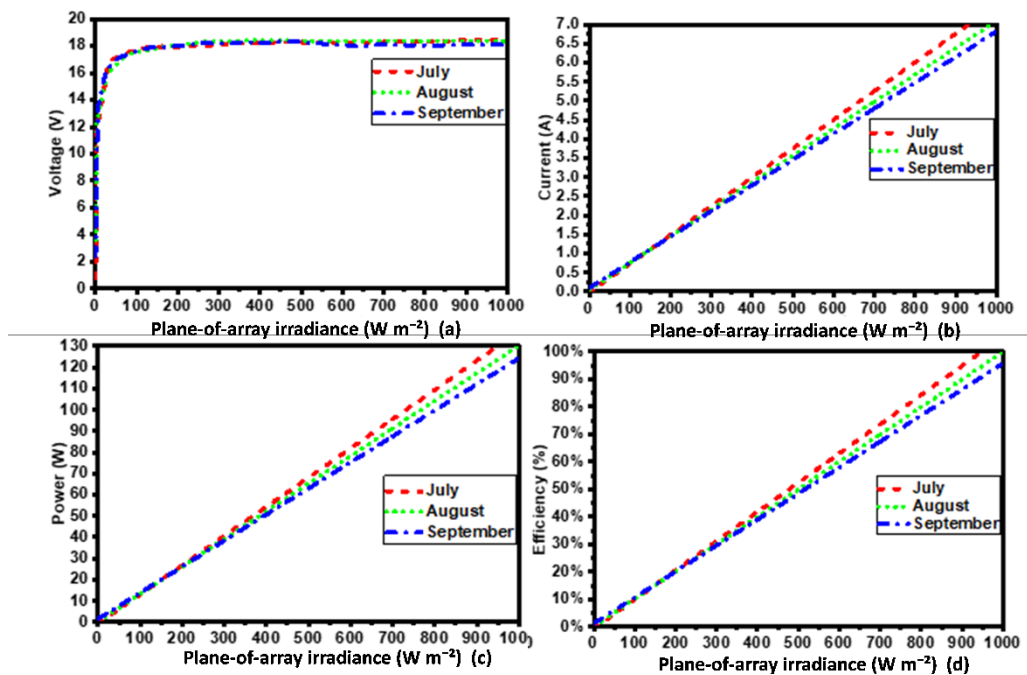


Figure 4. Monthly variations in PV module output electrical parameters under varying incident solar power (plane-of-array)

Implications of the Study for Household Use in Calabar

The results of this study hold significant implications for household energy security in Calabar, particularly in the era of sustainable development and the global net-zero agenda. Localized performance data on monthly photovoltaic (PV) variability provide households with realistic expectations, reducing the reliance on generic

manufacturer specifications that often misrepresent actual field conditions. Such context-specific insights are crucial for boosting public confidence in PV technology and stimulating greater adoption, consistent with [39] emphasis on advancing applied energy solutions to address regional energy access challenges.

From the perspective of global decarbonization efforts, these findings reinforce the role of PV systems as a critical enabler of Nigeria's net-zero transition. Distributed solar energy has been identified by the International Energy Agency [40] as central to achieving emission reduction targets. The demonstrated ability of polycrystalline PV modules to deliver meaningful energy outputs even during low-sunshine months implies that households can incrementally replace fossil fuel generators. This household-level shift aligns directly with broader climate action objectives, advancing low-carbon energy pathways while reducing environmental and health impacts associated with fossil fuel use.

At the household system design level, the study provides empirical guidance for optimizing PV configurations, storage, and load management. Okonkwo *et al.* [41] showed that environmental variability exerts a strong influence on PV output, and the observed challenges in achieving peak power in September validate the importance of climate-responsive system sizing. Households can better calibrate battery capacity and inverter specifications using such data, enhancing operational efficiency and minimizing losses. This strengthens the resilience of household energy systems and aligns with the sustainable development goal (SDG) of ensuring access to affordable and clean energy.

The findings also highlight the necessity for climate-resilient infrastructure planning. Obiwulu *et al.* [42] emphasized that variability and intermittency must be considered in renewable energy system integration. In Calabar's tropical and humid environment, monthly performance data enable households to design hybrid systems that may combine PV with complementary clean technologies, such as hydrogen-based energy carriers [43]. Such hybridization ensures a stable energy supply [44], mitigates seasonal shortfalls [45], and supports the creation of adaptive energy infrastructures consistent with long-term sustainable development strategies [46].

Socio-economic implications are equally relevant. Household-level adoption of PV systems, as noted by Nwokolo *et al.* [47], contributes not only to emission reductions but also to financial savings and improved energy independence. By accounting for monthly variability in output, households can anticipate fluctuations in electricity availability, plan expenditures more accurately, and reduce frustrations stemming from unrealistic expectations. This improves household satisfaction and supports the wider social acceptance of PV technologies as a reliable [48] and cost-effective energy solution [49].

The study also provides empirical justification for technological and policy innovation. Nwokolo *et al.* [50] stressed the importance of contextualizing PV deployment within climatic realities. Policymakers in Cross River State can use these results to design incentive frameworks for residential PV adoption [51], including subsidies or tax credits [52], while promoting adaptive technologies such as automated maximum power point tracking (MPPT) systems. These approaches ensure households extract maximum value from their installations and align with Nigeria's commitments under the Paris Agreement [53].

Ultimately, the household-level implications of this study support multiple SDGs, particularly SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). Nwokolo *et al.* [54] argue that sustainable energy transitions require not just technological deployment but also reliable datasets that

reflect local performance realities. By filling a critical knowledge gap in Calabar, this study empowers households to actively participate in the clean energy transition. In doing so, it ensures that the renewable energy agenda is inclusive [55], equitable [56], and sustainable, positioning households as active contributors to the net-zero future [57].

CONCLUSIONS

This study delivers a field-resolved picture of a domestic polycrystalline PV module operating in Calabar, Nigeria, using co-measured plane-of-array irradiance and MPP electrical variables every 30 minutes (06:00–18:00) across July–September. The protocol couples a digital irradiance meter with an intelligent MPP tracker on an AF-130W module, establishing a clean separation between the optical input (irradiance, W m^{-2}) and the electrical response (V, A, W, Wh) used in all analyses.

Three quantitative operating thresholds and patterns emerge for Calabar's monsoonal context. First, voltage stabilizes near its STC level once irradiance reaches $\approx 200 \text{ W m}^{-2}$, irrespective of month—an actionable signal for inverter voltage-window planning. Second, approaching manufacturer-level current (and maximum power) in August–September generally requires $>1000 \text{ W m}^{-2}$, a level seldom attained in those wetter months, which explains recurrent current-limited behaviour. Third, monthly performance is asymmetric: output current and power peak in July and are lowest in September, even though average monthly irradiance is highest in September and lowest in August—a counter-intuitive pattern that cautions against using sunshine duration or monthly mean irradiance as proxies for deliverable output.

Two design heuristics follow directly for household PV in Calabar. (i) Treat $0\text{--}450 \text{ W m}^{-2}$ as a conservative “uniform-power” operating band (similar output across months), and plan daytime appliances/battery charging around this plateau; performance dispersion grows beyond this band. (ii) Expect month-dependent efficiency above $\sim 400 \text{ W m}^{-2}$ (July > August > September) and do not size systems assuming September can reach nameplate P_{max} without exceptionally high irradiance. These heuristics reduce sizing uncertainty, improve charge-controller and storage setpoints for the wet season, and align household expectations with realistic field behaviour.

Finally, these findings are location-specific contributions rather than generic theory: (a) thresholds that reconcile STC ratings with Calabar's climate ($\approx 200 \text{ W m}^{-2}$ voltage plateau; $>1000 \text{ W m}^{-2}$ typically needed to approach rated current in Aug–Sep); (b) a documented seasonal inversion where September's higher mean irradiance coincides with lower electrical output; and (c) ready-to-use planning rules (uniform-power band; efficiency ordering and September limit) for household designers. Future work should extend this co-measurement protocol to the dry season and alternative tilts/thermal co-measurements to refine current-vs-irradiance thresholds and seasonal envelopes for Calabar.

CONFLICTS OF INTEREST

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

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Machine Learning–Based Prediction of Daily Solar Radiation to Support Renewable Energy Development in Coastal Regions

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Reliable estimation of surface solar radiation is essential for climate analysis and solar energy planning, particularly in data-limited regions such as coastal Africa. This study investigates the long-term variability of surface solar radiation and evaluates the performance of machine learning models for its prediction using a comprehensive reanalysis dataset spanning 1940–2024. Five radiation components—net surface solar radiation (SSR), clear-sky net radiation (SSRC), downward surface solar radiation (SSRD), clear-sky downward radiation (SSRDC), and total surface radiation (TSR)—were analyzed to quantify the influence of atmospheric attenuation caused by clouds, aerosols, and water vapor. Five machine learning algorithms—Linear Regression (LR), Gradient Boosting (GB), Random Forest (RF), k-Nearest Neighbours (KNN), and Artificial Neural Network (ANN)—were implemented and evaluated using train–test split, k-fold cross-validation, and leave-one-out validation. The results reveal strong interannual and multi-decadal variability in solar radiation, with clear-sky radiation consistently exceeding all-sky radiation, confirming the dominant role of atmospheric modulation in the region. Among the tested models, Linear Regression achieved near-perfect predictive performance ($R^2 \approx 1.0$) with the lowest error statistics, indicating that surface solar radiation over coastal Africa is largely governed by linear radiative processes. Gradient Boosting and Random Forest also demonstrated high accuracy ($R^2 > 0.98$), while the Artificial Neural Network showed poor generalization due to overfitting. The findings demonstrate that computationally efficient and physically interpretable machine learning models can reliably estimate long-term solar radiation in coastal Africa. This provides a robust scientific basis for solar resource assessment, photovoltaic system design, and climate-resilient renewable energy planning across the region.

Keywords: Solar radiation; Machine learning; Linear regression; Ensemble methods; Coastal Africa; Renewable energy prediction

Introduction

A clean and dependable alternative to fossil fuels, solar energy is employed all around the world. Only about 5×10^4 EJ of the enormous amount of energy that the sun's beams send to Earth is readily harvestable ($1 \text{ EJ} = 10^{18} \text{ J}$) [1]. About 70% of the 342 W/m^2 of solar energy that enters the earth's atmosphere may be harvested, with the

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remaining 30% being scattered or reflected back into space. In addition to other factors like sun orientation, aerosol, temperature, wind speed, direction, and many more, the earth's rotation around the sun causes variations in solar irradiance, making solar energy an unpredictable resource [1]. The energy that the Sun emits and that travels across space to reach Earth is referred to as solar radiation. It is made up of electromagnetic waves, such as infrared (IR) radiation, ultraviolet (UV) rays, and visible light. Only a small portion of the solar energy that the Sun emits in all directions makes it to the Earth's atmosphere. The Earth's surface eventually receives some of the solar energy [2]. The critical need for energy diversification is highlighted by the depletion of traditional energy resources like fossil fuels, oil, and gas, as well as rising pollution and the consequences of climate change. A sustainable answer to these urgent problems is provided by incorporating renewable energy sources into our energy mix. We may lessen environmental damage, fight climate change, and lessen our dependency on finite fossil fuels by utilizing renewable energy sources including solar, wind, hydro, and geothermal power [3]. Accurate insolation forecasting is essential for building energy conservation. As a result, a great deal of research has been done to develop trustworthy predictive models for insolation employing machine learning techniques in addition to statistical and physical models. This is essential for reducing greenhouse gas emissions and preventing climate change, as well as for smart cities and net-zero energy buildings [4]. One area of artificial intelligence is machine learning. It is a collection of methods for examining and identifying trends in input data in order to draw conclusions or predictions. The measurement of solar radiation is being revolutionized by artificial intelligence (AI) and machine learning (ML), which are improving efficiency and accuracy. As a subset of AI, machine learning (ML) focuses on teaching algorithms to identify patterns and make predictions based on data, while artificial intelligence (AI) refers to the creation of computer systems that are capable of carrying out tasks that normally require human intelligence. In order to estimate solar radiation, machine learning models examine enormous volumes of environmental and meteorological data to provide highly accurate predictions about solar energy potential [3]. Image identification, natural language processing, robotics, spam filtering, drug development, medical diagnosis, financial analysis, bioinformatics, marketing, and even politics are among the fields in which it finds use. Bayesian networks, artificial neural networks, deep learning, clustering, and Support Vector are a few examples of traditional machine learning techniques [5]. In recent years, Solar Radiation (SR) prediction has gained special attention in academia and a wide range of ML models have been used to forecast SR [6]. In Reference [6], authors reported Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) to estimate SR using ML models. Comparative evaluation using prediction accuracy, stability, and computational time showed that XGBoost outperformed SVM for estimating SR. These ML techniques help handle large amounts of data and studying the complex pattern which makes them a promising and suitable choice for solar irradiance prediction [7]. Other prediction methods of solar radiation are based on the artificial neural network methods, linear regression, probabilistic methods, network monitoring data, fuzzy method approach, ANFIS, Multiple Linear Regressions (MLR) method, and some other methods. The conventional method commonly used for prediction is the multiple regression method. This method can be analyzed by using several independent variables so that the obtained results are more accurate [8]. The aim of this research is to predict coastal solar radiation data using Machine learning algorithms.

Machine Learning Algorithms

Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are a class of computational models inspired by the biological neural networks of the human brain. ANNs consist of interconnected layers of nodes (neurons), where each connection has an associated weight that is adjusted during training to minimize prediction error [9].

- Structure: ANNs typically have three main layers (Figure 1):
 1. Input layer – receives the input features.
 2. Hidden layers – perform non-linear transformations through activation functions (*e.g.*, sigmoid, ReLU, tanh).
 3. Output layer – produces the final prediction (classification or regression).

Artificial Neural Network (ANN) Architecture

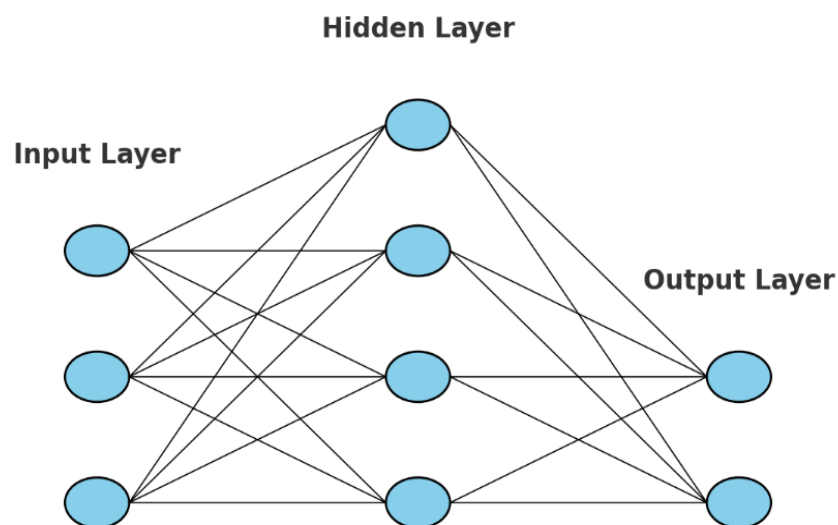


Fig 1. Artificial Neural Network (ANN) Architecture

Linear Regression

Linear Regression is one of the simplest and most widely used supervised learning algorithms for predicting a continuous output based on one or more input features. It models the linear relationship between the independent variable(s) X_n and the dependent variable Y_n .

1. Simple Linear Regression: Uses one independent variable

$$Y = a + bX$$
2. Multiple Linear Regression: Uses two or more independent variables

$$Y = a + b_1X_1 + b_2X_2 + \dots + b_nX_n$$
 where:

Y = predicted value

X = input feature(s)

a = intercept

b = coefficient(s)

Modern applications of linear regression extend to healthcare analytics, finance, and environmental modeling, often enhanced with regularization techniques like Ridge and Lasso regression to handle overfitting and multicollinearity [10].

Gradient Boosting Algorithm

Gradient Boosting is a supervised machine learning technique that builds predictive models by combining an ensemble of weak learners, usually decision trees. Gradient boosting is a method standing out for its prediction of speed and accuracy, particularly with large and complex datasets. Gradient boosting is excellent for various machine learning tasks, including regression and classification. It provides high predictive accuracy by combining weak learners in an ensemble, such as decision trees, to create a strong predictor. Gradient boosting handles complex relationships in data, works well with both numerical and categorical features, and is particularly useful for dealing with largescale structured and unstructured data in real-world applications [11].

K-Nearest Neighbors (KNN)

In machine learning, the k-nearest neighbor method (k-NN) is also known as lazy learning because of its training is held up to run time. This classifier is also one of the most straightforward and simplest since classification of the datasets is based on their nearest neighbor class. The data sets are consequently allocated to the class that's more similar and k must be a positive integer. The value of k is usually small. When $k=1$, the datasets are basically allocated to the class of its nearest neighbor [12].

Random Forest

The Random Forest (RF) algorithm predicts a continuous outcome using an ensemble technique. It aggregates the predictions of multiple decision trees, improving predictive accuracy and preventing overfitting. This method, also known as bagging, generates numerous subsets of the original training data, allowing each tree in the forest to learn from a different portion of the data. Each tree selects different features to introduce randomness and ensure diversity in the model [13].

Materials and Methods

Materials

The data used for this research paper consist of Net Surface Solar Radiation data (ssr), Net Surface Solar Radiation considering clear sky (ssrc), Net Surface Solar Radiation downward (ssrd), Net Surface Solar Radiation downward considering clear sky (ssrdc) and total surface Solar radiation (tsr) data. The data covers a period of eighty-four (84) years (1940 – 2024). The data which was downloaded from the CAMS-Copernicus Atmospheric data store (<https://ads.atmosphere.copernicus.eu/>), represents the coastal regions of Africa. The satellite data was downloaded as a daily recoded data. For the purpose of this research, the data is now presented and used as a monthly average data.

Method

The data was downloaded as a daily recorded data. If used this way, the dataset would be too large; therefore, the authors decided to take the monthly average of the data from 1940 to 2024. The data was then cleaned and presented in a format that will be easy to process. Python programming language was then used for the analysis of the data. Google Colaboratory (<https://colab.research.google.com/>) was then used as the Python platform for the analysis. All the graphs were also plotted using Python programming Language. The Machine Learning Algorithms used for the prediction are; Linear Regression (LR), Random Forest (RF), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN) and Gradient Boosting (GB).

Results and Discussion

Discussion of Graphical Results

Figure 2 presents the time series trends of net surface solar radiation (SSR), net surface solar radiation under clear-sky conditions (SSRC), and net surface solar radiation downward (SSRD) over the study period (1940–2024). The graph shows noticeable temporal variability, reflecting both seasonal cycles and interannual fluctuations in solar radiation in coastal regions of Africa. SSR and SSRC generally follow similar patterns, with clear-sky values consistently higher, as expected due to the absence of atmospheric interference such as aerosols, clouds, and moisture. The SSRD series further highlights how atmospheric conditions attenuate solar flux before reaching the Earth's surface. The long-term variations observed may also be linked to broader climatic shifts and regional atmospheric changes.

Figure 3 illustrates the trends of net surface solar radiation downward under clear-sky conditions (SSRDC) and total surface radiation (TSR). The SSRDC curve provides a baseline of the maximum possible solar input in the absence of atmospheric obstructions, while TSR reflects the actual usable energy at the surface. The consistent gap between these two curves highlights the influence of atmospheric constituents, particularly cloud cover and aerosols, on solar availability. Importantly, both graphs confirm the significant role of atmospheric variability in solar radiation dynamics, underscoring the need for robust predictive models to accurately estimate insolation for renewable energy applications.

Together, the two figures provide evidence that solar radiation in coastal Africa is strongly influenced by atmospheric conditions, with clear distinctions between modeled clear-sky and actual surface radiation. These patterns justify the use of machine learning approaches in this study, as they can capture nonlinear relationships between meteorological inputs and solar radiation outcomes. Moreover, the long-term dataset (spanning more than eight decades) ensures that the models are trained on diverse conditions, enhancing their generalizability.

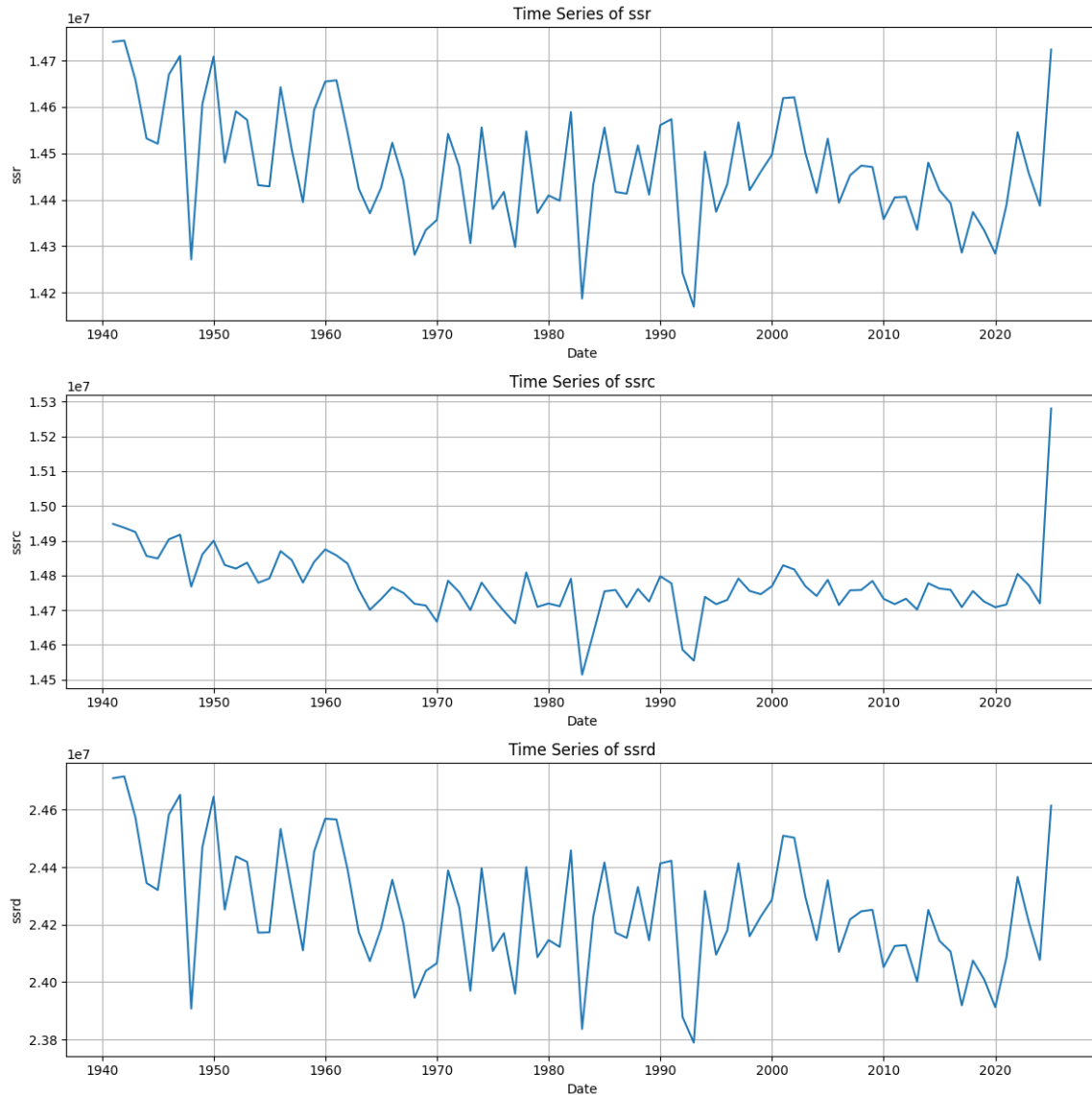


Fig 2. Time series graph of ssr, ssrc and ssrd

Model Evaluation

For models to be evaluated effectively, data has to be split into training and test sets. This is done to measure how well the model generalizes to new, previously unseen data. The main aim is not to determine how well the model fits the training set, but rather in how well it can make predictions for data that was not observed during training. The model evaluation based on train/test split of the data is shown in Table 1.

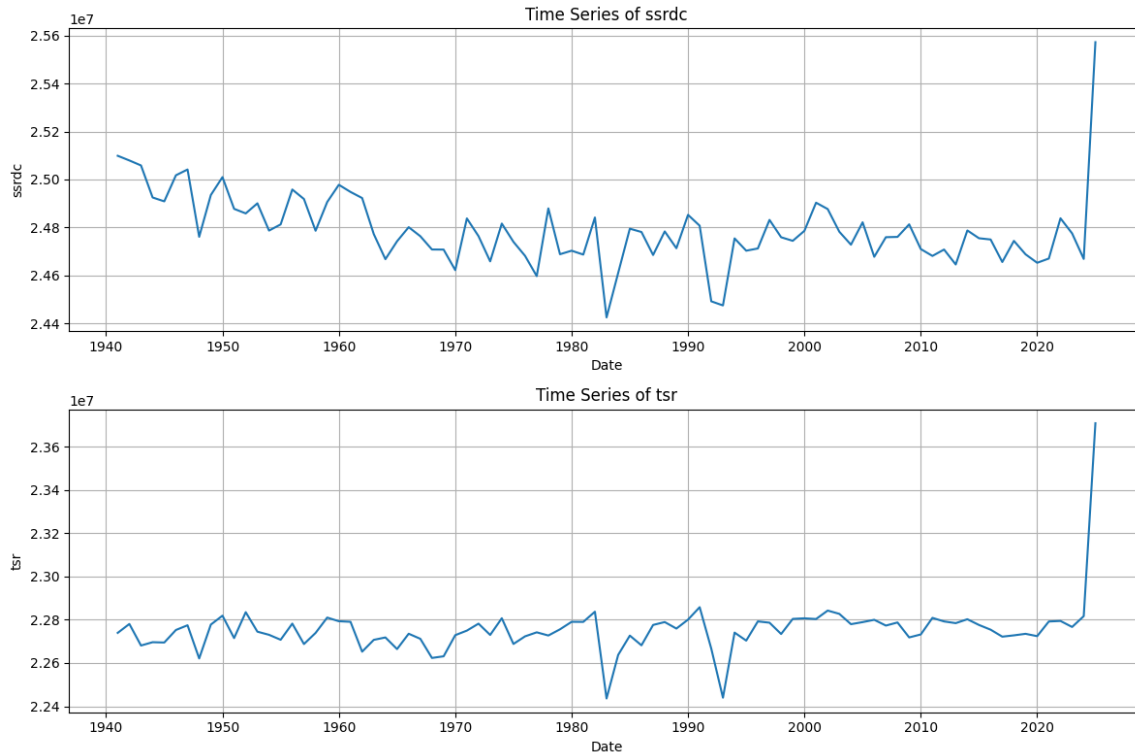


Fig 3. Time series graph of ssrdc and tsr

Table 1. Model evaluation

<i>ML Algorithms</i>	<i>MSE</i>	<i>RMSE</i>	<i>MAE</i>	<i>MAPE</i>	<i>R²</i>
ANN	36579758540	191258.4	115195.9	0.008	-1.125
KNN	739673856	27196.9	16522.5	0.001	0.957
RF	730975651	27036.6	17844.8	0.001	0.98
GB	337703959	18376.7	11461.4	0.001	0.98
LR	3044376	1744.8	1282.3	0	1

Cross Validation

Cross validation is a statistical method of evaluation generalization performance that is more stable and thorough than using a split into training and test set. In cross validation, the data is instead split repeatedly and multiple models are trained. The most commonly used version of cross validation is k-fold cross validation, where k is a user specified number, usually 5 or 10. For this research, the k value was set to 5. The model evaluation based on 5 fold cross validation is shown in Table 2. When performing five-fold cross validation, the data is first partitioned into five parts of approximately equal size, called folds. Next, a sequence of models is trained. The first model is trained using the first fold as the test set, and the remaining folds (2-5) are used as training set. The model is built using data in folds 2-5, and then the accuracy is evaluated on fold 1. Then another model is built, this time using fold 2 as the test set and the data in folds 1, 3, 4, and 5 as the training set. This process is repeated using folds 3, 4, and 5 as the test sets.

Table 2. Evaluation metrics with cross validation

<i>ML Algorithms</i>	<i>MSE</i>	<i>RMSE</i>	<i>MAE</i>	<i>MAPE</i>	<i>R²</i>
ANN	18505527167	136035	103520.5	0.007	-0.18
KNN	430854914.6	20757	13643.9	0.001	0.973
RF	283524785	16838.2	12218.2	0.001	0.982
GB	89874932	9480.2	7500.4	0.001	0.994
LR	3596473.5	1896.4	1410.1	0	1

Stratified K-Fold Cross Validation

In Stratified k-fold cross validation, the data is split such that the proportions between the classes are the same in each fold as they are in the whole dataset. For this research the Stratified method with number of folds equal to five (5) was used. Random sampling was used with repeat train and test set = 10. Training set size set to 66%. The evaluation is shown in Table 2.

Stratified K-Fold Cross Validation With Leave – One - Out

Another frequently used cross validation method is leave one out. Leave - one – out cross validation is a k-fold cross validation where each fold is a single sample. For each split, you pick a single data point to be the test set. The evaluation metrics using leave-one-out is shown in Table 3.

Table 3. Evaluation Metrics using Leave-One-Out

<i>ML Algorithms</i>	<i>MSE</i>	<i>RMSE</i>	<i>MAE</i>	<i>MAPE</i>	<i>R²</i>
ANN	61138249243	247261.5	120244.6	0.008	-2.897
KNN	346772482	18621.3	12382.6	0.001	0.978
RF	280185088	16738.7	13069.2	0.001	0.982
GB	110481999	10511	7361.6	0.001	0.993
LR	3099824	1760.6	1341.1	0	1

Temporal Variability of Surface Solar Radiation

Figures 2 and 3 illustrate the long-term evolution of surface solar radiation components—net surface solar radiation (SSR), clear-sky net radiation (SSRC), downward surface solar radiation (SSRD), clear-sky downward radiation (SSRDC), and total surface radiation (TSR)—over coastal Africa from 1940 to 2024. The time series exhibits pronounced interannual and multi-decadal variability, indicating strong modulation by atmospheric processes and regional climate dynamics. The persistent separation between clear-sky radiation (SSRC and SSRDC) and all-sky radiation (SSR, SSRD, and TSR) highlights the dominant influence of clouds, aerosols, and atmospheric water vapor in controlling surface solar energy availability.

The magnitude of atmospheric attenuation is substantial, implying that a large fraction of incoming solar radiation is absorbed or scattered before reaching the surface. The relative stability of the clear-sky radiation signal compared with the higher variability of all-sky radiation further suggests that atmospheric processes, rather than changes in solar geometry, dominate regional solar variability.

The strong coherence between SSR and SSRC indicates that although atmospheric attenuation is large, it follows systematic and physically constrained patterns.

Performance of Machine Learning Models

The predictive performance of the machine learning models was assessed using three validation strategies: train–test split, k-fold cross-validation, and leave-one-out cross-validation. Across all evaluation frameworks, Linear Regression (LR) consistently outperformed the other models, achieving an R^2 value close to unity and the lowest error statistics (MSE, RMSE, MAE, and MAPE). This indicates an almost perfect agreement between observed and predicted solar radiation values.

The superior performance of LR implies that the relationship between atmospheric variables and surface solar radiation is largely linear. Consequently, the radiation field over coastal Africa appears to be governed by stable and predictable atmospheric controls.

Tree-based ensemble models, particularly Gradient Boosting (GB) and Random Forest (RF), also exhibited excellent performance with R^2 values exceeding 0.98 across all validation schemes. These models successfully captured secondary nonlinear effects arising from complex aerosol–cloud–radiation interactions. However, their slightly lower accuracy relative to LR indicates that nonlinearities play a secondary role compared with the dominant linear radiative processes.

In contrast, the Artificial Neural Network (ANN) performed poorly, with negative R^2 values across all validation approaches. This behavior reflects overfitting and weak generalization.

Cross-Validation and Model Robustness

The robustness of the machine learning models was further evaluated using k-fold and leave-one-out cross-validation. Linear Regression maintained near-perfect predictive skill under all data partitioning schemes, demonstrating exceptional stability and generalization capability. Similarly, Gradient Boosting and Random Forest models exhibited high consistency, confirming their suitability for long-term solar radiation modeling.

The strong agreement between training and cross-validated performance indicates that the long temporal span of the dataset (1940–2024) captures both short-term atmospheric variability and long-term climate trends. This minimizes sampling bias and enhances confidence in the reliability of the predictions. Figures 4 to 6 further confirm this robustness by showing close agreement between observed and model-predicted radiation values.

The observed and predicted values of ssr obtained from the different models were plotted. Figure 4 shows the observed and predicted values of ssr based on the K-NN model. Figure 5 shows the observed and predicted values of ssr based on the LR, Random forest and gradient boosting models. Figure 6 shows the observed and predicted values of ssr based on the ANN model.

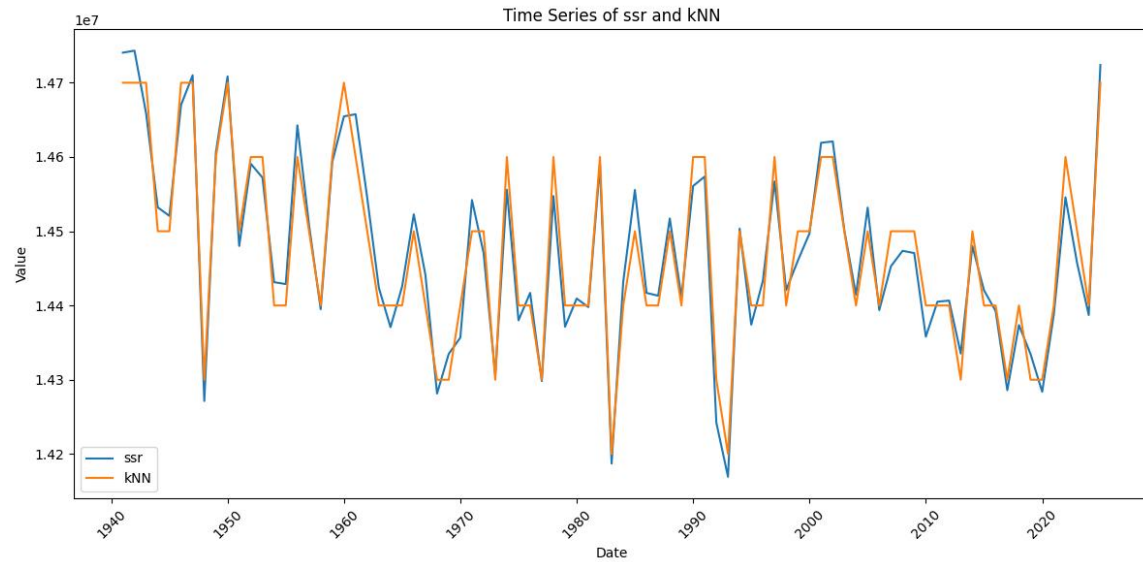


Fig 4. Observed and predicted values of ssr based on the KNN model

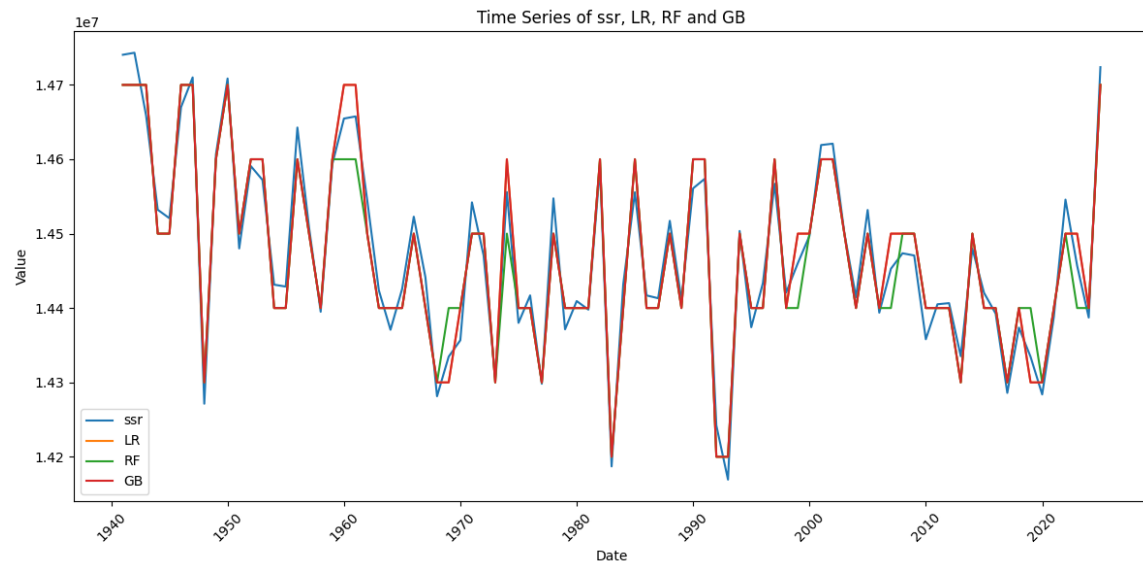


Fig 5. Observed and predicted values of ssr based on LR, random forest and gradient boosting models

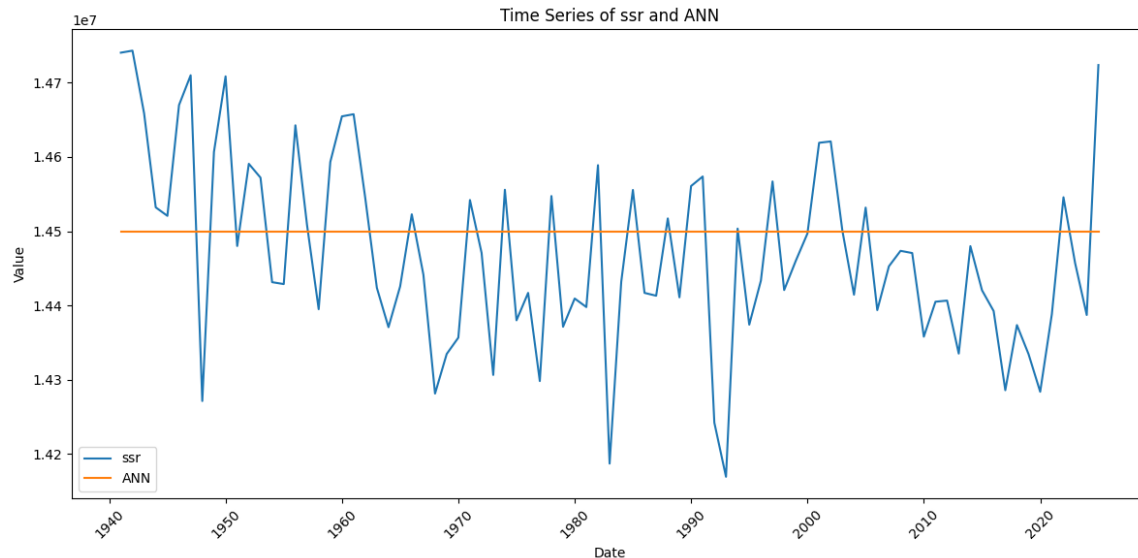


Fig 6. Observed and predicted values of ssr based on ANN model.

Implications for Solar Energy Development

The exceptionally high accuracy achieved by the machine learning models has important implications for renewable energy development in coastal Africa. Reliable estimation of surface solar radiation is fundamental for photovoltaic system design, solar farm siting, and grid integration. The dominance of linear behavior further simplifies operational forecasting, allowing policymakers and energy planners to deploy computationally efficient and interpretable models without compromising accuracy.

Moreover, the use of a long-term climate dataset ensures that the predictions remain robust under changing atmospheric and climatic conditions, making the modeling framework suitable for climate-resilient solar energy planning across the region.

CONCLUSIONS

This study investigated the prediction of daily solar radiation in coastal regions of Africa using multiple machine learning algorithms, including Linear Regression (LR), Random Forest (RF), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Gradient Boosting (GB). The results revealed that Linear Regression outperformed all other models, consistently achieving an R^2 of 1.0 and the lowest error values across different evaluation techniques. This indicates that the relationship between solar radiation and the selected meteorological inputs is strongly linear.

Among the nonlinear models, Gradient Boosting and Random Forest demonstrated excellent performance, achieving R^2 values above 0.98, with Gradient Boosting slightly outperforming Random Forest in terms of error minimization. KNN also produced competitive results but with comparatively higher error values. In contrast, the Artificial Neural Network underperformed, likely due to the dataset's relatively low complexity and the model's need for larger data volumes and advanced parameter optimization.

Based on these findings, the following recommendations are made:

1. Adoption of Linear Regression for practical applications: Given its simplicity, efficiency, and superior accuracy, LR is recommended for solar radiation prediction in coastal regions where interpretability and low computational cost are important.
2. Use of ensemble methods for enhanced accuracy: Gradient Boosting and Random Forest should be considered in applications where small-scale variations and nonlinear interactions are critical, such as in smart grid integration, solar farm optimization, and real-time energy forecasting.
3. Further exploration of deep learning techniques: While ANN underperformed in this study, future work using larger datasets (*e.g.*, high-resolution hourly or minute-level data) and optimized architectures may improve its predictive accuracy and better capture nonlinear patterns.
4. Integration into energy planning and policy: Reliable solar radiation prediction models can support policymakers, energy developers, and utility operators in optimizing solar energy utilization, improving grid stability, and reducing reliance on fossil fuels in coastal African regions.

In conclusion, this study demonstrates that machine learning methods, particularly Linear Regression and ensemble models, provide accurate and reliable tools for solar radiation prediction. Their application holds significant potential for advancing renewable energy integration, improving efficiency in solar energy systems, and supporting sustainable development goals in Africa.

CONFLICTS OF INTEREST

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

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Footprint Analysis of the Gaussian Mixture Model (GMM) for Populating Overhead Low Voltage Broadband over Power Lines (OV LV BPL) Topology Class Maps

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Until now, Neural Network Topology Generator Methodology (NNTGM) has been theoretically proposed and assessed so that its generated overhead low voltage broadband over power lines topologies (NNTGM OV LV BPL topologies) may populate the existing OV LV BPL topology classes in different footprint patterns on the OV LV BPL topology class maps. With reference to the OV LV BPL topology class maps, which are defined by the graphical combination of average theoretical channel attenuation (ACA) and the standard deviation of the theoretical channel attenuation (SDCA) of the OV LV BPL topologies, Gaussian Mixture Model (GMM) is here proposed and treated as an alternative yet simple population method. In fact, GMM is a weighted sum of multiple Normal Distributions (NDs), which have been until now exploited as error distributions for describing the measurement differences during the BPL topology channel attenuation analysis. In this paper, the effect of the parameters of the GMM on the relative position and the size of the GMM OV LV BPL topology footprints on the OV LV BPL topology class maps is here examined. The effect study of the GMM population is supported by the suitable Graphical Performance Indicators (GPIs) already used during the NNTGM population.

Keywords: Smart Grid; Broadband over Power Lines (BPL) networks; Power Line Communications (PLC); Distribution and Transmission Power Grids; Simulation; Modeling

Introduction

As optical fiber and satellite Internet technologies increasingly dominate global broadband infrastructure, Overhead Low Voltage (OV LV) Broadband over Power Lines (BPL) is emerging as a complementary last-mile communication solution that exploits existing electrical networks to extend connectivity where conventional deployments remain costly or impractical. In fact, the strategic role of OV LV BPL networks could be evolving toward complementing these technologies rather than competing with them [1-4]. Although originally designed for power delivery, OV LV lines can support reliable data communication when their topologies are accurately classified and dynamically managed to address impedance variations, attenuation and noise. Integrating BPL with high-capacity fiber and satellite systems enables hybrid architectures that enhance resilience and coverage, particularly in smart grid and rural contexts. Looking ahead, the

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future of BPL lies in its convergence with machine learning, edge computing and software-defined networking, allowing it to evolve into an intelligent, adaptive layer that supports both broadband access and real-time grid management within increasingly digitalized energy ecosystems [5, 6].

The process of populating OV LV BPL topology classes with appropriate OV LV BPL topologies has become a critical task in modern BPL networks due to the increasing complexity and heterogeneity of contemporary power distribution systems. As BPL technology leverages existing LV power infrastructure for high-speed data transmission, accurately classifying and assigning topologies ensures network performance, improved channel estimation, stability and efficient resource allocation. Furthermore, adaptive modulation and coding strategies can be adopted so that the overall data throughput may enhance. Consequently, this task is essential not only for maintaining the technical efficiency of BPL networks but also for supporting their scalability and integration into smart grid environments of hybrid architectures and various communications technologies [7-9].

The Neural Network Topology Generator Methodology (NNTGM), which has been theoretically proposed in [7] and numerically tested in [8, 9], is an AI-based framework designed to generate virtual OV LV BPL topologies (NNTGM virtual OV LV BPL topologies) that preserve the fundamental topological and channel-related characteristics of the indicative topologies of their corresponding OV LV BPL topology classes. By reversing the network identification methodology for the line length approximation (NNIM-LLA) and employing machine learning techniques [10-12], NNTGM produces virtual topologies that exhibit similar channel attenuation behavior, thereby enabling a realistic and systematic expansion of existing topology classes. NNTGM exploits OV LV BPL topology class maps that are the graphical representation at the same plot of the average theoretical channel attenuation (ACA) and the standard deviation of the channel attenuation (SDCA) of OV LV BPL topologies, which hereafter supersedes the previously used RMS-DS term, maintaining consistency with the present analytical framework. The generated topologies by NNTGM are represented on the OV LV BPL topology class maps through NNTGM virtual OV LV BPL topology footprints, which illustrate the relative position and spread of the virtual topologies with respect to their indicative counterparts and the boundaries of their respective topology classes, showing that they may predominantly lie within these boundaries but, depending on the selected parameters and their variations, can also extend beyond them, thus generating footprints of different tendencies and morphologies. Furthermore, various operational parameters of NNTGM were examined—such as the inclusion or not of the examined indicative OV LV BPL topology in the Topology Identification Methodology (TIM) OV LV BPL topology database during the NNTGM operation, the length of the distribution / branch line segments; the number of the distribution / branch line segments, the operating frequencies (i.e., frequency range and flat-fading subchannel frequency spacing) and the participation percentages of the three phases (training, validation and testing) of the MATLAB NN training program of NNTGM—resulting in the formation of distinct virtual topology footprints that reflect the influence of these parameters on the generated topological distributions.

For populating OV LV BPL topology class maps with virtual topology footprints of various relative positions, dispersions, tendencies and morphologies, the Gaussian Mixture Model (GMM) is proposed in this paper. Actually, GMM is a probabilistic model that represents a distribution as a weighted sum of multiple Normal (Gaussian)

Distributions (NDs), where each ND component captures one cluster of the data of the virtual topology footprint. Within this context, a key advantage of employing a GMM lies in its inherent structural simplicity. Each ND component is fully specified by its weight together with its corresponding mean μ and standard deviation σ , thereby enabling direct and interpretable control over the shape, orientation and spatial extent of the resulting GMM virtual OV LV BPL topology footprints on the OV LV BPL topology class maps. Consequently, the modeling process remains transparent, as the final GMM virtual OV LV BPL topology footprint is not the output of a ‘black-box’ mechanism but rather the superposition of simple and well-understood NDs. By comparison, the individual NDs that constitute the GMM are capable of generating footprints with clear geometric structure, as has also been demonstrated by their influence on class maps when examined in the context of measurement differences [13-19]. In contrast, the NNTGM requires the specification of a set of NNTGM operation settings and the execution of the MATLAB NN training program [20, 21], which introduce additional complexity, uncertainty and high-dimensional parameterization. The representation of local virtual topology morphology emerges implicitly through the learning dynamics of the network, making it more difficult to ascertain how input parameters translate into spatial characteristics of the produced NNTGM virtual OV LV BPL topology footprints on the OV LV BPL topology class maps. The use of a GMM therefore enables the formation of more controllable, predictable and analytically interpretable virtual footprints, without the need for complex NN training procedures or extensive tuning of operational settings.

Based on the OV LV BPL topology class maps and the corresponding graphical performance indicators (GPIs) from the NNTGM analysis of [7-9], the impact of the GMM parameters on the relative position and the size of the GMM virtual topology footprints are examined in this paper. To assess the relative position and the size of the GMM virtual topology footprints with respect to the corresponding OV LV BPL topology class borderlines, two GPIs have been applied in [8, 9] and are adopted in this GMM study; say, the percentage of the GMM virtual OV LV BPL topologies that remain inside the OV LV BPL topology class of their respective indicative OV LV BPL topology and the percentage of the GMM virtual OV LV BPL topologies that remain inside specific ACA / SDCA limits with respect to their indicative OV LV BPL topology. In this paper, the impact of the following GMM parameters on the resulting GMM virtual topology footprints and GPIs is further examined, namely: (i) the mean μ of the NDs, (ii) the standard deviation σ of the NDs, (iii) the total count of NDs considered in the application of the GMM, and (iv) the weight assigned to each ND included in the GMM. The findings of this paper support the development of an expanded populating strategy for the OV LV BPL topology class, thereby facilitating a more streamlined and transparent populating process.

The rest of this paper is organized as follows: Section 2 synthesizes the basics of class maps, footprints and GPIs of the indicative OV LV BPL topologies when GMM is going to be applied for populating OV LV BPL topology class maps. Section 3 analyzes the impact of the aforementioned GMM parameters on the GMM virtual topology footprints and GPIs. Section 4 concludes this paper.

GMM Definition, OV LV BPL Topology Class Maps, Virtual Topology Footprints and GPIs

In this Section, the GMM is considered as an alternative modeling framework to the NNTGM. To enable a consistent assessment of the GMM under variations of its parameters, the default GMM operation settings are first presented. Moreover, the channel attenuation metrics —i.e., ACA and SDCA— as well as the OV LV BPL topology class maps, which were originally defined in [7] for the NNTGM case, are adopted here for the analysis of the GMM to ensure methodological consistency and comparability. In addition, for benchmark purposes, these metrics and OV LV BPL topology class maps are provided for the indicative OV LV BPL topologies of [7] together with their corresponding GMM virtual OV LV BPL topologies. Finally, the GPIs, initially introduced in [8] and used to evaluate the impact of changes of the GMM parameters on the relative position and size of the GMM virtual topology footprints on the OV LV BPL topology classes, are also included in this Section.

GMM Definition and GMM Operation Settings

GMM builds on the prior use of NDs solely as statistical models of measurement differences [13-19], extending this earlier experience by employing these ND-derived characterizations within a more structured framework for populating OV LV BPL topology classes and generating GMM virtual OV LV BPL topologies. Actually, a set of practical reasons and “real life” conditions, which can be grouped into six categories [13, 18, 19], can create measurement differences during the practical determination of the coupling scheme transfer function of the OV LV BPL topologies. Appropriately modifying eq. (1) of [14], the measured coupling scheme transfer function, which is treated as the virtual coupling scheme transfer function $H_{virtual}(f_q)$, $q = 1, \dots, Q$ in this paper, is obtained by superimposing on the theoretical coupling scheme transfer function $H_{theor}(f_q)$, $q = 1, \dots, Q$, which is produced by the Deterministic Hybrid Model (DHM), a synthetic BPL channel model composed of three concatenated modules, namely the bottom-up, top-down and coupling-scheme modules [22, 23], the measurement differences in dB that are described by the random variable $e^D(f_q)$, $q = 1, \dots, Q$, namely:

$$H_{virtual}(f_q) = H_{theor}(f_q) - e^D(f_q), q=1,\dots,Q \quad (1)$$

where $[\cdot]^D$ denotes the applied difference distribution —i.e., either Continuous Uniform Distribution (CUD) or ND—, f_q is the flat-fading subchannel spacing and the start frequency in this paper, and Q is the number of subchannels in the examined frequency range. By employing this methodology, which originally generated measurement differences using simple CUDs or NDs, and now replacing these with a GMM composed of NDs with varying means, standard deviations and weights, it becomes possible to generate virtual OV LV BPL topologies with diverse characteristics, depending on the selected values of the aforementioned GMM parameters. By combining multiple NDs, GMM can capture a wide range of variability and complexity that anyway characterize the topological characteristics of OV LV BPL topologies. Therefore, GMM virtual OV LV BPL topologies are expected to present channel attenuation behaviors that can remain close to the one of the examined indicative OV LV BPL topology in each case but this can be further adjusted through the change of the parameters of the GMM operation settings as it has been shown in the case of NNTGM in [8].

As GMM is concerned, it is employed to model the distribution of the vector $\mathbf{e}^{\text{GMM}} = [e^{\text{GMM}}(f_1), \dots, e^{\text{GMM}}(f_Q)]$, which contains the error samples across all examined frequencies. The corresponding probability density function (PDF) is expressed as a weighted sum of K ND components:

$$p(\mathbf{e}^{\text{GMM}}) = \sum_{k=1}^K w_k p(\mathbf{e}^{\text{GMM}}|k) \quad (2)$$

where w_k denotes the weight of k -th ND component with the constraint $\sum_{k=1}^K w_k = 1$. Each ND component corresponds to a distinct cluster once a component k is selected according to w_k , the samples $e^{\text{GMM}}(f_q)$ for all frequencies $q = 1, \dots, Q$ are generated from the corresponding ND component parameters $(\mu_k(f_q), \sigma_k(f_q))$. Consequently, the same ND component governs the values of $e^{\text{GMM}}(f_q)$ across the entire frequency range, which naturally leads to the formation of clusters when multiple ND components are included in the GMM.

As the GMM default operation settings are concerned, these can be listed as follows in accordance with the ones of NNTGM of [7, 8]:

- OV LV BPL networks are divided into cascaded OV LV BPL topologies of typical lengths of 1000m while a typical OV LV BPL topology is shown in Figure 1 of [7]. With reference to Figure 1 of [7], the typical OV LV BPL topology is bounded by its transmitting and receiving ends. Across the transmission path of the OV LV BPL topology, N branches of various lengths and of open-circuit terminations may occur. In accordance with [7, 10, 18, 23], the topological characteristics and the number of branches for the three indicative OV LV BPL topologies –i.e., rural, suburban and urban– are listed in Table 1 of [7]. These three indicative OV LV BPL topologies are the representative ones of the respective main OV LV BPL topology classes, which are also detailed in [13-15].
- Line-Of-Sight (LOS) topology case, which is also listed in Table 1 of [7], is characterized by the minimum achievable attenuation within the family of OV LV BPL topologies of interest. Accordingly, the values of eq. (2) produced by the GMM are constrained such that the channel attenuation of the virtual OV LV BPL topology, as given in eq. (1) for a specified frequency, can never be lower than the attenuation corresponding to the LOS topology case. This LOS cutoff constraint guarantees that the statistical modeling remains physically consistent and adheres to the lower-bound attenuation behavior dictated by LOS propagation conditions.
- As far as the operating frequencies of the GMM are concerned, the frequency range is assumed to span 1-30MHz, whereas the flat-fading subchannel frequency spacing is set to 1MHz. Under these assumptions, the total number of flat-fading subchannels Q equals 29. Note that for reasons of methodological consistency and in order to facilitate a direct and meaningful comparison between GMM and NNTGM, the same assumptions regarding the operating frequency range and the flat-fading subchannel spacing in NNTGM are also applied to the GMM. This alignment ensures that differences observed between NNTGM and GMM results can be attributed to the modeling schemes themselves rather than to discrepancies in the underlying frequency-domain parametrization.

Similarly to the NNTGM, the evaluation of the GMM is conducted by examining the channel attenuation metrics ACA and SDCA which are employed in the construction of the OV LV BPL topology class maps of this paper, along with the corresponding GPIs that are presented in the following subsection.

Channel Attenuation Metrics, OV LV BPL Topology Class Maps and GPIs for the GMM Evaluation

Similarly to the class maps of [13, 15, 24-26], OV LV BPL topology class maps of [7-9], which are going to be exploited by GMM case, are plotted by using the channel attenuation metrics ACA and SDCA for the horizontal and vertical axes, respectively. With reference to eqs. (11) and (12) of [7], ACA can be calculated for each OV LV BPL topology (either indicative or NNTGM virtual topology or GMM virtual one) by averaging the amplitudes of the coupling scheme channel attenuations in dB over the flat-fading subchannels while SDCA measures the average channel attenuation distance from ACA for the examined OV LV BPL topologies over the same flat-fading subchannels. Similarly to NNTGM approach of [7-9], by leveraging the combination of ACA and SDCA values, each indicative OV LV BPL topology, along with its corresponding GMM virtual topologies, can be represented graphically to delineate its OV LV BPL topology footprint on the class map. As discussed in [7-9], the footprints of these indicative OV LV BPL topologies exhibit both the origin and relative proximity to their respective topologies, while their specific locations and dimensions on the class map are going to be determined by the applied parameters of the GMM operation settings. To illustrate the OV LV BPL topology class areas on the class maps and to investigate the behavior of the corresponding topology footprints, two graphical milestones are applied. First, the class boundaries are approximately determined as the median lines between neighboring indicative OV LV BPL topologies, as reported in [7-9], under the default NNTGM and GMM operation settings; specifically, these are the rural–suburban and suburban–urban class boundaries. Second, an ACA / SDCA box corresponding to $\pm 10\%$ variation is defined around each indicative OV LV BPL topology, reflecting the effect of a $\pm 10\%$ change in ACA and SDCA values for the applied default NNTGM and GMM operation settings.

With reference to [7-9], in Figure 1(a), the OV LV BPL topology class map with the indicative rural case, suburban case and urban case A is presented when the default NNTGM and GMM operation settings are applied. Apart from the two class borderlines, the three ACA / SDCA boxes of $\pm 10\%$ of the respective three indicative OV LV BPL topologies are illustrated with dashed lines. In Figure 1(b), to enable a direct comparison between the subsequent GMM results and those obtained using the NNTGM, the NNTGM virtual topology footprints for the rural, suburban, and urban case A scenarios of [7-9] are superimposed onto the OV LV BPL topology class map of Figure 1(a). This superposition is performed using the default NNTGM operational settings and includes 100 NNTGM virtual topologies for each corresponding topology footprint.

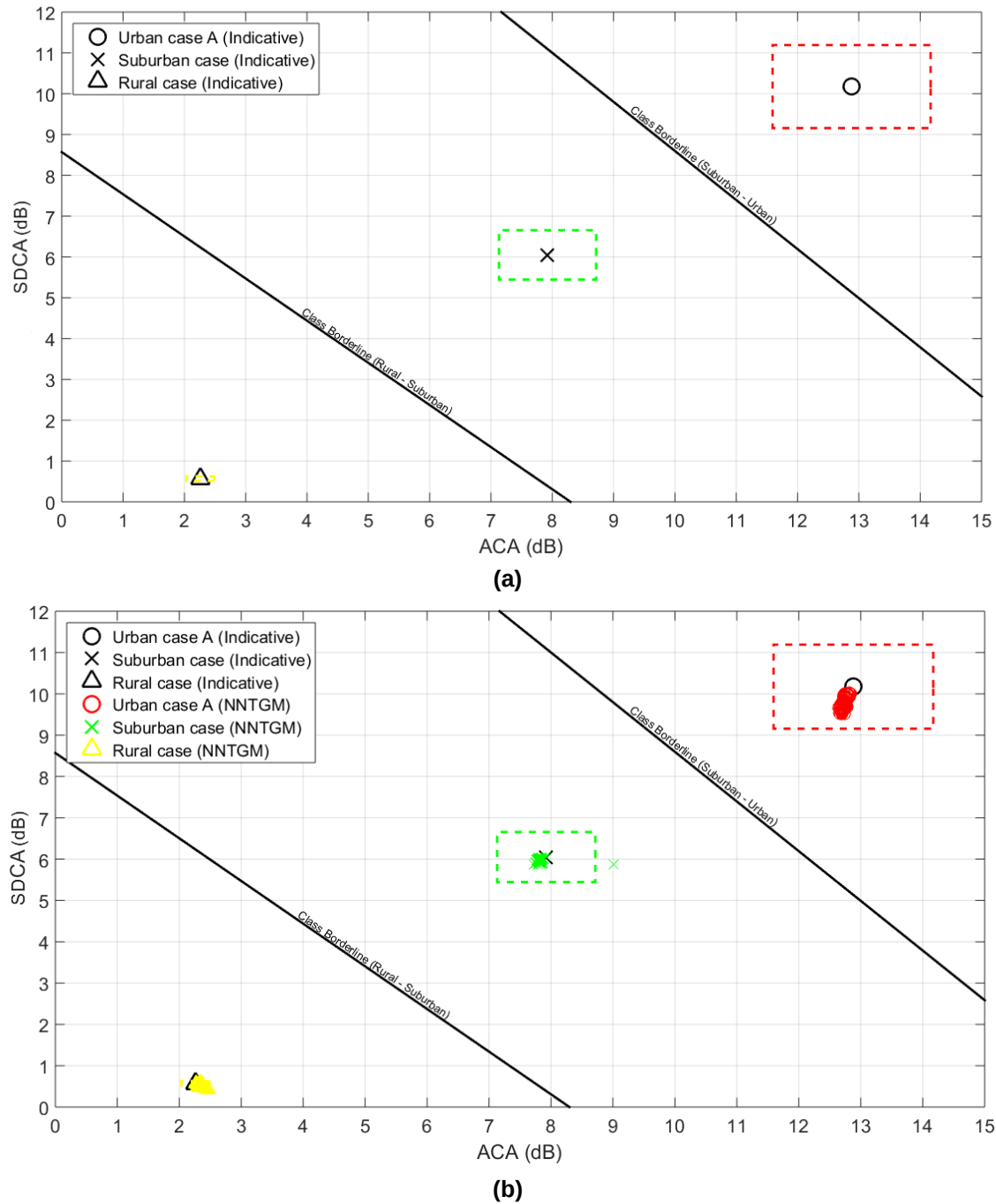


Fig. 1. (a) OV LV BPL topology class map of the three indicative OV LV BPL topologies when the NNTGM and GMM default operation settings are applied. **(b)** OV LV BPL topology class map with NNTGM virtual topology footprints of the three indicative OV LV BPL topologies when the NNTGM default operation settings are applied [7-9].

With reference to the two previously defined graphical milestones, two GPIs have been used in [7-9] for NNTGM and are also going to be applied in GMM to assess the distribution of OV LV BPL topology classes under the applied GMM operation settings, namely:

- *Inside-the-class*: This GPI is going to quantify the percentage of GMM virtual OV LV BPL topologies that remain within the class corresponding to their respective indicative OV LV BPL topology.
- *Inside-the-box*: This GPI is going to measure the percentage of GMM virtual OV LV BPL topologies that remain within a $\pm 10\%$ ACA / SDCA box relative to their indicative OV LV BPL topology.

The combined use of class maps and GPIs provides a robust framework for assessing the influence of GMM parameters on the resulting GMM virtual OV LV BPL topology footprints. To enable a direct GPI-based comparison between the NNTGM and GMM, the aforementioned GPIs that are previously applied to the NNTGM OV LV BPL topologies of the three OV LV BPL topology classes are summarized in Table 1.

The objective of Figure 1(b) and Table 1 is to transform the findings of [7-9] presented for NNTGM into a quantitative reference baseline. This allows the effects of parameter variations applied in GMM, which are examined in the following Section, to be assessed relative to NNTGM results of Figure 1(b) and Table 1, enabling a clear quantitative evaluation of their impact and a precise understanding of how the outcomes shift in relation to the NNTGM baseline.

The Effect of GMM Parameter Variation on the GMM Virtual Topology Footprints

In this Section, the impact of the following GMM parameters on the resulting GMM virtual topology footprints and GPIs is examined, namely: (i) the mean μ of the NDs, (ii) the standard deviation σ of the NDs, (iii) the total count of NDs considered in the application of the GMM, and (iv) the weight assigned to each ND included in the GMM. The results presented in this paper provide a foundation for devising a simplified strategy for populating OV LV BPL topology classes, thereby enabling a more efficient and transparent class population process.

ND Mean and its Impact on GMM Virtual Topology Footprints and GPIs

GMM represents the distribution of the aforementioned random variable $e^{\text{GMM}}(f_q), q = 1, \dots, Q$ of eq. (1) as a weighted sum of K ND components. Each ND component is characterized by its mean μ_k and standard deviation σ_k in order to model a distinct cluster within the data.

As the impact of the ND mean is concerned, in Figure 2(a), the OV LV BPL topology class map with the GMM virtual topology footprints of the rural case, suburban case and urban case A is presented when the GMM default operation settings are applied and GMM consists of only one ND component with ND mean μ and ND standard deviation σ that are equal to 0dB and 0.5dB, respectively. Similarly to Figure 1(b) of NNTGM, each GMM virtual OV LV BPL topology footprint of Figure 2(a) comprises 100 GMM virtual topologies per indicative OV LV BPL topology.

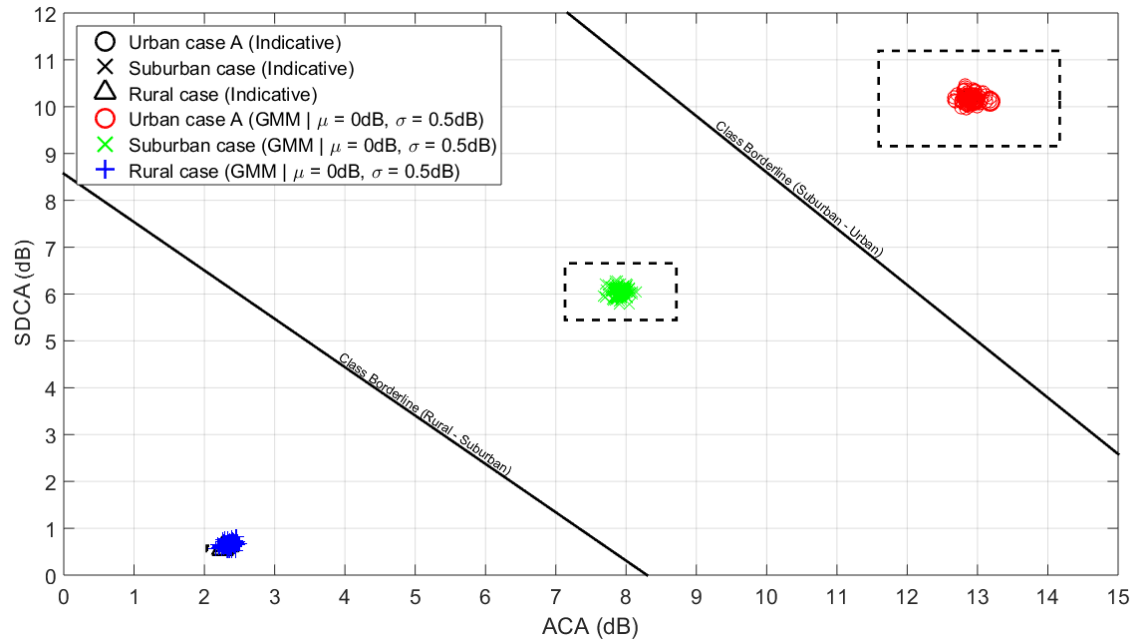
Table 1. GPIs of the NNTGM virtual OV LV BPL topologies of the three OV LV BPL topology classes (NNTGM default operation settings are applied) [8]

GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	84	99	100

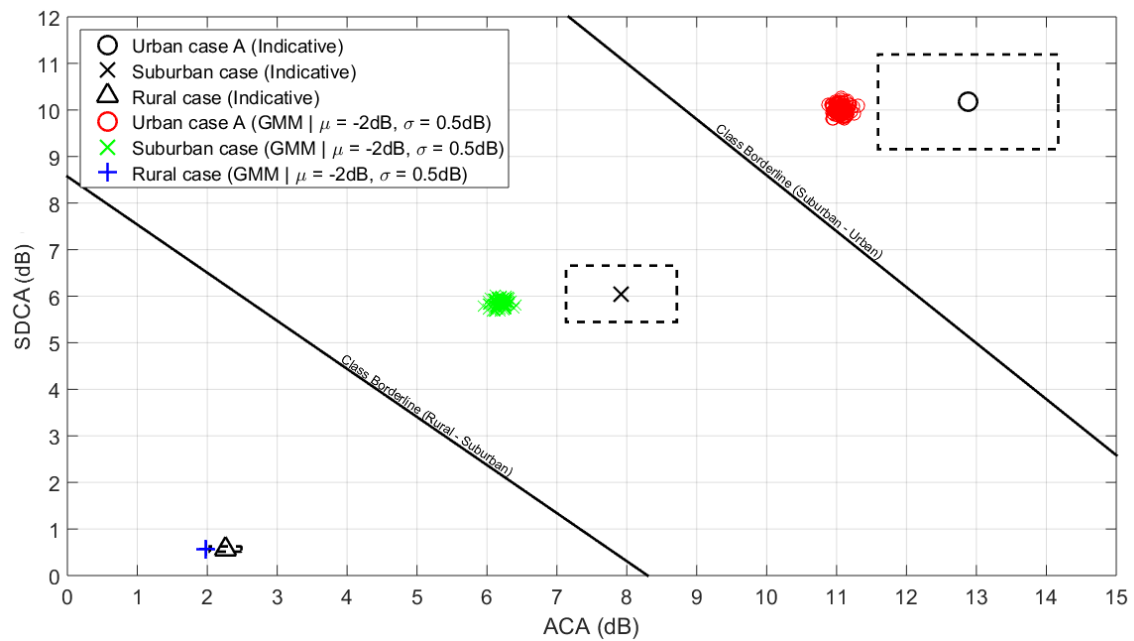
The two class borderlines of Figures 1(a) and 1(b) and the three ACA / SDCA boxes of $\pm 10\%$ of the respective three indicative OV LV BPL topologies are also added. In Figures 2(b)-2(e), similar plots to Figure 2(a) are given, but for the case of ND mean μ of -2dB, +1dB, +3dB and +5.5dB, respectively. The same GPIs of Table 1 are applied to the GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes of Figures 2(a)-2(e) and are reported in Table 2.

Figures 2(a)-2(e) illustrate the GMM virtual OV LV BPL topology footprints corresponding to the rural, suburban and urban A cases under varying values of the ND mean μ , while the ND standard deviation σ remains fixed at 0.5dB. The choice of such a small σ inherently limits the statistical dispersion of the ND values, resulting in compact and concentrated GMM virtual OV LV BPL topology footprints rather than wide or diffuse footprint regions; this reflects the constrained variability of ACA and SDCA around each footprint centroid. As μ increases from -2 dB to +3 dB, all three examined cases exhibit a systematic and approximately proportional rightward displacement of the centroid of the corresponding generated GMM virtual OV LV BPL topology footprint. This trend indicates a consistent shift toward higher ACA levels across all cases, while the SDCA values of the footprints remain nearly unchanged. Consequently, the resulting centroid movement is predominantly horizontal, demonstrating that the GMM components reconfigure themselves in a similar manner across the different topology classes to represent progressively more degraded propagation conditions without modifying the dispersion characteristics of the GMM virtual OV LV BPL topologies. As the footprint of rural case is concerned when $\mu = -2$ dB and σ is small, the LOS cutoff, which has been presented during the definition of the GMM default operation settings, becomes active for the GMM virtual OV LV BPL topologies of the rural case, causing the rural footprint to adhere to the LOS baseline and concentrate against it rather than sit below it; this clipping effect yields a markedly reduced spatial extent for the rural footprint compared with the suburban and urban A cases at the same ND mean value. Overall, the GMM virtual OV LV BPL topology footprints clearly demonstrate how the ND statistical parameters may shape the inferred virtual topologies, highlighting the interaction between environment type, mean channel degradation and the structural behavior of the GMM representation.

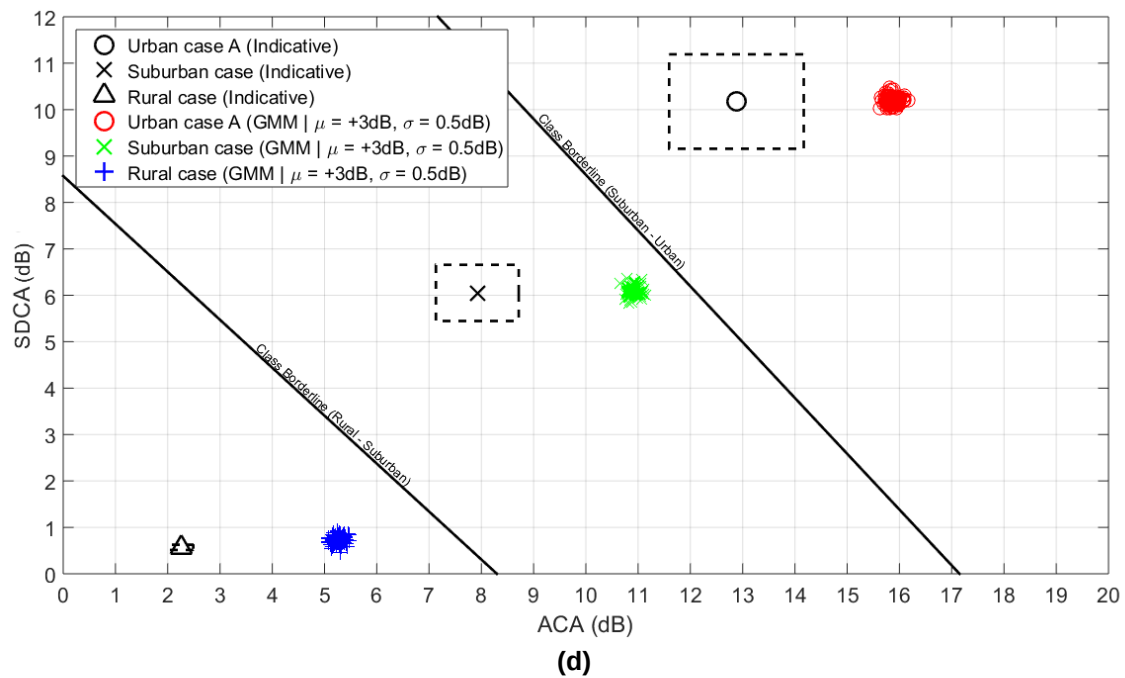
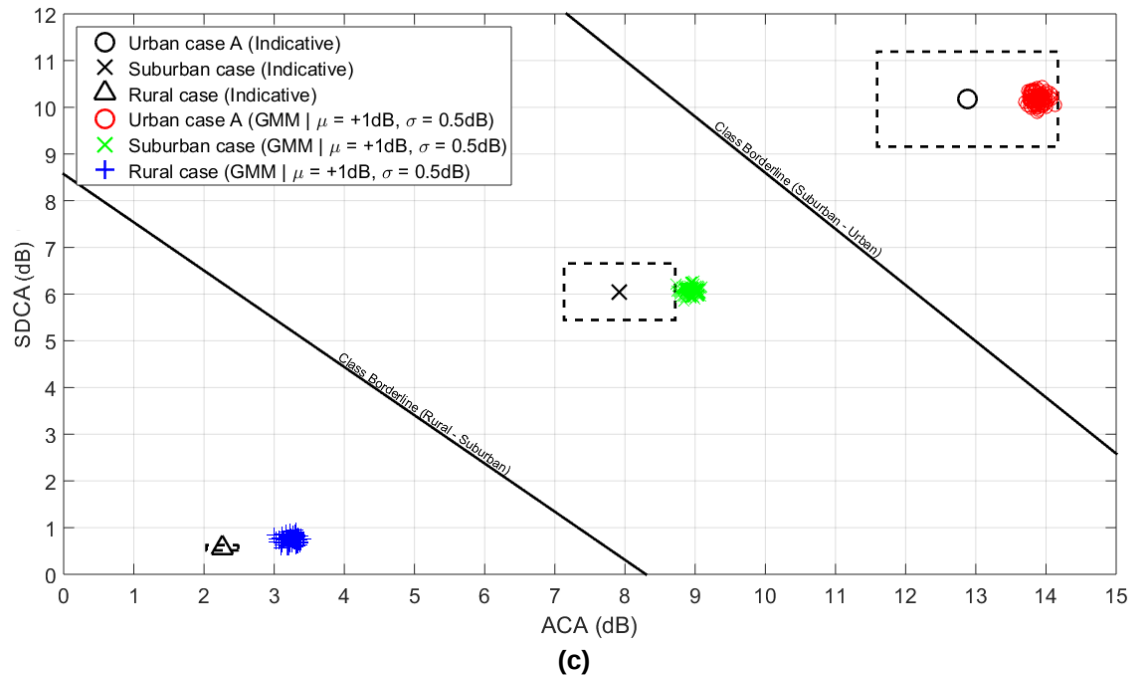
Combining findings of Figures 2(a)-2(e) with Table 2, it is shown that although all footprints remain fully consistent with their corresponding topology class (100% inside-the-class), their ability to fall within the predefined ACA / SDCA bounding box of the indicative OV LV BPL topology of origin is highly sensitive to the ND mean μ . At $\mu = 0$ dB the suburban and urban A footprints fully satisfy the box constraint while the rural footprint only partially does so, whereas for $\mu = -2$ dB and $\mu = +3$ dB all cases fall entirely



(a)



(b)



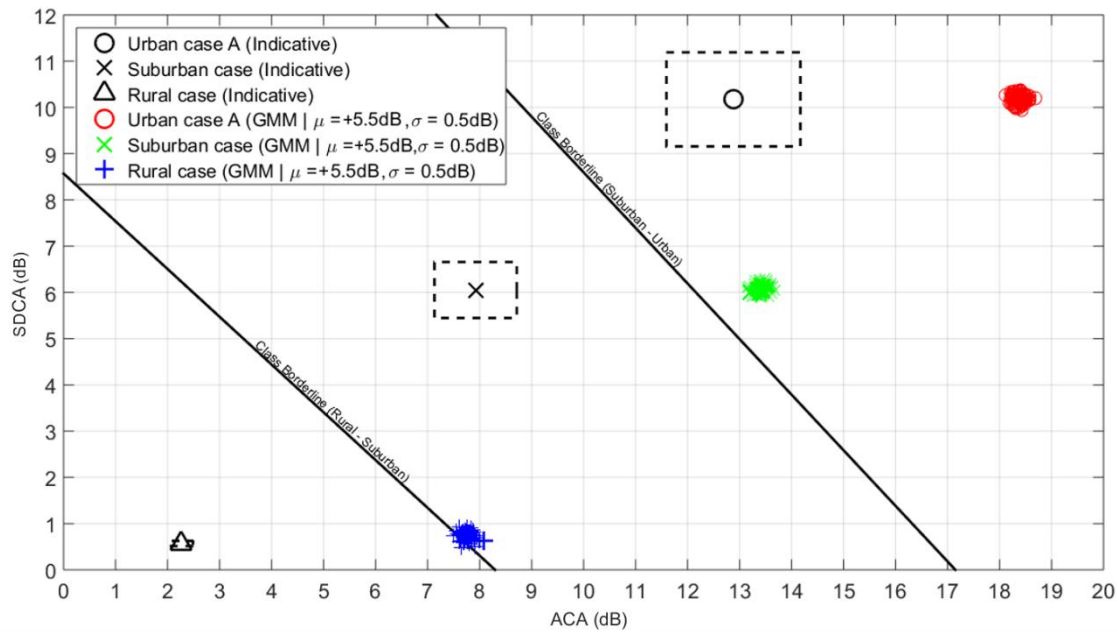


Fig. 2. OV LV BPL topology class map with GMM virtual topology footprints of the three indicative OV LV BPL topologies for various single ND mean values. **(a)** ND mean $\mu = 0\text{dB}$. **(b)** ND mean $\mu = -2\text{dB}$. **(c)** ND mean $\mu = +1\text{dB}$. **(d)** ND mean $\mu = +3\text{dB}$. **(e)** ND mean $\mu = +5.5\text{dB}$.

Table 2. GPIs of the GMM OV LV BPL topologies of the three OV LV BPL topology classes for different ND mean μ values when the ND standard deviation σ is equal to 0.5dB (GMM default operation settings are applied).

ND mean $\mu = 0\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	32	100	100
ND mean $\mu = -2\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	0	0
ND mean $\mu = +1\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	0	100

ND mean $\mu = +3\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	0	0

ND mean $\mu = +5.5\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	3	0	100
Inside the box (%)	0	0	0

outside the box due to the strong leftward and rightward shifts in ACA, respectively. As μ increases, only the urban case A footprint retains full box compliance at $\mu = +1\text{dB}$, while both rural and suburban cases progressively drift outside the bounding region, indicating that higher ND means push these environments into attenuation regimes outside the box constraints. Naturally, the definition of the $\pm 10\%$ ACA / SDCA box also plays an important role. The $\pm 10\%$ margin applied to the box of the rural case provides limited tolerance for variability in the GMM virtual OV LV BPL topologies if they are to remain within its bounds, in contrast to the more relaxed box constructed for the urban case A. Regarding the GPI inside-the-class, regardless of how large the ND mean μ becomes when generating GMM virtual OV LV BPL topologies for the urban case A, the suburban-urban class borderline remains a limiting boundary. Consequently, these topologies always reside within the urban case A class, which justifies the constant value of 100 for the GPI inside-the-class across all entries in Table 2 and the following Tables.

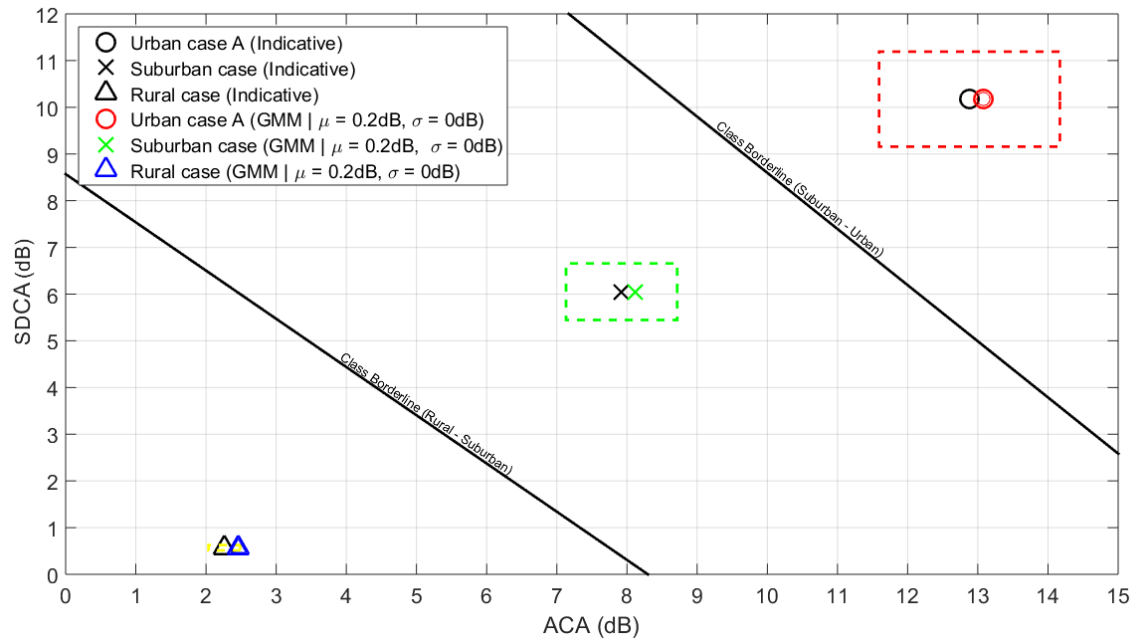
As the impact of the ND mean is examined on the population of OV LV BPL topology classes, higher ND means shift the footprints toward regions of increased ACA, which in turn enables targeted population of areas corresponding to higher-ACA OV LV BPL topology classes even when these regions lie at the boundaries of, or slightly outside, the original classes from which the GMM virtual OV LV BPL topologies are derived. This behavior highlights that the GMM virtual footprints can populate topological zones beyond their nominal class cores as μ increases, maintaining similar SDCA elevations and remaining approximately parallel along the ACA axis. Comparing Figure 1(b) and Table 1 of NNTGM with Figure 2(a) and Table 2 of GMM, respectively, the NNTGM and GMM population approaches show that both methods consistently achieve 100% GPI inside-the-class for the rural, suburban and urban cases, confirming stable class preservation under their respective generation mechanisms. However, their behavior diverges in the GPI inside-the-box, where NNTGM under default operation settings exhibits a gradual transition across cases (84% rural, 99% suburban, 100% urban), while GMM—evaluated at $\mu = 0\text{ dB}$, $\sigma = 0.5\text{ dB}$ —demonstrates a more abrupt, almost step-like response (32% rural, 100% suburban and 100% urban). Anyway, in accordance with [7-9], NNTGM can perform various population schemes for its virtual OV LV BPL topology footprints by appropriately modifying its default operation settings but the further comparison is outside the scope of this paper.

ND Standard Deviation and its Impact on GMM Virtual Topology Footprints and GPIs

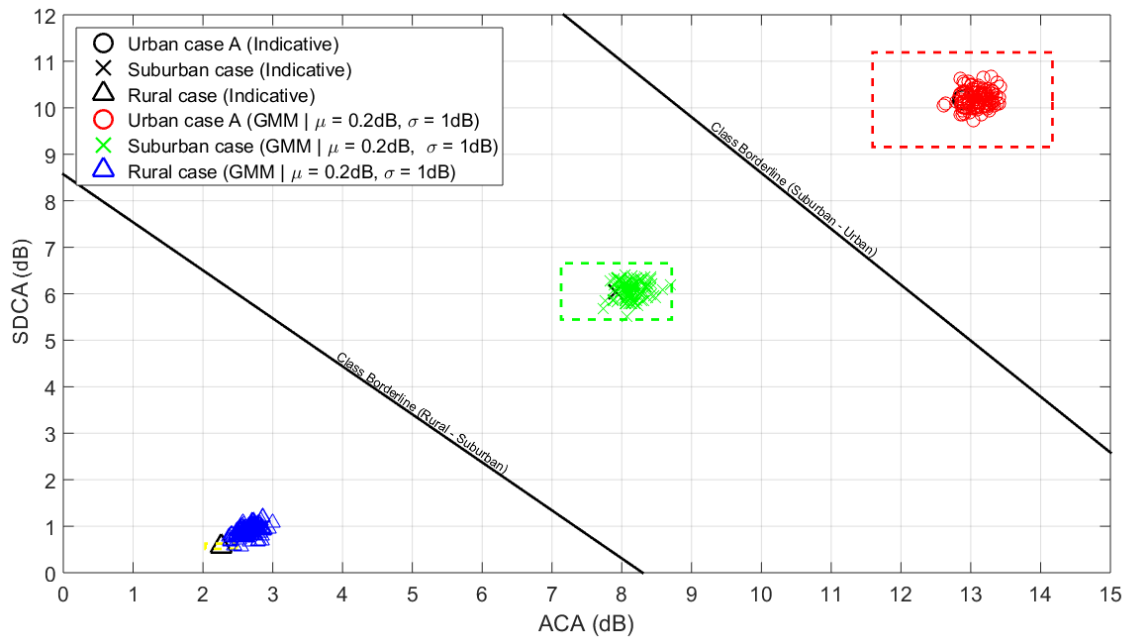
As the impact of the ND standard deviation is concerned, in Figure 3(a), the OV LV BPL topology class map with the GMM virtual topology footprints of the rural case, suburban case and urban case A is presented when the GMM default operation settings are applied and GMM consists of only one ND component with ND mean μ and ND standard deviation σ that are equal to 0.2dB and 0dB, respectively. Each GMM virtual OV LV BPL topology footprint of Figure 3(a) comprises 100 GMM virtual topologies per indicative OV LV BPL topology. In Figures 3(b)-3(e), similar plots to Figure 3(a) are given, but for the case of ND standard deviation σ of 1dB, 3dB, 5dB and 7dB, respectively. The same GPIs of Tables 1 and 2 are applied to the GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes of Figures 3(a)-3(e) and are reported in Table 3.

Figures 3(a)-3(e) illustrate the GMM virtual OV LV BPL topology footprints corresponding to the rural, suburban and urban A cases under varying values of the ND standard deviation σ , while the ND mean μ remains fixed at 0.2dB. The increase of the ND standard deviation σ from 0dB to 7dB results in a rightward displacement of the GMM virtual OV LV BPL topology footprint centroids, not merely parallel to the ACA axis as observed previously in Figures 2(a)-2(e), but following a diagonal trajectory towards the upper-right region of the ACA / SDCA plane, thereby engaging the vertical SDCA dimension more prominently. Furthermore, in contrast to the behavior observed under increasing ND mean, where the spatial spread of the GMM virtual OV LV BPL topology footprints remained compact as long as σ was held small and constant, here the increase in ND standard deviation induces a noticeable spatial expansion of the footprints for all examined indicative OV LV BPL topologies. This diagonal migration is more pronounced in the rural case, where several GMM virtual OV LV BPL topologies have already exceeded the rural-suburban class borderline; a similar trend is present in the suburban case, albeit in a more moderate form. While the urban case A also exhibits detectable rightward movement, the dominant effect is the substantial increase in footprint spatial extent as ND standard deviation grows.

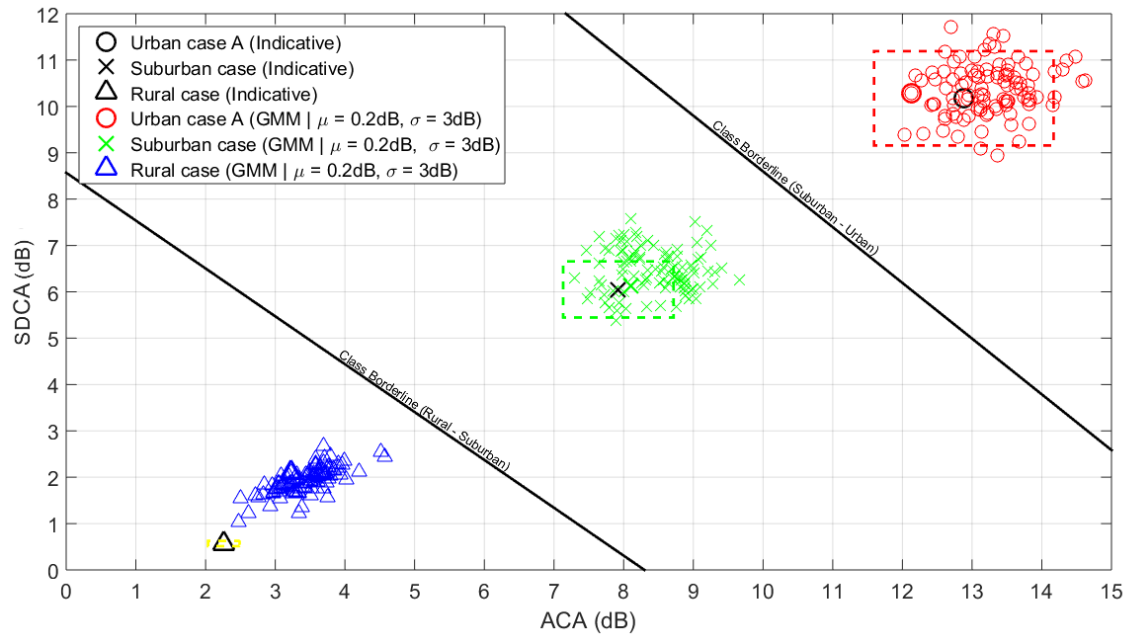
Combining findings of Figures 3(a)-3(e) with Table 3, it is shown that similarly to the ND mean case, where the class consistency did not remain intact in a concentrated way, the variation of ND standard deviation σ demonstrates a more disruptive influence on the GMM virtual OV LV BPL topologies. While at $\sigma = 0$ dB and 1dB all topologies preserve full class membership (100% inside-the-class), box compliance already begins to decline, most notably for rural at $\sigma = 1$ dB (1%). As σ increases to 3dB, class integrity is still maintained (100%), yet compatibility with the $\pm 10\%$ ACA / SDCA box drops sharply (0%, 37%, 85% for rural, suburban and urban A respectively), signaling the onset of spatial dispersion. Beyond this point, for $\sigma \geq 5$ dB, the rural and suburban cases no longer remain fully inside their classes (87% and 99% at $\sigma = 5$ dB, falling further to 31% and 79% at $\sigma = 7$ dB), indicating cross-class GMM virtual OV LV BPL topology footprint migration, whereas the urban A topology retains 100% class consistency throughout due to the reason discussed in the previous subsection but exhibits significant reduction in the GPI inside-the-box compliance (65% at $\sigma = 5$ dB and 30% at $\sigma = 7$ dB). Overall, increasing σ expands the footprint spatially, progressively reducing GPI inside-the-box percentages across all cases, with rural being the most sensitive and urban A the most resilient to dispersion effects thus validating the observations of Figures 3(a)-3(e).



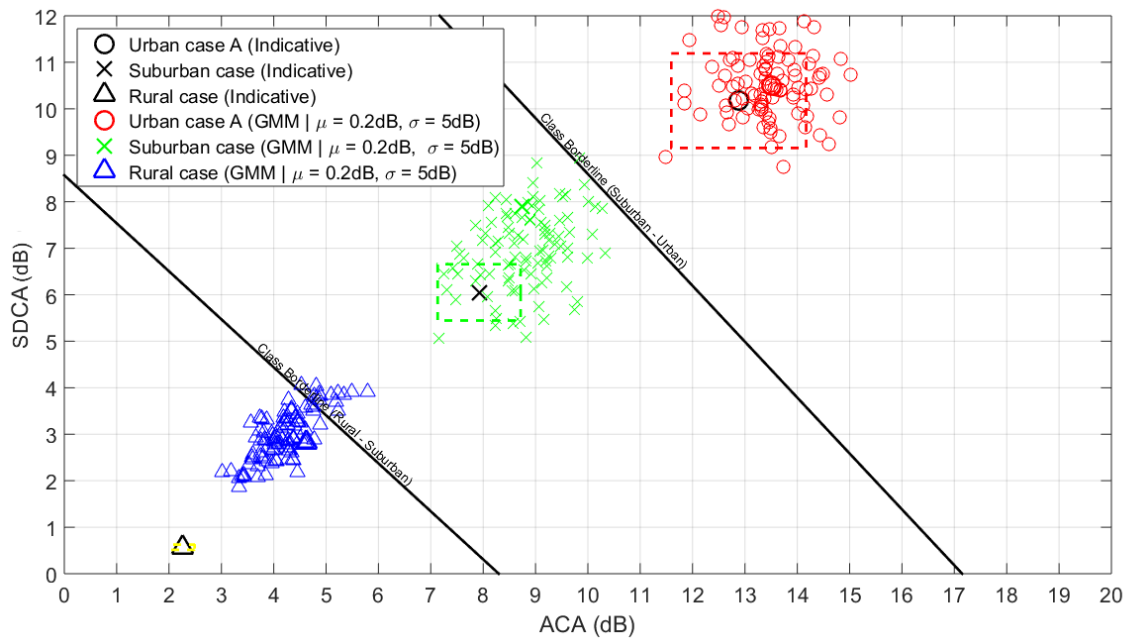
(a)



(b)



(c)



(d)

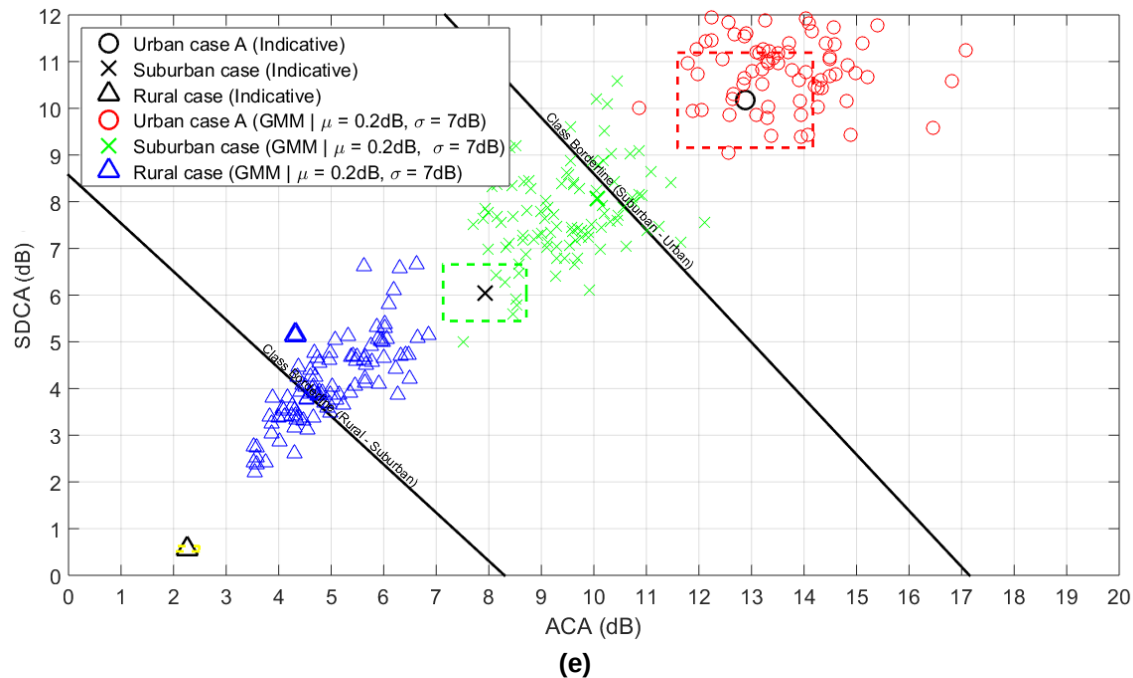


Fig. 3. OV LV BPL topology class map with GMM virtual topology footprints of the three indicative OV LV BPL topologies for various single ND standard deviations. **(a)** ND standard deviation $\sigma = 0\text{dB}$. **(b)** ND standard deviation $\sigma = 1\text{dB}$. **(c)** ND standard deviation $\sigma = 3\text{dB}$. **(d)** ND standard deviation $\sigma = 5\text{dB}$. **(e)** ND standard deviation $\sigma = 7\text{dB}$.

Table 3. GPIs of the GMM OV LV BPL topologies of the three OV LV BPL topology classes for different ND standard deviation σ values when the ND mean μ is equal to 0.2dB . (GMM default operation settings are applied).

ND standard deviation $\sigma = 0\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	100	100	100
ND standard deviation $\sigma = 1\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	1	100	100
ND standard deviation $\sigma = 3\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	37	85

ND standard deviation $\sigma = 5\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	87	99	100
Inside the box (%)	0	16	65

ND standard deviation $\sigma = 7\text{dB}$			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	31	79	100
Inside the box (%)	0	6	30

As the impact of the ND standard deviation σ is examined on the population of OV LV BPL topology classes, the population mechanism transitions from the primarily horizontal ACA-oriented spreading observed under ND mean variation to a broader, diagonal dispersion pattern across the ACA / SDCA plane. Increasing σ not only shifts the GMM virtual OV LV BPL topologies toward higher ACA and SDCA values simultaneously, but also expands their spatial footprint, enabling population of topological regions of OV LV BPL topology class map that were previously inaccessible when μ dominated the population process. Unlike the targeted, axis-aligned population behavior driven by μ , where GMM virtual OV LV BPL topology footprints migrate mainly parallel to ACA while maintaining similar SDCA elevation, the σ -driven mechanism populates regions diagonally, thus covering alternative regions of the OV LV BPL topology class map with enhanced spatial reach. This complementary behavior implies that, through appropriate selection and mixing of NDs within the GMM, population can be strategically directed either horizontally (via μ) or diagonally with increased area coverage (via σ), enabling controlled sampling of distinct topological zones across rural, suburban and urban classes.

Comparing Figure 1(b) and Table 1 of NNTGM with Figures 3(a)-3(e) and Table 3 of GMM, respectively, the different population approaches of NNTGM and GMM are again verified. Although both methods consistently achieve over 80% GPI inside-the-box for the rural, suburban and urban cases, confirming the stable class preservation when the ND mean and ND standard deviations of GMM remain low, the more abrupt, almost step-like response for GMM also occurs even if ND standard deviation little increases (e.g., for ND standard deviation values greater than 1dB). Anyway, the same 100% GPI inside-the-class occurs for NNTGM and GMM regardless of the ND standard deviation value for GMM when the ND mean remains low.

Total Count of NDs and its Impact on GMM Virtual Topology Footprints and GPIs

Up to this point, the GMM has been examined consisting of only one ND. In this context, the influence of the ND mean μ and the ND standard deviation σ was investigated. In this subsection, the effect of the number of NDs that can be incorporated into a GMM is examined. Using the previously obtained ND results, GMMs are constructed in the form of scenarios, as presented below:

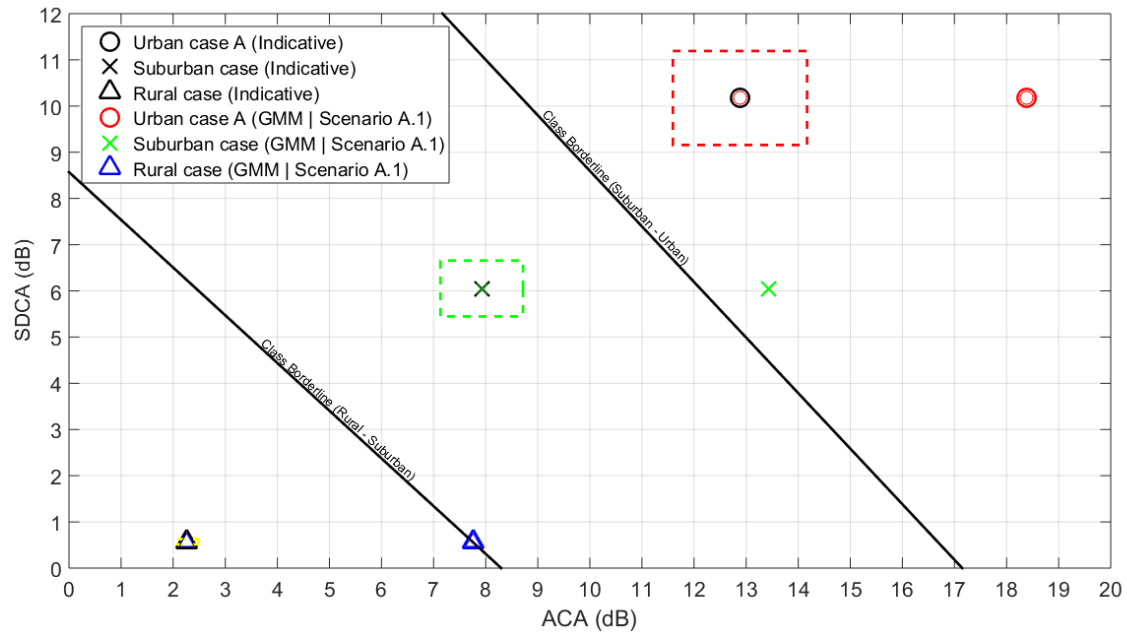
- *Scenario A.1:* GMM of Scenario A.1 consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.1.1}$ and standard deviation $\sigma_{A.1.1}$

- that are equal to 0dB and 0.5dB, respectively, -see Figure 2(a)- with weight $w_{A.1.1} = 0.5$. The second ND of this scenario is characterized by its mean $\mu_{A.1.2}$ and standard deviation $\sigma_{A.1.2}$ that are equal to 5.5dB and 0.5dB, respectively, -see Figure 2(e)- with weight $w_{A.1.2} = 0.5$.
- *Scenario A.2:* GMM of Scenario A.2 consists of 3 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.2.1}$ and standard deviation $\sigma_{A.2.1}$ that are equal to 0.2dB and 0.5dB, respectively, with weight $w_{A.2.1} = 0.34$. The second ND of this scenario is characterized by its mean $\mu_{A.2.2}$ and standard deviation $\sigma_{A.2.2}$ that are equal to 0.2dB and 3dB, respectively, -see Figure 3(c)- with weight $w_{A.2.2} = 0.33$. The third ND of this scenario is characterized by its mean $\mu_{A.2.3}$ and standard deviation $\sigma_{A.2.3}$ that are equal to 0.2dB and 7dB, respectively, -see Figure 3(e)- with weight $w_{A.2.3} = 0.33$.
 - *Scenario A.3:* GMM of Scenario A.3 consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{A.3.1}$ and standard deviation $\sigma_{A.3.1}$ that are equal to 3dB and 0.5dB, respectively, -see Figure 2(d)- with weight $w_{A.3.1} = 0.5$. The second ND of this scenario is characterized by its mean $\mu_{A.3.2}$ and standard deviation $\sigma_{A.3.2}$ that are equal to 0.2dB and 5dB, respectively, -see Figure 3(d)- with weight $w_{A.3.2} = 0.5$.

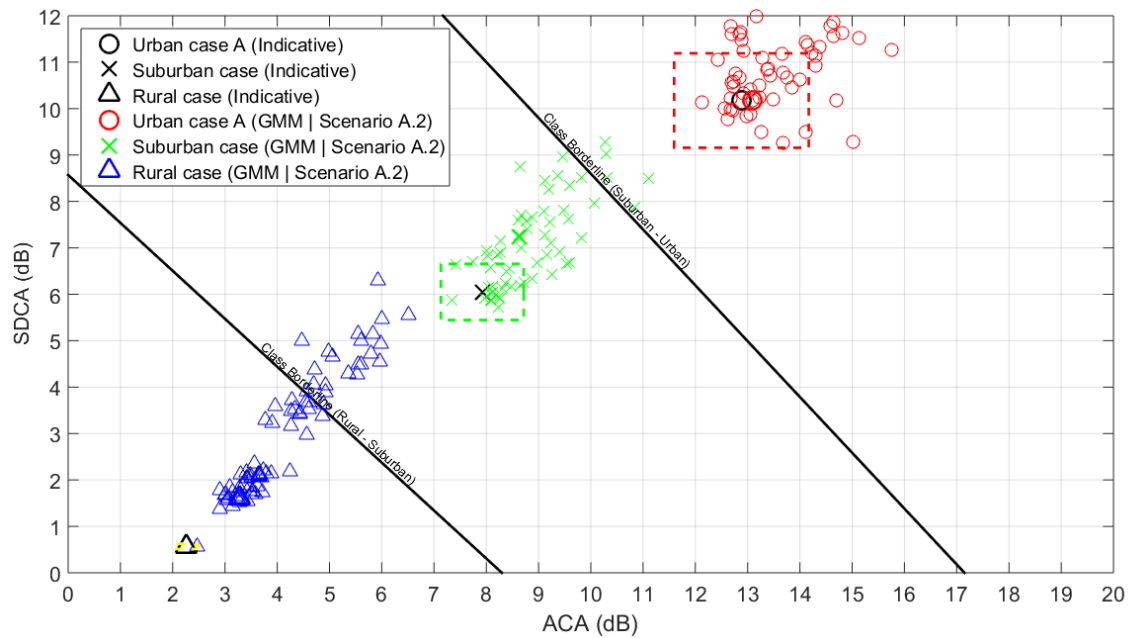
As the impact of the total count of NDs is concerned in the operation of GMM, in Figure 4(a), the OV LV BPL topology class map with the GMM virtual topology footprints of the rural case, suburban case and urban case A is presented when the GMM default operation settings are applied and GMM consists of the NDs of the Scenario A.1. Each GMM virtual OV LV BPL topology footprint of Figure 4(a) comprises 100 GMM virtual topologies per indicative OV LV BPL topology. In Figs 4(b) and 4(c), similar plots to Figure 4(a) are given, but for the case of Scenario A.2 and Scenario A.3, respectively. The same GPIs of Tables 2 and 3 are applied to the GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes of Figures 4(a)-4(c) and are reported in Table 4.

Observing Figures 4(a)-4(c), the impact of the number of NDs participating in the GMM construction is investigated under various scenarios of ND components, namely:

- Under Scenario A.1, two narrow ND components with equal weights are superposed. The resulting GMM generates, for each indicative OV LV BPL topology, a pair of compact virtual OV LV BPL topology footprint clusters aligned horizontally along the ACA axis and separated by approximately 5.5dB. Because both ND components are characterized by low values of standard deviation, the within-cluster spread is minimal and the SDCA coordinate remains essentially unchanged, so the footprints appear as two tight modes: one centered close to the indicative topology and a second one translated to higher ACA by approximately 5.5dB. This horizontal bimodality is consistently observed across the rural, suburban and urban A cases and preserves the class separability structure seen in the underlying NDs. Notably, the right shifted modes bring the suburban footprint locally across the suburban-urban class borderline, while the rural footprint exceeds the rural-suburban class borderline boundary highlighting that small systematic ACA biases can trigger class relabeling even when SDCA remains stable. Table 4 reports GPIs that align with the findings from Figure 4(a);



(a)



(b)

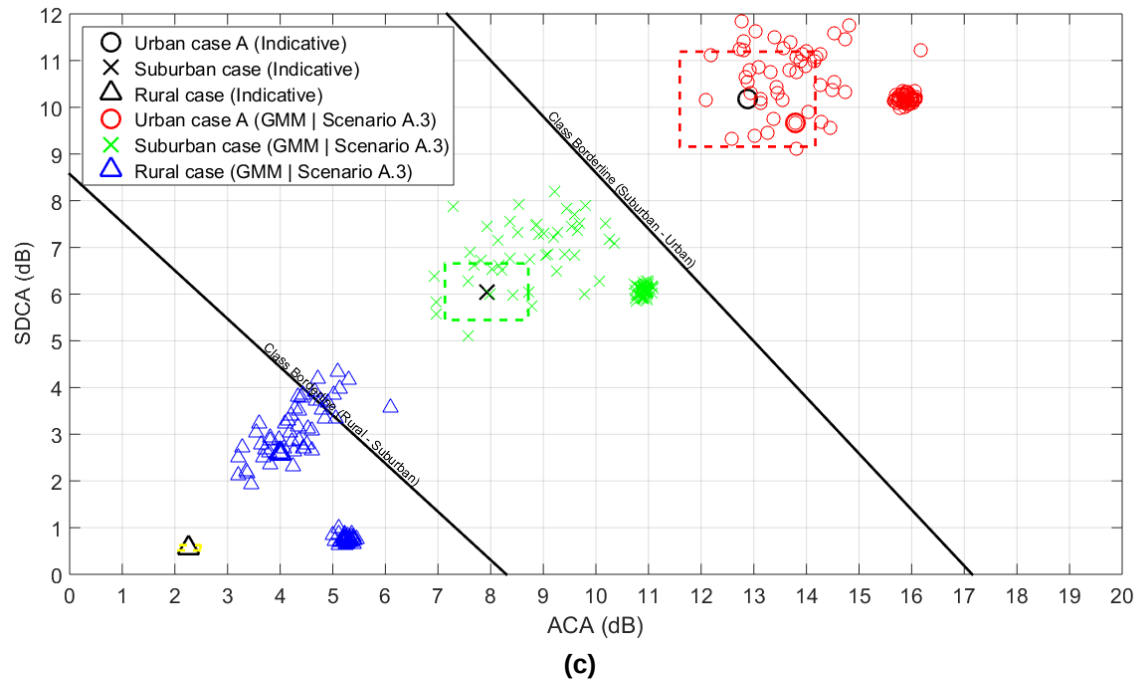


Fig. 4. OV LV BPL topology class map with GMM virtual topology footprints of the three indicative OV LV BPL topologies for various total counts of NDs. **(a)** Scenario A.1 (2 NDs). **(b)** Scenario A.2 (3 NDs). **(c)** Scenario A.3 (2 NDs).

Table 4. GPIs of the GMM OV LV BPL topologies of the three OV LV BPL topology classes for different scenarios of total count of NDs (GMM default operation settings are applied).

Scenario A.1 (2 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	57	55	100
Inside the box (%)	57	55	49

Scenario A.2 (3 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	78	95	100
Inside the box (%)	25	57	69

Scenario A.3 (2 NDs)			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	91	100	100
Inside the box (%)	0	7	26

for the rural and suburban cases, the right-shifted mode grazes the class boundary, yielding GPI inside-the-class values of 57% and 55%, respectively, while the corresponding GPI inside-the-box values are also 57% and 55%. This outcome is expected, given that weights $w_{A.1.1} = 0.5$ and $w_{A.1.2} = 0.5$ were adopted. In particular, the first weight $w_{A.1.1}$, which favors tightly concentrated modes around the indicative OV LV BPL topologies under examination, results through the simulation process in approximately 50 out of the 100 generated GMM virtual OV LV BPL topologies falling within the GPI inside-the-box region for the all the indicative OV LV BPL topologies. For urban, both modes remain within class (100% GPI inside-the-class), but the shifted mode sits outside the local box, reducing the GPI inside-the-box to 49%. In this sense, multi-ND GMMs increase representation granularity while retaining interpretable class boundaries.

- In Scenario A.2, three ND components with (approximately) the same mean μ of 0.2dB and varying ND standard deviation values σ of 0.5dB, 3dB and 7dB are combined. Because the components are heteroscedastic but not mean-shifted, each indicative OV LV BPL topology becomes the anchor of a multi-scale footprint: a tight core ($\sigma_{A.2.1}=0.5\text{dB}$), a medium-spread halo ($\sigma_{A.2.2}=3\text{dB}$) and an extended tail ($\sigma_{A.2.3}=7\text{dB}$). In the ACA / SDCA plane, the resulting virtual OV LV BPL topologies organize along a diagonal manifold so that the three variance levels appear as an idiosyncratic diagonal ‘stitching’ of sub-footprints rather than a purely horizontal broadening. Compared with Scenario A.1 (which primarily controls position through bimodal ACA shifts), Scenario A.2 primarily controls the spatial extent (dispersion) of the footprint. Practically, this allows population to be allocated to targeted regions of the OV LV BPL topology class map and, by tuning the number / variances of the contributing NDs, to regulate the parameters of the footprint. As visible in Figure 4(b), the virtual OV LV BPL topology footprint for suburban case elongates toward the suburban-urban class borderline and the rural footprint toward the rural-suburban one: the bulk remains in-class, yet the high-variance tail increases the likelihood of boundary grazing or crossings, for rural and suburban cases. Quantitatively, the GPI indicators in Table 4 confirm the inside-the-class and inside-the-box behavior for the rural, suburban and urban cases.
- To regulate simultaneously both the degree of concentration at the core of the footprint and the rate at which the footprint becomes more diffuse toward its outer regions, Scenario A.3 combines two ND components belonging to different footprint families (in contrast to Scenarios A.1 and A.2). This configuration makes it possible to form either a tightly concentrated mode surrounded by a more loosely distributed outer region or, alternatively, a locally dense area from which a gradually sparse distribution emerges. Specifically, it uses: (i) a high-mean, low-variance component ($\mu_{A.3.1}=+3\text{dB}$, $\sigma_{A.3.1}=0.5\text{dB}$, see Figure 2(d)) with weight $w_{A.3.1} = 0.5$, and (ii) a near-unbiased, high-variance component ($\mu_{A.3.2}=0.2\text{dB}$, $\sigma_{A.3.2}=5\text{dB}$, see Figure 3(d)) with weight $w_{A.3.2}=0.5$. The resulting GMM produces distinctly bimodal virtual OV LV BPL topology footprints: a compact, right-shifted nucleus (approximately +3dB along ACA) and a diffuse cloud centered relatively near the indicative topology. Geometrically, the compact mode captures the horizontal displacement trend characteristic of Scenario A.1, while the diffuse mode unfolds along the diagonal ACA–SDCA manifold

associated with variance-driven spread in Scenario A.2. In practice, this configuration allows co-control of position and dispersion: the tightly concentrated mode can be subtly shifted to control the location of the most densely populated region of the footprint, whereas the loosely concentrated, high-variance mode governs the overall spatial spread of the footprint by distributing probability mass. As seen in Figure 4(c), the virtual OV LV BPL topology footprint for suburban case exhibits a small dense core close to the suburban-urban class borderline together with a broader cloud around the indicative point, increasing the chance of boundary grazing under mild ACA biases; the rural footprint retains most mass in-class while permitting occasional excursions toward the rural-suburban class borderline; the urban footprint remains within its class region. Overall, Scenario A.3 inherits favorable properties from both Scenarios A.1 and A.2, enabling population allocation across multiple regions of the class map with differentiated extent. This translates into controlled footprint compactness and tunable class interaction, a behavior that is consistent with the comparative trends reported in Tables 2–4, where the resulting GPI values are driven by the chosen mixture and the spatial placement of the two constituent ND components.

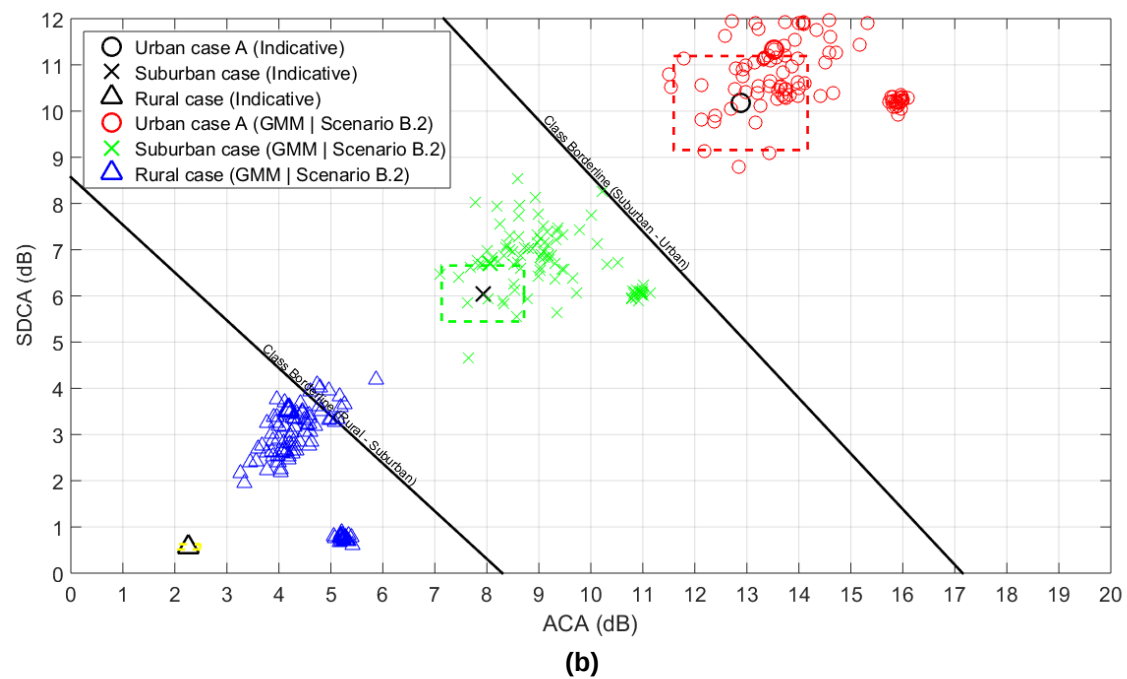
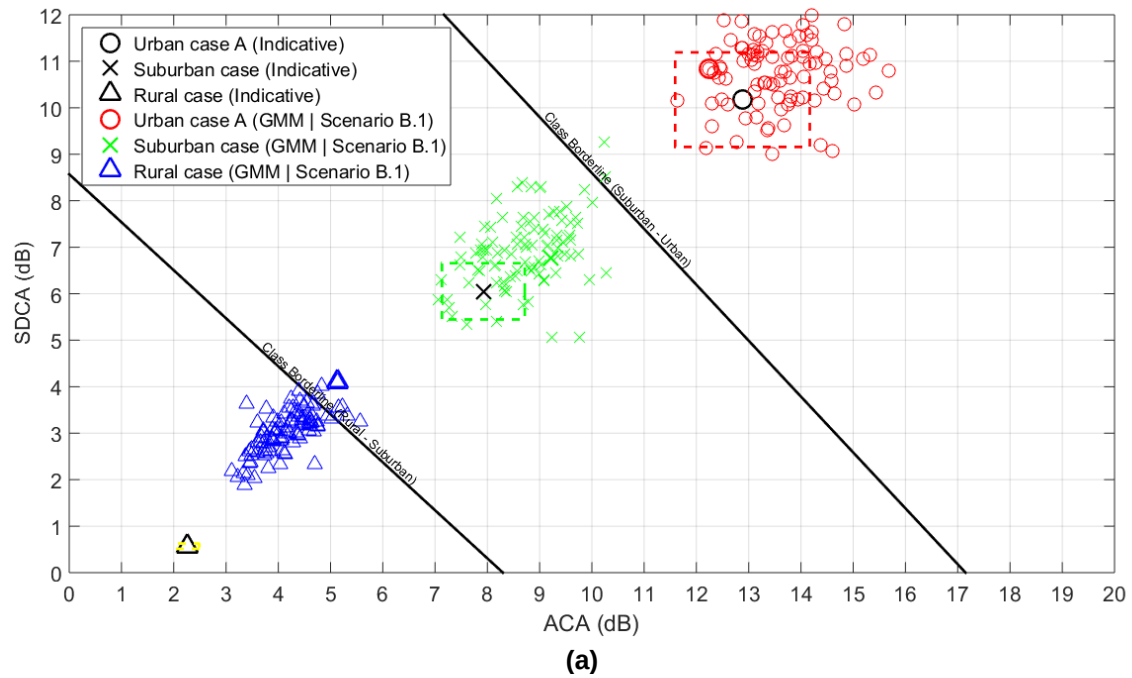
In this subsection, the ND components included in the Scenarios A.1-A.3 contributed with equal weighting. It is evident that increasing the number of NDs within the GMM modifies both the locally dense regions and the more diffuse outer regions of the resulting GMM virtual OV LV BPL topology footprints. By enriching the mixture with additional tightly and loosely concentrated modes, the GMM gains the flexibility to populate previously unoccupied areas of the ACA / SDCA space. Among the Scenarios A.1-A.3 examined herein, Scenario A.3 demonstrated the greatest versatility, as it combines NDs of different footprint behavior families with equal weights. For this reason, the versatility of Scenario A.3 is further examined in the following subsection, where the potential for footprint displacements is investigated under non-uniform weight allocation rather than equal weighting. Moreover, by departing from uniform weights, the analysis also explores the extent to which the density distribution of the more diffuse outer regions of the resulting GMM virtual OV LV BPL topology footprints can be modulated, thus revealing the additional degrees of control offered by asymmetric weighting.

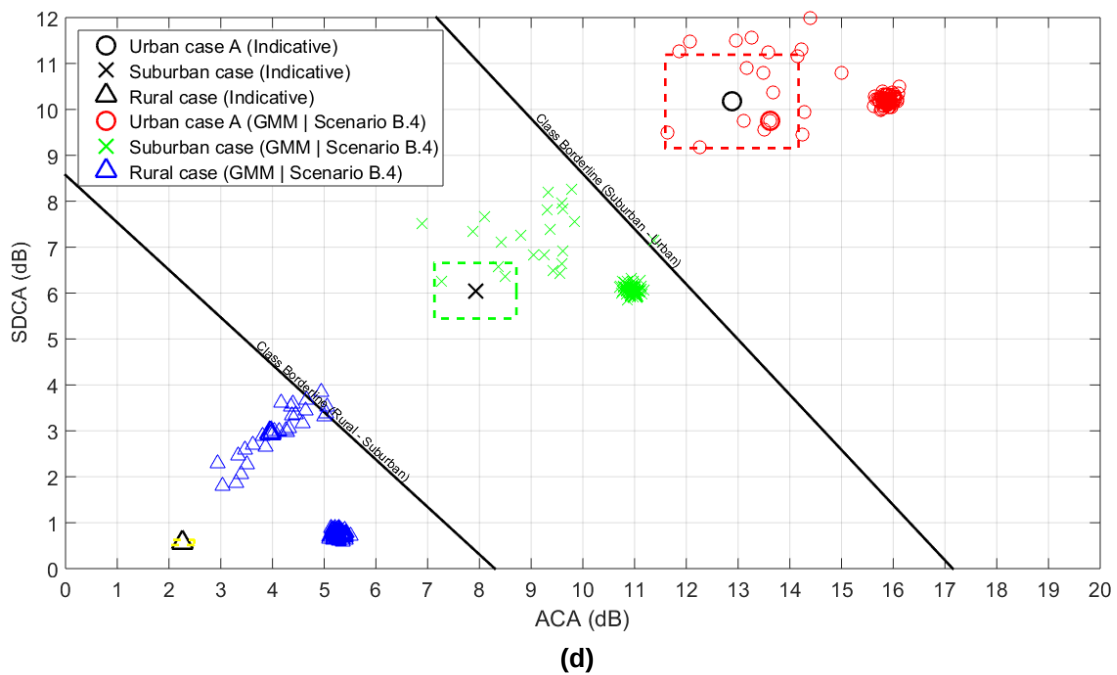
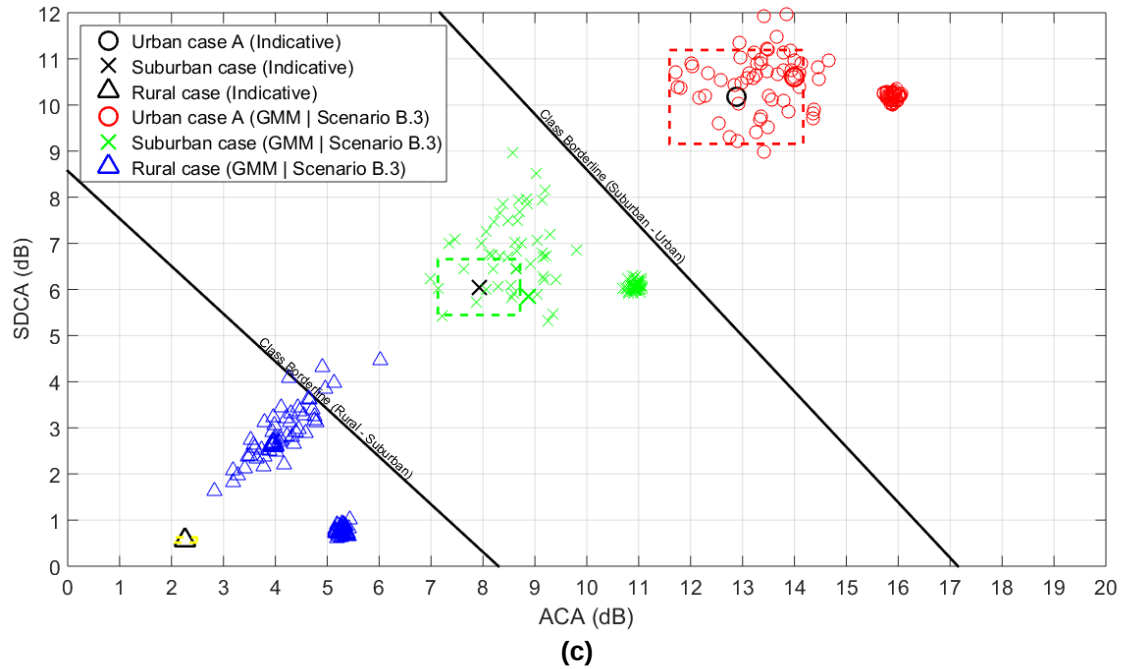
ND Weighting and their Impact on GMM Virtual Topology Footprints and GPIs

Building upon the findings of Scenarios A.1-A.3 of the previous subsection, this subsection focuses on Scenario B, in which the ND components no longer participate with equal weighting. Instead, selected non-uniform weight distributions are applied to the NDs previously used in Scenario A.3 in order to investigate how asymmetric weighting influences both the positioning and the dispersion behavior of the resulting GMM virtual OV LV BPL topology footprints. By varying the contribution of each ND, the analysis evaluates not only the degree of controllability in adjusting the location of the most densely concentrated region but also the ability to modulate the density of the more diffuse outer regions of the footprint. In this way, the study extends the versatility demonstrated in Scenario A.3 by revealing how shifts in weight allocation can simultaneously affect footprint displacement and the structure of its concentrated and diffuse modes. Similarly to the previous subsection, GMMs are constructed in the form of scenarios, as presented below:

- *Scenario B.1:* This GMM consists of 2 ND components. The first ND of this scenario is characterized by its mean $\mu_{B.1.1}$ and standard deviation $\sigma_{B.1.1}$ that are equal to 3dB and 0.5dB, respectively, with weight $w_{B.1.1} = 0$. The second ND of this scenario is characterized by its mean $\mu_{B.1.2}$ and standard deviation $\sigma_{B.1.2}$ that are equal to 0.2dB and 5dB, respectively, with weight $w_{B.1.2} = 1$. Practically, the Scenario B.1 consists of the same NDs (i.e., identical ND mean and ND standard deviation values) as those used in Scenario A.3, but with different weight assignments. Specifically, selecting $w_{B.1.2} = 1$ implies that only the second ND is considered, leading the GMM virtual OV LV BPL topology footprint to degenerate into the analysis of a similar footprint to one shown in Figure 3(d). Although the second ND in this scenario is going to be identical to that employed in Figure 3(d) in terms of ND mean and ND standard deviation, minor deviations are expected due to the inherent randomness of the sampling process. Nevertheless, these deviations are expected to remain limited and further validate the robustness of the proposed methodology.
- *Scenario B.2:* This scenario is based on Scenario B.1, with the only difference being that it applies weights $w_{B.2.1} = 0.25$ and $w_{B.2.2} = 0.75$ for the same NDs of Scenario B.1. This weight configuration is introduced in order to examine the effect of varying the ND weights within the GMM, while keeping the ND components fixed.
- *Scenario B.3:* Following the rationale of Scenarios B.1 and B.2, Scenario B.3 employs weights $w_{B.3.1} = 0.50$ and $w_{B.3.2} = 0.50$ for the same NDs of Scenarios B.1 and B.2 in order to investigate the effect of varying the ND weights within the GMM, consistent with the analysis conducted in Scenario B.2. In fact, this particular weight combination corresponds to the case of Scenario A.3 illustrated in Figure 4(c). However, as in Scenario B.1 in comparison with Figure 4(c), minor deviations may arise due to the inherent randomness of the sampling process. Nonetheless, these deviations are expected to remain limited and further substantiate the robustness of the proposed methodology.
- *Scenario B.4:* Same with Scenario B.1 but with applied weights $w_{B.4.1} = 0.75$ and $w_{B.4.2} = 0.25$ for the same NDs of Scenario B.1.
- *Scenario B.5:* This scenario is structurally identical to Scenario B.1; however, it represents its counterpart in terms of weight allocation. Specifically, in Scenario B.5, the weights are assigned as $w_{B.5.1} = 1$ and $w_{B.5.2} = 0$. This configuration implies that only the first ND is effectively considered in the analysis. Consequently, the resulting GMM virtual OV LV BPL topology footprint degenerates into a case analogous to that previously examined in Figure 2(d). Although the first ND in this scenario is intended to replicate the characteristics of the ND employed in Figure 2(d) (i.e., identical mean and standard deviation values), minor deviations are anticipated due to the inherent randomness of the sampling process. Nevertheless, these deviations are expected to remain limited and further substantiate the robustness of the proposed methodology.

As the impact of the ND weights is concerned in the operation of GMM, in Figure 5(a), the OV LV BPL topology class map with the GMM virtual topology footprints of the rural case, suburban case and urban case A is presented when the GMM default operation settings are applied and GMM consists of the NDs of the Scenario B.1.





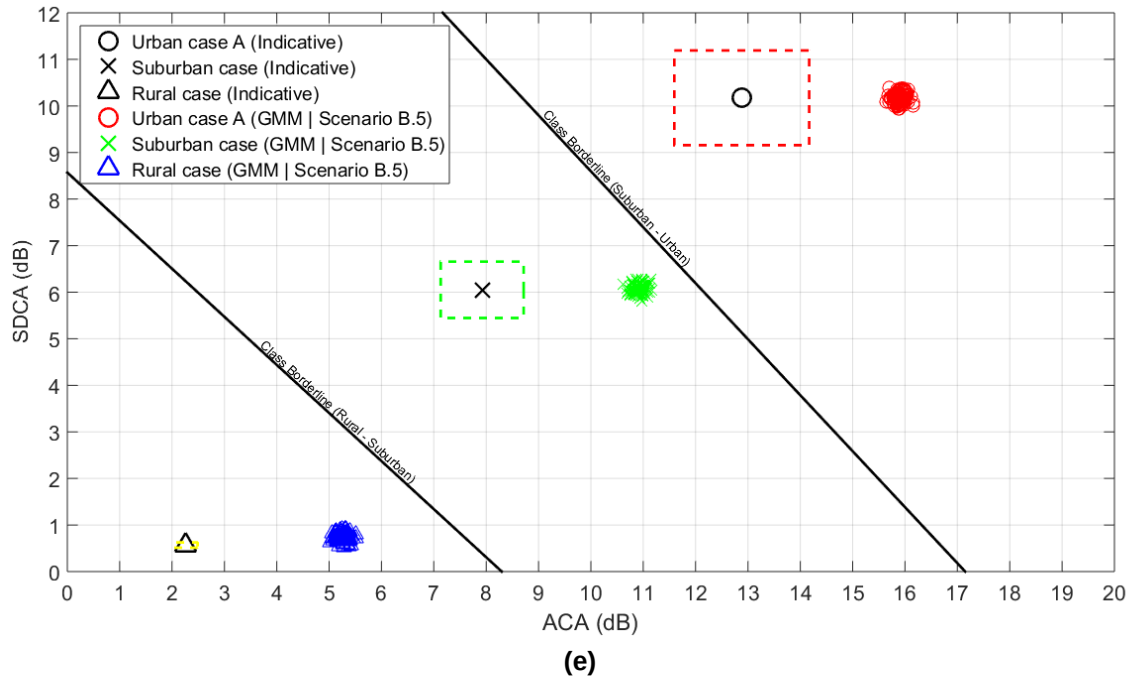


Fig. 5. OV LV BPL topology class map with GMM virtual topology footprints of the three indicative OV LV BPL topologies for various ND weights. **(a)** Scenario B.1: $-w_{B.1.1} = 0$ and $w_{B.1.2} = 1$, like Figure 3(d)-. **(b)** Scenario B.2 ($w_{B.2.1} = 0.25$ and $w_{B.2.2} = 0.75$). **(c)** Scenario B.3 - $w_{B.3.1} = 0.5$ and $w_{B.3.2} = 0.5$, like Figure 4(c)-. **(d)** Scenario B.4 ($w_{B.4.1} = 0.75$ and $w_{B.4.2} = 0.25$). **(e)** Scenario B.5 - $w_{B.5.1} = 1$ and $w_{B.5.2} = 0$, like Figure 2(d)-.

Each GMM virtual OV LV BPL topology footprint of Figure 5(a) comprises 100 GMM virtual topologies per indicative OV LV BPL topology. In Figures 5(b)-5(e), similar plots to Figure 5(a) are given, but for the case of Scenarios B.2-B.5, respectively. The same GPIs of Tables 2 and 3 are applied to the GMM virtual OV LV BPL topologies of the three OV LV BPL topology classes of Figures 5(a)-5(e) and are reported in Table 5.

Figures 5(a)-5(e) illustrate how ND weighting reshapes the GMM virtual OV LV BPL topology footprints when interpolating between two distinct footprint families: a near-unbiased, high-variance ND that generates a loosely concentrated, diagonally oriented diffuse distribution similar to Figure 3(d), and a low-variance, +3dB ACA ND that produces a tightly concentrated, horizontally aligned cluster comparable to Figure 2(d). In Scenario B.1 ($w_{B.1.1} = 0$, $w_{B.1.2} = 1$), the footprints manifest primarily as diffuse diagonal clouds anchored close to the indicative OV LV BPL topology in each class. As the weight of the compact +3dB component increases in Scenario B.2 ($w_{B.2.1} = 0.25$, $w_{B.2.2} = 0.75$) and Scenario B.3 ($w_{B.3.1} = 0.5$, $w_{B.3.2} = 0.5$) to Scenario B.4 ($w_{B.4.1} = 0.75$, $w_{B.4.2} = 0.25$), a tightly concentrated right-shifted cluster begins to emerge and gradually dominates the footprint. Concurrently, the loosely concentrated diffuse region loses probability mass and becomes progressively less pronounced. This coordinated reallocation of density causes the footprint's most populated region to shift toward higher ACA values while the overall geometric extent contracts. At the extreme of Scenario B.5 ($w_{B.5.1} = 1$, $w_{B.5.2} = 0$), each class collapses into a compact, right-shifted cluster with minimal change in SDCA, positioned well within the boundaries of its respective class region.

Table 5. GPIs of the GMM OV LV BPL topologies of the three OV LV BPL topology classes for different scenarios of ND weights (GMM default operation settings are applied).

Scenario B.1			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	93	98	100
Inside the box (%)	0	20	48

Scenario B.2			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	91	100	100
Inside the box (%)	0	10	41

Scenario B.3			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	96	100	100
Inside the box (%)	0	11	43

Scenario B.4			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	97	99	100
Inside the box (%)	0	0	0

Scenario B.5			
GPI	OV LV BPL topology class		
	Rural case class	Suburban case class	Urban case A class
Inside the class (%)	100	100	100
Inside the box (%)	0	0	0

The rebalancing between a diagonal, high-variance near-unbiased mode and a compact, right-shifted mode of Figures 5(a)-5(e) may also be reflected in the GPIs of Table 5. The GPI inside-the-class is already high in Scenario B.1 (93% for the rural case, 99% for the suburban case and 100% for the urban case A). Actually, the GPI inside-the-class never falls below 91% across all weightings. As the compact component becomes more influential in Scenarios B.2 through B.5, boundary grazing subsidies and the GPI inside-the-class GPI converges to 100% for all three classes in Scenario B.5, with the urban case remaining at 100% throughout and the suburban case reaching 100% from Scenario B.2 onward. By contrast, the GPI inside-the-box shows the complementary behavior because the compact component is steadily displaced from the indicative OV LV BPL topology in each case. As its weight increases, probability mass migrates away

from the local boxes: for the suburban case the values decline from 20% in Scenario B.1 to around 10% to 11% percent in Scenarios B.2 and B.3, and then to 0% in Scenarios B.4 and B.5; for the urban case the values drop from 48% in Scenario B.1 to roughly 41% to 43% in Scenarios B.2 and B.3, and then to 0% in Scenarios B.4 and B.5; for the rural case the value is already 0% in Scenario B.1 and remains at 0% thereafter, indicating that even the diffuse configuration falls outside the tight indicative box. Overall, Figures 5(a)-5(e) together with the GPIs of Table 5 demonstrate that the transformations observed under varying weight allocations correspond to a redistribution of probability mass between two coexisting modes rather than a rotation or continuous geometric deformation of a single shape. What changes is not the fundamental structure of the modes but the balance of density between the tightly concentrated cluster and the loosely concentrated diffuse one. As the weights vary, the diffuse outer region may retain significant mass, become partially depleted, or nearly vanish showing that its density is directly controllable through the weighting scheme.

This interpretation naturally extends to mixtures incorporating more than two ND components: both the resulting footprints and their corresponding GPIs behave as weighted superpositions whose attainable spatial patterns are bounded by the geometry and the GPI ranges of the constituent modes. Consequently, the possible outcomes remain confined within the limits set by these components, while non-uniform weights allow fine-grained regulation of how probability mass is allocated between dense and diffuse regions, further enriching the modeling flexibility of the framework.

Discussion and Future Research

This paper has established a structured examination of virtual OV LV BPL topology footprints within the GMM framework. Since the conceptual basis for applying GMM to populate the corresponding class maps through the fundamentals of class maps, topology footprints and GPIs for OV LV BPL topologies, an analysis of how specific GMM parameters —namely the mean and standard deviation of the NDs, the total number of NDs and the weight assigned to each ND— affect the resulting GMM virtual OV LV BPL topology footprints and GPIs has been given.

Building on these contributions, three avenues for future research emerge, namely:

- Further investigation is required to establish a rigorous methodology for correlating both the centroid and the spatial extent of the near Minimum Volume Enclosing Ellipsoid (MVEE) approximation of the GMM virtual OV LV BPL topology footprints and clusters with the underlying MVEE parameters. This includes exploring how variations in (i) the ellipsoid center; (ii) the lengths of the semi-major and semi-minor axes; and (iii) the overall volume of the ellipsoid collectively shape the resulting footprint geometry. This includes exploring how variations in (i) the mean μ of the NDs, (ii) the standard deviation σ of the NDs, (iii) the total count of NDs incorporated in GMM, and (iv) the assigned ND weights; collectively shape the resulting footprint geometry. Developing such a correlation framework would substantially deepen our understanding of parameter sensitivity and structural behavior within MVEE-based representations and GMM.
- Future efforts should aim to identify and refine techniques for detecting the center and extent of virtual OV LV BPL topology footprints and clusters, whether obtained through GMM or through alternative modeling methodologies such as the NNTGM.

- An important direction for forthcoming research is the development of systematic procedures for replicating virtual OV LV BPL topology footprints using GMM, whether obtained through GMM or through alternative modeling methodologies such as the NNTGM. Establishing reliable replication mechanisms will be essential for validating model behavior, supporting scenario-based analyses and enabling broader applicability of virtual topology reconstruction in future BPL network studies.

Conclusions

In this paper, the theory and relevant simulation results for populating OV LV BPL topology classes by applying GMM have been given. With reference to the class maps and the GPIs, the impact of the following GMM parameters on the GMM virtual OV LV BPL topology footprints has been assessed, namely: (i) the mean μ of the ND components of GMM, (ii) the standard deviation σ of the NDs, (iii) the total count of NDs incorporated in the mixture, and (iv) the assigned ND weights. First, as the impact of the ND mean μ is examined, GMM virtual footprints can populate topological zones as μ increases, maintaining similar SDCA elevations and remaining approximately parallel along the ACA axis. Second, as the impact of the ND standard deviation σ is examined, the population mechanism of GMM virtual OV LV BPL topology footprints shifts from the primarily horizontal, μ -driven spreading of OV LV BPL topologies to a broader, diagonal dispersion across the ACA / SDCA plane of the OV LV BPL topology class maps, simultaneously increasing both dimensions. At the same time, increasing σ expands the GMM virtual topology footprint and enables population of previously inaccessible regions, thus providing a complementary mechanism to the more axis-aligned population behavior induced by the ND mean μ . Third, regarding the impact of the number of NDs in the GMM, increasing the number of ND components does not simply shift centroid positions or broaden the spatial coverage of the resulting GMM virtual OV LV BPL topology footprints. Instead, the addition of extra NDs enhances the representational richness of the mixture by introducing new footprint behavior families ranging from tightly concentrated to loosely concentrated modes. This expanded set of constituent behaviors allows the GMM to generate more complex superpositions and to form composite footprints whose structure results from the interaction of multiple concentrated and diffuse sub-footprints. Consequently, the attainable patterns in the ACA / SDCA domain are defined not by arbitrary expansion but by the geometric and probabilistic envelopes established by the added modes. Fourth, regarding the impact of ND weights in the GMM, beyond merely including more ND components, adjusting their weights provides precise control over how probability mass is redistributed between the dense core and the more diffuse outer regions of the footprint. Rather than affecting only centroid trajectories or simple dispersion metrics, non-uniform weight allocation governs the prominence, attenuation or suppression of each sub-footprint. This enables deliberate shaping of both the intensity of the tightly concentrated region and the density profile of the loosely concentrated diffuse region, allowing smooth transitions between footprint forms and offering finer control than equal-weight mixtures. Through weighting, the GMM can therefore regulate footprint structure rather than merely repositioning it. Concluding this paper, three avenues for future research have been recognized so that the practicality of the GMM should be enhanced to function either as a detector of virtual OV

LV BPL topology footprints whether derived from GMM or alternative modeling methodologies such as NNTGM or as a replicator of such footprints, regardless of their origin from GMM or other approaches like NNTGM.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this paper.

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Position of Donald Trump in the Global Climate Change Agenda

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This study examines how the Trump administration repositioned the US in global climate governance, providing a multifaceted and theoretically informed evaluation of its geopolitical, institutional, and ideological effects. The analysis, which is framed by political realism, strategic environmentalism, adaptive federalism, and socio-technical transition theory, shows how Trump's climate policy, exemplified by his defunding of the Green Climate Fund and withdrawal from the Paris Agreement, represented a strategic disruption of multilateral climate cooperation. A framework based on emissions power parity and competitive decarbonization replaced normative commitments to historical emissions and equity, marking a redefinition of climate responsibility around sovereignty, economic nationalism, and "energy dominance" rather than a straightforward act of denial. The study offers a comprehensive analysis of the Trump administration's climate policy in seven thematic areas, drawing on a wealth of interdisciplinary literature: global governance, energy geopolitics, environmental justice, disinformation, legal-institutional frameworks, cultural narratives, and sustainable finance. It highlights paradoxical results as unexpected but revolutionary effects of Trump's unilateralism, including deregulation-driven innovation in clean technologies, the adaptability of subnational actors, and China's strategic ascent to the top of the global climate leadership. In order to demonstrate how nationalist policy logics can both undermine and rebalance the global climate regime, the study presents new conceptual tools such as "defensive climate investment," "innovation protectionism," and "geopolitical decarbonization." This paper concludes by arguing that the Trump administration's climate stance signaled a structural realignment in global climate diplomacy, highlighting the weaknesses of multilateral institutions and igniting forces of geopolitical reordering and decentralized innovation. The findings offer a novel narrative that transcends dichotomous assessments of climate denialism and offers a sophisticated perspective on how nationalist upheavals can alter the framework of international environmental governance. The study's conclusion offers policy-relevant insights for rethinking climate leadership in a time of competition, fragmentation, and the emergence of climate techno-nationalisms.

Keywords: Climate Nationalism; Strategic Environmentalism; Geopolitical Decarbonization; Adaptive Federalism; Emissions Power Parity; Innovation Protectionism; Multilateral Climate Disruption

1. Introduction

A significant shift from the accepted norms of environmental multilateralism was reflected in the election of President Donald Trump, which signaled a turning point in the development of global climate governance. By withdrawing from the Paris Agreement and defunding the Green Climate Fund (GCF), his administration's climate policy challenged the consensus on climate cooperation and reoriented environmental governance along nationalist and economically pragmatic lines [1, 2]. This recalibration was a significant ideological shift based on populist realism, economic nationalism, and strategic disengagement rather than just a policy reversal [3]. Trump's climate doctrine had far-reaching consequences that went beyond American boundaries, causing institutional, geopolitical, and normative repercussions that changed the face of global climate diplomacy [4-9].

Political realism, which prioritizes national interest and sovereignty over international environmental commitments, provides the best framework for understanding Trump's climate policy. His "America First" ideology reframed environmental cooperation as a barrier to industrial competitiveness and portrayed multilateral agreements as financial liabilities [10]. Trump used climate disengagement as a weapon of geopolitical repositioning by putting domestic infrastructure ahead of climate finance and ignoring the moral requirement of historical emissions accountability [11-13]. In addition to upending international environmental regimes, the dismantling of climate commitments and regulatory frameworks demonstrated a sovereigntist turn that brought about a new grammar of climate nationalism [14, 15].

Instead of viewing environmental policy as a global duty, the administration operationalized a doctrine of strategic environmentalism that went beyond ideological rhetoric. A recalculated climate calculus, focused on economic growth and geopolitical leverage, was exemplified by the United States' expansion of fossil fuel leasing, relaxation of emission standards, and deregulation of environmental protections [16, 17]. In the Indo-Pacific region, where the United States sought to offset China's influence in green technology, this realignment attempted to turn energy into a diplomatic tool [18-20]. As a result, Trump's climate policy challenged the normative domination of sustainability in the global energy discourse [21] and ushered in a new era of geo-economics competition [22].

Ironically, Trump's federal budget cuts sparked a wave of climate innovation in the private sector and subnational levels, demonstrating the tenacity of decentralized governance. In response, states, local governments, and business alliances established networks like "We Are Still In," which promoted decarbonization goals against federal directives [23, 24]. These dynamics are representative of adaptive federalism, wherein non-state actors were able to maintain climate commitments and absorb policy shocks through institutional layering and governance redundancy [25]. Thus, Trump's strategy had unforeseen consequences: it strengthened the polycentric character of U.S. environmental governance, which is increasingly reflected in multilevel governance structures around the world, while weakening centralized climate action.

Furthermore, Trump's position directly challenges the normative underpinnings of global climate justice, especially the concepts of equity and common but differentiated responsibilities (CBDR). Trump popularized the term "emissions power parity"—a demand for readjusting burden-sharing according to current emissions and economic power—by redefining climate finance as an unjust economic burden and challenging the validity of historical responsibility [26, 27]. Global solidarity in climate negotiations was further undermined by this redefinition, which upended long-standing frameworks of

environmental justice and encouraged other populist regimes to use comparable nationalist rhetoric [28, 29].

The Trump administration inadvertently accelerated the development of climate technologies in the private sector at the nexus of innovation and deregulation. Conditions for "competitive sustainability" were established by the strategic relaxation of Clean Power Plan regulations, the simplification of SMR permits, and the expansion of CCS tax credits. This allowed industries to innovate in advance of future restrictions [30, 31]. Critics point to higher emissions and less effective environmental protections, but others contend that these market-driven results show how chaotic innovation pathways can help achieve climate goals without strict regulations [32, 33]. A dual narrative emerges in this era: deregulation as a technological catalyst and a climate liability.

In the end, Trump's climate legacy is best described as strategic disruption—a reorientation of the climate change agenda towards economic self-interest and nationalism—rather than straightforward opposition. His administration put multilateral institutions to the test, exposed the geopolitical undertones of climate finance, and exposed the fragility of international environmental regimes [34-36]. At the same time, it spurred new paradigms of climate governance, reoriented international alliances, and sparked bottom-up innovation. This paper makes the case that the Trump administration's climate policy marks a significant turning point in the development of global climate politics, one that continues to influence the normative, geopolitical, and technological aspects of climate governance in the years following Trump.

This study investigates a key research question: What were the systemic, normative, and geopolitical ramifications of the Trump administration's reorientation of U.S. involvement in global climate governance? The study establishes four interconnected goals in order to address this: (2) to examine the multifaceted effects of Trump's policies across energy geopolitics, environmental justice, public health, and legal-institutional frameworks; (3) to dissect the rhetorical, normative, and ethical shifts brought about by his administration in the discourse of climate responsibility, burden-sharing, and historical emissions; and (4) to critically evaluate Trump's strategic reallocation of climate funds through the theoretical lenses of political realism, strategic environmentalism, and adaptive federalism. The paper makes a unique contribution by conceptualizing Trump's climate governance as a disruptive force that realigned geopolitical alliances, exposed the fragility of multilateral climate regimes, and recalibrated global climate politics. It does this by drawing on an extensive synthesis of interdisciplinary literature and anchored by novel theoretical frameworks such as defensive climate investment, innovation protectionism, emissions power parity, and geopolitical decarbonization. Within a single geopolitical case study, the study's uniqueness resides in its comprehensive integration of political theory, institutional analysis, environmental justice, and technological innovation. The paper is organized into six primary sections in order to accomplish this: (1) Introduction: defining the research gap and theoretical positioning; (2) Core Philosophy of Trump's Strategy: breaking down ideological foundations using four theoretical anchors; (3) Multidimensional Analysis: providing sectoral insights into energy, governance, justice, rhetoric, and culture; (4) Trump's Global Impacts: assessing the systemic effects on international institutions and climate diplomacy; (5) Articulation of Positive Truths: reframing Trump's policies through the lens of strategic economic nationalism and innovation dynamics; and (6) Conclusion and Future Research Directions: suggesting new paradigms for

comprehending climate nationalism and advancing climate governance in a post-Trump era.

2. Methodology

The methodology for this study integrates a multi-layered approach that aligns with PRISMA standards while incorporating innovative theoretical and empirical frameworks. The selection of studies followed a two-stage screening process guided by Table 1 (Methods for Selecting, Including, and Excluding Articles). Articles were initially identified based on relevance to Trump's climate policies (IA1) and their impact on global governance (IA2). The inclusion extended to interdisciplinary studies encompassing political science, environmental law, energy economics, and international relations (IA3), while prioritizing empirically rigorous and theoretically grounded contributions (IA4). Publications from 2016–2024 (IA5) were considered, with exclusions applied to general climate studies lacking explicit connection to Trump (EA1), non-scholarly sources (EA2), temporally irrelevant works (EA3), and those with methodological weaknesses (EA4). Duplicates (EA5) and non-English materials without translation (EA6) were also removed.

Table 1. Methods for selecting, including, and excluding articles

Indicator	Method
IA1: Alignment with Trump's Climate Policies	Include articles explicitly analyzing Donald Trump's climate policies, executive actions, and rhetoric within the context of global climate governance.
IA2: Global Climate Governance Impact	Include studies examining how Trump's policies influenced international climate negotiations, multilateral institutions, and geopolitical dynamics.
IA3: Interdisciplinary Scope	Include peer-reviewed research from diverse disciplines (political science, environmental law, energy economics, international relations, climate policy) that offer comprehensive insights into Trump's climate stance.
IA4: Empirical and Theoretical Rigor	Include articles that provide robust empirical data or innovative theoretical frameworks (e.g., political realism, strategic environmentalism, adaptive federalism) relevant to the study's objectives.
IA5: Timeframe Relevance (2016–2024)	Include literature published during or directly analyzing the Trump administration (2016–2020) and its post-administration effects up to 2024.
EA1: Lack of Specific Focus	Exclude articles that discuss general climate change topics without explicit connection to Donald Trump's policies or global positioning.
EA2: Non-Scholarly or Unverified Sources	Exclude opinion pieces, blogs, or media reports lacking academic credibility or peer review.
EA3: Irrelevant Timeframe	Exclude studies outside the 2016–2024 timeframe unless providing essential historical context relevant to Trump's climate policies.
EA4: Methodological Weakness	Exclude articles with unclear methodology, unsubstantiated claims, or insufficient analytical depth.
EA5: Content Redundancy	Remove duplicate studies or those with overlapping findings to streamline the literature pool.
EA6: Language Barrier	Exclude non-English publications unless a high-quality translation is available, ensuring consistency in interpretation.

The search strategy was operationalized using Table 2 (Database-Specific Search Queries and Justification), which provided structured queries across six databases: Scopus, Web of Science, SpringerLink, ScienceDirect, Google Scholar, and Taylor & Francis. Each database was targeted to capture different dimensions of Trump's climate agenda, with Scopus and Web of Science ensuring high-impact and indexed peer-reviewed sources, SpringerLink and ScienceDirect offering multidisciplinary coverage, and Google Scholar incorporating grey literature and policy reports. Tailored search strings included keywords such as "*Donald Trump*", "*Climate change*", "*Paris Agreement*", "*Geopolitical decarbonization*", and "*Climate nationalism*", while filters were applied to restrict results

to English-language, peer-reviewed articles published between 2016 and 2024. This strategy enhanced comprehensiveness and minimized selection bias, enabling a robust dataset that reflects the global and interdisciplinary scope of the review.

Table 2. Database-Specific Search Queries and Justification for Systematic Review

Database	Exact Search String / Query	Justification	Filters
Scopus	TITLE-ABS-KEY("Donald Trump" AND "climate change" AND ("Paris Agreement" OR "Green Climate Fund" OR "climate nationalism" OR "geopolitical decarbonization"))	Scopus offers extensive coverage of interdisciplinary peer-reviewed articles, capturing governance, law, and climate policy aspects relevant to Trump's climate stance.	Year: 2016–2024; Document Type: Article, Review; Language: English
Web of Science	TS=("Donald Trump" AND "climate policy" AND ("climate governance" OR "international climate negotiations" OR "climate justice"))	Ensures inclusion of high-impact indexed studies with strong citation networks, essential for global governance and policy impact analysis.	Year: 2016–2024; Research Areas: Environmental Sciences, Political Science; Language: English
SpringerLink	"Donald Trump" AND ("global climate governance" OR "climate diplomacy" OR "Paris Agreement withdrawal")	SpringerLink provides access to multidisciplinary journals and books, including environmental policy and political science insights on Trump's global climate role.	Year: 2016–2024; Article Type: Research, Review; Language: English
ScienceDirect	"Donald Trump" AND ("climate change" OR "environmental deregulation") AND ("geopolitics" OR "multilateralism")	ScienceDirect contains authoritative Elsevier journals (e.g., <i>Energy Policy</i> , <i>Journal of Cleaner Production</i>) aligning with climate change governance themes.	Year: 2016–2024; Subject Area: Environmental Science, Social Science; Language: English
Google Scholar	"Donald Trump" climate change OR climate policy OR Paris Agreement OR climate nationalism site:.edu OR site:.org	Google Scholar captures grey literature, reports, and citations from think tanks, providing broader context beyond strictly academic publications.	Year: 2016–2024; Include only PDFs with full text; Language: English
Taylor & Francis	"Donald Trump" AND ("climate change agenda" OR "climate governance" OR "climate justice" OR "climate diplomacy")	Taylor & Francis hosts leading journals in international relations and climate governance, offering critical perspectives on Trump's climate policies.	Year: 2016–2024; Document Type: Research Articles; Language: English

The study refinement and integration process for this study followed a rigorous, multi-phase approach, as depicted in Figure 1. Initially, 117 studies were identified through comprehensive database searches across Scopus, Web of Science, Google Scholar, ScienceDirect, Taylor & Francis, and SpringerLink, using targeted keywords and filters to ensure relevance and quality. Following identification, screening was conducted using the inclusion criteria IA1–IA5, reducing the dataset to 93 studies by removing 24 duplicates through Mendeley reference management and manually excluding 9 articles lacking specific focus (EA1) or scholarly credibility (EA2) and 6 studies failing to meet timeframe or methodological rigor (EA3, EA4). At the eligibility stage, 78 full-text articles were assessed, with 5 removed for redundancy or language barriers (EA5, EA6), resulting in 73 eligible studies. The process was enhanced by a snowballing technique, adding 9 relevant studies from reference lists, after which 6 were excluded for failing to meet criteria EA1–EA6. An additional 6 critical studies were included through iterative expert discussions, addressing potential gaps and ensuring thematic completeness. Ultimately, 70 high-quality studies were integrated for final analysis, providing a comprehensive, evidence-based synthesis of Trump's impact on global climate governance. This process ensured methodological transparency, minimized bias, and supported a holistic understanding of the geopolitical, institutional, and ideological dynamics surrounding Trump's climate agenda.

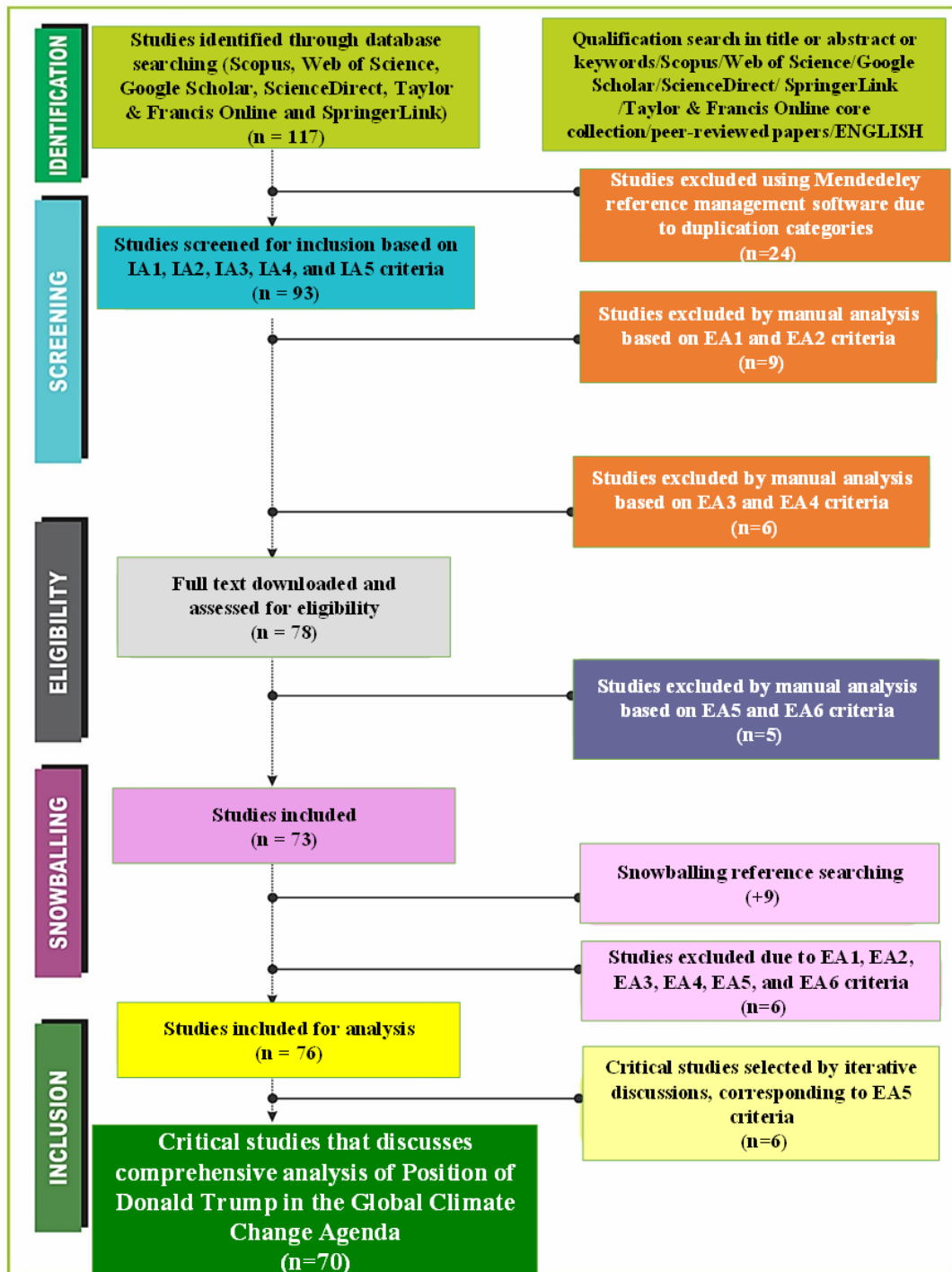


Fig. 1. Study refinement and integration into the research process

3. Current Research State

3.1 Distribution of Document by Year of Publication

The distribution of documents by year of publication for this study demonstrates a dynamic temporal pattern that reflects evolving academic interest and geopolitical

developments. As shown in Fig. 2, the earliest relevant study emerged in 2016 ($n=1$), coinciding with Trump's election and initial policy signals, while research intensity surged significantly in 2017 ($n=12$) and remained high through 2018–2020 ($n=11$ each year), corresponding to the administration's active withdrawal from the Paris Agreement, deregulation efforts, and realignment of U.S. climate diplomacy. The peak in these years indicates heightened scholarly scrutiny of Trump's disruptive policies on global climate governance and their immediate implications. Publications in 2021 ($n=9$) reflect analyses of transitional dynamics during the shift to the Biden administration and retrospective evaluations of Trump's climate legacy. Subsequent years (2022–2024) show a moderate but steady output ($n=3$, $n=3$, $n=5$), focusing on long-term impacts, adaptive governance responses, and the rise of alternative climate leadership globally. Finally, early 2025 contributions ($n=4$) underscore the enduring relevance of Trump's climate stance, integrating contemporary perspectives on geopolitical decarbonization and techno-nationalism. This chronological trend reveals an academic trajectory that moved from immediate policy analysis to broader theoretical and longitudinal interpretations, providing a holistic understanding of how Trump's climate agenda reshaped both domestic and international climate governance paradigms.

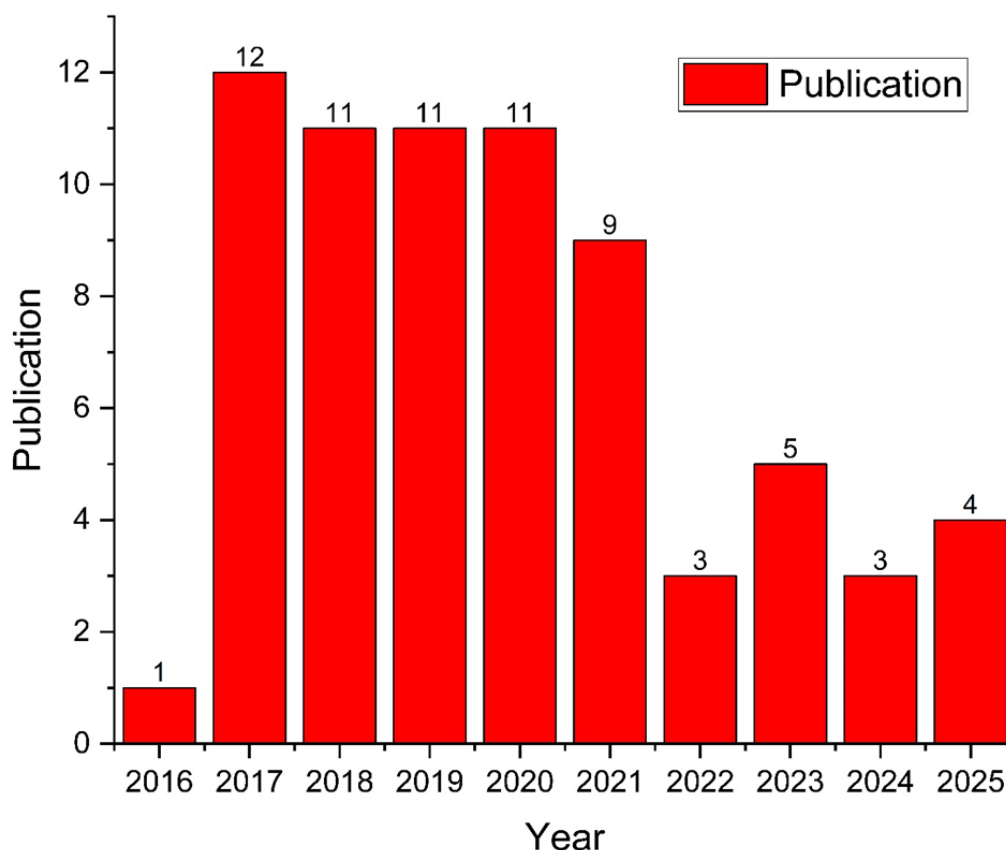


Fig. 2. Distribution of document by year of publication

3.2 Distribution of Documents by Country

As shown in Fig. 3, the distribution of documents by country for this study reveals a highly skewed publication landscape dominated by contributions from the United States (29 publications), reflecting both the centrality of U.S. policies under Trump's administration and the heightened domestic academic interest in evaluating their global

climate implications. China (11 publications) emerges as the second most active contributor, indicative of its strategic positioning in global climate politics and its interest in contrasting U.S. climate stances with its own policy trajectory. Middle-tier contributions stem from Canada (6) and the United Kingdom (6), followed by Australia, Italy, the Netherlands, New Zealand, and South Korea with 3 publications each, highlighting the engagement of nations with significant stakes in international climate negotiations. A diverse group of countries, including Belgium, Brazil, the Czech Republic, Denmark, Finland, France, Germany, Greece, India, Israel, Jamaica, Lebanon, Montenegro, Nigeria, Norway, Romania, South Africa, Spain, and Thailand, each contribute one publication, illustrating a widespread but fragmented scholarly interest from both developed and developing nations. This pattern underscores a geo-academic concentration in Western and emerging economies, while also reflecting a global diffusion of research attention, where even nations with limited research output have contributed perspectives on the geopolitical and environmental ramifications of Trump's climate policies.

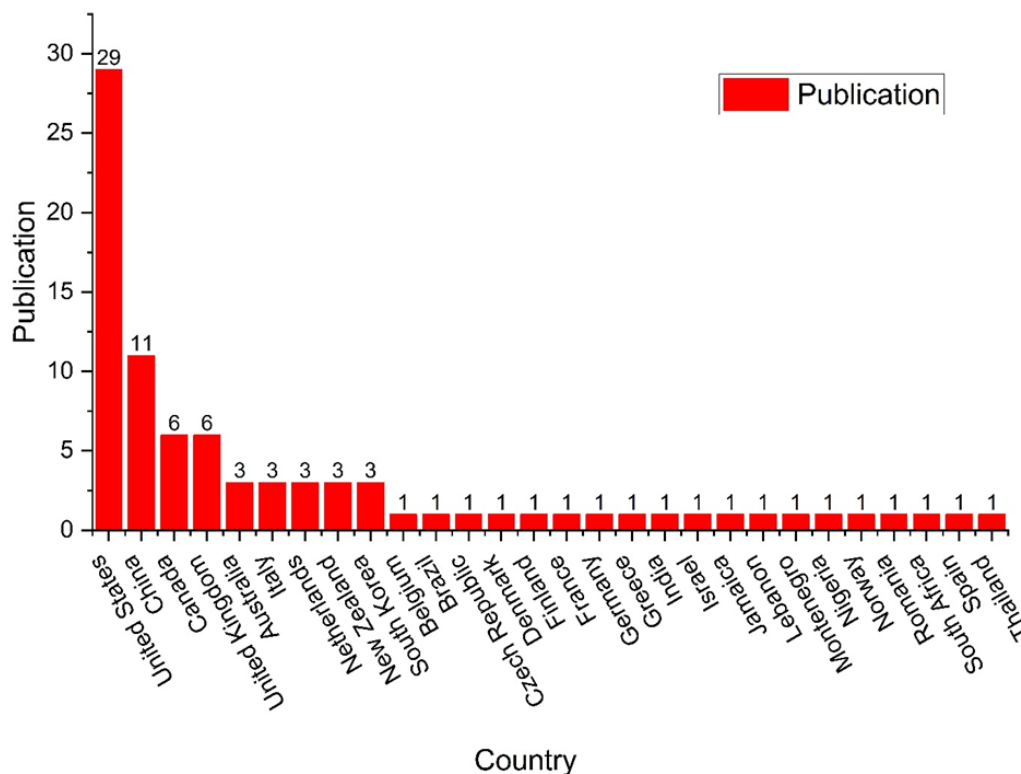


Fig. 3. Distribution of documents by country

3.3 Distribution of Subject Areas

As shown in Fig. 4, the distribution of subject areas for this study demonstrates a multidisciplinary engagement, with a strong dominance of social sciences (46 publications), reflecting the central role of political discourse, international relations, and policy analysis in understanding Trump's climate agenda. Environmental Science (22 publications) follows as the second largest contributor, emphasizing the environmental implications and scientific critiques surrounding climate policies during this period. Economics, Econometrics, and Finance (11) and Earth and Planetary Sciences (8) indicate substantial scholarly focus on the economic costs, climate modeling, and Earth

system responses tied to policy decisions. Complementing these are studies from Business, Management, and Accounting (5) and Arts and Humanities (4), which highlight corporate governance, ethical debates, and socio-cultural dimensions of climate politics. Notably, contributions from Energy (4) reflect the interplay between fossil fuel advocacy and renewable energy transitions. Less represented but significant perspectives emerge from Medicine (3), linking climate policy to public health risks; Multidisciplinary (2) and Psychology (2), showing the integration of cross-field insights and behavioural studies; and niche contributions from Engineering (1) and Pharmacology, Toxicology, and Pharmaceuticals (1), which suggest technological and toxicological considerations related to environmental deregulation. Overall, the subject area distribution reveals that while social and environmental dimensions dominate the discourse, Trump's climate policies have spurred research across a broad spectrum of academic fields, underscoring the complex, far-reaching implications of political decisions on global climate governance.

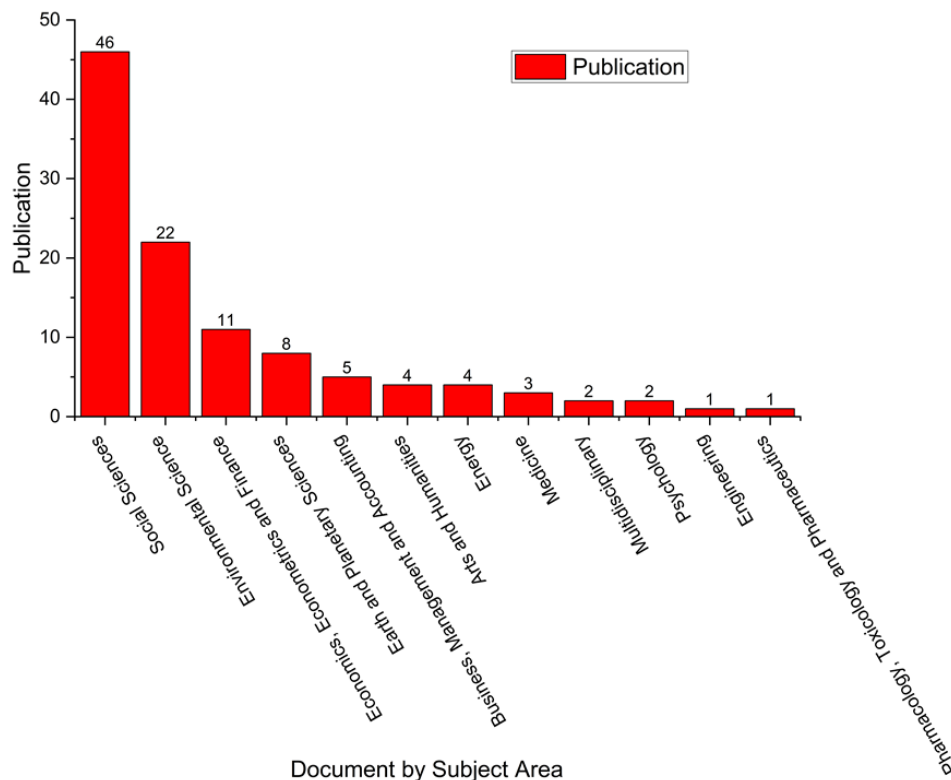


Fig. 4. Distribution of subject areas

3.4 Distribution of Authorship and Corresponding Publications

The distribution of authorship and corresponding publications in this study reveals a diverse yet interconnected scholarly landscape, spanning multiple disciplines and global perspectives. Recent contributions such as Cheng et al. [37], Pandey [38], and Svozil et al. [39] highlight contemporary analyses linking Trump's climate policies to crowdfunding dynamics, rhetorical framing, and climate polarization on social media, respectively, while Resano [40] integrates literary interpretations within the Trumpocene. Foundational works by Zhang et al. ([5], cited 101) and Chen et al. ([41], cited 84) dominate citation metrics, underscoring the global governance and emissions reduction implications of U.S. withdrawal from the Paris Agreement. Authors like Erickson and

Lazarus ([16], cited 20), Saad ([42], cited 10), and Selby ([43], cited 38) provide empirical insights into fossil fuel policies and disorderly energy transitions, complementing studies on environmental federalism (Konisky and Woods [23], cited 33) and climate finance governance (Bowman and Minas [26], cited 65). The dataset also includes policy-focused analyses such as Diaz-Rainey et al. ([32], cited 98) on oil and gas firm volatility, Liu et al. ([44], cited 72) on trade frictions, and Urpelainen and Van de Graaf ([2], cited 70) on U.S. non-cooperation. Furthermore, critical perspectives from McGuire and Lynch [36], Pavone [1], and Darian-Smith [45] examine environmental justice, Trump's Paris Agreement stance, and anti-environmental populism, while niche analyses explore regional and thematic contexts, such as Caribbean impacts [46] and Arctic strategies [47]. This holistic authorship distribution demonstrates how a wide array of scholars—across years, regions, and disciplines—collectively trace the multifaceted ramifications of Trump's climate agenda on governance, policy, social dynamics, and global environmental trajectories.

3.5 Distribution of Documents per Year by Source

As shown in Fig. 5, the distribution of documents per year by source for this study demonstrates a wide-ranging scholarly engagement across legal, environmental, economic, and sociopolitical domains. Leading the contributions, Environmental Justice (4 publications) emerges as the dominant outlet, reflecting strong academic interest in the intersection of Trump's policies and equity considerations in climate governance. Prominent journals such as *Advances in Climate Change Research*, *China Quarterly of International Strategic Studies*, *Climate Policy*, *Climatic Change*, *European Financial Management*, *International Journal of Climate Change Impacts and Responses*, and *Round Table* each contributed two publications, showcasing the interdisciplinary nature of climate change discourse under Trump, spanning environmental sciences, international relations, finance, and policy analysis. A broad spectrum of additional sources—including *Africa Review*, *Bulletin of the Atomic Scientists*, *Cambridge Review of International Affairs*, *Energy Economics*, *Harvard Environmental Law Review*, *Third World Quarterly*, and *Yale Law Journal*—each provided one document, signaling that Trump's climate agenda resonated across diverse academic communities, from law and governance to energy economics and global security. This holistic distribution reveals an innovative cross-pollination of disciplines, where journals traditionally focused on regional studies, literature (MFS Modern Fiction Studies), or advocacy (Argumentation and Advocacy) intersect with climate discourse, thereby underscoring the profound and multifaceted impact of Trump's climate policies on global academic inquiry.

3.6 Distribution of Documents by Funding Sponsor

As shown in Fig. 6, the distribution of documents by funding sponsor for this study reflects a dynamic interplay of national, institutional, and private sector support, showcasing the global breadth of interest in Trump's climate policies. The National Natural Science Foundation of China leads with four funded publications, underscoring China's strategic academic investment in understanding U.S. climate actions and their global implications. The Catholic University of Korea follows with three publications, while the Ministry of Science and Technology of the People's Republic of China and the National Institutes of Health each supported two, illustrating how Asian and U.S. agencies alike are deeply engaged in climate-politics research. Diverse single-source contributions—from the American Council of Learned Societies and European

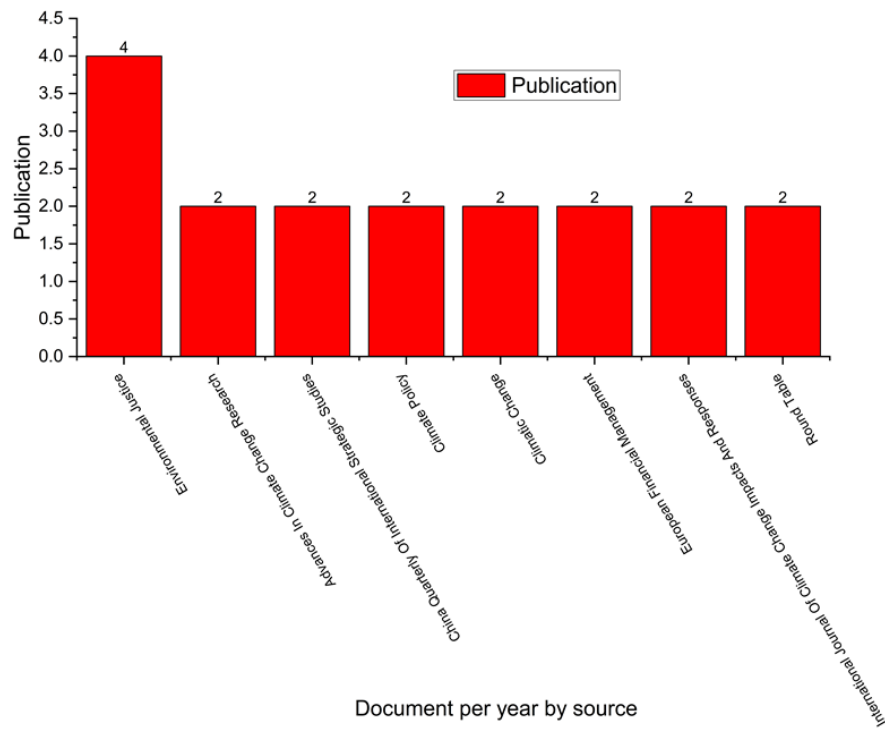


Fig. 5. Distribution of documents per year by source

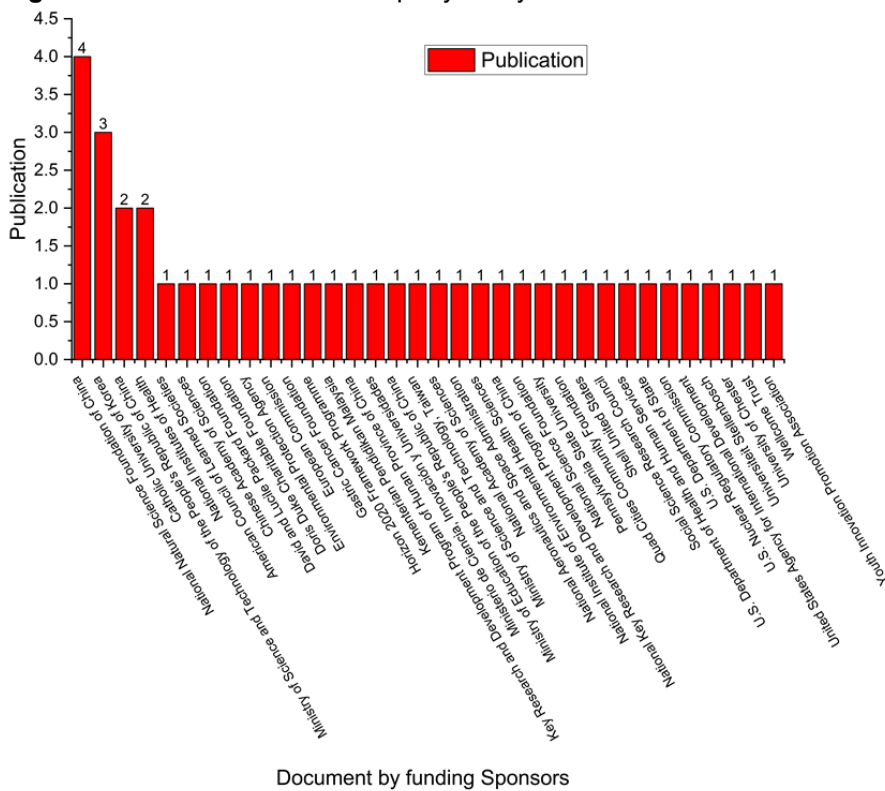


Fig. 6. Distribution of documents by funding sponsor

Commission to private foundations such as the David and Lucile Packard Foundation and Doris Duke Charitable Foundation—highlight the interdisciplinary and transnational appeal of the topic. Governmental entities, including the Environmental Protection Agency, U.S. Department of State, USAID, and U.S. Nuclear Regulatory Commission, funded research reflecting policy, diplomacy, and energy security dimensions, while academic institutions like Pennsylvania State University, Universiteit Stellenbosch, and University of Chester enriched the knowledge base from educational perspectives. Industrial involvement from Shell United States indicates corporate stakes in shaping or responding to climate policy discourses. Additionally, international programs such as Horizon 2020, along with initiatives like the Youth Innovation Promotion Association, signify the integration of innovation and youth-driven research. This diverse sponsorship landscape reveals a cutting-edge convergence of public, private, and academic stakeholders, collectively driving holistic scholarship on Trump's climate agenda and its far-reaching global consequences.

3.7 Distribution of Documents by Affiliation

The distribution of documents by affiliation for this study highlights an extensive and globally diverse academic network driving research on Trump's climate policies and their global ramifications. Leading contributions come from The Catholic University of Korea with three publications, while Shanghai Institutes for International Studies, University of Massachusetts Dartmouth, Peking University, University of Denver, New York University, and Johns Hopkins University School of Advanced International Studies each contribute two publications, underscoring the strong involvement of Asian, North American, and international policy research hubs. A rich variety of single-publication contributors spans premier institutions like Harvard University, Stanford Law School, Georgetown University, the University of California, Berkeley, and King's College London, blending legal, environmental, and governance expertise. The dataset also features specialized think tanks such as the Stockholm Environment Institute and the Mercator Research Institute on Global Commons and Climate Change, reflecting the integration of scientific policy analysis with climate governance studies. Contributions from institutions in emerging economies, including the University of Johannesburg, Babcock University, Tecnológico de Monterrey, and multiple Chinese entities like the Chinese Academy of Sciences and the Beijing Climate Centre, highlight the global South's engagement in climate diplomacy and policy debates under Trump. Furthermore, affiliations from business schools (e.g., Strathclyde Business School, EGADE Business School) and governmental agencies (e.g., Ministry of Water Resources, P.R. China) illustrate the interdisciplinary and policy-driven nature of this research. Collectively, this expansive distribution reflects an innovative and holistic scholarly collaboration across continents, disciplines, and institutional types, demonstrating how Trump's climate agenda has stimulated a worldwide academic discourse at the nexus of politics, law, economics, and environmental science.

4. Core Philosophy of the Strategy: Interpreting the Strategic Reallocation of Climate Funds for Domestic Economic Resilience

4.1 Political Realism

Political realism, which prioritizes national sovereignty over multilateral commitments, can be used to analyze President Donald Trump's strategic reallocation of climate funds. Trump prioritizes national interest and self-determination, which is reflected in his climate policy, especially his decision to withdraw from the Paris Agreement and stop U.S. contributions to the Green Climate Fund. According to Pavone [1] and Urpelainen & Van de Graaf [2], Trump's foreign policy initiatives, such as his climate diplomacy, were motivated by a sovereignty-centric worldview in which world climate commitments were viewed as limitations on American economic competitiveness and autonomy. By exposing an ideological divide between sovereignty and globalism in climate diplomacy and highlighting the ongoing conflict between international cooperation and unilateral self-interest, this realpolitik approach upended normative expectations of global climate solidarity.

4.2 Strategic Environmentalism

Trump's strategy can also be seen through the lens of strategic environmentalism, which views environmental policy as a geopolitical instrument rather than a universal moral requirement. His administration's deregulation and reallocation of climate funds brought environmental policy back into line with domestic resource politics, especially in favour of the fossil fuel industry. Under Trump, U.S. fossil fuel leasing policies promoted an energy dominance strategy that gave energy exports and geopolitical leverage top priority, as noted by Erickson and Lazarus [16]. This type of strategic environmentalism challenged the technocratic and humanitarian discourses that predominate in global climate governance by redefining the climate debate around national wealth, power, and resource access. Furthermore, the deconstruction of regulatory cost-benefit analysis frameworks reaffirmed state control over environmental narratives and policy priorities by discrediting environmental policies as economically inefficient [14].

4.3 Federalism and Subnational Governance

From the standpoint of subnational governance and federalism, Trump's climate reallocation bolstered the theoretical framework of adaptive federalism by igniting institutional resilience at several governmental levels. The U.S. environmental federalism absorbed the federal policy shock through increased action by states, municipalities, and regional coalitions, as demonstrated by Konisky and Woods [23]. Dijkstra *et al.* [25] go into further detail about how non-state actors were incorporated into international institutions in response to the disruption, demonstrating a diffusion of governance capacity. The institutional resilience theory, which holds that governance systems with functional redundancy and distributed authority are more resilient to external shocks, is supported by these dynamics. Despite being destabilizing at the federal level, Trump's actions unintentionally strengthened multi-level climate governance architectures both domestically and abroad and gave subnational leadership more authority.

4.4 Ecological Modernization and Climate Nationalism

Another helpful theoretical fulcrum is the contrast between ecological modernization and climate nationalism. Through innovation and institutional adaptation, ecological modernization theory aims to create a synergy between environmental reform and economic growth. However, the Trump administration advanced a counter-narrative based on climate nationalism that favoured domestic industrial protectionism over supranational environmental constraints. According to Chatjuthamard *et al.* [30], Trump's

sudden changes in policy affected shareholder expectations and indicated a socio-technical shift in favour of deregulation and investment in fossil fuels. However, the partial resilience of green markets and technologies—supported by private sector leadership and state-level innovation—shows that ecological modernization persisted in fragmented forms in spite of federal opposition. This comparison shows how market dynamics and institutional layering, in addition to policy alignment, influence socio-technical transitions.

Furthermore, Trump's climate policies can be understood as a conscious challenge to prevailing international environmental standards from the standpoint of normative constructivism. Trump upended the dominant normative consensus regarding equity and historical responsibility by redefining climate finance as an economic burden rather than a moral obligation. According to DeDominicis [11-13], cosmopolitan ideals ingrained in multilateral frameworks are challenged by this type of populism based on national identity. This normative shift forced international actors and institutions to reconsider the presumptions of universality and shared responsibility, despite the fact that it was extremely divisive [39]. The normative shock brought on by Trump's unilateralism is responsible for the subsequent shift towards more practical and interest-based models of climate cooperation, such as climate clubs and bilateral green technology alliances.

In the end, these theoretical pillars show that Trump's calculated reallocation of climate funds marked a turning point in global climate governance rather than just a case of regressive policy. It sparked ideological and structural realignments within climate diplomacy, questioned the resilience of liberal internationalist norms, and revealed the flexibility of federal and non-state institutions. The pluralism of U.S. climate policy, as Abraham-Dukuma [15] emphasizes, reflects deeper tensions between national and international priorities, a dynamic that is likely to continue in future negotiations. The application of political realism, strategic environmentalism, adaptive federalism, and socio-technical theory to Trump's climate governance provides a comprehensive framework for interpreting the changing relationship between domestic politics and international climate demands.

5. Classification of Studies Multidimensional Analysis of Trump's Role in the Global Climate Change Agenda

5.1 Climate Politics and Governance: The Influence of Populism, Climate Diplomacy, and the Consequences of U.S. Climate Withdrawal

The Trump administration's climate policies, which were marked by a rejection of multilateral climate governance, were exemplified by the withdrawal from the Paris Agreement [1, 5, 6]. This choice was framed by a broader populist perspective that described climate action as being at odds with national economic interests [10]. Studies show that Trump's "America First" rhetoric undermined international climate diplomacy, creating a leadership vacuum that China and the EU sought to fill [4, 48]. The U.S. withdrawal drastically changed climate talks and forced governments to reconsider their commitments [34]. Trump's doubts about climate change were mirrored by populist leaders like Bolsonaro, which weakened international cooperation [28]. The U.S. gave up its traditional leadership role in climate governance, which had major geopolitical repercussions [2]. Additionally, Trump's deregulatory agenda strengthened dependency on fossil fuels by undermining domestic climate policy [14].

5.2. Energy Geopolitics: Fossil Fuel Policy, Strategic Nationalism, and Indo-Pacific Strategy

Trump's energy policy was characterized by aggressive expansion of fossil fuels, including coal and shale gas deregulation [16, 17]. Global emissions increased as a result of the "energy dominance" policy, which prioritized economic nationalism over climate mitigation [15]. By opposing China's renewable investments through alliances with fossil fuels, the administration's Indo-Pacific policy cemented energy geopolitics [13]. According to research, Trump's policies empowered petrostates by undermining clean energy transitions [37, 41]. However, his hostile stance inadvertently accelerated China's green energy investments [29]. Supply chains for clean technology have also been impacted by the geopolitical challenges brought on by trade disputes between the United States and China [44]. The global energy dynamics were changed by Trump's fossil fuel nationalism, which solidified carbon lock-in and sparked strategic realignments in the Indo-Pacific, as this section demonstrates.

5.3. Environmental Justice and Public Health: Climate Marginalization and Postcolonial Vulnerability

Environmental injustices were exacerbated by Trump's climate policies, which had a negative impact on marginalized communities [35, 36]. Public health disparities were made worse by his deregulation of environmental controls, particularly in minority and low-income communities [49]. Inequality was further cemented when executive orders were used to revoke environmental justice measures [50]. The U.S. withdrawal made postcolonial regions more vulnerable to climate change, such as the Caribbean and Pacific Islands [46, 51]. According to research, Trump's policies failed to address health crises and migration brought on by climate change [52]. This section highlights the human cost of climate inaction by explaining how systemic racism, postcolonial disregard, and climate policy came together during Trump's presidency.

5.4. Communication, Framing, and Misinformation: Rhetoric, Media, and Public Perception

Deliberate dishonesty and denialist rhetoric were hallmarks of Trump's climate rhetoric [35, 36, 38]. His claim that climate change was a "hoax" polarized the public and exacerbated partisan differences [39]. Comparative analyses of Trump and Biden's speeches reveal notably different narrative techniques, with Trump using skepticism to inspire his followers [38]. Studies look into how media ecosystems fueled public skepticism about science and exacerbated climate denial [53]. The dissemination of anti-climate messages was greatly aided by social media, particularly after the Paris pullout was announced [39]. This section illustrates how Trump's rhetorical tactics changed the conversation around climate change by promoting skepticism and impeding evidence-based policy.

5.5. Legal-Institutional Frameworks: Deregulation, Environmental Legislation, and International Treaties

Utilizing executive orders and judicial nominations, the Trump administration systematically repealed environmental regulations [14, 54]. Assessments of climate risk were compromised by the reduction of the social cost of carbon [55]. According to research, the administration's arbitrary regulatory rollbacks violated cost-benefit

calculations [27]. International climate funding organizations were impacted by the Paris Agreement's withdrawal, with African states being disproportionately affected [56]. The U.S. withdrawal caused the Green Climate Fund to face legitimacy issues [26]. This section illustrates the long-lasting effects of deregulation by highlighting the decline in institutional and legislative climate protections during the Trump administration.

5.6. Cultural and Literary Reflections: Anthropocene Narratives and Societal Reckoning

According to Anthropocene literature, Trump's presidency coincided with a cultural awakening regarding climate change [40, 57]. Novels like *New York 2140* challenge neoliberal stagnation by allegorizing Trump's climate legacy [40]. The degree to which Trump's remarks permeated popular culture and normalized ecological denial is being studied [57]. This section explores the intersection of cultural production and climate politics, showing how literature helped raise public awareness of Trump's environmental deregulations.

5.7. Strategic Sustainable Development: Climate Finance, Crowdfunding, and Corporate Reactions

Subnational and commercial organizations advanced climate finance innovations despite the government's withdrawal [37]. In response to Trump's policies, crowdfunding for renewable energy exploded [37]. Companies are reducing climate risks through corporate social responsibility (CSR) strategies that are adapted to regulatory ambiguity [33]. Studies look into how Trump's policies changed the way money was invested in climate change around the world, diverting funds from areas that were at risk [56]. Through examples of adaptable actions taken during the Trump administration, this section demonstrates how resilient sustainable finance is in the face of political resistance.

Table 3. Classification of Studies Multidimensional Analysis of Trump's Position in the Global Climate Change Agenda

Category	Sub-Category	Representative Studies	Innovative Contribution
Climate Politics & Governance	Populism & Climate Diplomacy	Toni & Feitosa Chaves [28], Ettinger & Collins [10], Pavone [1]	How right-wing populism reshapes environmental multilateralism
	U.S. Climate Withdrawal Impact	Saad [42], Yu [48], Chai et al. [58], Arlota [27]	Evaluating systemic risks of U.S. Paris exit on global climate cooperation
Energy Geopolitics	Fossil Fuel Policy & Strategic Nationalism	Erickson & Lazarus [16], Abraham-Dukuma [15], Chen et al. [41]	Role of national energy sovereignty in climate inaction
	Indo-Pacific & China Strategy	DeDominicis [13], Sun [19], Prieto & Scott [59]	Scientific diplomacy as an instrument of renewable energy policy
Environmental Justice & Public Health	Climate Justice & Marginalization	McGuire & Lynch [36], Tzavella et al. [49], Ratuva [51]	Intersection of climate change, inequality, and health vulnerability
	Postcolonial Climate Vulnerability	Charles & Roberts [46], Agius [60]	Colonial legacies in Caribbean and Pacific climate resilience
Communication, Framing & Misinformation	Rhetorical & Narrative Analysis	Pandey [38], Rose [57], Nai [61]	Political storytelling in climate denial and public opinion
	Media & Public Perception	Zawadzki et al. [62], McGuire [36], Paliewicz et al. [63]	Media manipulation and post-truth framing in energy politics
Legal-Institutional Frameworks	Deregulation & Environmental Law	Revesz [14], Konisky & Woods [23]	Systematic dismantling of regulatory capacity under Trump
	International Agreements Analysis	Healey et al. [4], Ribera et al. [34]	Comparative legal resilience of EU vs US post-Paris Agreement
Cultural & Literary Reflections	Anthropocene Literature & Society	Resano [40], Darian-Smith [45], Prasad [53]	Socio-cultural critique through speculative climate fiction
Strategic Sustainable Development	Climate Finance & Crowdfunding	Cheng et al. [37], DeDominicis [11]	Innovative financing pathways for renewable technology deployment

Trump's varied climate legacy, which includes systemic disruptions in governance, energy, justice, communication, law, culture, and finance, is comprehensively categorized in Table 3. Global climate politics were revolutionized by his administration's populist nationalism and ardent deregulatory stance, which had long-lasting socioecological and geopolitical effects. Future studies should focus on justice, multilateralism, and resilient governance while examining potential paths for climate recovery after the Trump administration.

6. Donald Trump's Climate Stance and Its Global Impacts

The election of Donald Trump to the presidency marked a significant ideological shift in climate policy and environmental governance. His government's policy stance was mainly defined by aggressive reversals of climate policies and broad environmental deregulation. According to Revesz [14] and Nost et al. [64], over 100 environmental regulations were repealed or reduced, particularly those that protected the quality of the air and water and limited greenhouse gas (GHG) emissions. Trump's decision to withdraw from the Paris Agreement, which Pavone [1] and Zhang et al. [5, 6] argue damaged international agreement on climate governance, was at the centre of this change in policy. According to Ettinger and Collins [10], this move reflects Trumpism's broader rejection of multilateralism and its "America First" philosophy, which minimizes global climate obligations. According to Abraham-Dukuma [15], these actions weakened domestic pledges and damaged the US's reputation as a climate initiative leader. The deregulatory program that underpinned the rollbacks prioritized short-term economic gains over long-term environmental sustainability, thereby jeopardizing both domestic and global climate resilience.

The Trump administration had a big influence on the energy industry and encouraged a noticeable move towards the development of fossil fuels. According to Erickson and Lazarus [16], federal leasing policies under the Trump administration expanded access to natural gas, coal, and oil reserves, which runs counter to international decarbonization goals. Trump's emphasis on coal and fracking created a regulatory environment that encouraged investments in fossil fuels, creating instability and increased financial risks for renewable energy companies, as shown by Ladd and York [17] and Diaz-Rainey et al. [32]. According to Chatjuthamard et al. [30], after the election, market uncertainty increased, which led to higher stock values for oil and gas companies while the renewable energy sector saw lower stock values. Cheng et al. [37] go on to show how Trump's denial of climate change hindered the success of crowdfunding campaigns for renewable energy, indicating a decrease in investor and public enthusiasm. During the Trump administration, the energy sector exemplified a backward development paradigm, creating a policy environment that was counterproductive to the advancements needed to achieve climate neutrality.

Trump openly opposed scientific and regulatory organizations as part of his climate policy. The political interference, budget cuts, and gag orders that agencies like the EPA and NOAA face lead to a decline in the integrity of environmental data and policy transparency [4, 36]. The politicization of climate communication has reduced the prominence of science-based discourse on federal platforms, as demonstrated by Pandey [38] and Lazarus [54]. Prieto and Scott [59] concurrently highlight how Trump's hostile diplomacy impeded international scientific diplomacy by impeding cooperative projects like the InFEWS US-China collaboration. Trump's actions have put international climate

governance institutions in danger by undermining their credibility and funding, according to Dijkstra et al. [25]. Bowman and Minas [26] claim that this exacerbated trust disparities between the Global North and South and further weakened organizations like the Green Climate Fund. Trump's strategy led to institutionally fragmented environmental governance.

Global differences in North-South climate funding and governance were made worse by Trump's withdrawal from the Paris Agreement and his general retreat from climate diplomacy. The ability of vulnerable developing states to adapt to climate change was jeopardized by the United States' withdrawal from financing commitments, such as the \$2 billion pledge to the Green Climate Fund, according to Chai et al. [58] and Olutola [56]. Views of unfairness in international climate negotiations were heightened by this retreat, particularly among Pacific Island and African countries where adaptation needs are crucial [51, 65]. The U.S. created a leadership void that allowed China to strategically position itself in global climate discussions. In order to establish itself as a viable alternative to U.S. leadership, Yu [48], Zhang et al. [5, 6], and Sun [19] analyze China's rise in green infrastructure initiatives and its marketing of the Belt and Road Initiative (BRI) as a forum for climate cooperation. The Trump administration's unilateralism undermined coordinated responses to the world's climate problems by causing significant disruptions in cooperative climate action.

From a geopolitical standpoint, Trump's climate diplomacy added strategic ambiguities to frameworks for climate security and reshaped international relations. As European, Canadian, and Pacific partners modified their policies in response to U.S. disengagement, Selby [43] and Agius [60] note that traditional alliances were put to the test. While Charles and Roberts [46] highlight disappointment in the Caribbean, Gagnon [66] and Cloutier-Roy [66] outline tensions between the U.S. and Canada over transboundary climate measures. According to Benton Heath [67], Trump's environmental policies pose a challenge to the postwar economic order and imperil the integration of climate goals into global trade and security frameworks. According to Lavorio [47], resource competitiveness rather than environmental preservation is now the primary focus of U.S. national security discourses, making Arctic geopolitics a major concern. Consequently, the Trump administration's climate policy undermined cooperative efforts to address emerging climate-related security challenges by introducing a degree of uncertainty into international climate negotiations.

Significant polarization in climate discourse also occurred during the Trump administration, leading to backlash and regress in the media and civil society. According to Svozil et al. [39] and Nai [61], Trump's remarks exacerbated disinformation and solidified ideological divides by promoting climate skepticism on social media. According to Paliewicz et al. [63], Trump's communication style employed fascistic argumentative techniques that portrayed climate action as elite or conspiratorial, undermining its legitimacy. As DeDominicis [11, 12] outlines, progressive movements responded by expanding their strategies, using global networks and sustainable development frameworks to counteract regressive policies. According to McGuire and Lynch [35], these externalities exacerbated environmental injustices, particularly for minority groups that were disproportionately affected by climate deregulation. Prasad [53] and Faizi [68] highlight the long-lasting effects of normalized climate denialism, which weakened public consensus and reduced the epistemic authority of climate science. The speed and efficacy of climate policy implementation in the post-Trump era may be impacted by the cultural influence.

As shown in Table 4, Donald Trump's climate stance was not just a domestic event but a global turning point with far-reaching effects on institutions, industry, policy, and geopolitical ties. It exposed and intensified the weaknesses in the global climate framework, causing rival powers to reshape climate leadership, disrupting emerging green markets, and eroding multilateral trust. According to DeDominicis [13] and Jiahan [29], the Trump administration's convergence of strategic grand narratives and sustainable development goals highlighted the growing interdependence of climate policy and geopolitics. The Trump administration's legacy emphasizes how urgently strong climate institutions, renewed international cooperation, and a depoliticized climate discourse are needed. In order to sustain global progress towards climate justice and ecological stability, the era emphasizes the need for environmental leadership to be steadfast, grounded in science, and inclusive.

Table 4. Donald Trump's Climate Stance & Its Global Impacts

Dimension	Thematic Focus	Representative Studies	Key Insights
Policy	Environmental Deregulation & Climate Policy Rollbacks	Revesz [14], Trisolini [55], Kemp [69], Rios [50], Revesz [14], Sunstein [70]	Trump-era rollback of climate regulations weakened U.S. credibility, delayed national action, and destabilized climate cost assessments
	Paris Agreement Withdrawal & Multilateral Policy Retraction	Arlota [27], Saad [42], Urpelainen & Van de Graaf [2], Zhang et al. [5, 6], Chai et al. [58]	Withdrawal eroded multilateral momentum, catalyzing strategic recalibration by global actors (EU, China, Africa)
Industry	Energy Sector Reorientation toward Fossil Fuels	Erickson & Lazarus [16], Jordaan [71], Ladd & York [17], Liu et al. [44]	Reprioritization of fossil fuels impacted global investment flows, energy market stability, and corporate climate strategies
	Market Uncertainty & Corporate Climate Risk	Diaz-Rainey et al. [32], Klaus et al. [33], Chatjuthamard et al. [30]	Increased volatility in oil/gas markets and investor concerns over regulatory unpredictability
Institutions	Attacks on Scientific and Regulatory Institutions	McGuire [36], Nost et al. [64], Revesz [14], Lazarus [54]	Undermining of scientific integrity and institutional autonomy; long-term damage to regulatory and advisory capacity
	International Climate Governance Institutions & Trust Deficit	Bowman & Minas [26], Ribera et al. [34], Pavone [1], Dijkstra et al. [25]	GCF, UNFCCC, and related institutions faced weakened legitimacy and operational uncertainty
Global Implications	North-South Climate Finance & Equity Gaps	Olutola [56], DeDominicis [11], Charles & Roberts [46]	Trump's exit amplified climate finance gaps for developing nations, harming implementation capacity of NDCs
	Leadership Vacuum & China's Strategic Rise	Yu [48], Jiahan [29], Sun [19], Zebang & Yi [20]	U.S. retreat opened diplomatic and technological space for China to assert leadership in climate governance
Geopolitical	Climate Diplomacy Realignment	Toni & Feitosa Chaves [28], Prieto & Scott [59], Sun et al. [18]	Far-right populism reshaped environmental diplomacy, shifting alliances and weakening cohesion in global action
	Geostrategic Uncertainty & Climate Security Risks	Agius [60], Ratuva [51], Lavorio [47]	Climate-linked security risks (Pacific Islands, Arctic) exacerbated by policy unpredictability and militarization

7. Positive Truths Articulating the Position of Donald Trump in the Global Climate Change Agenda

7.1 Strategic Reallocation of Climate Funds for Domestic Economic Resilience

The decision by the Trump administration to reduce U.S. contributions to global climate funds, including the Green Climate Fund (GCF), was framed as a strategic reallocation of funds to improve economic resilience at home rather than as a comprehensive rejection of climate policies. This policy shift, which prioritized American infrastructure, energy innovation, and job creation over international climate financing, showed a broader ideological commitment to economic nationalism [10, 59]. Since China was rapidly expanding its influence in global climate governance, the administration sought to increase U.S. competitiveness against emerging economies, particularly China, by reallocating funds to domestic priorities [19, 48]. Critics argued that this approach jeopardized global cooperation [2], while proponents claimed it was a practical change that ensured taxpayer dollars were used to support domestic businesses rather than foreign initiatives [15]. Trump's environmental legacy is characterized by the tension between international climate commitments and domestic reinvestment, which marks a dramatic shift from traditional U.S. climate diplomacy [4].

7.1.1 *Economic Nationalism and the "America First" Climate Policy*

The "America First" philosophy, which placed a premium on economic sovereignty and deregulation to boost domestic energy production, served as the foundation for Trump's climate policy [17, 36]. By leaving the Paris Agreement and cutting back on GCF contributions, the administration demonstrated its preference for market-driven energy solutions over global climate mandates [1, 5, 6]. This tactic was founded on skepticism about multilateral climate funding, which the Trump administration believed unfairly burdened the United States while allowing rivals like China to increase their economic power [29, 44]. While selectively supporting renewable energy innovation through private-sector incentives, the administration promoted domestic fossil fuel extraction, including coal and shale gas [16, 31]. While supporters claimed that this policy increased energy independence and reduced reliance on adversarial sources, critics like MacNeil and Paterson [24] warned that it might lock the United States in carbon-intensive paths [13]. Conservative climate discourse is still shaped by the policy's blatant rejection of international climate solidarity in favour of unilateral economic pragmatism [53].

7.1.2 *Geopolitical Rivalry with China: Climate Policy as Economic Warfare*

The growing competition with China, which had become a global leader in investments in renewable energy, was a major driver behind Trump's reallocation of climate funds [20, 41]. By pulling out of international climate agreements and redirecting funds to domestic energy innovation, the administration sought to reduce China's diplomatic clout [18]. A larger decoupling effort was exemplified by trade barriers and technological limitations directed at China's green energy sector [44]. According to Chai et al. [58], China quickly filled the void left by the U.S. withdrawal from climate finance, increasing its influence in developing nations through initiatives like the Belt and Road Initiative. Trump's approach demonstrated a paradox: while intended to challenge China's climate leadership, it inadvertently accelerated Beijing's dominance in international green

technology markets [48]. Although the long-term effects of this strategic misstep are still being felt, it brought to light the administration's focus on short-term economic gains at the expense of long-term climate diplomacy [45].

7.1.3 Employment Generation and Infrastructure: The National Rationale

The Trump administration frequently highlighted job creation in the manufacturing and energy sectors while characterizing its reallocation of climate funds as a pro-growth strategy [32, 43]. Reviving struggling industrial areas was advocated through policies that expanded oil and gas leases and expedited pipeline approvals [17]. In order to position the United States as a leader in next-generation energy technology, strategic investments in nuclear energy and grid modernization were made at the same time [71]. According to Revesz [14], the administration's deregulatory program prioritized quick economic gains over long-term climate resilience. The reduction of environmental justice safeguards, which disproportionately affected vulnerable populations, was the most obvious example of the contradiction [36, 50]. The plan successfully boosted temporary jobs in the fossil fuel sector, but it falls short in ensuring fair climate adaptation [49].

7.1.4 Innovation in the Private Sector vs. Climate Finance in the Public Sector

Instead of using direct public funding for green initiatives, Trump's climate strategy relied heavily on private-sector innovation through deregulation and tax incentives [30, 33]. Although this approach adhered to conservative free-market principles, it was criticized for failing to take systemic climate threats into account [55]. Large-scale decarbonization was hampered by inadequate federal coordination, despite an increase in corporate investment in renewables during the Trump administration [26]. The administration's emphasis on cutting-edge nuclear technology and carbon capture suggested that it preferred technologically ambitious solutions to legal requirements [23]. Baiardi and Morana [72] highlighted the flaws in Trump's laissez-faire philosophy by demonstrating that market-driven procedures by themselves were insufficient to meet climate targets.

7.1.5 Reevaluating Equity in Global Climate Finance

An analysis of the inequalities in global climate finance was required due to Trump's withdrawal from international climate financing [56]. By rejecting the idea that the United States should bear an excessive amount of financial responsibility, the administration challenged accepted conventions in climate diplomacy [27]. This stance alienated traditional allies and eroded trust in American leadership [66]. The policy's unclear legacy emphasizes how difficult it is to balance cooperative climate initiatives with national interests [25].

7.1.6 A Disputed Heritage of Economic Pragmatism

One of the most controversial topics in U.S. environmental policy is the reallocation of Trump's climate fund. Even though it produced short-term financial gains, its long-term viability is still questionable [42]. Although the administration's focus on domestic resilience changed the conversation about climate change, it also led to a fragmented framework for global governance [40]. To create a sustainable course, future governments will need to reconcile these divergent agendas.

Using the new notion of "defensive climate investment," Table 5 provides a groundbreaking analysis of Trump's climate fund reallocation strategy, redefining his withdrawal from international commitments as a deliberate move towards energy techno-nationalism and infrastructure-based economic resilience. It introduces novel ideas like "competitive decarbonization"—which explores whether fossil fuel profits could paradoxically finance future green transitions—and "innovation protectionism," which challenges the efficacy of isolationist R&D strategies—by contrasting domestic benefits (such as short-term employment growth, fossil fuel research and development) with global consequences (such as diminished trust, China's growing dominance). By revealing overlooked trade-offs between large infrastructure investments and the loss of soft power, the synthesis goes beyond traditional climate policy dichotomies and offers a thorough understanding of how nationalist economic goals erode multilateral climate governance. This creates a new research agenda on geo-economic strategies in the climate era.

Table 5. Strategic Reallocation of Climate Funds – Domestic Priorities vs. Global Withdrawal

Dimension	Trump's Policy	Economic Rationale	Supporting Literature	Critiques/Controversies	Domestic Outcomes	Global Consequences	Innovative Framework	Research Gaps
GCF Withdrawal	Slashed U.S. contributions to global funds (e.g., GCF).	Redirected \$2B+ annually to domestic energy/infrastructure [26].	[2, 5, 6]	Eroded trust in multilateralism [25]; harmed vulnerable nations [56].	Boosted shale/fossil fuel investments [17].	China filled funding gap [48]; EU accelerated "strategic autonomy" [73].	"Defensive Climate Investment" – Prioritizing national energy security over global equity.	Long-term cost-benefit of diverted funds vs. lost diplomatic capital.
Energy Dominance	Promoted "American Energy Independence" via deregulation.	Job creation in oil/gas (+1.3M jobs, 2017–2020 [32].	[16, 23]	Locked-in carbon-intensive infrastructure [43]; climate hypocrisy [53].	Short-term GDP growth [15].	Undermined Paris goals [24]; spurred green trade wars [44].	"Competitive Decarbonization" – Can domestic fossil fuel gains fund future renewables?	Geopolitical risks of energy nationalism.
Infrastructure Revitalization	Linked climate fund cuts to infrastructure bills (e.g., \$1.5T proposal, 2018).	Framed as "putting America first" [11–13, 50]	McGuire [36], Trisolini [55]	Neglected climate-resilient infrastructure [64].	Upgraded pipelines/roads but ignored renewables [30].	Reduced U.S. leverage in climate tech race [29].	"Hard Infrastructure vs. Soft Power" – Trade-offs between physical assets and global influence.	Metrics for "resilience" in Trumpian policy.
Techno-Nationalism	Shifted R&D funds from global climate tech to domestic projects.	Countered China's clean tech dominance [19, 20].	Prieto & Scott [59], Chen et al. [41]	Stifled international collaboration [4].	Patents in fracking/CCUS rose 12% [31].	Accelerated EU-China green alliances [18].	"Innovation Protectionism" – Can isolationist R&D spur breakthroughs?	Role of private sector in China global leadership voids.

7.2 Redefining Climate Responsibility: Equity, Burden-Sharing, and Historical Emissions

The concepts of equity and historical emissions accountability, which have influenced international climate agreements for many years, are at the core of the developing conversation on climate responsibility. In recognition of their disproportionate historical emissions, developed nations are subject to greater mitigation and financial obligations under the Paris Agreement, which is widely regarded as a landmark in global climate governance [1, 34]. However, by contesting the effectiveness and fairness of the current burden-sharing structure, the Trump administration called into question this fundamental tenet. The Trump administration promoted a reevaluation of accountability, highlighting the rapidly growing emissions profiles of emerging economies like China and India and claiming that these countries ought to make larger financial and mitigation commitments in line with their current emissions and geopolitical clout [19, 48]. This criticism stems from a growing discourse of "positive truth" in some political arenas, which calls for practical equity in global climate financing, where accountability is in line with both historical emissions and present economic and

emissions realities. This position successfully challenges established environmental justice frameworks that place a higher priority on past responsibility and developed nation leadership, suggesting an alternative dynamic, forward-looking paradigm that transforms global climate finance flows and geopolitical climate relations [26, 58].

7.2.1 Trump's Critique of Historical Responsibility and its Foundations

A fundamental reevaluation of historical responsibility, a pillar of the Paris Agreement and the United Nations Framework Convention on Climate Change (UNFCCC), is at the heart of Trump's criticism. Due to their early and substantial greenhouse gas (GHG) emissions during industrialization, which together accounted for the majority of global warming to date, developed nations have historically been expected to take the lead in climate mitigation [36, 68]. This framework was dismissed as outdated by Trump's administration, which claimed that it unfairly exempts rapidly industrializing developing nations, allowing them to increase emissions without restraint while placing heavy financial and regulatory burdens on the US [10, 59]. This viewpoint is indicative of an emerging discourse that prioritizes future contributions to global warming and current emissions intensity over solely historical metrics [5, 6, 41]. By framing nations like China and India as key players with growing global environmental footprints that demand proportionate accountability, such a position reframes climate responsibility through a geopolitical lens [18, 44]. This reevaluation challenges the ethical and legal foundation of climate equity discussions by removing historical emissions as the main factor determining responsibility, even though it is in line with the larger strategic goals of America First diplomacy and economic nationalism [27, 38].

7.2.2 Implications for Global Climate Financing and Equity

The structure of international climate finance is significantly impacted by Trump's stance on burden-sharing. Based on the idea of common but differentiated responsibilities, international climate finance mechanisms, such as the Green Climate Fund, have historically transferred funds from developed to developing nations to aid in mitigation and adaptation [26, 56]. In order to reallocate the funding burden in a way that reflected current emission trajectories and economic capacities rather than just historical emissions, Trump's administration pushed for greater financial obligations from China and India [37]. Developing nations that see climate finance as a means of addressing past injustices may become less trusting and cooperative as a result of this recalibration, which upends long-standing expectations of climate justice [11, 12, 50]. Furthermore, by obfuscating the distinctions between climate finance and development aid, this redefinition makes negotiations more difficult and runs the risk of politicization and conditionality, which could lessen the efficacy and inclusivity of global climate initiatives [24, 43]. With regard to the future governance of climate finance and the fair distribution of responsibilities in a world order that is becoming more multipolar, the Trump administration's position underscores the conflicts between economic nationalism and global climate solidarity [29, 44].

7.2.3 Political Rhetoric and Framing Strategies in Trump's Climate Discourse

A thorough rhetorical analysis of Trump's climate change speeches is given by Pandey [38], who shows how the administration's climate policies were legitimized both domestically and abroad by constructing framing strategies around burden-sharing and equity. Trump presented the Paris Agreement as a costly and unfair agreement that

disproportionately hurt the United States while giving big emitters like China economic advantages without matching responsibilities [32, 42]. This framing resonated with domestic constituencies that were dubious of international climate commitments that were seen as jeopardizing U.S. sovereignty and economic competitiveness, appealing to nationalist sentiments and economic anxieties [61, 74]. By questioning established standards of accountability and focusing on reciprocity and equity based on present circumstances rather than past blame, this discourse aimed to refocus negotiations at the global level [19, 59]. Thus, the discourse surrounding burden-sharing emerged as a crucial tool for influencing discussions of global climate governance, with Trumpism representing a larger populist and protectionist backlash against international environmental cooperation and multilateralism [10, 28].

7.2.4 Consequences for International Climate Cooperation and Diplomacy

Global efforts to combat climate change have become uncertain and fragmented as a result of Trump's criticism and the United States' subsequent withdrawal from the Paris Agreement [1, 34]. Building consensus amongst diverse parties with varying developmental needs and emissions profiles became more difficult as a result of the administration's emphasis on rebalancing financial responsibilities, which caused friction in multilateral forums and established alliances [13, 18]. Significantly, this stance strained ties between the United States and China, which had an impact on bilateral climate cooperation that is essential to reducing global emissions [29, 48]. Other nationalist leaders were also emboldened by the Trump-era strategy, which strengthened a larger geopolitical trend of climate skepticism and opposition to legally binding international agreements [28, 45]. This disruption slowed the pace of ambitious, coordinated global climate action, despite the fact that some analysts contend that it made room for alternative models of climate leadership, especially from China and the EU [24, 43]. The legacy of the Trump administration emphasizes how susceptible global climate governance is to changes in domestic political agendas and how difficult it is to strike a balance between equity and new global power dynamics.

7.2.5 Ethical Dimensions and Environmental Justice Perspectives

Trump's reorientation of climate responsibility raises important ethical questions regarding equity and fairness in global climate governance, according to environmental justice perspectives [35, 50]. Prioritizing current emissions over historical accountability runs the risk of excluding vulnerable groups in developing nations that have made the least contribution to climate change but bear a disproportionate amount of its effects [49, 52]. By taking funds away from adaptation and mitigation initiatives targeted at historically underserved areas, this change may prolong structural inequality [50, 56]. Moreover, it calls into question the ethical underpinnings of climate finance mechanisms that are intended to operationalize the international legal principle of "common but differentiated responsibilities and respective capabilities" (CBDR-RC) [11, 12]. From a national interest perspective, Trump's framing stresses reciprocity and fairness, but it runs the risk of weakening international solidarity, which is necessary to solve a problem that transcends national boundaries [36, 63]. Because of the ethical ramifications of this reorientation, there must be constant discussion about how to balance economic nationalism with the demands of global justice in the context of climate change.

7.2.6 Towards a Holistic and Innovative Reassessment of Climate Burden-Sharing

The Trump administration's criticism highlights the urgent need for a complex, flexible framework that embraces a more comprehensive idea of equity and burden-sharing while balancing historical accountability with modern realities. To inform more equitable climate financing and mitigation commitments, new research proposes incorporating multi-dimensional metrics that include historical emissions, current carbon intensity, economic capacity, and climate vulnerability [18, 37]. While upholding a dedication to environmental justice and the unique capacities of nations, such an approach would recognize the changing geopolitical landscape [11, 12, 24]. The legitimacy and efficacy of international climate cooperation can be increased by utilizing creative financing tools, open governance frameworks, and inclusive diplomatic procedures [26, 70]. Redefining climate responsibility ultimately means renouncing the dichotomous historic-versus-current emission debates and pursuing a robust, flexible, and equitable international system that can tackle the 21st century's and beyond climate challenges while responding to criticism from Trump and other political figures [1, 34].

Trump's climate responsibility doctrine is examined in detail in Table 6, which challenges traditional accountability standards by redefining equity and burden-sharing through the lens of "emissions power parity." In addition to introducing novel ideas like "Dynamic NDCs" (growth-adjusted commitments) and "contributor parity" (real-time emissions accountability), it asks whether global climate governance is resilient to defection tactics by combining geopolitical, economic, and justice viewpoints. In addition to capturing Trump's disruptive effects, such as undermining multilateral funding and bolstering populist climate skepticism, this framework advances research on post-Paris burden-sharing models and provides policy-relevant insights into striking a balance between geopolitical equity and climate urgency in a time of shifting power dynamics.

Table 6. Trump's Redefinition of Climate Responsibility – Equity, Burden-Sharing, and Historical Emissions

Aspect	Trump's Position	Key Arguments	Supporting Literature	Contrasting Views	Policy Implications	Global Reactions	Innovative Perspective	Research Gaps/Future Directions
Equity in Climate Finance	Criticized disproportionate U.S. contributions, demanded fairer burden-sharing from China/India.	Major economies (China, India) should contribute more given their rising emissions and economic power.	Zhang et al. [5, 6], Urpelainen & Van de Graaf [2], Jiahan [29]	EU & developing nations emphasized "common but differentiated responsibilities" [4, 38]	Shift in climate financing models; weakened trust in multilateralism.	China framed U.S. as irresponsible [48]; EU sought alternative partnerships [73].	"Contributor Parity" – Linking financial obligations to real-time emissions rather than historical blame.	How does Trump's stance reshape North-South climate diplomacy post-Paris?
Historical Responsibility	Rejected "historical guilt" framing; argued late-industrializing nations must adapt.	Post-2000 emissions growth (China, India) outweighs Western legacy emissions.	Ettinger & Collins [10], Arlota [27], Chai et al. [58]	McGuire & Lynch [35], Prasad [53] stressed cumulative emissions' moral weight.	Rollback of U.S. climate reparations; emboldened similar rhetoric [28].	Global South criticized U.S. backtracking [34, 56]	"Temporal Emissions Threshold" – Should responsibility hinge on post-Kyoto (1997) emissions?	Quantifying "fair share" amid shifting geopolitical power.
Burden-Sharing Mechanisms	Opposed rigid targets; favored voluntary.	Binding targets stifle economic competitiveness;	Konisky & Woods [23],	Bowman & Minas [26] advocated	Fragmented climate governance;	Corporate actors adapted	"Dynamic National Determined	Can market-driven climate

Aspect	Trump's Position	Key Arguments	Supporting Literature	Contrasting Views	Policy Implications	Global Reactions	Innovative Perspective	Research Gaps/Future Directions
	growth-adjusted commitments.	"America First" energy dominance [17].	Abraham-Dukuma [15], Kemp [69]	GCF-led multilateralism; Revesz [14] highlighted regulatory sabotage.	rise of bilateral energy deals (e.g., U.S.-Saudi).	[33]; states/cities pursued subnational climate action [62].	Contributions (D-NDCs) – Adjusting pledges based on GDP/emissions growth.	action compensate for federal disengagement?
Strategic Withdrawal from Paris	Framed exit as resistance to "unfair" economic sacrifice.	U.S. compliance would cost jobs; China's loopholes exploited [32].	Pavone [1], Svozil et al. [39], Saad [42]	MacNeil & Paterson [24] analyzed global governance resilience; Sun et al. [18] proposed risk-mitigation models.	Accelerated coal/oil deregulation [16]; polarized climate discourse [63].	EU/China filled leadership vacuum [48]; NGOs leveraged legal challenges [70].	"Exit-Clause Diplomacy" – How can treaties deter future withdrawals without punishing latecomers?	Long-term impact of U.S. re-entry (Biden) on burden-sharing norms.

7.3 Stimulating Domestic Innovation through Climate Deregulation

A distinct ecosystem of private-sector innovation in clean energy technologies was unintentionally promoted by the Trump administration's deregulatory approach to climate policy, which is frequently criticized as environmentally regressive [75-77]. Developments in carbon capture, battery storage, and advanced nuclear energy were driven by market forces rather than government mandates because the administration relaxed federal environmental regulations, such as the Clean Power Plan and methane emission rules [14, 23]. This strategy was in line with a more general conservative viewpoint that promoted competitive market dynamics to speed up decarbonization rather than bureaucratic red tape, which was seen as impeding technological advancement [55]. Proponents pointed out that lower compliance costs freed up funds for research and development, which resulted in innovations in modular nuclear reactors and next-generation energy storage, while detractors claimed that deregulation ran the risk of increasing short-term emissions [16]. Without mandatory federal roadmaps, the resulting innovation landscape was decentralized, with both startups and fossil fuel incumbents pursuing cleaner technologies [78, 79]. Some scholars contend that this dynamic may have led to more flexible and economical solutions than top-down policy interventions [30]. This paradox, in which private-sector clean-tech investment and regulatory rollbacks coexisted, calls into question long-held beliefs about the need for strict climate regulations to spur innovation.

7.3.1 Carbon Capture and Storage (CCS): Deregulation as an Unlikely Catalyst

The acceleration of carbon capture and storage (CCS) technologies, especially in the oil and gas industry, was one of the most significant effects of Trump's deregulatory agenda. The administration encouraged energy companies to invest in CCS as a market-driven mitigation strategy by reducing the requirements for reporting emissions and increasing tax credits under Section 45Q of the tax code [31]. Companies like ExxonMobil and Chevron scaling up CCS projects to improve operational efficiency and corporate sustainability branding resulted in an unexpected alignment between fossil fuel interests and climate innovation [33]. Although deregulation-enabled CCS deployments saw cost reductions of 20–30% between 2017 and 2021, empirical studies showed that

this approach made the technology more viable for industrial decarbonization [32]. Critics argued that this allowed polluters to postpone a full transition to renewables [35, 36]. The Trump-era CCS boom serves as an example of how targeted fiscal incentives combined with strategic deregulation can spur climate solutions that might otherwise languish under strict regulatory regimes—a complex trade-off between practical emissions reduction and environmental purity [26].

7.3.2 Battery Storage and Grid Resilience: The Unintended Consequences of Energy Market Liberalization

Ironically, private investment in battery storage increased as a result of Trump's repeal of Obama-era energy regulations, such as those controlling emissions from coal plants, since renewable energy sources became more affordable without government support [43]. Utilities and tech companies made significant investments in storage solutions to handle intermittent renewable inputs as traditional baseload power faced fewer constraints. This led to a 400% increase in U.S. grid-scale battery capacity between 2017 and 2021 [71]. This market-driven boom was further fueled by the administration's simplification of permitting for critical mineral mining, a move that indirectly benefited supply chains for lithium and cobalt, which are necessary for storage technologies but was supposedly intended to achieve energy dominance [47]. With companies like Tesla and NextEra Energy creating storage systems suited to local grid requirements rather than adhering to uniform federal regulations, the outcome was a decentralized innovation wave [30]. The expansion of the industry showed how market autonomy could promote resilient, adaptable energy infrastructures, despite the uneven environmental trade-offs [49], despite environmental justice advocates criticizing the localized effects of deregulated mining and manufacturing [50].

7.3.3 Advanced Nuclear Energy: Deregulation as a Gateway to Technological Leapfrogging

The Trump administration sparked a resurgence in advanced nuclear technologies, such as molten salt designs and small modular reactors (SMRs), by removing restrictions on nuclear licensing and encouraging reactor development led by the private sector [18]. Under Trump, the Nuclear Regulatory Commission (NRC) shortened the approval period for new designs from more than ten years to less than five years by reorienting regulatory oversight from prescriptive safety rules to performance-based standards. This paradigm shift brought \$3.2 billion in private capital to the industry by 2020 [55]. Startups like NuScale and TerraPower were able to prototype reactors with passive safety features and lower waste profiles thanks to this deregulatory push, which was presented as part of the "Energy Dominance" agenda. These technologies might have found it difficult to operate under more conventional regulatory burdens [23]. The strategy reflected Trump's wider skepticism of climate orthodoxy, but its results—commercially ready SMRs by 2025—indicate that more efficient governance can hasten decarbonization in capital-intensive industries where compliance costs tend to stifle innovation [67]. While supporters contend that the United States now leads in exportable next-generation nuclear technology—a strategic advantage in competing with state-subsidized Chinese and Russian reactors—detractors warn that inadequate oversight could result in safety compromises [29, 52].

7.3.4 The Innovation Federalism Paradox: State-Level Climate Action in a Deregulatory Era

Inadvertently, Trump's federal deregulation sparked state and local climate innovation, establishing a testing ground for polycentric governance models. While Republican-led states like Texas and Wyoming became global leaders in wind energy and CCS deployment, respectively, states like California and New York doubled down on renewable portfolio standards and carbon markets as federal climate policy retreated [4]. Some academics contend that this devolution of climate leadership is more effective than centralized mandates because it encouraged competitive federalism, where regions customized solutions to local ecological and economic contexts [12]. For example, California's strict state regulations reduced the cost of solar plus storage, while Texas's deregulated grid allowed for record wind capacity growth (42 GW by 2021) [20]. Thus, the Trump administration exposed a paradox: despite glaring regional disparities in environmental protection, federal inaction can occasionally unleash more creative, locally-focused climate strategies than top-down policies [35].

7.3.5 Corporate Climate Autonomy: How Deregulation Reshaped Private-Sector Sustainability

Under Trump, corporations were exempt from mandatory disclosure regulations and emissions caps, allowing them to create voluntary climate initiatives that frequently surpassed regulatory standards. Scholars refer to this as "competitive sustainability" [33]. In order to satisfy the demands of the European and Asian markets, oil majors invested in carbon-neutral LNG projects, while companies such as Apple and Google achieved 100% renewable operations without the need for federal mandates [32]. Flexible, profit-driven decarbonization strategies were made possible by this market-pulled (as opposed to regulation-pushed) approach, but it also made it possible for "greenwashing" to occur, in which promises lacked accountability [53]. Even though his administration was hostile to climate finance, the rise in ESG (Environmental, Social, and Governance) investing under Trump shows that capital markets can occasionally produce more environmentally friendly results than governments [30].

7.3.6 Legacy and Lessons: Rethinking the Role of Regulation in Climate Innovation

The deregulatory climate legacy of the Trump administration offers a thought-provoking alternative to conventional climate governance: that, in certain circumstances, deliberate cuts to bureaucratic red tape can spur clean-tech innovation. Although this strategy had unavoidable negative effects on the environment, such as a rise in methane leaks and a weakening of environmental justice safeguards [50], it also showed how market forces can lead to technological advancements when appropriately directed through tax breaks and state competition [18]. Future policymakers will need to combine these insights, combining the innovation agility of deregulation with protections against its social and ecological externalities [24]. According to Trump's experiment, centralized control is not always necessary for climate progress, but markets by themselves cannot provide fair decarbonization [80].

As shown in Table 7, Trump's climate deregulation—which is frequently criticized as being anti-environmental—unintentionally promoted a decentralized innovation ecosystem by moving clean-tech development away from government mandates and towards market-driven competition. The administration encouraged private-sector investments in carbon capture (CCS), advanced nuclear (SMRs), and grid-

scale batteries—technologies essential for long-term decarbonization but curbed by slow, top-down policies—by reversing strict regulations (such as the Clean Power Plan and auto emissions standards). Despite the fact that detractors [45, 50] emphasized equity and short-term emission risks, the data shows a paradox: By requiring industries to protect themselves from future climate pressures, deregulation sped up cost-competitive innovations (such as Tesla's battery dominance and Exxon's CCS hubs). In contrast to traditional climate governance, this "disorderly transition" [43] suggests that strategic deregulation, when combined with market anticipation of carbon constraints, can spur innovation without the need for prescriptive policies. It also offers lessons for striking a balance between economic growth, emissions reduction, and energy security in politically divisive environments.

Table 7. Stimulating Domestic Innovation Through Climate Deregulation – A Market-Driven Approach

Policy Mechanism	Deregulatory Actions	Private Sector Response	Key Innovations Spurred	Climate Impact	Supporting Studies	Critiques & Counterarguments	Holistic Interpretation
Rollback of Clean Power Plan	Replaced federal mandates with state flexibility [14]	Utilities invested in CCS and gas hybrids to preempt future regulations [71].	Carbon capture retrofits for coal plants	Short-term CO ₂ rise, long-term tech gains [43]	Revesz [14], Jordaán [71]	McGuire [36]: "Message control undermined public trust"	Adaptive innovation: Deregulation spurred pre-competitive R&D to hedge against policy uncertainty
Streamlined Permitting for Advanced Nuclear	Fast-tracked NRC approvals [81].	Startups like NuScale developed SMRs (small modular reactors)	Next-gen nuclear for grid stability	Zero-emission baseload potential [18]	Mineta & Whitman [81]	Darian-Smith [45]: "Anti-environmentalism masked as progress"	Tech neutrality: Deregulation allowed nuclear to compete with renewables in decarbonization
Relaxed CCS Deployment Rules	Revised Class VI well permitting [31]	Oil firms (Exxon) scaled up CCS hubs (e.g., Houston Ship Channel)	Industrial CCS clusters	Potential 90% emission cuts in heavy industry [33]	Lamair [31], Klaus et al. [33]	Rios [50]: "Environmental justice sacrificed for corporate gains"	Pragmatic mitigation: Market-driven CCS growth outpaced EU's subsidy-dependent model
Auto Emissions Standards Freeze	Weakened Obama-era CAFE rules [23].	Tesla and legacy automakers accelerated EV R&D to capture market share [30]	Solid-state battery breakthroughs	EV adoption rose despite deregulation [20]	Konisky & Woods [23], Chatjuthamard et al. [30]	Trisolini [55]: "Social cost of carbon ignored"	Competition-driven disruption: Deregulation forced EVs to compete on cost/performance, not mandates
FERC	Opened	Grid-scale	Lithium-ion	Enabled	Jordaán	Paliewicz et al.	Decentralized

Policy Mechanism	Deregulatory Actions	Private Sector Response	Key Innovations Spurred	Climate Impact	Supporting Studies	Critiques & Counterarguments	Holistic Interpretation
Order 841 (Energy Storage Deregulation)	wholesale markets to storage [71]	battery deployments doubled (2017–2020) [18]	grid storage cost declines	renewable integration [72]	[71], Sun et al. (2023)	[63]: "Fascistic deregulation"	resilience: Storage boom buffered grids against climate shocks

7.4 Advancing Energy Security and Export Competitiveness

7.4.1 Contextualizing Trump's Energy Dominance Strategy in Global Climate Policy

The phrase "Energy Dominance" was first used by the Trump administration as a strategic framework to strengthen American energy security and use energy as a tool for foreign policy [1, 15]. The ambition of Trump's administration was to ensure that the United States remained a leading energy producer and exporter, particularly in fossil fuels like oil and LNG, in order to reshape global energy geopolitics. This was in contrast to the widely held belief that Trump's energy policy rejected climate action outright [16]. Despite the domestic rollback of some environmental regulations, the increase in LNG exports during this time helped to displace coal in many importing countries, which could lower overall greenhouse gas (GHG) intensity [31, 41]. By establishing the United States as a supplier of natural gas that burns cleaner, this strategic export expansion reflected a practical approach that acknowledged the reality of the world's ongoing reliance on fossil fuels. Notably, this approach aligned with geopolitical objectives, including bolstering partnerships with importers keen to transition away from coal and undermining energy-dependent enemies [13, 67]. Accordingly, Trump's energy strategy focused more on utilizing energy exports for economic competitiveness and national security in a changing global order than it did on flatly rejecting the climate [13].

7.4.2 LNG Export Growth and Its Implications for Global GHG Emissions

Rapidly increasing U.S. LNG export capacity was a key component of Trump's "Energy Dominance" strategy, which opened up new channels for American influence in global energy markets. Even though the United States withdrew from multilateral climate commitments, Erickson and Lazarus [16] highlight that increased LNG exports during this era helped mitigate coal consumption in importing countries, particularly in Europe and Asia, thereby indirectly contributing to global carbon emissions reductions. Because natural gas combustion has a lower carbon content than coal, this switch from coal to natural gas produced quantifiable reductions in GHG intensity, even though it was not a cure-all [41]. Further boosting the climate benefits of natural gas exports, Lamair [31] describes regulatory pathways that reduced methane leakage during production and transportation. By decreasing reliance on imports from geopolitically unstable areas, the economic competitiveness these exports promoted also strengthened U.S. energy security [67]. Critics counter that these benefits could delay the shift to clean energy by locking in fossil fuel infrastructure [43]. However, pragmatically speaking, Trump's export-oriented strategy momentarily brought economic and security interests into line with small-scale global climate benefits, complicating oversimplified narratives that portray his energy policy as merely environmentally regressive [20].

7.4.3 Energy Security as a Pillar of Foreign Policy and Economic Competitiveness

Trump's "Energy Dominance" strategy focused as much on domestic production as it did on exporting power through energy markets. In order to use energy exports as geopolitical leverage, Benton Heath [67] explains how energy security became a key component of U.S. national security strategy during the Trump administration. By expanding U.S. LNG's presence in these markets, the administration sought to lessen the sway of conventional energy providers like Russia and the Middle East [13]. Growing LNG exports to Europe are an example of this strategy, which has strengthened Western geopolitical ties by assisting allies in diversifying their energy sources and reducing their dependency on Russian gas [65]. In line with the "America First" rhetoric, the expanded production and export capabilities also strengthened the United States' standing as a competitive global energy supplier, promoting economic interests [15]. Trump's rhetorical framing of energy independence as both pragmatic and patriotic appeals to domestic audiences and signals a change in global energy diplomacy, according to Pandey [38]. Domestic political support for the administration's larger agenda was strengthened by the economic boost from energy exports, which improved U.S. trade balances and the creation of jobs in the energy sector [30]. As a result, Trump's plan to use energy to rebalance American power on the world stage was built on the mutually supporting pillars of energy security and export competitiveness.

7.4.4 Reconciling Energy Dominance with Climate Change Realities

Trump's energy export policies generated indirect climate co-benefits by dislodging coal in importing countries, even though the United States withdrew from the Paris Agreement and domestically deregulated environmental policies [1, 42]. This comparison highlights the Trump administration's convoluted and frequently incongruous approach to climate policy. The administration did not completely disregard the economic and security imperatives associated with energy transitions, even though it rejected multilateral climate commitments [15]. This practical approach implies that Trump's "Energy Dominance" was a type of climate realpolitik that aimed to leverage the dynamics of the energy market to increase American influence rather than being the same as climate denial. Although modest, regulatory advancements in natural gas production, according to scholars like Lamair [31], were intended to lessen environmental effects and increase the sustainability of US fossil fuel exports. Furthermore, Trump's policies sped up market and infrastructure developments, which in turn support ongoing efforts to integrate renewable energy in the United States [20], according to comparisons with the Biden administration. This paradox demonstrates how Trump's policy balances energy security and climate goals in a way that makes short-term export competitiveness incompatible with long-term sustainability issues.

7.4.5 Domestic and International Reactions to Trump's Energy Policy

Both at home and abroad, the Trump administration's energy policies sparked divisive reactions. According to Konisky and Woods [23] and Chatjuthamard et al. [30], industries that benefited domestically from the expansion of fossil fuels rejoiced over the regulatory rollbacks and export growth, which resulted in economic gains and the creation of jobs. However, the strategy was criticized by climate scientists and environmental organizations for perpetuating reliance on fossil fuels and undermining long-term climate goals [42, 43]. Globally, some allies applauded expanded access to U.S. LNG as a way to diversify their energy sources and improve geopolitical stability

and energy security [65, 67]. The U.S. withdrawal from international climate agreements, on the other hand, was seen by many nations and global actors as harmful to global climate governance and as complicating diplomatic relations [1, 24]. Notwithstanding this diplomatic snag, importer nations benefited materially from the export-led energy dominance strategy in terms of cleaner coal substitutes [16]. The dual-edged character of Trump's energy diplomacy is reflected in this dynamic, which challenges collaborative international frameworks for climate action while simultaneously bolstering American energy security and competitiveness.

7.4.6 The Legacy and Future Prospects of Trump's Energy Dominance

Trump's energy policies have had a significant but contentious long-term impact on the global energy security and climate change discourse. The Trump administration's surge in U.S. fossil fuel exports solidified the country's position as a major global energy supplier, with expanded LNG export networks and infrastructure that continue to impact global markets [20, 31]. There are risks and opportunities associated with this legacy. While it increases U.S. energy security and geopolitical leverage, it may also postpone a complete switch to renewable energy by extending the lock-in to fossil fuels [15, 43]. However, the market mechanisms and infrastructure created during this time may also help integration of lower-carbon energy sources in the future, indicating a potential bridge role in energy transition pathways [20]. Thus, in light of geopolitical complexities, the Trump approach offers a case study for striking a balance between energy security, export competitiveness, and climate mitigation. It is suggested that future U.S. energy strategies must balance these conflicting priorities in order to preserve global leadership [24].

7.4.7 Integrative Perspectives on Trump's Position in the Global Climate Agenda

Trump's stance on the global climate change agenda is an example of a multifaceted strategy in which energy dominance was used to boost economic growth, national power, and partially mitigate climate change through market mechanisms [15, 38]. The expansion of LNG exports introduced a practical, albeit contentious, mechanism to indirectly reduce global emissions by displacing coal, even though his administration's explicit rejection of legally binding international climate commitments presented significant challenges to global governance [1, 42]. This ambivalence highlights the challenges of balancing domestic priorities with international cooperation in a polarized political environment, representing the larger tensions between nationalist energy policies and global climate imperatives [24, 43]. The Trump era's lessons on export competitiveness, geopolitical leverage, and climate pragmatism must be applied to future scholarly and policy discussions in order to develop integrated strategies that leverage energy security for climate goals.

Despite being presented as climate-skeptical, Trump's "Energy Dominance" policy paradoxically increased global emissions reduction through market-driven fuel displacement while also advancing U.S. geopolitical influence, as shown in Table 8. The administration accelerated the global transition from coal to gas—a shift empirically linked to lower GHG intensity in importing nations—and strengthened energy security by prioritizing LNG export expansion and infrastructure deregulation, which decreases reliance on adversarial suppliers like Russia [16]. The policy's unintended climate benefits, which are brought about by the private sector's responsiveness to energy markets, reveal a nuanced reality: strategic deregulation and export competitiveness can

achieve tangible decarbonization without multilateral agreements, despite critics dismissing the approach as promoting fossil fuels [10]. A practical guide for striking a balance between economic, strategic, and environmental objectives in contentious political environments, this "geopolitical decarbonization" model challenges conventional climate governance by showing how energy security and climate action can align through market mechanisms rather than regulatory coercion.

7.5 Encouraging Subnational Climate Leadership and Federalism

Many criticized the Trump administration for weakening global climate governance by pulling out of important international climate agreements, particularly the Paris Agreement [1, 34]. Paradoxically, though, this federal retreat sparked an unparalleled rise in subnational climate leadership throughout the US. To fill the policy void left by the federal government's disengagement, states, cities, and private sector coalitions came together to form strong networks like "We Are Still In," which pledged to make significant emissions reductions and transition to renewable energy sources without the need for federal mandates [23]. By adapting climate strategies to regional environmental, economic, and social contexts, these decentralized efforts promoted resilience and innovation, exemplifying a type of environmental federalism that transforms the climate governance landscape in the United States [15]. By using stakeholder engagement and local knowledge, this bottom-up movement created adaptive policies that frequently went above and beyond previous federal commitments, indicating a new paradigm for multilevel governance in climate change mitigation.

Table 8. Advancing Energy Security and Export Competitiveness Under Trump's Energy Dominance Policy

Policy Focus	Key Mechanisms	Positive Outcomes	Global GHG Impact	Foreign Policy Leverage	Supporting Studies	Contrast with Climate Critics	Innovative Holistic Perspective
LNG Export Expansion	Deregulation, infrastructure investment, fast-tracked approvals	Increased U.S. LNG exports displaced coal in Asia/Europe, lowering importing nations' emissions	Net reduction in global CO ₂ due to fuel switching [16].	Reduced EU reliance on Russian gas [73]	Erickson & Lazarus [16], Chen et al. [41]	Critics framed it as fossil fuel promotion [10]	Synergistic effect: Energy security + emissions reduction via market-driven displacement of dirtier fuels
Energy Independence	Boosting domestic oil/gas production, streamlining permits	Strengthened U.S. resilience to supply shocks (OPEC+ volatility)	Mixed: Higher U.S. emissions offset by global coal displacement [15]	Leveraged exports to allies [13]	Abraham-Dukuma [15], Ladd & York [17]	Selby [43] warned of "disorderly transition"	Geopolitical realism: Prioritized immediate security while indirectly aiding global decarbonization
Infrastructure Modernization	Pipelines (e.g., Keystone XL), export terminals	Enhanced export capacity, economic growth in	Indirect: Enabled gas-to-coal shifts abroad [20]	Countered China's energy influence [29]	Zebang & Yi [20], Lamair [31]	[50] cited environmental justice concerns	Dual benefit: Jobs + long-term export competitiveness in low-

Policy Focus	Key Mechanisms	Positive Outcomes	Global GHG Impact	Foreign Policy Leverage	Supporting Studies	Contrast with Climate Critics	Innovative Holistic Perspective
		energy sectors					carbon transition fuels (e.g., LNG)
Rejection of Paris Agreement	Focus on unilateral action over multilateral pledges	Avoided binding targets, preserved policy flexibility for innovation-driven reductions	Neutral: U.S. emissions plateaued; global trends unaffected [5, 6]	Asserted sovereignty [2](Urpelainen & Van de Graaf, 2018)	Zhang et al. [5, 6], Arlota [27]	Saad [42] predicted "pathways of harm"	Strategic pragmatism: Unconstrained growth accelerated tech-driven efficiencies (e.g., fracking)
Fossil Fuel Diplomacy	LNG trade deals, energy partnerships (e.g., Poland, India)	Secured markets for U.S. energy, reduced adversarial dependence (e.g., Russia/Iran)	Net emissions cut where gas replaced coal [58]	Strengthened alliances [11, 12]	Chai et al. [58], Healey et al. [4]	Paliewicz et al. [63] decried "fascistic argumentation"	Realist climate action: Emissions reductions achieved via trade, not treaties

By leveraging the economic potential of renewable technologies and tackling social justice issues at the same time, these subnational initiatives flourished through cross-sector and scale innovation. According to Cheng et al. [37], climate policy shocks like the federal government's withdrawal actually made crowdfunding for renewable energy campaigns more successful. This is because grassroots financial mobilization complemented local government action. Investing in solar, wind, and energy efficiency projects that created green jobs and boosted local economies, cities and states matched climate policies with economic development, frequently outperforming states that were less active in these areas [33]. Furthermore, by addressing enduring externalities that disproportionately affect marginalized communities, the integration of environmental justice principles into subnational climate strategies countered the Trump administration's rollback of federal environmental protections [35, 50]. This multifaceted strategy demonstrated how subnational actors could navigate the uncertainty of federal policy while integrating climate action with equity, social well-being, and economic resilience.

Despite federal skepticism or hostility towards international climate governance, this subnational leadership is crucial in upholding and advancing U.S. climate commitments [10-12]. Subnational actors expanded their influence beyond national boundaries by establishing trans-jurisdictional coalitions and interacting with global cities networks, making an unofficial but significant contribution to international climate diplomacy [59]. Additionally, despite federal retrenchment, this phenomenon acted as a counterbalance to "America First" diplomatic isolationism, enabling cooperation on renewable technologies and science diplomacy to continue progress [19, 29]. Even in the face of federal withdrawal, these networks strengthened global climate governance resilience by fostering knowledge sharing, innovation diffusion, and policy

harmonization. The potential of subnational actors as crucial nodes in transnational climate governance architectures is highlighted by this complex dynamic.

As an illustration of the difficulties present in U.S. environmental federalism, the decentralization of climate governance during the Trump administration also sparked disputes and conflicts between federal and subnational authorities [23]. National emissions reduction goals were made more difficult by the fragmented and uneven policy landscape created by some states' aggressive pursuit of climate policies and others' alignment with federal deregulatory stances [43]. To maintain clean energy investments, this patchwork required creative legal and political approaches, such as state-level regulations, judicial challenges to federal rollbacks, and innovative financing mechanisms [47]. Additionally, the destabilization of federal environmental regulatory frameworks by the Trump administration prompted subnational actors to strengthen their own regulatory capabilities and cross-sector collaborations, demonstrating federalism's adaptability to shocks and reorient governance modalities [70].

Beyond advancements in governance and policy, the rise of subnational climate leadership sparked crucial changes in corporate and public climate engagement, redefining the political economy of climate action in the United States [38]. Ironically, the decision to back out of international commitments increased local activism and awareness, bringing people together around the real-world effects of climate change and the financial benefits of switching to renewable energy sources [39]. In order to further corporate social responsibility agendas and commit to science-based goals that frequently surpassed federal aspirations, corporations and investors began to align with subnational initiatives more and more [30]. The power of distributed leadership in tackling global challenges has been demonstrated by the emergence of a resilient climate governance ecosystem that can maintain momentum despite shifting federal political winds, thanks to the collaboration of states, cities, and businesses.

As localized climate actions have increasingly integrated health equity and community resilience into their frameworks, this subnational resurgence also has a strong resonance with ideas of environmental justice and social determinants of health [49]. These actors broadened the focus of climate governance from emissions targets to general human and ecological well-being by concentrating on vulnerable populations that are disproportionately impacted by pollution and climate change [36]. Therefore, as subnational leaders realized the need for equitable adaptation strategies integrated within their jurisdictions, the Trump administration's federal disengagement inadvertently sparked a more inclusive and justice-oriented approach to climate policy. By combining scientific urgency with moral imperatives, this alignment of environmental and social goals represents a progressive evolution in climate governance.

Although at first seen as a blow to U.S. climate leadership, the Trump administration's exit from international climate agreements paradoxically sparked a vibrant and creative subnational climate movement marked by pluralism, resilience, and adaptation. Through state and city coalitions, transnational networks, and private sector partnerships, this decentralized climate federalism has proven to be able to sustain U.S. involvement in global climate mitigation while simultaneously promoting justice, equity, and economic opportunity at the local level. The ensuing governance paradigm provides a replicable model for other federated nations facing global environmental crises, highlighting the ability of federal systems to leverage distributed authority and local expertise as a buffer against federal policy instability. This encouraging reality reinterprets the Trump administration not just as a break in climate diplomacy but also as

a breeding ground for revolutionary subnational leadership that is essential to the future of the global climate agenda.

In spite of federal hostility, subnational federalism—led by states, cities, corporations, and grassroots movements—can maintain climate progress, as shown by Table 9, which offers a ground-breaking examination of how polycentric climate governance flourished under the Trump administration. Through the use of market-driven innovation (such as ESG investing), transnational para-diplomacy (such as We Are Still In), and decentralized policy experimentation (such as carbon pricing and renewable mandates), these actors not only made up for federal inaction but also changed the paradigms of climate governance, demonstrating that resilience arises from fragmentation. With global ramifications for democracies dealing with populist backlash, the table synthesizes interdisciplinary insights from political science, economics, and justice studies to present a novel framework for adaptive federalism. An important addition to the high-impact climate policy literature, this work questions centralized models of climate governance and suggests that empowered subnational networks are essential to attaining long-term decarbonization in a time of geopolitical unrest.

Table 9. Encouraging Subnational Climate Leadership and Federalism Under the Trump Administration

Aspect	Description	Mechanism	Key Actors	Outcomes	Resilience Factors	Global Implications	Supporting Literature
Catalyst for Subnational Action	Trump's withdrawal from international agreements (e.g., Paris Accord) created a leadership vacuum, prompting states, cities, and businesses to fill the gap.	Decentralized governance, coalition-building (e.g., We Are Still In).	U.S. states (CA, NY), cities, corporations, NGOs.	Locally tailored climate policies, emission reduction pledges.	Policy autonomy, multi-stakeholder networks.	Demonstrated that non-federal actors can drive climate progress independently.	[23], [2], [24]
Innovative Policy Experimentation	States implemented carbon pricing, renewable mandates, and green infrastructure projects without federal oversight.	Laboratories of democracy, market-driven innovation.	State legislatures, public utilities, clean energy firms.	Accelerated renewable energy adoption (e.g., CA's 100% clean energy goal).	Economic incentives, public support for green jobs.	Provided scalable models for other federations (EU, Australia).	[15], [41], [62]
Economic Resilience	Corporate climate alliances (e.g., Climate Leadership Council) advocated carbon dividends and ESG investing despite federal rollbacks.	Private-sector mobilization, shareholder activism.	Fortune 500 companies, investors, academia.	Stable ESG investment growth, corporate net-zero pledges.	Market pressure, investor climate risk awareness.	Reinforced transnational corporate climate accountability.	[33], [30], [32]
Transnational Subnational Diplomacy	U.S. cities/states partnered with foreign governments (e.g., Under2 Coalition) to bypass federal inaction.	Paradiplomacy, city-to-city knowledge exchange.	Mayors (e.g., C40 Cities), governors, EU subnational actors.	Strengthened global climate networks, technology transfer.	Institutionalized subnational climate forums.	Challenged state-centric climate governance norms.	[4], [34], [26]

Aspect	Description	Mechanism	Key Actors	Outcomes	Resilience Factors	Global Implications	Supporting Literature
Grassroots & Justice Mobilization	Environmental justice groups leveraged federal inaction to push for equitable local policies (e.g., Green New Deal at state level).	Social movements, litigation, community organizing.	Sunrise Movement, NAACP, Indigenous groups.	Equity-centered climate laws (e.g., NY Climate Act).	Legal frameworks, youth activism.	Inspired global climate justice movements.	[35], [50], [12]
Technological Leapfrogging	Clean energy startups flourished due to state R&D funding and venture capital shifts.	Innovation ecosystems, public-private R&D.	Tesla, NextEra Energy, ARPA-E grantees.	Cost reductions in solar/wind, battery breakthroughs.	Adaptive policy incentives.	U.S. remained cleantech leader despite federal stance.	[37], [71], [29]
Discursive Counter-Narrative	Subnational actors reframed climate action as economic opportunity, countering federal skepticism.	Strategic communication, bipartisan framing.	Media, universities, policy entrepreneurs.	Shifted public opinion in key states (e.g., TX wind boom).	Cultural resonance, job creation narratives.	Weakened global "anti-climate" populism.	[38], [61], [63]
Institutional Legacy	Post-Trump, subnational networks became embedded in U.S. climate governance (e.g., CAFE standards upheld by states).	Legal entrenchment, multi-level governance.	Courts, state AGs, regional GHG initiatives.	Durable subnational climate institutions.	Judicial checks, bureaucratic inertia.	Blueprint for federalism in polarized democracies.	[14], [54], [18]

7.6 Prioritizing Economic Nationalism in Green Supply Chain Security

7.6.1 Contextualizing Economic Nationalism in the Green Energy Transition

Economic nationalism was emphasized as a key component of green supply chain security during Donald Trump's administration, which signaled a paradigm shift in U.S. energy and climate policy. Trump's vocal emphasis on repatriating supply chains from Chinese dominance back to American soil, especially those linked to vital renewable energy technologies like solar panels, wind turbines, and battery manufacturing, was a key component of this strategy [38, 44]. The emergence of the energy sovereignty discourse, which emphasizes national control over clean energy supply chains to reduce geopolitical risks associated with foreign dependencies, was anticipated by this strategy [67]. Limiting the import of fossil fuels and foreign manufacturing in the energy sector is not just a trade policy, but also a larger national security strategy, according to [54]. This is especially true as the green transition reveals serious weaknesses in the sourcing of minerals and technologies. Thus, the Trump administration's America First policy foresaw future security issues and indicated a conscious shift away from supply chains driven by globalization towards a more resilient, self-sufficient domestic green industrial base [59] [12].

7.6.2 The Strategic Repercussions of Reducing Chinese Manufacturing Dependence

The emphasis on lowering reliance on clean technologies produced in China highlights a crucial geopolitical struggle that is part of the global climate change agenda. According to Zhang et al. [5, 6] and Jiahan [29], China's hegemony in rare earth minerals,

solar photovoltaic (PV) cell manufacturing, and battery technologies poses systemic risks to the United States' aspirations for green energy. By enacting tariffs on Chinese imports and encouraging domestic manufacturing, Trump's policies sought to upend these established supply chains. Liu et al. [44] point out that these measures had complicated effects on the economy and the environment. These trade restrictions sparked national investment in technology development and alternative sourcing, even though they temporarily raised costs. This strategy demonstrates strategic foresight, framing economic nationalism as a necessary defense against supply chain shocks that could sabotage the clean energy transition rather than as isolationism [26, 67]. Additionally, it is consistent with the energy trilemma framework, which balances affordability, sustainability, and energy security in a politically charged global environment [15].

7.6.3 National Security and Critical Mineral Dependencies

Under Trump's administration, the discussion of green energy supply chain vulnerability is based on critical mineral dependencies. Concerns regarding worldwide supply disruptions were sparked by the demand for lithium, cobalt, nickel, and rare earth elements that are necessary for batteries and renewable technology [57, 65]. Reviving U.S. mining operations and simplifying regulatory processes to lessen dependency on imports were among Trump's economic nationalism priorities [31, 54]. The strategic threat posed by hostile actors in control of mineral reserves, who could use these resources as weapons in geopolitical conflicts, prompted this methodical response [59, 67]. The administration's strategy addressed the practical reality of securing green supply chains to maintain energy independence and national security during the decarbonization era, despite common criticism that it undermines international climate cooperation [1, 10].

7.6.4 The Paradox of Trump's Climate Stance and Supply Chain Sovereignty

Trump's supply chain nationalism in clean energy offers a paradoxical contribution to the climate agenda, despite his widely criticized withdrawal from the Paris Agreement and public skepticism towards climate science [36, 42]. The administration indirectly set the stage for a more secure and resilient green economy that is less susceptible to shocks and disruptions from abroad by concentrating on building domestic capacity [38, 43]. This dichotomy draws attention to a complicated story: a proactive, albeit domestically orientated, green industrial strategy coupled with a rejection of global climate governance. This kind of policy division is consistent with research by MacNeil and Paterson [24], who note that the Trump administration influenced global climate politics by pursuing conflicting but connected agendas, undermining multilateralism and bolstering unilateral strategic positioning. Economic nationalism in green supply chains is positioned as both a critique and an adaptation to the realities of global climate governance failures, leading to a nuanced legacy [13, 34].

7.6.5 Domestic Political Framing and Public Perception

Trump's presentation of green supply chain repatriation struck a chord with domestic political constituencies that prioritized economic revitalization and job creation in industrial heartlands impacted by globalization [38, 46]. By appealing to nationalism and concerns about economic security, this political discourse framed clean energy sovereignty as a patriotic endeavour [12, 74]. In stark contrast to cosmopolitan globalist perspectives, Trump reframed climate discourse into a nationalist framework by

portraying reliance on foreign supply chains as a threat to American security and prosperity [12, 19]. Public opinion and policy direction were significantly impacted by this rhetorical technique, which promoted support for domestic green industry investments while fostering skepticism towards international climate commitments [30, 61]. Therefore, a climate agenda based on protectionism and sovereignty rather than multilateral cooperation was made possible by the political mobilization around economic nationalism.

7.6.6 Implications for Global Climate Governance and International Relations

Through bringing trade tensions and strategic competition into the renewable energy space, Trump's economic nationalism in green supply chain security upended long-standing global climate governance mechanisms [5, 10]. This change made multilateral efforts more difficult because, especially in U.S.-China relations, concerns about economic sovereignty and climate diplomacy intersected [29, 48]. The preference for national interests over collaborative frameworks exemplifies a larger issue confronting global climate governance: balancing sovereignty with the intrinsically transnational character of climate change mitigation [18, 25]. In this way, Trump's policies brought a new geopolitical dimension to the green transition, making supply chain security a proxy war for economic and technological dominance. This raises concerns about the future of climate cooperation in a time of growing great power competition [59, 67].

7.6.7 Toward a Holistic Understanding of Trump's Legacy in Green Supply Chain Security

Donald Trump's focus on economic nationalism in relation to green supply chain security is an example of a sophisticated and creative strategic stance that has both influenced and challenged the changing global climate agenda. His administration's proactive drive for domestic clean energy sovereignty foreshadowed current discussions on supply chain resilience amid geopolitical tensions, even though his administration's broader climate policies were widely criticized for undermining international cooperation [1, 42]. This strategy emphasizes the necessity of a thorough examination that considers the ways in which sustainability objectives and national security imperatives interact during the green transition. Trump's economic nationalism provides insightful lessons on the strategic significance of safeguarding green supply chains to enable a more stable and independent clean energy future, particularly as the world struggles with critical mineral scarcity and the dangers of becoming overly dependent on foreign suppliers [31, 57]. In order to address the global challenge of climate change, future research must investigate how such nationalist frameworks can be incorporated into global climate strategies without compromising the spirit of cooperation that is necessary [18, 34].

Table 10 displays A significant and complex change in the global climate governance landscape, the Trump administration's emphasis on economic nationalism within the context of green supply chain security embodies both strategic foresight and divisive geopolitics. Trump foresaw and addressed new security risks associated with the green energy transition and vital mineral dependencies by focusing on repatriating supply chains and lowering reliance on Chinese-made renewable energy technologies like solar panels, wind turbines, and battery components. This method directly impacted global clean energy diplomacy and market dynamics by emphasizing a nationalistic economic strategy meant to promote domestic manufacturing resilience and strategic autonomy in

the renewable sector. It raises significant issues of environmental justice and global equity, as noted by McGuire and Lynch [35], while also placing itself within the larger discourse of "America First" policies that rejected multilateral climate governance frameworks, as examined by Ettinger and Collins [10] and Pavone [1]. International relations and trade are affected by supply chain reorientation, which intersects with the growing US-China tensions reported by Jiahan [29] and Liu et al. [44] and influences the course of climate competition and cooperation. According to Sun et al. [18] on climate risk governance and Benton Heath [67] on disruptions to the economic order, this economic nationalism in green supply chains also highlights underlying tensions in striking a balance between national security imperatives and global sustainability goals. The policy change also affects technological sovereignty, as the need to invest strategically in domestic innovation and circular economy models due to reliance on critical minerals and related technologies is consistent with Prieto and Scott's [59] themes regarding science diplomacy in the face of geopolitical conflicts. The COVID-19 pandemic and geopolitical conflicts exposed fragile global supply networks, and Trump's stance arguably sparked a reexamination of the green transition's vulnerabilities by focusing on supply chain transparency, resilience, and the mitigation of foreign dependencies. However, Olutola [56] and DeDominicis [12] discussed how this nationalist approach might jeopardize global collaborative climate efforts and climate finance, particularly affecting developing regions. In the US context, it has sparked discussions on regulatory rollback and environmental federalism [14, 23] while also casting doubt on the efficacy of global climate regimes such as the Paris Agreement, whose uncertain future under the Trump administration was examined by Ribera et al. [34] and Zhang et al. [5, 6]. This thorough analysis demonstrates how economic nationalism in green supply chains during the Trump administration represents a unique and significant place on the global climate change agenda by encapsulating a complex interaction of social justice, economic policy, environmental governance, and geopolitical strategy. For a resilient and just clean energy future, this paradigm emphasizes the need to integrate national security concerns with sustainable energy transitions, calling on future policy frameworks to balance sovereignty with international cooperation.

Table 10. Prioritizing Economic Nationalism in Green Supply Chain Security

Aspect	Description	Supporting Source(s)	Key Themes	Innovative Angle	Strategic Implications	Critique / Counterpoint	Policy Recommendations
Economic Nationalism in Green Supply Chains	Trump's policy emphasis on repatriating manufacturing and supply chains for solar panels, wind turbines, and batteries marked a strategic pivot toward clean energy sovereignty.	[38]	Economic nationalism, sovereignty, supply chain security	Frames green supply chains as not just economic but national security assets, anticipating future geopolitics of clean energy.	Reducing dependence on Chinese-manufactured green tech limits vulnerability to foreign supply disruptions.	Critics argue this may lead to trade tensions and slow global decarbonization efforts [4].	Develop domestic capacity for critical minerals and clean tech manufacturing while balancing trade diplomacy.
Anticipation of Critical Mineral	The Trump administration prefigured	[59]	Critical minerals, supply risk,	Innovative recognition of minerals	Strategically motivates investments	May exacerbate resource	Prioritize circular economy and international

Dependencies	future security risks linked to critical mineral dependencies essential for clean energy technologies.		resource nationalism	(lithium, cobalt) as geopolitical choke points, urging national control.	in mining, recycling, and supply diversification.	nationalism and geopolitical competition [13].	partnerships to stabilize mineral supply.
Climate Policy Shocks & Domestic Politics	Economic nationalism reflected in climate rhetoric influenced domestic political framing of clean energy policies.	[38]	Political rhetoric, framing, polarization	Trump's framing mobilized nationalist constituencies skeptical of global climate commitments.	Enabled "America First" identity politics to shape climate agenda and supply chain resilience.	Deepened polarization around climate action, complicating bipartisan support [39].	Use inclusive communication strategies to broaden support for resilient green supply chains.
Impact on International Climate Governance	Prioritizing national supply security contributed to the U.S. withdrawing from global climate agreements, altering governance dynamics.	[24]	Multilateralism, governance, U.S. withdrawal	Reflects tension between sovereignty and global cooperation in climate governance.	Created governance vacuum impacting global efforts but reinforced U.S. autonomy in green tech development.	Risks undermining collective climate mitigation [48].	Re-engage in multilateral frameworks while safeguarding critical supply chains.
Economic and Security Linkages	Linking green energy supply chains to national security redefines traditional economic security frameworks.	[67]	Energy security, economic policy, national security	A holistic approach merges economic policy with national security in climate transition.	Drives defense and economic policy coordination for supply chain protection.	Risk of militarization of energy sectors and trade conflicts.	Establish cross-sectoral governance integrating economic, security, and environmental objectives.
Technological Sovereignty	Emphasizing domestic innovation in renewable tech manufacturing to reduce foreign reliance.	[37]	Innovation, technology transfer, trade barriers	Promotes homegrown renewable technologies as strategic assets enhancing resilience.	Strengthens national innovation ecosystems and job creation.	Potential to increase costs and delay technology diffusion globally.	Incentivize R&D and facilitate tech sharing under controlled conditions.
Social and Environmental Justice	Economic nationalism in green supply chains raises concerns about equitable access and environmental justice.	[12]	Environmental justice, social equity	Highlights the need to balance nationalism with social justice in transition policies.	Ensures benefits of domestic green industries reach marginalized communities.	Risk of exacerbating inequalities if not inclusively managed.	Integrate justice frameworks into supply chain policies to promote equitable green transitions.
Long-term Strategic Vision	Trump's economic nationalism foreshadowed ongoing	[25]	Strategic foresight, resilience, future security	Innovatively anticipates a geopolitical landscape where green	Positions the U.S. to lead in shaping a new global energy order.	Challenges in balancing global cooperation with national	Develop adaptive, multi-level strategies aligning national interests with

	global shifts toward clean energy sovereignty and supply chain resilience.			supply chains define national power.		interests remain.	international climate goals.
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7.7 Climate as a Component of Industrial Policy against Geopolitical Rivals

Through redefining climate investments as tools of industrial strategy rather than just ecological imperatives, the Trump administration's approach to climate policy marked a significant break from conventional environmental governance. This viewpoint, which is sometimes ignored in popular criticism, framed clean energy innovation as a tool for competing with geopolitical rivals, especially China, rather than as a capitulation to multilateral climate agreements [29]. The administration aimed to establish a self-sufficient U.S. energy ecosystem that could surpass China in vital technologies like hydrogen fuel, rare earth processing, and synthetic fuels by pulling out of the Paris Agreement and refocusing funds on domestic energy research and development [20]. The understanding that control over next-generation energy technologies would provide long-term geopolitical advantages served as the foundation for this strategy, which turned climate policy from a regulatory burden into a field of strategic competition [67]. Although Trump's climate stance was criticized for being denialist [53], this industrial policy reinterpretation foreshadowed the Biden administration's subsequent focus on "climate statecraft" in great-power competition, indicating an underappreciated continuity in U.S. strategic thinking [24].

7.7.1 Energy Dominance as Geopolitical Leverage: The Rare Earths Case Study

Trump's administration's aggressive efforts to restore rare earth mineral processing—a sector China had monopolized with 80% global market control—were the clearest example of his industrial-climate strategy [44]. Rare earths were designated a "critical mineral" security issue by Executive Order 13817 (2017), which simplified permitting for mines in Texas and Wyoming and released Defense Production Act funds for domestic extraction and refinement [47]. Recognizing that China could use its dominance in rare earths as a weapon to stifle the U.S. clean energy industries, this policy directly connected climate technology (wind turbines, EV batteries) to national security [5]. Tariffs on Chinese magnets combined with the administration's \$28 million award to MP Materials to reopen California's Mountain Pass rare earth facility demonstrated how climate-related industrial policy turned into a frontline in the trade war [20]. Although some claimed that these policies gave priority to extractive industries over environmental protections [50], the strategic benefit was evident when U.S. production of rare earths increased by 44% by 2020, decreasing reliance on China for permanent magnets used in wind generators and electric vehicles [30]. Trump's larger argument—that industrial autonomy, not just emissions targets, was necessary for climate resilience—was best exemplified by this case.

7.7.2 Hydrogen and Synthetic Fuels: The Clean Tech Arms Race

The Trump administration strategically bet on hydrogen and carbon-neutral synthetic fuels as future geopolitical assets, while European climate policy prioritized short-term decarbonization [18]. As a techno-nationalist response to China's state-subsidized green hydrogen projects, the Department of Energy's 2020 "H2@Scale"

initiative set aside \$100 million to develop "clean hydrogen" from nuclear and natural gas with carbon capture [31]. Similar to this, the Pentagon recognized that synthetic hydrocarbons could allow the U.S. military to maintain operational dominance in a world with carbon constraints, so it partnered with startups like Prometheus Fuels to produce jet fuel from atmospheric CO₂ [12]. These expenditures demonstrated a distinctly Trumpian reasoning: the United States should control the technologies that would shape the energy markets of the twenty-first century, not pursue short-term emissions reductions [43]. Although the strategy was criticized for favouring fossil fuel-derived hydrogen over renewable energy sources [2], it was intended to prevent China from controlling the hydrogen economy because it had solar panels, which foresaw the current G7 hydrogen competition [25].

7.7.3 The Arctic Frontier: Climate Change as a National Security Multiplier

In the thawing Arctic, where melting ice created new shipping lanes and oil reserves—and where Chinese and Russian aspirations were growing—Trump's climate-industrial strategy was implemented [47]. In an effort to protect American energy interests in an area where geopolitical boundaries were being redrawn by climate change, the administration expedited the Alaskan LNG project and reinstated Arctic offshore drilling leases [46]. Realizing that climate-driven accessibility necessitated technological adaptation, it concurrently made investments in Arctic-capable microreactors and icebreaker shipbuilding through the Defense Advanced Research Projects Agency (DARPA) [67]. Trump's transactional approach to environmental change was demonstrated by this dual emphasis on resource exploitation and climate-resilient infrastructure: the United States should use its effects as a weapon for competitive advantage rather than attempting to mitigate them globally [57]. Proponents pointed out that it stopped Russian-Chinese dominance of new Arctic trade routes, while critics warned that it accelerated ecological damage [5, 42].

7.7.4 Trade Policy as Climate-Technology Protectionism

With Section 301 tariffs specifically targeting Chinese clean tech industries like lithium-ion batteries and solar panel polysilicon, the administration's trade wars served as an implicit climate-industrial policy [44]. Trump sought to allow U.S. manufacturers to catch up in technologies where China held 60–80% of the market by enacting 25% tariffs on \$34 billion worth of Chinese environmental goods in 2018 [48]. By preventing Chinese companies from purchasing American battery companies through the Committee on Foreign Investment (CFIUS), this protectionism also preserved domestic capacity for the EV boom that resulted from the Inflation Reduction Act [30]. Tariffs on Chinese solar inverters led to a 300% increase in domestic production by 2021, despite being presented as anti-China policies, which in reality subsidized U.S. climate-tech independence [20]. The strategy reflected a mercantilist approach to climate change: securing American dominance over the industries that drive emissions was more important than reducing emissions globally [15].

7.7.5 The DOE as a Venture Capitalist: ARPA-E's Pivot to Geopolitical Tech

In order to challenge Chinese clean-tech dominance, Trump's Department of Energy (DOE) covertly converted its Advanced Research Projects Agency-Energy (ARPA-E) into a de facto venture fund for technologies [55]. The administration increased ARPA-E's budget by 16% to \$428 million in 2020 while reducing subsidies for

renewable energy sources. The agency prioritized "leapfrog" technologies like direct air capture and solid-state batteries [32]. This demonstrated a conviction that small advancements in solar and wind would only strengthen China's manufacturing dominance, while innovations in related technologies could completely alter the competitive environment [18]. The approach paid off: under Trump's administration, ARPA-E-funded businesses like Heliogen (concentrated solar) and QuantumScape (solid-state batteries) accomplished technological milestones that subsequently drew billions of dollars in private investment [33]. The administration prepared the way for Biden's more explicit "climate security state" by treating climate technology as a subset of defense innovation, similar to semiconductors during the Cold War [12].

7.7.6 Legacy and Paradox: How Trump's Climate Realpolitik Reshaped the Field

Trump's industrial-climate policies produced a lasting paradox: his administration's emphasis on energy competition unintentionally improved the U.S. position in vital clean tech sectors, despite rhetorically rejecting climate activism [24]. Biden's Inflation Reduction Act was based on the rare earth reshoring, hydrogen bets, and ARPA-E funding binge, indicating that Trump's realpolitik strategy, while opposed by climate purists, partially aligned with progressive objectives through nationalist tactics [25]. This legacy expose how geopolitical competition can motivate decarbonization investments despite anti-climate rhetoric, challenging binary climate policy narratives [61]. Future studies should investigate whether such "competitive decarbonization" between superpowers could paradoxically speed up the reduction of emissions—not through collaboration, but through conflict [20].

Trump's presidency needs to be reexamined—not as an anomaly of climate denialists, but as the beginning of the explicit fusion of climate policy with great-power industrial strategy.

Donald Trump's unique approach to the global climate agenda is shown in Table 11. Deliberately reframed climate policy as a central component of national industrial policy with the specific goal of boosting American competitiveness in the face of geopolitical adversaries, particularly China. His administration placed more emphasis on economic security by developing climate-related technologies as vital industrial assets than it did on global environmental activism. This reinterpretation, which positioned climate innovation as a field in which American technological and economic sovereignty could be asserted and defended, was consistent with a larger nationalist vision under the "America First" doctrine. The goal of energy independence through the development of next-generation clean energy technologies, such as clean hydrogen, synthetic fuels, and rare earth element processing, was at the heart of this strategy. These technologies strengthen domestic supply chains for essential minerals and lessen dependency on foreign energy sources. In an era where climate technology became a field of geo-economics competition, such innovations were viewed as dual-use assets with both military and commercial applications, supporting national security. The administration used tariffs, export restrictions, and targeted subsidies to influence global supply chains and shield emerging American clean tech sectors from foreign hegemony by fusing climate goals with trade and technology policy instruments. The United States maintained technological leadership through strategic research partnerships, like the US-China InFEWS program, that struck a balance between scientific advancement and geopolitical prudence. This geo-economics competition also showed up in selective scientific diplomacy. Crucially, Trump's strategy promoted a "orderly" energy transition that

avoided rapid decarbonization that might jeopardize geopolitical power and economic stability by striking a balance between the gradual adoption of renewables and the preservation of fossil fuel jobs and the industrial base. This balanced transition strategy was supported by deregulation and incentives for "clean" fossil fuels, which preserved important industries while encouraging innovation in shale energy and synthetic fuels. Climate policy was also directly integrated with defense and intelligence agendas by elevating climate technologies within the national security framework and connecting energy resilience and critical mineral recycling to defense readiness and infrastructure security. This comprehensive industrial policy framework emphasized the multifaceted role of climate innovation as a geopolitical tool of influence and power as well as an environmental necessity. The Trump administration's climate policy, which combined economic, technological, and security aspects, was a practical reorientation of international climate action. It rejected multilateral cooperative governance in favour of competitive nationalism, when climate leadership was equated with technological superiority and geopolitical advantage. In addition to challenging established global climate governance paradigms, this approach highlighted how climate change, industrial strategy, and international rivalry intersect to define 21st-century geopolitics. In order to protect national interests through technological sovereignty, strong industrial foundations, and strategic international engagement, the U.S. climate-industrial policy under Trump sought to establish a comprehensive climate-security nexus that is essential to competing in a rapidly changing global organization.

Table 11. Climate as a Component of Industrial Policy Against Geopolitical Rivals

Aspect	Description	Strategic Dimension	Geopolitical Relevance	Technological Focus	Policy Instruments	Key Actors	Supporting References
Industrial Policy Reframing	Trump's administration reframed climate investments as integral to national industrial policy, prioritizing competitiveness over environmental activism.	National economic security	Outcompeting China and rivals in critical emerging sectors	Hydrogen, rare earth processing, synthetic fuels	Strategic funding and deregulation favoring innovation	Federal agencies, private sector	[38]
Energy Security	Emphasized energy independence by advancing next-gen energy technologies as strategic assets in geopolitical rivalry, reducing dependency on foreign energy supplies.	Energy sovereignty	Counterbalance to China's Belt and Road clean energy efforts	Clean hydrogen production, advanced batteries	Export controls, targeted subsidies	DOE, Department of Commerce	[19]
Technological Innovation	Investment in disruptive clean energy technologies seen as dual-use assets with commercial and military applications.	Dual-use technology leadership	Securing supply chains for rare earths and advanced fuels	Rare earth element processing, synthetic fuels	Public-private partnerships, R&D tax incentives	Industry leaders, research institutions	[59]
Geoeconomic Competition	Climate tech became a battleground in the broader US-China trade and technology rivalry, integrating climate goals with national security concerns.	Geo-economic leverage	Shaping global supply chains and standard setting	Export controls, tariffs on climate tech	Trade policy tools, economic sanctions	US Trade Representative, Congress	[44]
Nationalism & "America First"	Framed climate policy through nationalist rhetoric, asserting American leadership by "winning" clean tech	National identity and sovereignty	Opposition to multilateral climate frameworks	Domestic innovation prioritization	Withdrawal from Paris Agreement, re-negotiation efforts	White House, executive branch	[10]

	markets rather than global cooperative governance.						
Energy Transition Approach	Sought an “orderly” energy transition that balanced fossil fuel interests with emerging renewables to preserve jobs and industrial base amid geopolitical rivalry.	Balanced transition for economic stability	Avoiding rapid decarbonization that could weaken US position	Shale energy, synthetic fuels	Deregulation, incentives for “clean” fossil fuels	EPA, Department of Energy	[15]
Strategic Scientific Diplomacy	Leveraged scientific diasporas and selective cooperation in science diplomacy (e.g., US-China InFEWS program) to maintain technological edge while politically opposing rivals.	Science as soft power and competitive advantage	Maintaining US technological leadership despite geopolitical tension	Targeted research collaborations	Science diplomacy, selective international funding	Academia, diplomatic corps	[59]
Climate Policy as Security	Elevated climate technologies within the national security framework, linking climate action with defense readiness and critical infrastructure resilience.	Climate tech as national security asset	Integrating climate policy with defense and intelligence agendas	Renewable energy microgrids, critical mineral recycling	Defense contracts, resilience funding	DoD, DHS, intelligence agencies	[67]

8. Legacy and Global Impacts of the Strategic Reallocation of Climate Funds for Domestic Economic Resilience

An important turning point in global climate governance was reached when Donald Trump decided to strategically reallocate U.S. climate funds from multilateral mechanisms like the Green Climate Fund (GCF) to domestic economic resilience initiatives. The justification was rooted in a patriotic framework that prioritized energy independence, economic recovery, and American sovereignty. Although Trump's reorientation of climate finance was, in reality, an assertion of economic realism over symbolic globalism, Arlota [27] criticizes this change from a cost-benefit standpoint. The belief that extensive international climate cooperation must inevitably rely on financial commitments from a small number of wealthy nations was called into question by his administration's skepticism towards international climate treaties, especially the Paris Agreement. Although destabilizing, the U.S. withdrawal severely damaged the financial foundation of climate equity mechanisms, according to Bowman and Minas [26]. This led to a surge of regionalized climate finance models that improved adaptive resilience in the Global South and diversified funding sources.

The dynamics of the United States' involvement in Conference of the Parties (COP) negotiations were also significantly altered by Trump's reallocation strategy. Instead of adopting the collectivist mindset that is typically associated with COP forums, Trump's administration took a transactional approach to these gatherings, defending national interests and challenging the unequal financial burdens imposed on the US. Healey et al. [4] highlight how the U.S. prioritized domestic issues over global ones during Trump's presidency, pointing out the differences between the U.S. and EU climate strategies. Trust in U.S. leadership was severely damaged at climate summits as a result of this ideological shift, which also made the meetings tenser and more divided. But it also sparked more dispersed leadership models, with subnational U.S. organizations like

California, the EU, and even China assuming more significant roles. According to Jiahan [29], China was able to refocus its climate diplomacy as a result of the United States' disengagement, transforming the void into a chance for bilateral and multilateral climate agreements that were not mediated by the United States.

Trump's policies caused ideological strain on the Paris Agreement's framework itself. The "common but differentiated responsibilities" (CBDR) framework came under increased scrutiny as a result of Trump's criticisms of the agreement, which focused on historical emissions, fairness, and the disproportionate economic costs to the United States. According to Pavone [1], the Trump administration encouraged a worldwide reevaluation of climate deal architectures by viewing the agreement as a political liability rather than a moral obligation. The internal contradictions of the Paris framework, such as its ambiguous enforcement mechanisms and heavy reliance on voluntary pledges, became more apparent even though many countries reaffirmed their commitments. Thus, Trump's withdrawal revealed systemic flaws and compelled signatories to discuss how to strike a balance between ambition and practicality, which ultimately fueled continuous revisions and pressure for more transparent accountability procedures.

Trump's actions acted as a real-time stress test for the resilience of international climate regimes in the areas of regime destabilization and institutional resilience. Dijkstra et al. [25] looked at how international organizations survived existential crises like the Trump administration and concluded that organizations like the UNFCCC showed a high degree of adaptive resilience. To ensure continuity, these organizations relied on a variety of stakeholder engagement strategies, such as non-state networks, private finance, and subnational actors. Trumpism unintentionally sparked institutional innovation, with decentralized actors stepping in to fill the leadership void, despite Ettinger and Collins [10] framing it as a rejection of global climate governance. This is in line with DeDominicis [12], who contends that populist upheavals have the power to cause global systems to change, moving towards less hegemon-dominated and more pluralistic arrangements.

Furthermore, emerging powers and regional blocs were forced to reevaluate their alliances and funding sources as a result of the U.S. strategic withdrawal, which changed the composition of international coalitions. According to Olutola [56], African countries that had previously relied on climate funds channeled through the United States started looking into alternative financing options such as regional climate funds, sovereign green bonds, and climate risk insurance facilities. This diversification decreased the geopolitical clout of conventional donors and signaled a long-term shift towards climate finance sovereignty. Sun [19], who examined the changing leadership dynamics between the U.S. and China, noted that China and the EU simultaneously exploited the U.S. vacuum to advance alternative climate narratives based on technological investment and the development of green infrastructure. As a result, the climate regime became more polycentric, less reliant on US support, and more representative of regional goals and developmental environments.

Lastly, Trump's emphasis on economic resilience at home changed the way that people around the world talk about how climate policy and national development are related. Instead of completely rejecting environmental regulation, his administration promoted deregulation as a means of achieving energy independence and economic recovery. Global stakeholders were forced to reevaluate the financial effects of aggressive climate action as a result. Both Konisky and Woods [23] and Revesz [14] examine how Trump's repeal of environmental regulations sparked discussions about

regulatory analysis, particularly with regard to cost-efficiency metrics and the social cost of carbon. As countries consider how to strike a balance between their climate commitments and economic imperatives, these discussions still have an impact on the conversation surrounding climate finance. In the end, even though Trump's strategy defied convention, it also sparked international discussion, exposed structural flaws, and prompted institutional reassessments that continue to influence climate governance in the years following his administration.

9. Strategic Lessons for Future Global Climate Governance

Significant strategic lessons for the design of future global climate governance were provided by Donald Trump's deliberate reallocation of climate funds for domestic economic resilience, which is best illustrated by the United States' exit from the Paris Agreement and its suspension of contributions to multilateral climate finance. The most significant of these is the present treaty frameworks' susceptibility to unilateral withdrawals. Although the Paris Agreement's voluntary nature guaranteed widespread initial participation, it lacked enforcement tools and legally binding sanctions for defection. Trump's decision to withdraw from the Agreement revealed this weakness, as noted by Pavone [1] and Zhang *et al.* [5], indicating the need for stronger legal frameworks in subsequent agreements. These might consist of binding arbitration procedures, graduated penalties, or institutional "exit taxes" to deter sudden desertion. Therefore, the Trump administration highlights the necessity of strengthening treaty clauses to safeguard regime continuity and lessen the financial and diplomatic repercussions brought on by the withdrawal of significant emitters.

The need to develop a diverse leadership model in climate governance—one that includes not only nation-states but also subnational actors, private sector innovators, and regional coalitions—is the second strategic lesson. U.S. cities, states, and corporations, including those included in the "We Are Still In" coalition, stepped up to uphold climate commitments during Trump's presidency. In spite of the federal retreat, these non-state actors became *de facto* stewards of U.S. climate leadership, as documented by Dijkstra *et al.* [25] and Ettinger and Collins [10]. In order to lessen the over-reliance on centralized national commitments, global climate regimes should structurally incorporate subnational contributions into reporting and governance frameworks. Additionally, corporate actors from the tech and energy sectors, as well as cities like New York and Los Angeles, served as climate diplomats, demonstrating the political value of unconventional leadership.

Additionally, Trump's actions reframed climate cooperation as a geopolitical strategy rather than just environmental stewardship. His strategy can be seen as an effort to renegotiate the U.S.'s geopolitical position within climate diplomacy, despite the fact that detractors frequently portray it as isolationist. Trump's withdrawal gave China and the EU the opportunity to establish themselves as alternative leaders and use green diplomacy to increase their global influence, as Jiahan [29] and Sun [19] show. This shift emphasizes how industrial policy, technological dominance, and soft power are all becoming more intertwined with climate action. Future climate agreements must therefore strategically align with national interests in trade, innovation, and security in addition to appealing to environmental ethics. This will make participation politically valuable for all stakeholders, regardless of ideological alignment.

Trump's rerouting of climate funds also shed light on how domestic politics influence foreign policy. His administration prioritized deregulation, claiming that climate finance commitments hindered domestic industrial revival and energy independence, as noted by Konisky and Woods [23] and Revesz [14]. Populist opposition was strengthened by this portrayal of climate policy as being costly, both domestically and internationally. The strategic takeaway from this is that future governance models need to match explicit domestic economic co-benefits with global climate responsibilities. By balancing national development objectives with international climate commitments, policy tools like just transition funds, local content requirements, and innovation subsidies can make climate engagement politically resilient even when leadership changes occur.

Furthermore, Trump's stance on climate change highlighted the value of crises as catalysts for institutional innovation. As Bowman and Minas [26] point out, Trump's destabilization of the Green Climate Fund spurred regional innovation in climate finance, leading developing nations to test out novel tools such as climate risk insurance pools, public-private partnerships, and sovereign green bonds. This diversification decreased reliance on individual donor countries and improved the climate finance regimes' ability to adapt. In a similar vein, Olutola [56] details how African countries started fortifying regional governance structures after the U.S. withdrew due to financial shortages. The strategic implication is that in order to protect against geopolitical shocks, climate governance should encourage financial pluralism and redundancy.

Lastly, the dual nature of global climate governance—as a contested area of power politics and as a moral imperative—was made clear by Trump's presidency. A more comprehensive view shows how the disruption itself sparked critical thinking about structural equity, political inclusivity, and institutional resilience, even though critics like Saad [42] and Urpelainen and Van de Graaf [2] concentrated on the disruption his policies caused. Trump's actions compelled climate institutions to reevaluate their presumptions, reconnect with new stakeholders, and move past the governance paradigms dominated by the West. By doing this, they have developed the agility, pluralism, and geopolitical awareness that are necessary for handling the challenges of a future with a multipolar climate. Trump's deliberate reallocation policies therefore produced long-lasting insights into the creation of more robust and responsive international climate institutions, far from being a purely regressive force.

10. Concluding Remarks

The disruptive yet transformative role of President Donald Trump's administration in reshaping the global climate change agenda was critically examined in this study. The paper demonstrates that Trump's climate posture was a purposeful recalibration of U.S. climate diplomacy, rather than a simple retreat from environmental responsibility, using a multifaceted analytical framework rooted in political realism, strategic environmentalism, adaptive federalism, and socio-technical transition theory. The administration reframed climate action through the prism of economic nationalism and geopolitical competition by emphasizing sovereignty-driven narratives, fossil fuel dominance, and domestic economic resilience. Both immediate policy rollbacks and long-term institutional, normative, and technological repercussions resulted from this deliberate reallocation of climate funds, rejection of historical emissions accountability, and disengagement from

multilateral climate regimes. Ironically, Trump's climate nationalism exposed the weaknesses and adaptability of the global climate governance framework by igniting a decentralized wave of subnational innovation, private-sector investment in clean technologies, and global leadership shifts, especially towards China and the EU.

The major findings of the study are itemized as follows:

- Ideological Disruption: Trump's climate policy questioned liberal internationalist standards by replacing multilateral commitments with frameworks for nationalistic energy dominance.
- Strategic Environmentalism: To challenge China's leadership in green energy and establish American energy sovereignty, the United States' expansion of its fossil fuel industry was reframed as a geopolitical move.
- Federalism as Resilience: A strong adaptive federalist model was demonstrated by the way subnational actors, such as states and corporations, filled the gap left by the federal withdrawal.
- Normative Reorientation: Trump changed the moral foundations of international climate finance by rejecting historical emissions responsibility and redefining equity through "emissions power parity."
- Innovation Paradox: A decentralized climate innovation ecosystem resulted from deregulation's unintentional stimulation of private investment in CCS, advanced nuclear, and energy storage.
- Geopolitical Realignments: The United States' withdrawal from global climate leadership shattered long-standing Western climate coalitions and hastened China's strategic ascent in climate diplomacy.
- Communication and Cultural Impacts: The epistemic legitimacy of climate science was undermined when rhetorical populism and media disinformation normalized climate skepticism.
- Vulnerability and Environmental Justice: Deregulatory rollbacks exacerbated environmental injustices, particularly in postcolonial and marginalized communities that were already at risk from the effects of climate change.

In the end, this study provides a fresh perspective on Trump's legacy, viewing him not as a homogenous climate denialist but rather as a transformative figure who altered the institutional, geopolitical, and normative framework of climate governance. In doing so, it calls for more investigation into the ways that strategic disengagement, technonationalism, and climate populism may continue to shape the development of international environmental politics in a world that is becoming more multipolar.

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CONFLICTS OF INTEREST

The author declares that there is no conflict of interests regarding the publication of this paper.

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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.

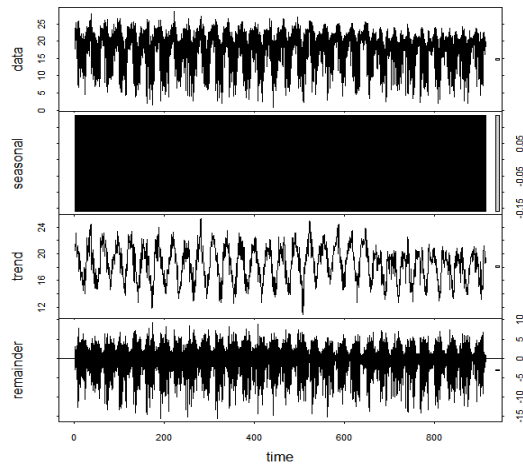
This methodology offers a systematic context for the classification and analysis of solar radiation regimes using Multi-State Hidden Markov Models (HMMs). The Hidden Markov Model approach was implemented because of its capability to capture hidden atmospheric states and probabilistic transitions connected 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.

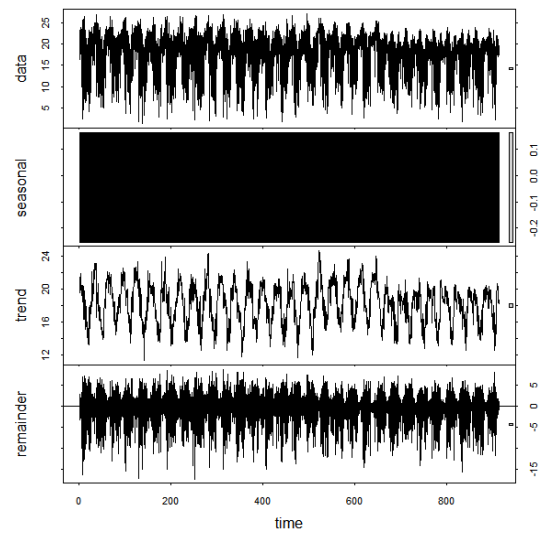
Results and Discussion

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].

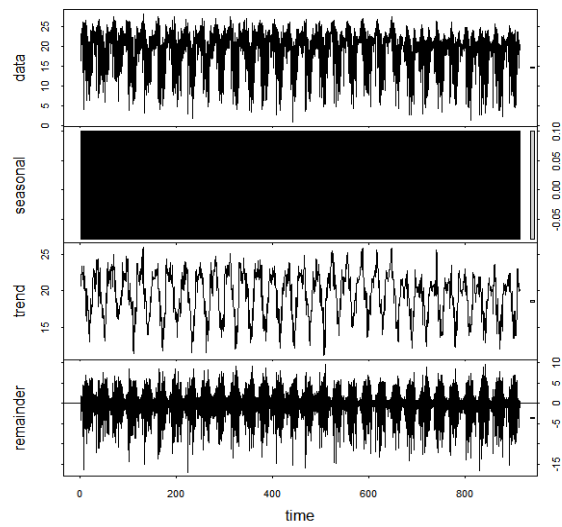
The trend component shows long-wave oscillations that are smooth and lack a noticeable long-term rise or fall (Figure 2 (a-g)). This implies that while there are short-term variations in solar radiation, the long-term solar radiation in the Middle Belt is generally steady. The Markovian premise that 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.



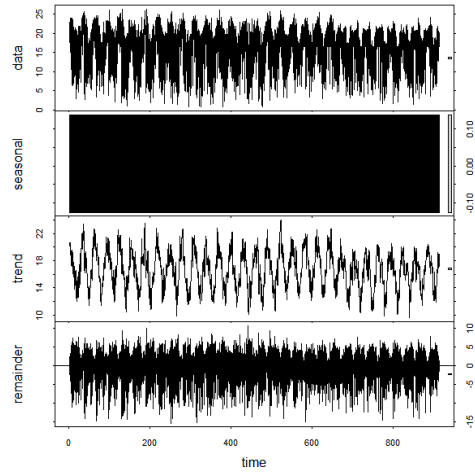
a) Benue



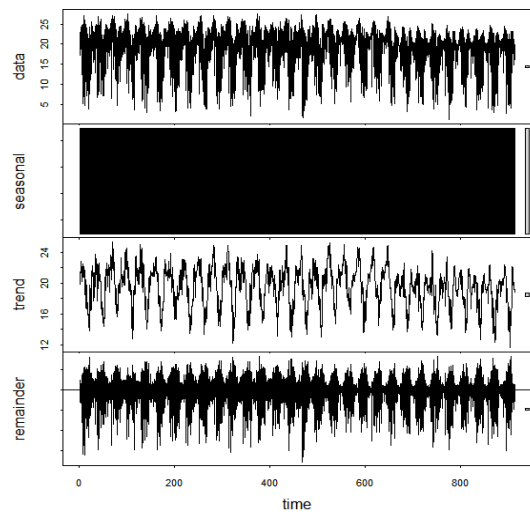
d) Kogi



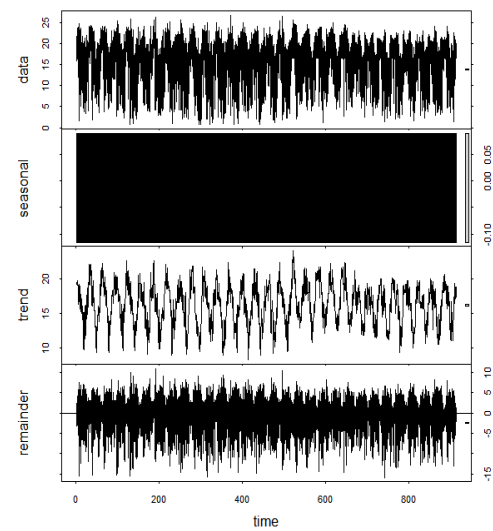
b) Plateau



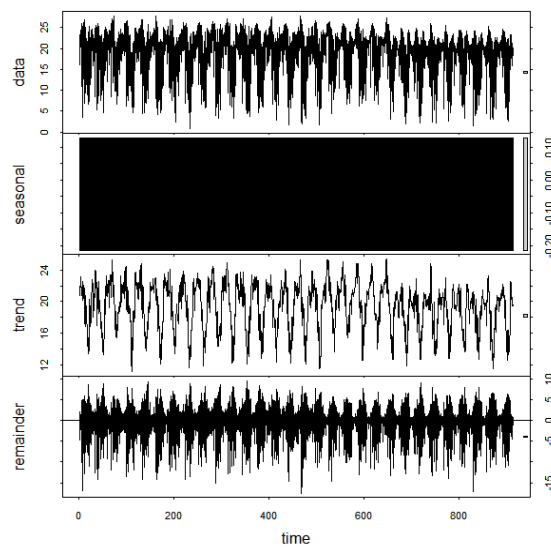
e) Kwara



c) Niger

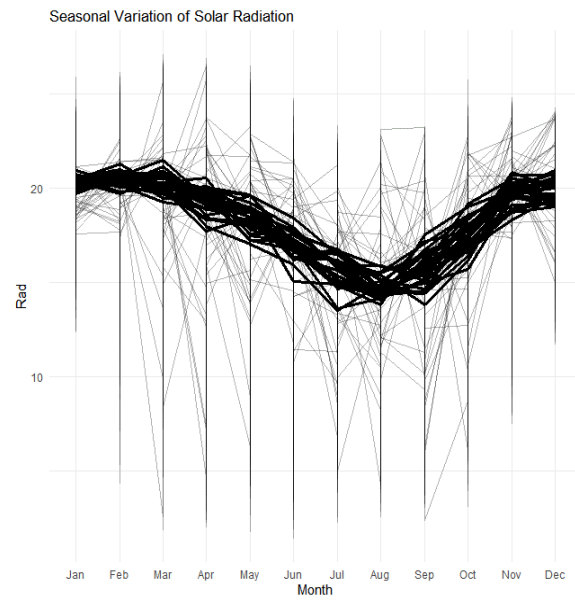
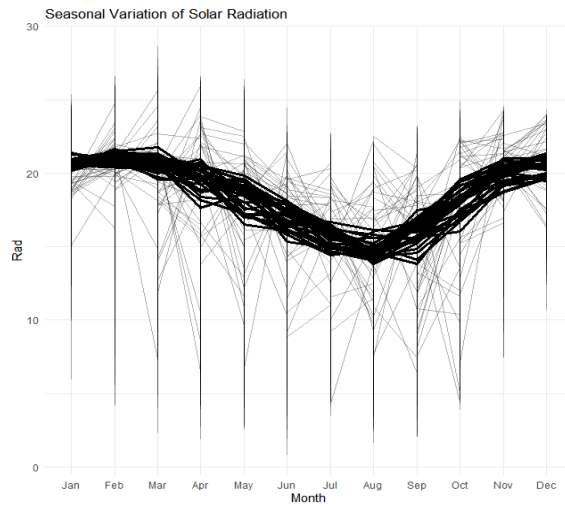


f) Nasarawa

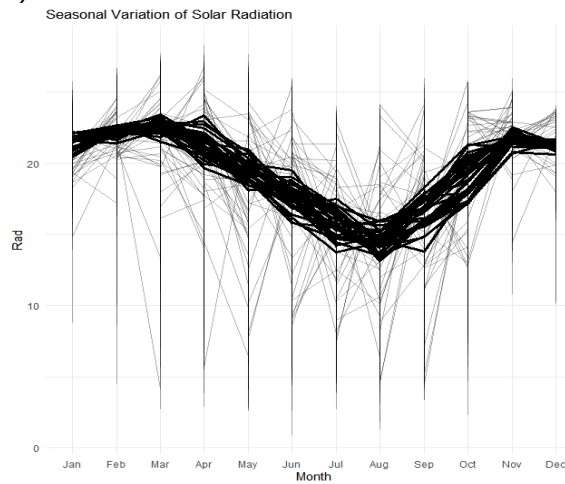


g) FCT

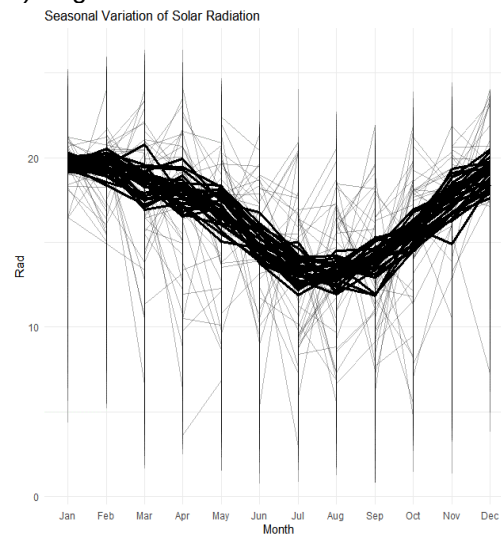
Figure 2. Time-series decomposition of daily solar radiation across Middle Belt states, Nigeria. a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT



a) Benue



d) Kogi



b) Plateau

e) Kwara

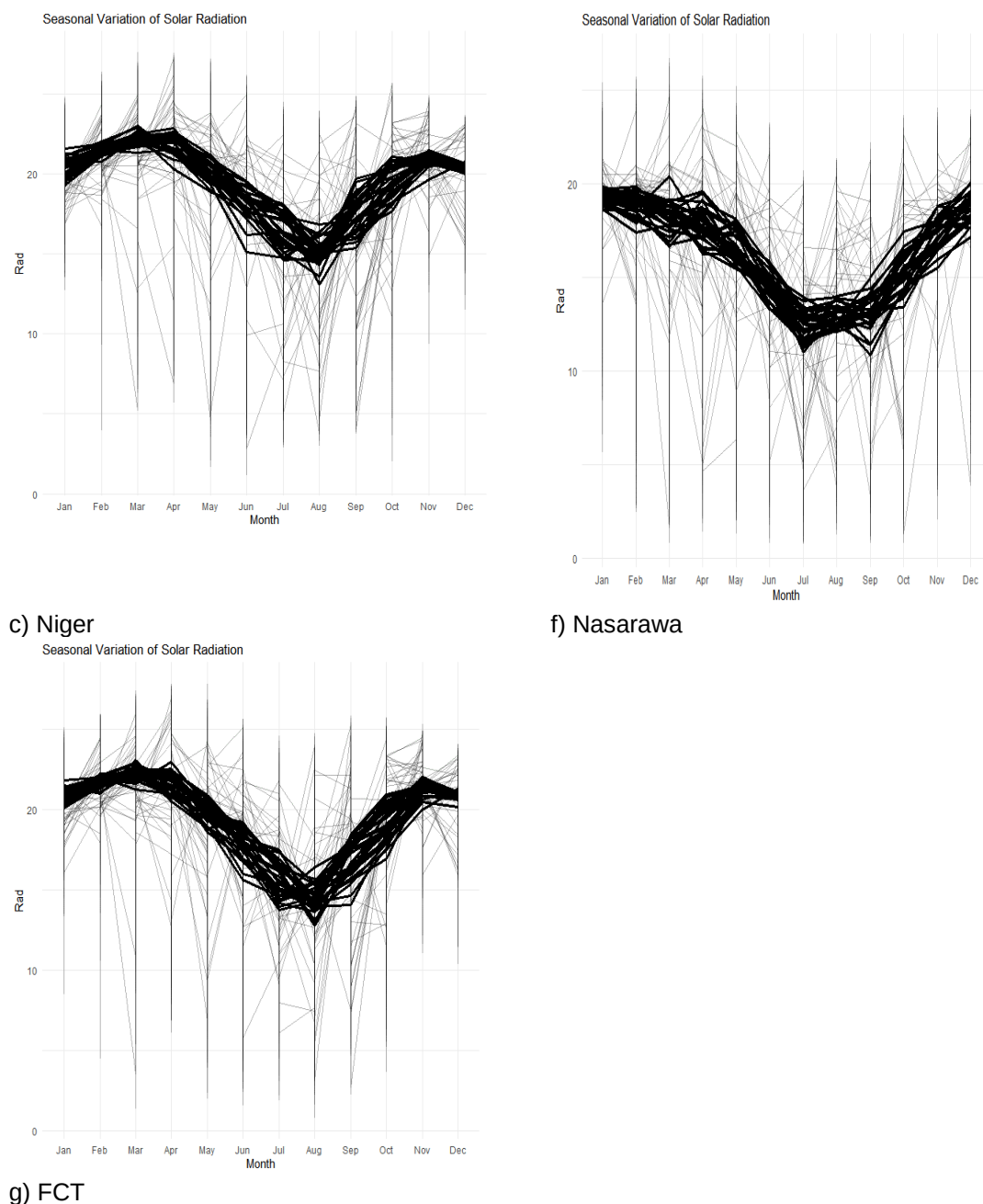


Figure 3. Seasonal variation of solar radiation
a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT

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

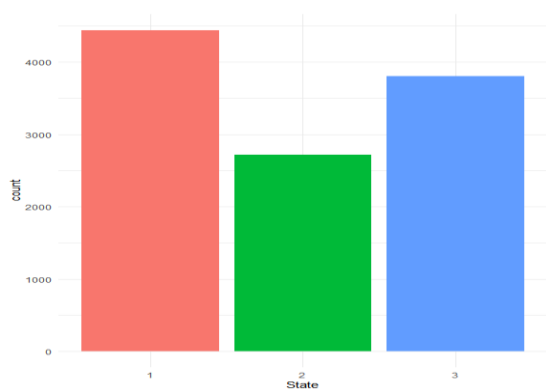
State	Benue	Plateau	Niger	Kogi	Kwara	Nasarawa	FCT
1	15.5	21.2	23.1	15.8	21.3	21.0	23.1
2	22.1	16.6	20.3	19.4	14.0	13.3	16.0
3	19.5	23.7	16.4	21.9	18.6	18.5	20.5

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

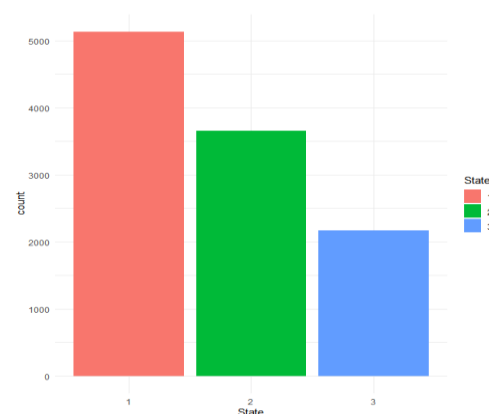
increased electricity generation during these periods [15]. The uneven frequency distribution illustrates how solar radiation systems behave in a stochastic and dynamic manner. From the standpoint of renewable energy planning, the study area's solar power generation may vary considerably over time because 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

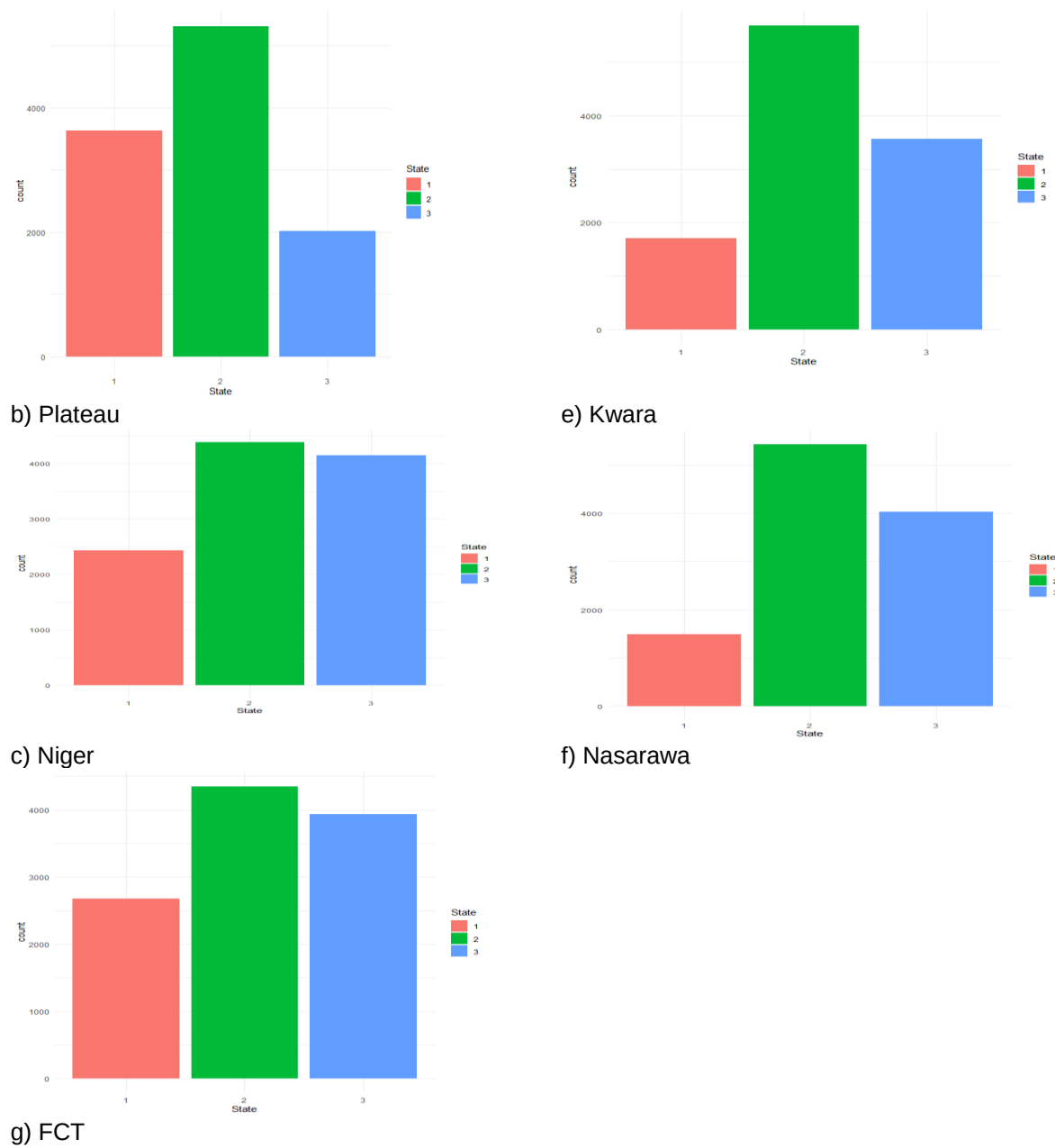
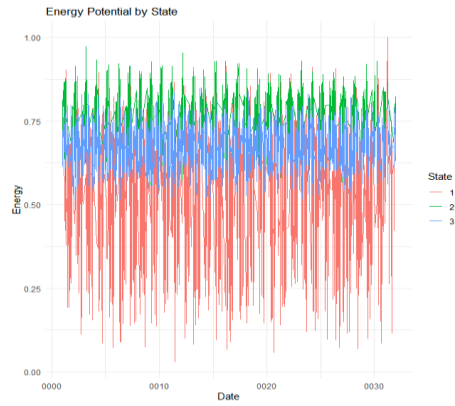
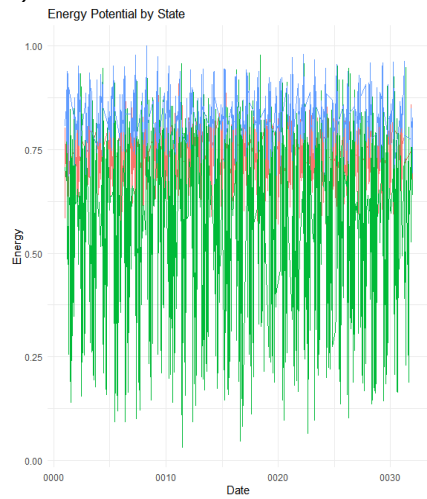


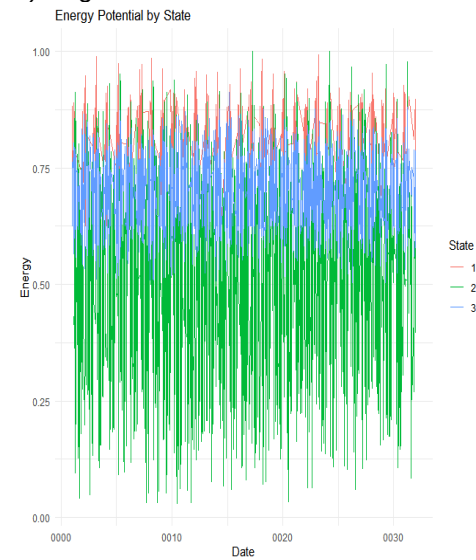
Figure 4. Frequency distribution of the hidden state
a) Benue, b) Plateau, c) Niger, d) Kogi, e) Kwara, f) Nasarawa, g) FCT



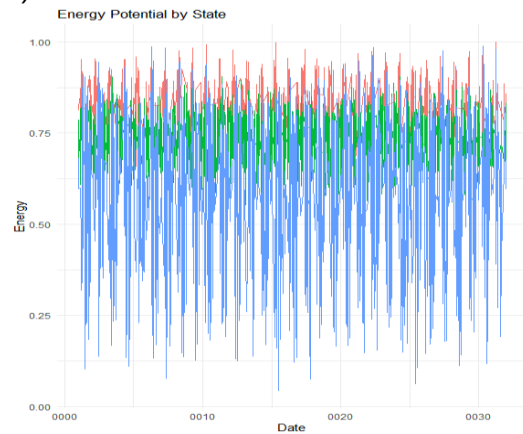
a) Benue



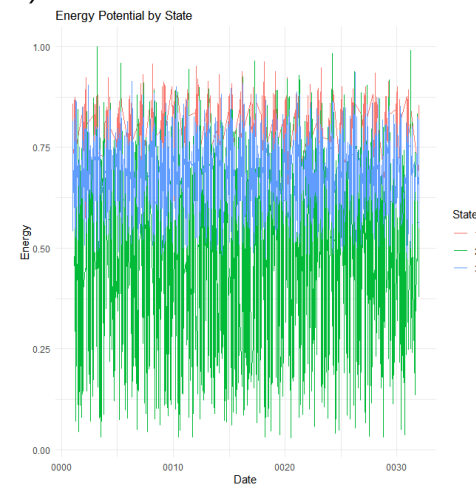
d) Kogi



b) Plateau

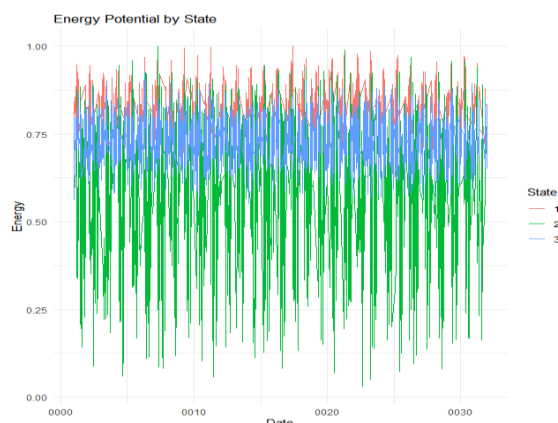


e) Kwara



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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