Optimizing ETo model selection: Spatial insights for climate-smart decision making

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Abstract: This study investigates the performance evaluation of 17 empirical evapotranspiration (ETo) models against the FAO-PM reference using the ERA5 dataset with a 0.1^0x 0.1^0 grid resolution from 1959 to 2022 using two multi-criteria decision analysis (MCDA) methods, VIKOR and MMOORA. The study focuses on spatial performance metrics to assess the suitability of these models across diverse climatic regions in Nigeria. Results reveal substantial spatial variations in model performance. Temperature-based models by Linacre, Ivanor, and Papadakis show stronger performance in the northern region with a KGE value greater than or equal to 0.5 but perform worse across the south. Conversely, radiation-based models exhibit worse performance across all the grid cells, showing the need for adjustments to accurately simulate local evapotranspiration processes. Mass transfer-based models Penman, Mahringer, Trabert, and WMO consistently display promising performance with a KGE value of greater than 0.5, with select models surpassing optimal KGE values across all the grid cells. Through the application of VIKOR and MMOORA, this study emphasizes the significance of spatial performance metrics in accurately selecting the suitability of ETo models for diverse climatic regions, advocating for the VIKOR method's superior efficacy in identifying appropriate models across varied geographical contexts.

Keywords: Spatial Performance, MCDA, VIKOR, MMOORA, Nigeria.

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1 Introduction

Evapotranspiration (ET) is a critical component of the hydrological cycle, representing the combined water loss from the land and plant surface to the atmosphere through evaporation and transpiration processes (Albertson and Kiely, 2001; Van den Hoof et al., 2013). Accurate estimation of ET is crucial for water resource management, irrigation scheduling, drought monitoring, climate change impact assessment, and climate modeling (Akoko et al., 2020; Anderson et al., 2012; Cruz-Blanco et al., 2014; Wanniarachchi and Sarukkalige, 2022). Many empirical ET models have been developed over the years, employing different combinations of meteorological variables to predict ET rates (El-Mahdy et al., 2021; Mattar, 2018; Muhammad et al., 2022). However, selecting the most appropriate model for a specific application can be challenging

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because of their varying performance across different climates, vegetation types, and topographies (Granata, 2019; Guisan and Zimmermann, 2000; Title and Bemmels, 2018). With the diverse climate and water resource challenges in Nigeria and other countries around the globe, selecting the most appropriate empirical ET models becomes difficult for different climatic regions and is very paramount in designing irrigation systems and planning and climate change studies. Empirical ET models provide a simplified approach to estimating ET based on readily available meteorological data, such as temperature, humidity, radiation, and wind speed. These models vary in complexity and data requirements, ranging from simple temperature-based to more complex radiation-based models. The Penman-Monteith (PM) model is widely recognized as the most accurate empirical ET model, but its data requirements can be challenging to fulfill, particularly in regions with limited meteorological data availability (Abdullah and Malek, 2016; Koudahe et al., 2018; Ndulue and Ranjan, 2021). Evapotranspiration is a significant factor in climate modelling, as it influences the energy balance of the Earth's surface and contributes to feedback mechanisms within the climate system (Salam et al., 2020; Valipour, 2015; Valipour et al., 2017; Vinukollu et al., 2011; Xu and Singh, 2005).

Accurate ET estimation is essential for improving climate models and understanding the effects of climate change on regional water resources. To address this challenge, multi-criteria decision-making (MCDM) methods have emerged as valuable tools for ranking ET models based on their performance against multiple criteria. ET models are evaluated based on multiple criteria, such as their accuracy, robustness, and applicability under different conditions. Balancing these criteria can be challenging, as some models may perform well in one aspect but not in others. The performance of ET models can vary significantly across different climatic changes, elevations, and vegetation types. Models that perform well in one region may not be suitable for another. Ranking evapotranspiration models using MCDM methods offers a valuable tool for selecting the most appropriate model for specific water resource management, agriculture, and climate modeling applications.

These methods provide a systematic approach to evaluating ET models based on multiple criteria, considering their performance across different climates and vegetation types. By selecting the most suitable ET model, decision-makers can optimize water resource allocation, improve agricultural practices, and enhance climate modeling capabilities. In this study, 17 empirical ET models were evaluated across four distinct climate zones of Nigeria: the Northern Guinea Savanna, Southern Guinea Savanna, Derived Savanna, and Tropical Forest zones. The VIKOR and MMOORA MCDM methods were employed to rank the models based on their performance in terms of four key statistical metrics: Kling-Gupta efficiency (KGE), Nash-Sutcliffe efficiency (NSE), percentage (PBIAS), and normalized root-mean-square error (NRMSE). The PM model was used as the reference model against which the performance of the other models was compared

. The results of the study revealed that the WMO model exhibited the best overall performance for most of Nigeria, followed by the Penman models. This suggests that the WMO model, with its relatively simple structure and data requirements, can provide a reliable and practical ET estimation tool for a wide range of climate zones in Nigeria. Interestingly, the WMO model's performance was favourable in all the regions of the country that experience distinct dry and wet seasons. The study highlighted the heterogeneous performance of different ET models across the climate zones of Nigeria. The Nigerian climate condition exhibited the most significant variation in model performance, showing that the selection of an appropriate ET model for this region requires careful consideration of local climate conditions and data availability.

The research aims to address a critical gap wherein the mean performance metrics observed across all grid cells do not singularly dictate the decision-making process in model selection. Instead, the spatial performance metrics serve as a more comprehensive indicator, offering an actual percentage-based accuracy of a model's usability within the specified study area. This approach facilitates a framework that understands how models perform across different geographic locations, providing more weighted insights crucial for informed decision-making in climate change processes regarding model suitability and usability within. Moreover, it also provides valuable insights into the selection of empirical ET models for different climate zones. Water resource managers, engineers, and researchers can utilise these results to enhance the accuracy of ET estimation and climate change projection and inform effective water management strategies in various sectors, including agriculture, hydrology, and climate change adaptation.

2 Data and methods

2.1 Study area

2.1.1 Nigeria geography and climate

Nigeria is situated within the tropical zone, with a diverse climate and extensive topography, ranging from lowland coastal plains in the south to plateaus and mountains in the north. The country's total area of 923,768 km^2 (Ayodele et al., 2021; Salubi and Elliott, 2021). The country's topography varies, with lower elevations in the north, higher elevations around the Jos Plateau in the central region and Mambilla plateau in the northeast (ranging from 1,200 to 2,000 meters), and coastal lowlands in the south (Akpensuen and Timothy Namo, 2023; Odunuga and Badru, 2015). Nigeria's temperature varies throughout the year and across different regions. The southern regions experience average temperatures ranging from 25°C to 30°C with hot, humid summers and warm, dry winters (Abatan et al., 2019; Ojeh et al., 2016). The northern regions have lower temperatures, averaging between 20°C to 25°C with milder summers and cooler winters and a maximum temperature of 35°C to 40°C (Animashaun et al., 2023; Ogbonna and Harris, 2008). Nigeria has two primary seasons: a dry season from November to March characterized by minimal rainfall, and a wet season from April to October marked by abundant rainfall (Awhari et al., 2022; Eruola et al., 2021; Ibe and Nymphas, 2010). Nigeria borders with Niger to the north, Chad and Cameroon to the east, and Benin to the west. It has a coastline along the Gulf of Guinea to the south and stretches for approximately 853 kilometers along the Gulf of Guinea (Oloyede et al., 2022; Shiru et al., 2019).

The country experiences tropical weather, with hot and humid summers and warm and dry winters. Rainfall patterns vary significantly across regions, with the highest rainfall occurring in the southern region, averaging between 2,000 and 4,000 mm per year (Ojemade et al., 2019; Ozor et al., 2011). The lowest rainfall is experienced in the northern and northwestern regions, with an average of 250 to 500 mm per year (Eruola et al., 2021; Eze, 2018). Evapotranspiration levels vary based on temperature, humidity, and vegetation cover, with higher potential ET in the north due to high temperatures, while the south experiences high ET supported by high humidity and abundant rainfall. Nigeria is a country with a diverse climate, extensive topography, and a unique geographical location within the tropics. Figure 1 shows a map of Nigeria with elevations at different grid points.

2.2 ERA5 DAILY dataset

The study used the Fifth Generation of ECMWF Atmospheric Reanalyses of the Global Climate (ERA5). The ERA5 represents a global dataset of numerous atmospheric and land variables from 1959 to the present at a high resolution (spatial grid of 0.10; 9 km). It consists of satellite historical observation data with additional existing observatory gauging records and improved numerical prediction models. The daily maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity (*RH*), wind speed (*WS*), surface pressure (*SP*), and solar radiation (*SR*) data, were extracted https://cds.climate.copernicus.eu/cdsapp#!/dataset/rea nalysis-era5-land (accessed on 23 June 2023). Numerous studies have used these data for global (Lian et al., 2018; Song et al., 2023), Malaysia (Makama and Lim, 2020), Iraq (Al-Hasani and Shahid, 2022), India (Purnadurga et al., 2019), Africa (Weerasinghe et al., 2020), West Africa (Adeyeri and Ishola, 2021) and Nigeria (Adeyeri and Ishola, 2021; Ojegbile et al., 2023) to evaluate climate change. Table 1 shows the 17 empirical models used for *ETo* estimation and ranking for Nigeria.

Table 1 List of 17 empirical evapotranspiration models

No.	**Model**	**Inputs**	**Equation**	**References**
			Temperature-based	
1	Linacre	*T*	$ET_0 = \dfrac{\dfrac{700(T \pm 0.006z)}{100-L} + 15(T - T_d)}{80 - T}$	(Linacre, 1977)
2	Kharrufa	*T*	$ET_0 = 0.34pT^{1.3}$	(Kharrufa, 1985)
3	Ahooghalandari-1	*T, RH*	$ET_0 = 0.252\left(\frac{R_a}{\gamma}\right) + 0.221T_{mean}(1 - \frac{RH_{mean}}{100})$	(Ahooghalandari et al., 2016)
4	Ahooghalandari-2	*T, RH*	$ET_0 = 0.29\left(\frac{R_a}{\gamma}\right) + 0.15T_{max}(1 - \frac{RH_{mean}}{100})$	(Ahooghalandari et al., 2016)
5	Ivanov	*T, RH*	$ET_0 = 0.00006(25 + T)^2(100 - RH)$	(Romanenko, 1961)
6	Papadakis	*T, RH*	$ET_0 = 2.5(e_{ma} - e_a)$	(Papadakis, 1965)
			Radiation-based	
7	Abtew	*T, Rs*	$ET_0 = 0.53(\frac{R_s}{\gamma})$	(Abtew, 1996)
8	Makkink	*T, Rs*	$ET_0 = 0.61\left(\frac{T}{T+15}\right)\frac{R_s}{58.5} - 0.12$	(Makkink, 1957)
9	Turc	*T, Rs*	$ET_0 = 0.013\left(\frac{\Delta}{\Delta+\gamma}\right)(R_s + 50)$	(Turc, 1961)
			Mass-transfer-based models	
10	Mahringer	*T, RH, u*	$ET_0 = (0.15072)\sqrt{3.6u}(e_s - e_a)$	(Mahringer, 1970)
11	Penman	*T, RH, u*	$ET_0 = (2.625 + \frac{0.000479}{u})(e_s - e_a)$	(Penman, 1948)
12	Rohwer-2	*T, RH, u*	$ET_0 = (3.3 + 0.891(u))(e_s - e_a)$	(Rohwer, 1931)
13	Szasz	*T, RH, u*	$ET_0 = 0.00536(T + 21)^2(1 - \frac{RH}{100})^{\frac{2}{3}} f(u)$ $f(u) = (0.0519u) + 0.905$	(Szasz, 1973)
14	Trabert	*T, RH, u*	$ET_0 = (0.3075)\sqrt{u}(e_s - e_a)$	(Trabert, 1896)
15	WMO	*RH, u*	$ET_0 = 0.1298 + 0.0934(u))(e_s - e_a)$	(WMO et al., 1966)
16	Albrecht	*T, RH, u*	$ET_0 = 0.1005 + 0.297(u))(e_s - e_a)$	(Albrecht, 1950)
17	Meyer	*T, RH, u*	$ET_0 = (0.375 + 0.05026(u))(e_s - e_a)$	(Meyer, 1926)

NOTE: *ETo* is the reference evapotranspiration (mm day^{-1}), *Rs* is the total solar radiation (MJ m^{-2} day^{-1}), *Ra* is extraterrestrial radiation (MJ m^{-2} day^{-1}), *Rn* is net solar radiation (MJ m^2 day^{-1}), *u* is wind speed at 2 m (m s^{-1}), *RH* is relative humidity (%), T, T_{max}, T_{min} are average, maximum, and minimum air temperature (°C), *TF* is mean air temperature (°F), *Td* is the daily dewpoint air temperature in (°C), *TD* is the difference between the T_{max} and T_{min} (°C), e_{ma} is the saturation vapour pressure at the monthly mean daily maximum temperature (kPa), and e_a and e_s represent actual and saturation vapour pressure (kPa), except for Penman, Papadakis, and Rohwer (kPa). *Rs* is solar radiation in MJ m^{-2} day^{-1}, α is a constant (1.26), *KPEC* is a calibration coefficient (1. 2), p is a constant having two values (0.27 and 0.28), *f(u)* donates a function of wind speed, L is the latitude at each point (degree), z is the elevation (m), λ represents latent heat of evaporation (MJ Kg^{-1}), Δ is the slope of saturation vapor pressure-temperature curve (kPa °C^{-1}), γ is the Psychometric constant (KPa °C^{-1}).

2.3 Statistical metrics indices

The accuracy of the empirical models in estimating observed evapotranspiration on different spatial grids was evaluated using four statistical metrics: normalized root means square error (NRMSE), percent bias (% BIAS), Nash-Sutcliffe efficiency (NSE), and Kling-Gupta efficiency (KGE). NRMSE measures the size of the errors in the modelled data, showing its accuracy. BIAS quantifies the tendency of empirical models to underestimate or overestimate the observed ET_o. A lower NRMSE shows better model performance because it represents less error between the model prediction and the observed data, and Nash-Sutcliffe Efficiency (NSE) values less than 0 show that the model performs worse than simply using the average of the observed data, and higher NSE values closer to 1 indicate better model performance. Table 2 show the performances metrics used evaluating the ET models.

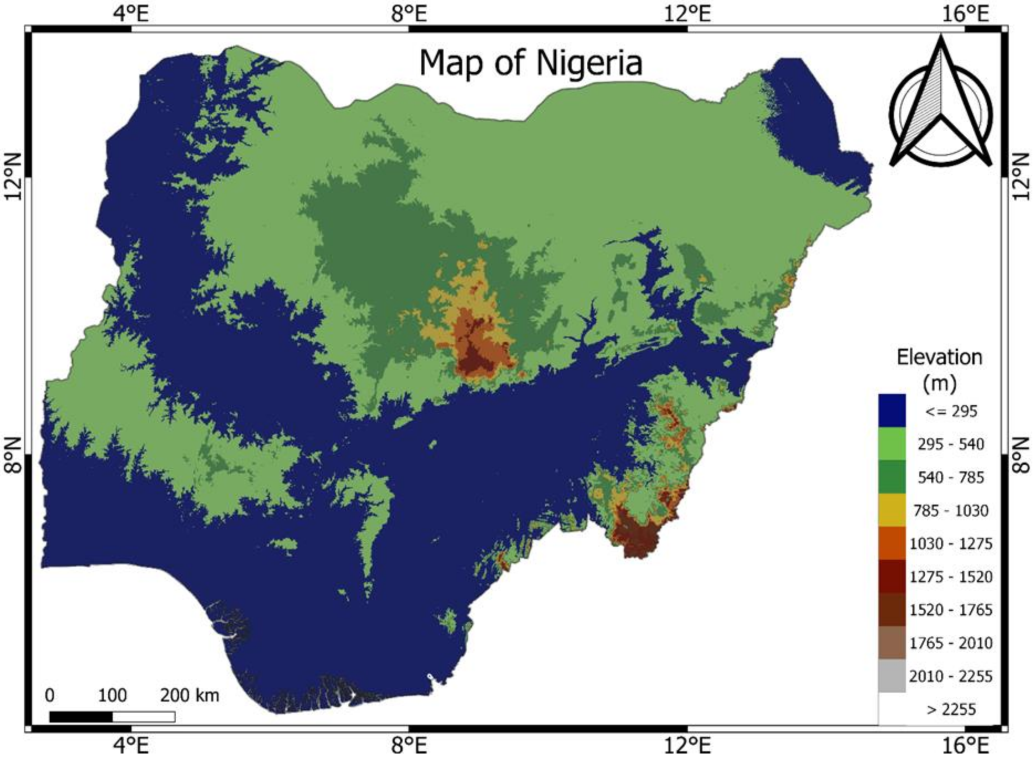

Figure 1 Map of Nigeria elevation

Table 2 Performance evaluation metrics

Performance metrics	Equation	Range	Optimum
Kling-Gupta efficiency (KGE)	$KGE = 1 - \sqrt{(r-1^2) + (\beta-1)^2 + (\gamma-1)^2}$	-∞to 1	1
Nash–sutcliffe efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^{n}(ET_{0m,i} - ET_{0obs,i})^2}{\sum_{i=1}^{n}(ET_{0m,i} - \overline{ET_{0m,\iota}})^2}$	-∞to1*	1*
Percentage bias (PBIAS)	$\%BIAS = 100x\left[\frac{\sum_{i=1}^{n}(ET_{0m,i} - ET_{0obs,i})}{\sum_{i=1}^{n} ET_{0m,i}}\right]$	-∞to∞	0
Normalised root mean square error (NRMSE)	$NRMSE = \frac{\sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}(ET_{0m,i} - ET_{0obs,i})^2\right]}}{\frac{1}{n}\sum_{i=1}^{n} ET_{0m,i}}$	0to +∞	1

2.4 Ranking the ETo models

The study assessed a MCDM approach to comprehensively evaluate evapotranspiration models. We evaluate the individual strengths of both the VIKOR and MMOORA methods, enabling a holistic assessment of model performance. By assessing these established MCDM techniques, the VIKOR and MOORA techniques assign weights to individual models based on their respective rankings. The calculation of each model's weight, as determined by Equation 1, contributed significantly to the computation of the integrated index (I_x). This methodological approach shows the study's commitment to scientific rigour and its dedication to providing a comprehensive understanding of ET model performance.

$$I_x = \sum_{i=1}^{n} \frac{1}{rank}, \quad for\ only\ the\ top\ 10\ rank \quad (1$$

3 Results

3.1 Performance of empirical ETo relative to standard FAO-PM

Figure 2 (a-q) presents density scatter plots of the evapotranspiration estimates obtained from various empirical models against the reference FAO-PM ET_o values for all grid points within the Nigerian climate zone. Among the temperature-based models—Linacre, Ahooghaladari1, Ahooghaladari2, Ivanor, Papadakis, and Kharrufa—the mean KGE values were 0.092, 0.00, -0.10, 0.33, 0.19, and -0.48, respectively, indicating that all these models consistently underestimated the observed reference FAO PM values across the country's climate zones. the radiation-based models—Abtew Makkink and Turc—also exhibited underestimation with mean KGE values of 0.07, 0.10, and 0.07 concerning the observed FAO PM, showing these models performed suboptimal across all climate zones due to variations in solar radiation and air temperature. These plots Figure 2 (k-q) clearly shows that among the mass-transfer-based models, Mahringer, Penman, Trabert, and WMO are the best mass-transfer-based models to estimate the referenced FAO-PM ETo in all climatic zones, with a mean KGE value of 0.74, 0.72, 0.62, and 0.89 exhibiting good performance in approximating the reference FAO-PM ETo across all climatic zones, while Rohwer-2 (0.20), Albrecht (-0.33), Meyer (0.28), and Szas (0.37) underestimate the observed FAO PM, respectively. The model means KGE values, which quantify the overall agreement between modelled and observed ET_o, are remarkably good. These results demonstrate the efficiency of these models in replicating ET_o across the different climatic conditions of Nigeria, as they consistently yield estimates of ET_o that closely match the standard FAO-PM ETo values.

3.2 Temperature-based models

The performance of temperature-based evapotranspiration models varies across Nigeria's climate zones. The Linacre, Ivanor, and Papadakis models exhibit KGE values ranging from 0 to 0.8 in tropical savannah climates in most central regions and Sahelian hot and semi-arid climates in northern Nigeria. However, their performance deteriorates in the southern regions, with KGE values falling below 0. Meanwhile, the Kharrufa and Ahooghaladari2 models consistently underperform across all grid cells, with KGE values below 0.4 shown in Figure 3. Across the northern region of Nigeria, 95% of the grid cells exhibit NSE values ranging from 0 to 0.8. The Kharrufa model is the only exception, consistently underperforming with NSE values below 0.2. In contrast, temperature-based models perform poorly in the southern region, with NSE values exceeding ≥ -0.8. In the northern region, the performance of the empirical models varies; for example, Linacre, Ahooghaadari1, Ahooghaadari2, and Kharrufa exhibit PBIAS values ranging from -20% to 20%, indicating relatively good performance in 58% of the grid cells. However, Ivanor and Papadakis show a wider range of PBIAS values, from 0 to 60%, suggesting less consistent performance. In contrast, all the ET models exhibit PBIAS values greater than or equal to 80% in the entire southern zone of the tropical monsoon climate.

This indicates that the models underestimate ET in this region, with the underestimation increasing towards the south. Across the southern zone, the NRMSE values for all empirical evapotranspiration models are exhibiting NRMSE values less than or equal to 120% with 70% of grid cells. However, in the northern zone, the NRMSE values are more variable, ranging from 20% to 80%. Table 3 shows the mean statistical metrics and performance results for the six temperature-based methods assessed across all grid cells in Nigeria. Upon analysing the table, it becomes evident that none of the models are generally good for evapotranspiration estimation due to their overall underperformance. This suggests that the effectiveness of these models varies spatially, and their optimal performance is likely restricted to specific regions or climate zones within the country.

Table 3 The statistical performance of the twenty temperature models with the FAO P-M model for daily ETo

Temperature based methods					
s/no	Models	KGE (mm day^{-1})	NSE	PBIAS %	NRMSE %
1	Linacre	0.092	-1.99	61.01	125.63
2	Ahooghaladari1	0.00	-2.40	61.51	133.72
3	Ahooghaladari2	-0.10	-3.16	68.14	146.66
4	Ivanor	0.33	-0.22	54.20	99.78
5	Papadakis	0.19	-1.47	73.82	126.91
6	Kharrufa	-0.48	6.66	86.61	195.07

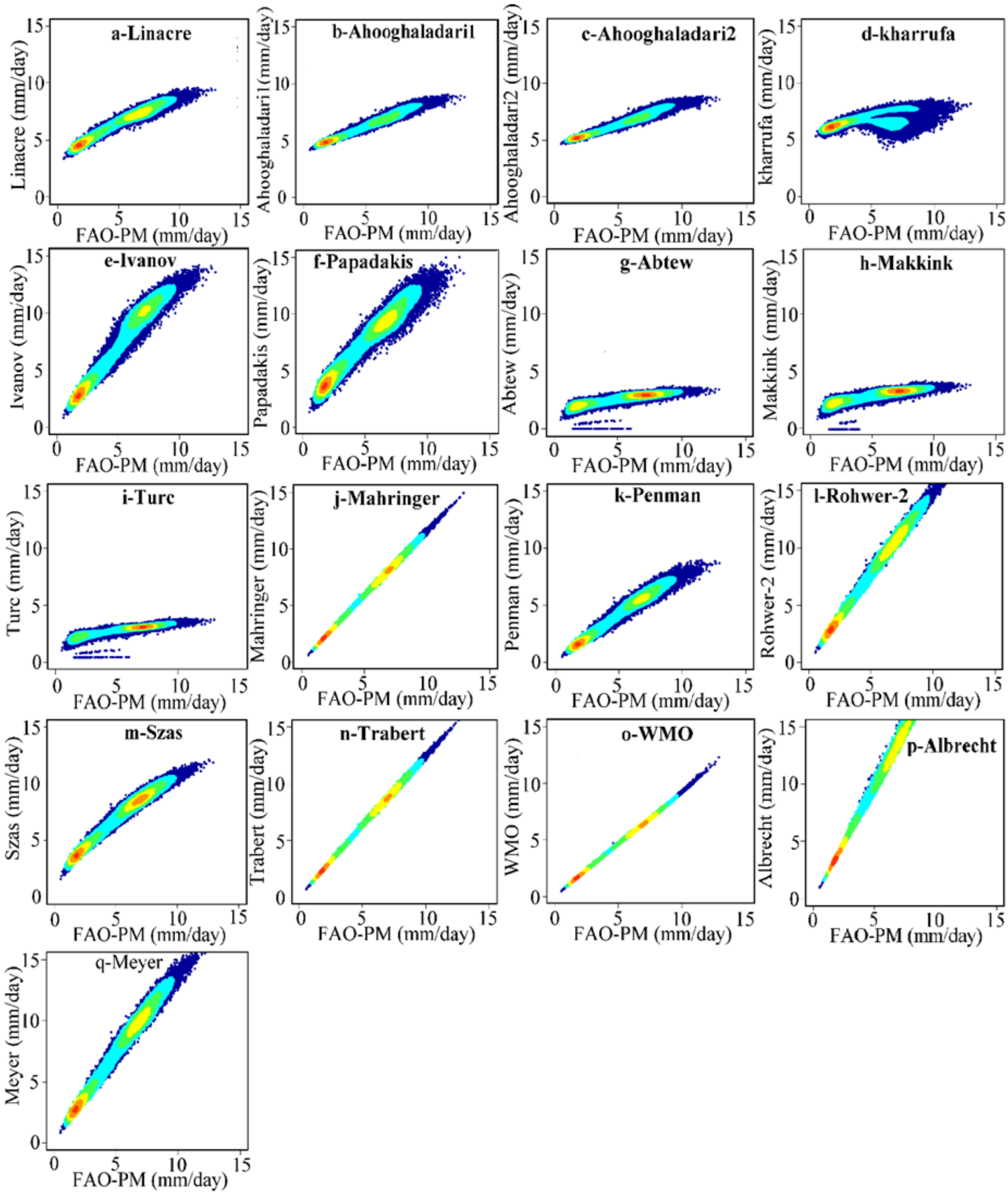

Figure 2 Density scatter plot for 17 models

3.3 Radiation based models

The spatial distribution of the KGE values for the radiation-based models Makkink, Turc, and Abtew exhibits low performance across Nigeria, with KGE values below or equal to 0.4 observed for 97% of the grid points. This shows that all three models underestimate the observed reference FAO PM as shown in figure 4. The performance is poor in the northern part of the country, with KGE values less than or equal to 0.2. The coastal and extreme northern regions also display NSE values less than or equal to -0.8, showing significant underperformance. While the PBIAS values range from 0 to -60% across the grid in most parts of Nigeria, the three models show performance ranging from 0 to 80% within the 25% of the grid cell in the southern zone of the tropical monsoon climate. The NRMSE values for all three models are greater than or equal to 40% across the grid, with values greater than or equal to 100% in the northern zone. This could be attributed to the intricate local variability in Nigeria's diverse climatic zones, including variations in topography, vegetation, and microclimates, posing challenges for these radiation-based models to accurately represent specific regions. Table 3 shows the mean statistical performance of the radiation based on the FAO PM across the country. Table 4 illustrates the mean statistical performance metrics of the radiation-based models concerning the FAO-PM across different regions of the country.

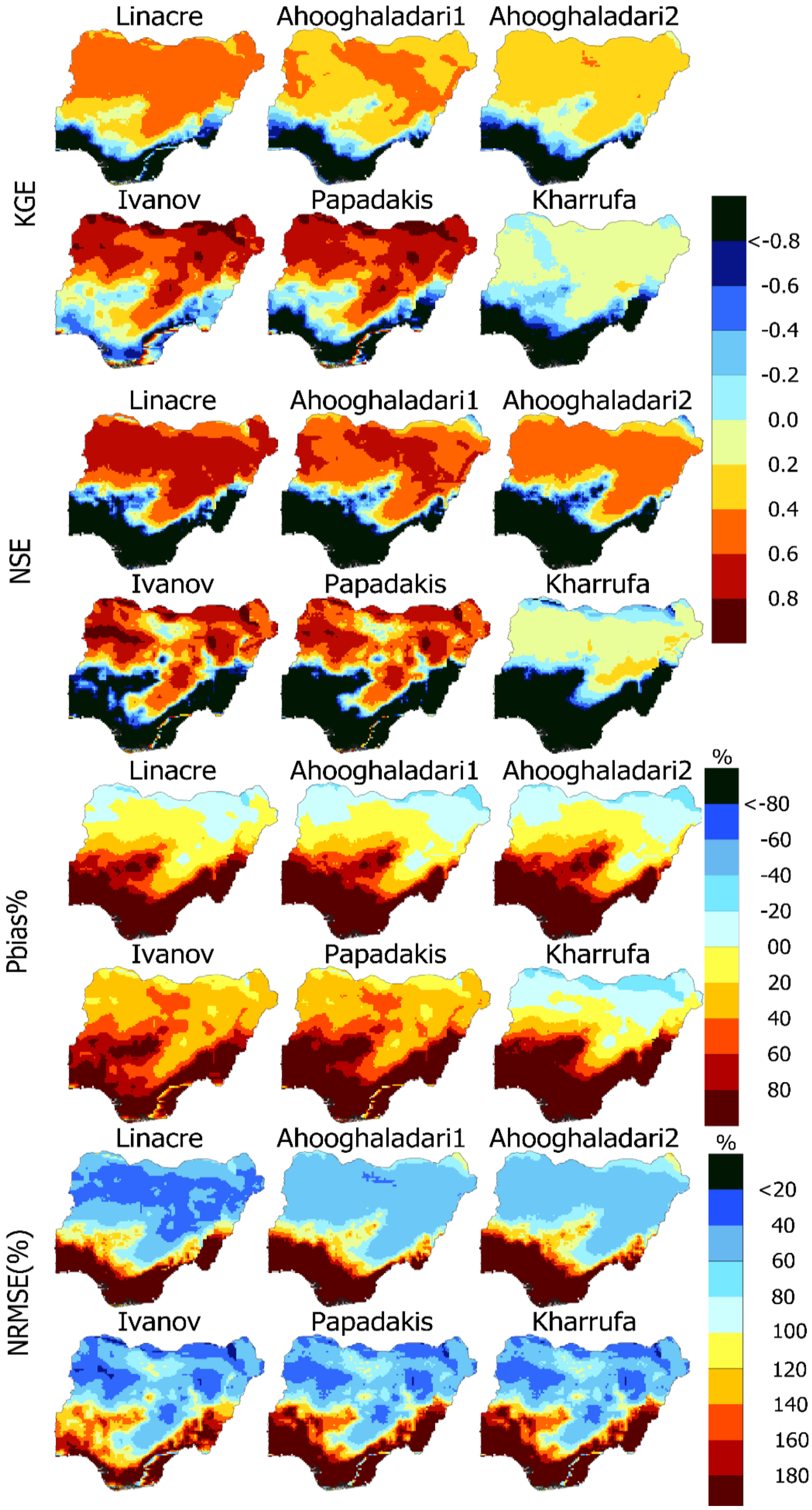

Figure 3 Spatial distribution of performance metrics of Temperature-based model

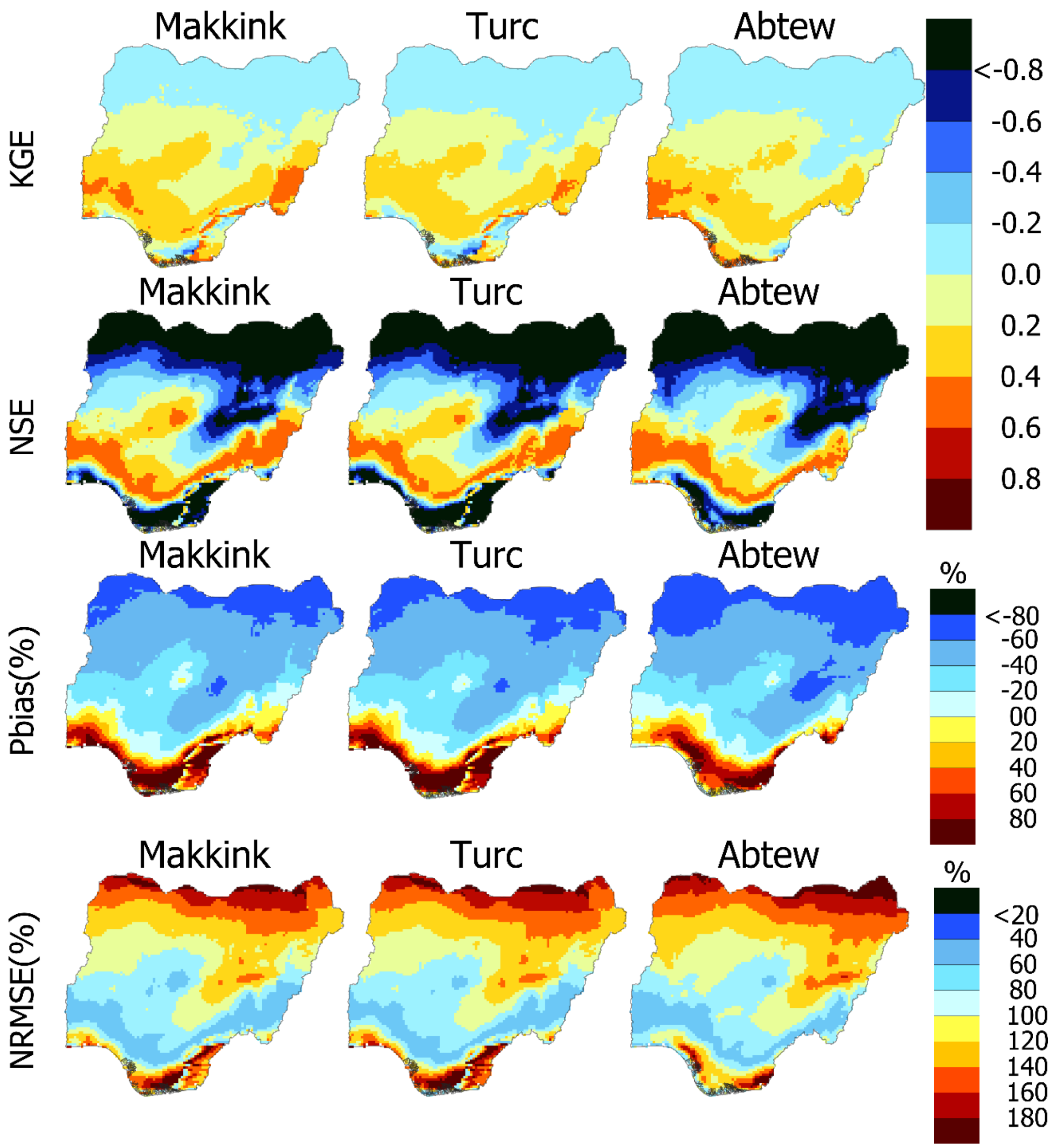

Figure 4 Spatial distribution of performance metrics of radiation based model

Table 4 Statistical performance of the three radiation-based models against the FAO P-M model for daily ETo

Radiation based methods					
s/no	Models	KGE (mm day^{-1})	NSE	PBIAS%	NRMSE%
1	Abtew	0.07	-0.53	-34.41	119.66
2	Makkink	0.10	-0.45	29.03	116.40
3	Turc	0.07	-0.53	-28.27	119.41

3.4 Mass transfer-based empirical models

Figure 5 shows an evaluation of KGE values for various evapotranspiration estimation models across Nigeria, which revealed strong performance across the entire Nigerian climate zone. The Penman, Mahringer, Trabert, and WMO models showed consistently robust performance throughout Nigeria, with KGE values consistently greater than or equal to 0.4. While the Szász and Meyer models exhibited promising performance in the northern region, with KGE values ranging from 0.4 to 0.8, their efficacy deteriorated in the southern regions, yielding KGE values of less than or equal to 0.2. Conversely, the Albrecht models consistently underperformed across all grid cells in Nigeria, with KGE values consistently less than or equal to 0.0. The Penman, Mahringer, Trabert, and WMO models showed consistently NSE values greater than or equal to 0.4 across all the grid cells, while Albrecht had an NSE value less than -0.8. The PBIAS across the grid cell show that the WMO and Penman had values between 20 to -20. This can be shown by the mean values of the performance metrics presented in Table 5.

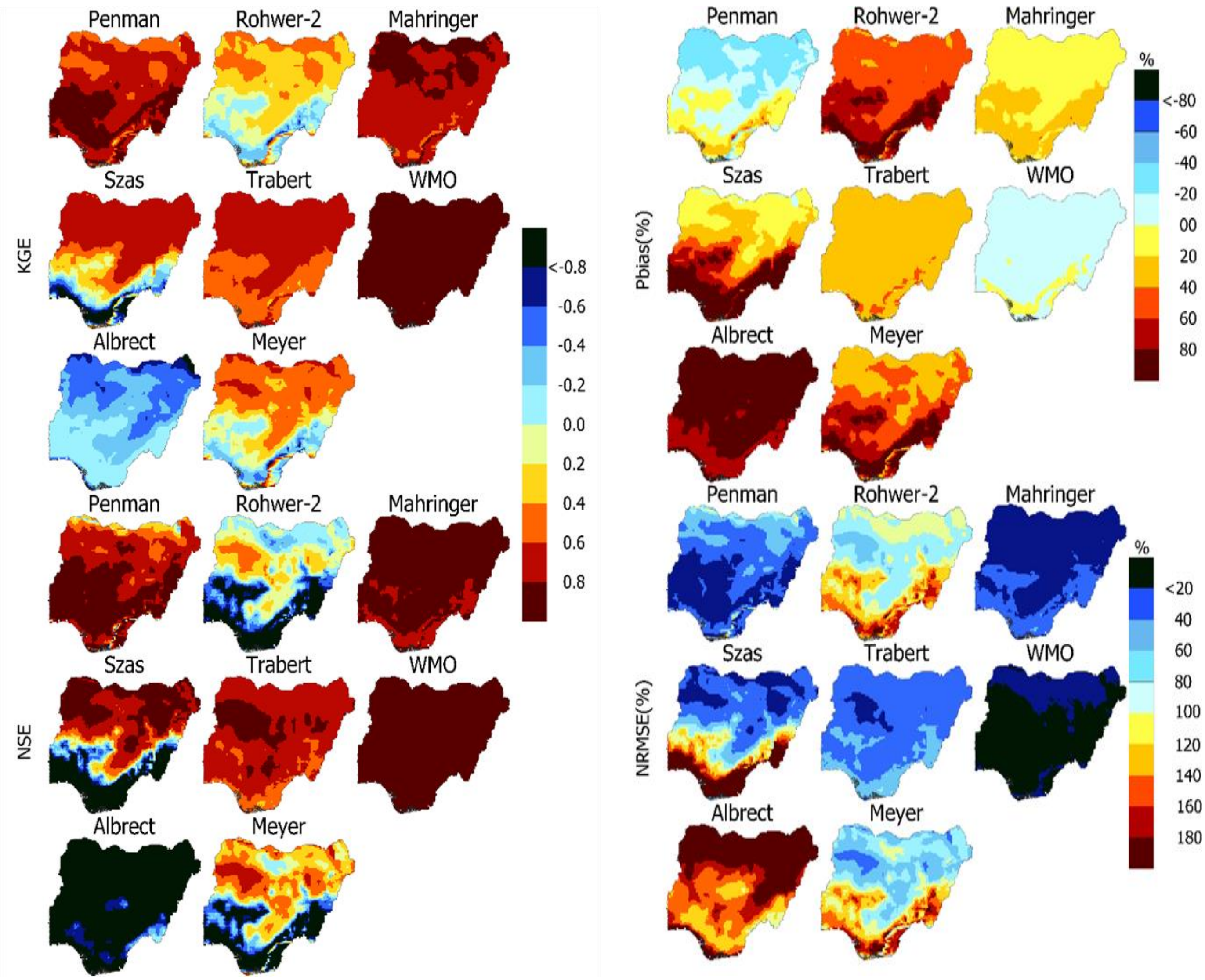

Figure 5 Spatial distribution of performance metrics of mass transfer based model

Table 5 Statistical performance of the Eighth mass-based models against the FAO P-M model for daily ETo

Mass transfer-based methods					
s/no	Models	KGE (mm day^{-1})	NSE	PBIAS%	NRMSE%
1	Mahringer	0.74	0.86	18.96	35.94
2	Penman	0.72	0.74	-10.17	47.83
3	Rohwer-2	0.20	-0.30	59.62	111.30
4	Trabert	0.62	0.71	27.92	52.97
5	WMO	0.89	0.97	6.63	17.27
6	Albrecht	-0.33	-2.49	90.10	181.58
7	Meyer	0.28	-0.14	54.67	101.76
8	Szas	0.37	-0.47	55.16	95.28

3.5 Ranking of empirical models

The spatial distribution of the two Multi-Criteria Decision Analysis (MCDA) methods used for ranking suitability in estimating evapotranspiration (ET) across Nigeria is shown in Figures 6 and 7. Table 5 presents the ranking of individual MCDA methods based on their respective weights across grid cells in Nigeria. Figure 5 and Table 6 illustrate the application of the VIKOR method to determine the top-performing models at each grid point across Nigeria. The data from these figures and tables highlights significant findings and the performance of the empirical models. The temperature-based Linacre model emerged as the most optimal model, covering approximately 65% of all grids and covering the three major climatic zones (ranging from 5 to 9) across Nigeria. Conversely, Ahooghaladari1 covered approximately 30% of grids, predominantly concentrated in the northeast and northwest regions of the country. The radiation based Makkink model secured the top rank, encompassing approximately 15% of grids in the southwest and northeast regions. Similarly, the Abtew radiation-based method held the second position, representing approximately 9% of the southwest region. The mass transfer model WMO was ranked as the overall best model across all climatic zones, achieving a 100% ranking in all grid cells. Penman, as the second mass transfer-based model, performed exceptionally well, securing a 98% ranking across cells in all climatic zones.

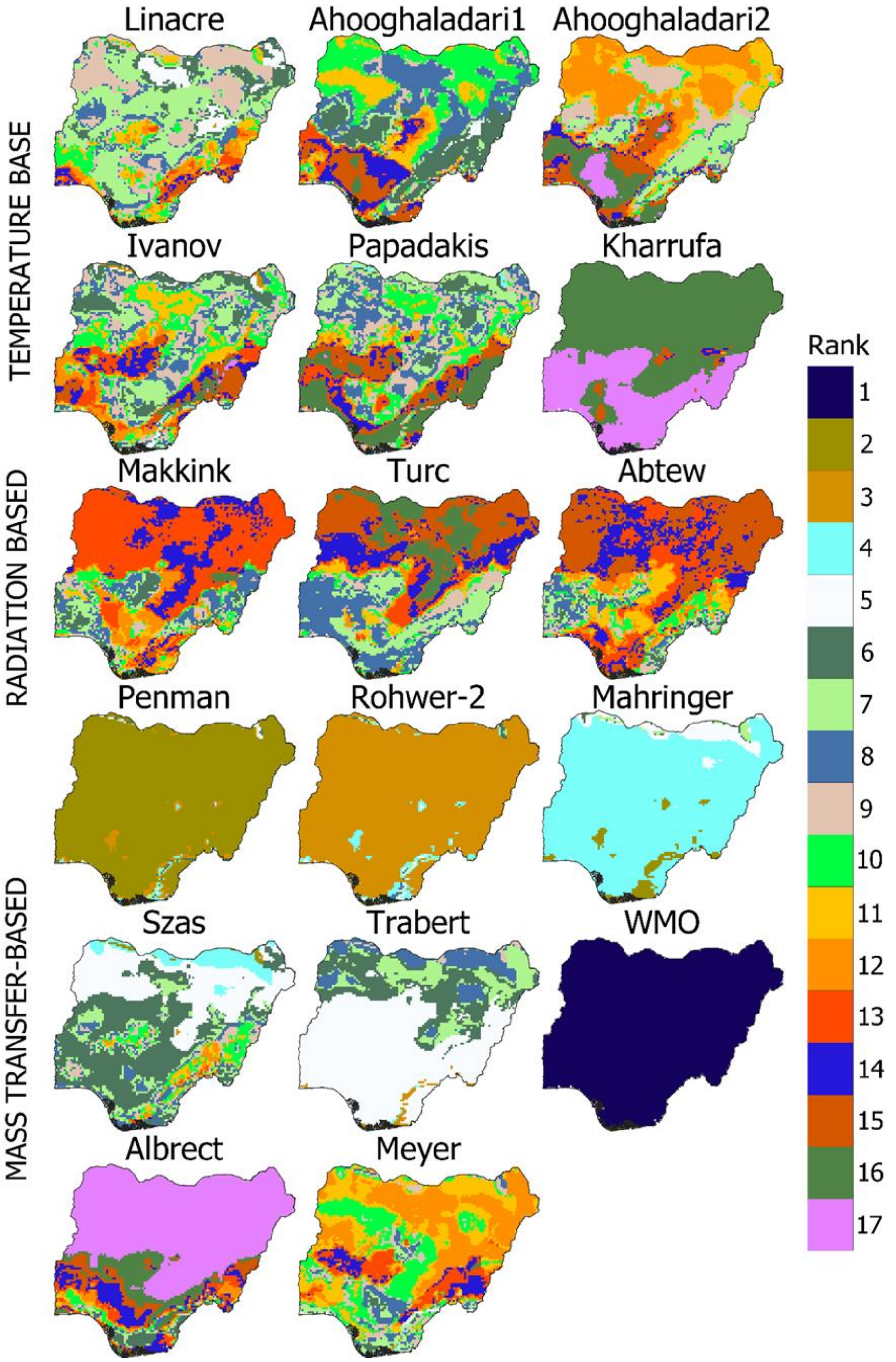

Figure 6 Spatial distribution VIKOR METHODS

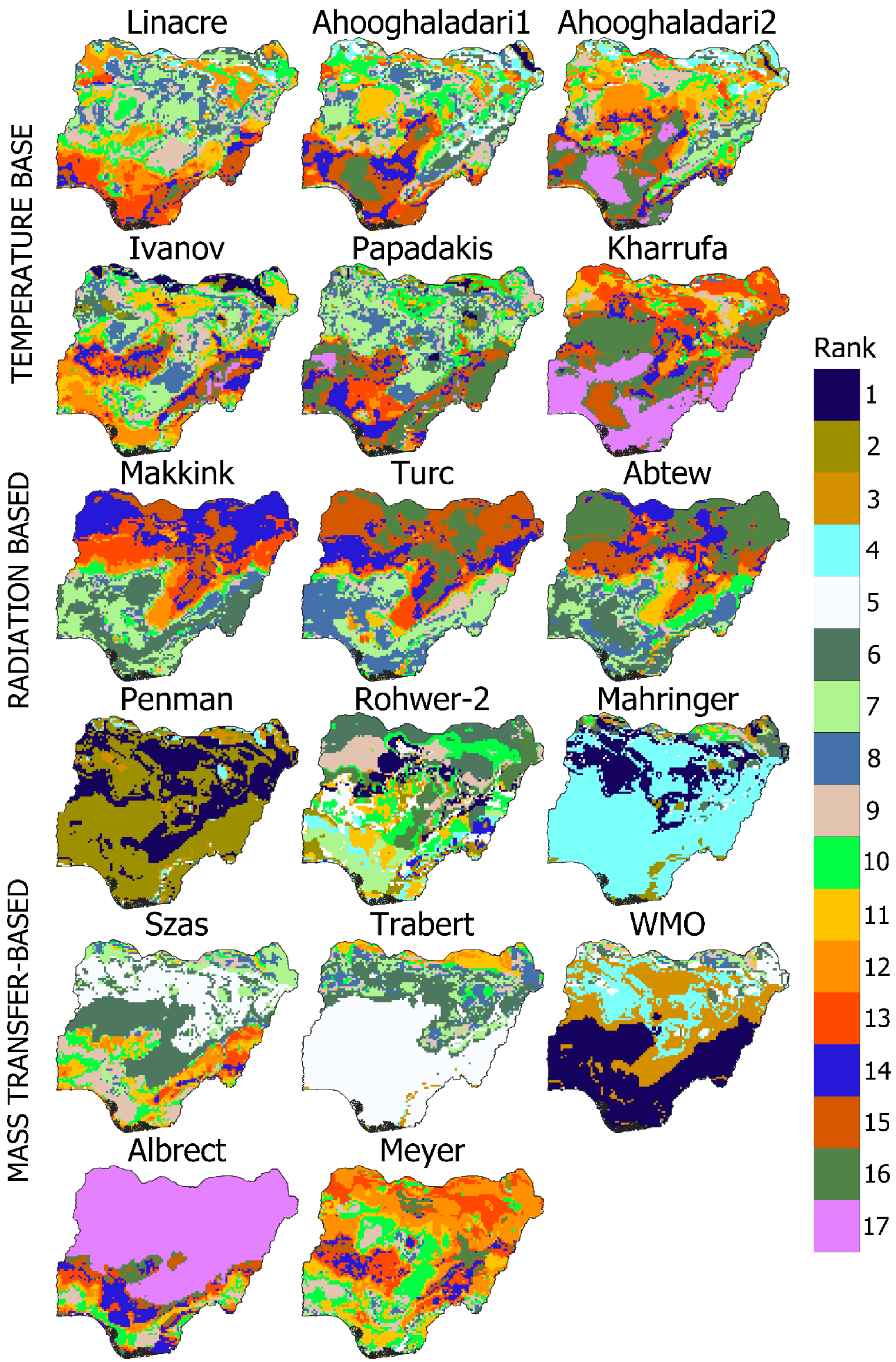

Figure 7 Spatial distribution MMOORA METHODS

Table 5 Ranking of the empirical models for the Nigeria

	VIKOR			MMOORA		Rank
	Model	*Wm*	Rank	Model	*Wm*	
Temperature-based	Linacre	8.43	7	Linacre	9.92	8
	Ahooghaladari1	9.80	8	Ahooghaladari1	9.86	7
	Ahooghaladari2	11.67	12	Ahooghaladari2	11.32	12
	Ivanor	9.86	9	Ivanor	9.97	9
	Papadakis	10.70	10	Papadakis	10.66	10
	Kharrufa	16.28	17	Kharrufa	14.42	16
Radiation-based	Makkink	11.75	13	Makkink	10.80	11
	Turc	12.77	15	Turc	12.04	15
	Abtew	12.72	14	Abtew	11.75	14
Mass transfer-based	Penman	2.10	2	Penman	1.79	1
	Robwer-2	3.10	3	Robwer-2	2.79	2
	Mahringer	4.01	4	Mahringer	3.66	4
	Szas	6.36	6	Szas	7.62	6
	Trabert	5.75	5	Trabert	6.20	5
	WMO	1.00	1	WMO	2.88	3
	Albrecht	15.65	16	Albrecht	15.59	17
	Meyer	10.88	11	Meyer	11.55	13

Figure 7 shows the spatial distribution using the MMOORA MCDA at each grid cell across the Nigerian climatic zone. In the temperature-based model, Ahooghaladari1, Lincare, and Ivanov are the first three base models across the region. The radiation-based methods Makkink, Abtew, and Turc were ranked in the range of 6 to 9, with about 35% in the south and some parts of the northeast. The mass transfer model Penman ranks as the first best model in all the climatic zones (ranks as 1 and 2) in all the grid cells (98%). Robwer-2 is the second mass transfer-based model within the ranked (1, 5, 6, and 9) based on 100% of cells in all climatic zones, and WMO is the third mass transfer-based model within the ranked (1, 3, and 4).

4 Discussion

The conventional practise of selecting empirical models based on mean performance metrics across an entire study area can lead to suboptimal choices, as some models may exhibit strong performance in specific regions despite their average performance across the entire area. This discrepancy is particularly pronounced in areas with complex climatic conditions. While conventional model selection performance criteria such as KGE, NRMSE, NSE, PBIAS, and R^2 provide a general assessment of model performance, they may not accurately reflect the suitability of models across diverse climatic regions. To address this limitation, spatial performance metrics offer a more refined approach to model selection by evaluating model accuracy across the entire country while considering its spatial variability. This approach is relevant given that different models are developed for specific climate conditions and incorporate various input parameters, such as temperature, relative humidity, wind speed, and solar radiation. By analysing the spatial distribution of model performance, we can gain a more comprehensive understanding of model suitability and identify areas where they can be effectively used. This approach can lead to improved model selection and more accurate predictions and development in diverse climatic regions.

This study evaluates a spatial performance evaluation framework to comprehensively assess the efficacy of 17 empirical evapotranspiration models against the FAO-PM reference evapotranspiration estimates. Using established performance metrics KGE, NSE, PBIAS, and NRMSE, across Nigeria's grid cells, the study unveils significant spatial variations in model performance.

Temperature-based models, encompassing Linacre, Ivanor, and Papadakis, demonstrate superior performance in the northern region, attaining KGE values ranging from 0.4 to 0.8. However, their performance decreases in the southern region, with KGE values below 0.2 and PBIAS values exhibiting a range of 20% to -20%. This discrepancy highlights the sensitivity of these models to regional climatic variations. Radiation-based models, encompassing Abtew, Makkink, and Turc, exhibit relatively weaker performance across the nation regarding mean and spatial distribution. This observation suggests that these models may require specific adjustments or modifications to simulate evapotranspiration processes effectively. The mass transfer-based models, including Penman, Mahringer, Trabert, and WMO, showcased spatial distribution values of greater than or equal to 0.4 across all grid cells. Szas and Meyer showed relatively favourable performance in the northern zone, while Albrecht exhibited poorer performance across all grid cells. Notably, Penman, Mahringer, and WMO were the sole models displaying mean optimal KGE values surpassing 0.7, as stated in the table.

This study employed two established multi-criteria decision analysis (MCDA) methods, VIKOR and MMOORA, to comprehensively evaluate the performance of 17 empirical evapotranspiration models using four performance metrics. The performance of the rankings was assessed through statistical metrics. Both MCDA methods consistently show that mass transfer-based models, notably WMO, Penman, and Robwer-2, outperform other model categories. Temperature-based models Linacre, Ahooghaladari1, and Ivanor demonstrate moderate performance, while radiation-based models exhibit less favourable performance. Overall, the study underscores the paramount importance of incorporating spatial performance metrics and ranking procedures when selecting appropriate ETo models for specific regions. The VIKOR method emerges as the superior choice for model selection because of its consistent performance across 98% of grid cells, demonstrating its effectiveness in identifying the most suitable ETo models for diverse climatic conditions and provide closeness to the ideal solution in climate models selection and evapotranspiration (Opricovic and Tzeng, 2004).

5 Conclusion

This study evaluated the performance of seventeen empirical ET models for Nigeria, taking PM ET as the reference. The VIKOR and MMOORA methods were used in this study to rank the seventeen overall empirical models for Nigeria using four statistics. The results show that WMO, Penman, and Rohwer-2 have had better raking and spatial distribution in performance than the temperature-based models Linacre and Ahooghaladari1 in the entire country, demonstrating that VIKOR methods had a better ranking than the MMOORA method. The spatial distribution of model performance metrics further reinforces the notion that the choice of ET model should be tailored to the prevailing climate conditions of the region. By considering local or global climate characteristics, researchers and practitioners can select ET models that are more likely to produce accurate and reliable evapotranspiration estimates. This approach is crucial for various applications, including water resource management and agricultural planning, where accurate evapotranspiration estimates are essential for informed decision-making.

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