# Ranking of Empirical Evapotranspiration Models in Different Climate Zones of Pakistan

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# Abstract

Accurate estimation of evapotranspiration (ET) is vital for water resources development, planning and management, particularly in the present global warming context. A large number of empirical ET models have been developed for estimating ET. The main limitations of this method are that it requires several meteorological variables and an extensive data span to comprehend the ET pattern accurately, which is not available in most developing countries. The efficiency of 30 empirical ET models has been evaluated in this study to rank them for Pakistan to facilitate the selection of suitable models according to the availability of data. Princeton Global Meteorological Forcing daily climate data with a 0.25°×0.25° resolution for 1948–2016 was utilized. The ET estimated using Penman-Monteith (PM) was considered as the reference. Multi-criteria group decision-making (MCGDM) was used for the ranking of the models for Pakistan. The results showed the temperature-based Hamon as the best model for most Pakistan, followed by Hargreaves-Samani and Penman models. Hamon also showed the best performance in terms of different statistical metrics used in the study with a mean bias (PBias) of -50.2%, mean error (ME) of -1.62 mm and correlation coefficient ($R^2$) of 0.65. Ivan showed the best performance among the humidity-based models, Irmak-RS and Ritch among the radiation-based models and Penman among the mass transfer-based models. Northern Pakistan was the most heterogeneous region in the relative performance of different ET models.


# 1. Introduction

Evapotranspiration (ET) plays a vital role in hydrological processes and water resources management, including irrigation scheduling (Shahid 2011), vapour flux modelling (Fisher et al. 2009), surface water runoff modelling (Wigmosta et al. 1994), water balance estimation (Jaber et al. 2016), groundwater recharge estimate (Salem et al. 2017; Salehie et al. 2022c), reservoir management (Ismail et al. 2017), water stress assessment (Mohsenipour et al. 2018) and climate change impact assessment (Shiru et al. 2018; Salehie et al. 2022a, b). ET is responsible for nearly two-thirds of water losses from the earth's surface. The most significant consequence of climate change on many service sectors would from the modification of ET (Hamed et al. 2022a, b). However, the highest impacts of the ET changes would be on agriculture and irrigation. Accurate ET calculation is, therefore, crucial for agricultural water resources development, planning, and management (Ahmed et al. 2018; Hamed et al. 2022c).

Eddy covariance, remote sensing and weighted lysimeter are some of the direct experimental methods used to determine actual ET in addition to more indirect approaches such as catchment water balances, hydrometeorological equations and energy balances (Rana and Katerji 2000). However, the lysimeter estimation of ET is considered the most accurate technique (Gavilán et al., 2006; Tao et al., 2018). Lysimeter records total precipitation received and total soil water lost from a vegetative surface to estimate the actual ET and thus, provides a direct and accurate estimation of actual ET. A defined coefficient based on surrounding landuse is then used to estimate potential ET from actual ET. The major drawback of lysimetric estimation is its cost and complexity. Reliable ET estimation using a lysimeter needs skilled technical persons and a long time (Liou and Kar 2014; Zhang et al. 2016). The major

drawback of the eddy covariance method is its uncertainty. Many remote sensing methods based on eddy covariance have been developed and used for ET estimation in recent years (Ha et al. 2015; Noumonvi et al. 2019). It can provide high spatial and temporal resolution of ET estimates globally. However, the estimated ET is prone to complex nonlinear bias in space and time, which is often very difficult to correct (Muhammad et al. 2021).

The limitations of experimental and remote sensing methods and the increasing availability of weather observation data have led to many empirical ET models. ET relies on the balance of energy in the atmosphere and the amount of water released by plants (Pereira et al. 1997). Therefore, the empirical ET models are classified based on their required inputs. ET has been classified into different groups (Muhammad et al. 2019). However, most literature grouped it into four: (i) temperature, (ii) radiation, (iii) mass transfer, and (iv) combined. Most of these empirical formulations are area-specific as they were developed considering the regional climate and were suitable for implementation in a specific region (Muhammad et al. 2019). Some of them have been developed by modifying the established methods. However, the use of the models depends on their skill in estimating the ET of a region of interest. Only a few empirical formulations have been globally recognized, such as the Penman-Monteith (PM) method (Penman 1948). The main limitations of this method are that it requires several meteorological variables and an extensive data span to comprehend the ET pattern accurately. Furthermore, getting long-term data of multiple climatic factors in most developing countries is difficult (Ahmed et al. 2017a; Nashwan et al. 2019b). The limitations have made the PM method unsuitable for ET estimates in many regions.

A huge number of global research have been undertaken to find the most appropriate ET model (Ali and Shui 2009; Tabari et al. 2013; Bogawski and Bednorz 2014; Hosseinzadeh Talaee et al. 2014; Muniandy et al. 2016; Song et al. 2019; Sobh et al. 2022). Nandagiri and Kovoor, (2006) evaluated the performance of several ET models over different climatic zones of India. They showed that the temperature-based 'Hargreaves method' provides ET estimates close to the PM med in all regions, except the radiation-based 'Truc method' in the humid region. Wei et al., (2019) compared the skills of several eddy covariance ET methods in arid regions and showed that 'Shuttleworth-Wallace' was the best method. Ndulue et al., (2019) assessed the relative skills of 15 solar radiation models in ET estimation at three humid tropical stations. They showed large variability in the performance of different methods in different stations. Singh *et al.*, (2021) compared the performance of five ET models in the northern region of India and found 'Hargreaves' as the best one after PM in the region. Islam and Alam, (2021) revealed that 'Abtew' is the best out of 15 ET models in Bangladesh. Sobh et al., (2022) evaluated the performance of 31 empirical equations compared to PM in arid Egypt and found that 'Ritchie' was the best one.

The performance of these models in a certain place frequently depends on the local climate (Muhammad et al. 2019). Therefore, finding a suitable model based on the availability of data and the performance of the ET estimate model is a challenging endeavour. Such assessment is vital for predominantly arid Pakistan, where the influence of evapotranspiration on the hydrological process and water resources is more significant than in other climatic zones. However, studies related to identifying and ranking ET models according to required climate variables are absent for Pakistan. Only a single study was

conducted by Azhar et al., (2014) to assess the skill of a few models in estimating ET in the Semiarid region of Pakistan. They employed in-situ data of eight locations for this purpose. The results revealed that the 'reduced set PM method' best estimates ET where all variables required for PM are unavailable. The study evaluated only five ET models using observed data of eight locations for only five years (2005–2009). In some cases, ET data based on assumptions or using models were employed as observation, which has limited the acceptability of the results. Habeeb et al., (2021) evaluated the performance of only Hargreaves method and its modified version in estimating ET in Pakistan. They showed the modified version of Hargreaves performs better than its original version in estimating ET in Pakistan.

The performance of 30 empirical ET models has been evaluated in this study to rank them for Pakistan according to required climate variables. The PM ET was considered as the reference in the study. Existing literature suggests that the PM method provides very near to observed ET all over the globe. Therefore, it has been widely used as the reference for performance evaluation of other empirical models where in-situ data for a longer period is not available (Nandagiri and Kovoor 2006a; Islam and Alam 2021; Habeeb et al. 2021). Previous studies used different statistics to assess the performance of ET for their ranking in a region (Muniandy et al. 2016; Muhammad et al. 2019). Statistical metrics often give contradictory results, making the ranking of ET estimation methods challenging (Nashwan and Shahid 2019a; Nashwan et al. 2019b). Therefore, Kling-Gupta Efficiency, an integrated statistical metric, was used to rank ET models in this study.

## 2. Area Description And Data

# 2.1. Pakistan geography and climate

Pakistan is located in South Asia (SA) between latitudes 23°–38° N and longitudes 61°–78° E, with a geographical area of 795,000 $km^2$ that spans from mountains (more than 1000 m high) in the north to flat coasts in the south (Fig. 1). It has a primarily dry climate, with a freezing winter (December to February) and a blistering summer (June to August) (Khan et al. 2021). In between winter and summer, there are two seasons, a warm fall (September to November) and a dry spring (March to May) (Sheikh 2001). The temperatures in the country range from − 15°C in the northern Himalayas to more than 35°C in the southern areas. The precipitation also ranges from less than 125 mm/year in the southwestern region to nearly 1000 mm/year in the north (Yasmeen and Hameed 2018; Iqbal et al. 2019). Given its dry environment, the country receives an annual rainfall of less than 500 mm for the vast majority of its land area, with just a small section exceeding 1000 millimetres (Ahmed et al. 2017b). The annual mean ET ranges from less than 10 mm/year in the north and more than 1900 mm/year in the south (Ahmed et al., 2019a).

Pakistan has five climate zones based on temperature (Fig. 1) (Khan et al. 2019): the hot desert climate in the southwest (Zone I), the southeast and east plains with moderate winter and hot summer (Zone II), the

elevated central region with cold winter and moderate summer (Zone III), cold sub-Himalayan ranges in the north, and a cold mountain climate in the far north.

## 2.2. Princeton Daily Data

The study was accomplished using Princeton Global Meteorological Forcing (PGF) daily maximum temperature ($T_{max}$), minimum temperature ($T_{min}$), relative humidity (RH), wind speed (WS), surface pressure (SP) and solar radiation (SR) data with a spatial resolution of 0.25°×0.25° and temporal extent of 1948–2016 (Sheffield et al. 2006), obtained via http://hydrology.princeton.edu/data/pgf/v3/0.25deg/daily/. The global in-situ datasets are combined with the NCEP/NCAR reanalysis to create the PGF data by the Land Surface Hydrology Research Group of Princeton University. Numerous studies used this data for global (Tian et al. 2022) and regional climate analysis, including in Africa (Nashwan and Shahid 2019b; Nashwan et al. 2019a; Mubialiwo et al. 2020, 2021; Onyutha et al. 2020), Asia (Houmsi et al. 2019; Pour et al. 2019; Khan et al. 2020), Canada (Wong et al. 2021), and USA (Tran et al. 2022). Figure 2 presents the spatial distributions of daily average ET obtained using the Penman-Monteith (PM) method, ranging from nearly 0.4 in the southern coastal zone to 3.7 mm in the western desert. ET decreases gradually to the north and reaches its minimum in the northern Himalayan region.

## 3. Method

# 3.1 Evapotranspiration (ET)

Data of Pakistan's pan ET over a longer period at multiple locations are unavailable. Therefore, this study employed the PM method (Allen et al., 1998) to estimate the ET from meteorological variables. Studies across the globe showed a high correlation between monthly pan evaporation and the PM estimated ET (Hazrat Ali et al. 2000; Ali and Shui 2009; Tukimat et al. 2012; Tabari et al. 2013; Bogawski and Bednorz 2014; Gocic and Trajkovic 2014; Hosseinzadeh Talaee et al. 2014; Djaman et al. 2015; Muhammad et al. 2019; Song et al. 2019). The ET is estimated using the PM equation as below:

$$ET = \frac{0.408\Delta(SR - G) + \gamma \frac{900}{T_{av} + 273} WS(e_s - e_a)}{\Delta + \gamma(1 + 0.34WS)} \quad (1)$$

where $e_s$ indicates vapour pressure, G is the soil heat flux, $\Delta$ is the slope in vapor pressure versus temperature data, $\gamma$ is the latent heat of evaporation, and $T_{av}$ is the mean temperature.

This study evaluated the performance of 30 empirical ET models to rank them for Pakistan according to required climate variables considering PM estimated ET as a reference. The list of the empirical ET models, their class, and the input needed are given in Table 1.

Table 1
List of the empirical ET models used in this study, their class and input requirements

| | No | Model | References | Parameter |
|---|---|---|---|---|
| Temperature-based | 1 | Hamon | (Hamon 1963) | $T$ |
| | 2 | Blaney-Criddle | (Doorenbos and Pruitt 1977) | $T$ |
| | 3 | Linacre | (Linacre 1977) | $T$ |
| | 4 | Kharufa | (Kharrufa 1985) | $T$ |
| | 5 | Hargreaves-Samani | (Hargreaves and Samani 1985) | $T$, $T_{min}$, $T_{max}$, $R_a$ |
| | 6 | Trajkovic | (Trajkovic 2007) | $T$, $T_{min}$, $T_{max}$, $R_a$ |
| | 7 | Ravazzani | (Ravazzani et al. 2012) | $T$, $T_{min}$, $T_{max}$, $R_a$ |
| RH-based | 1 | Ivanov | (Romanenko 1961) | $T$, RH |
| | 2 | Papadakis | (Papadakis 1965) | $T$, RH |
| | 3 | Schendel | (Schendel 1967) | $T$, RH |
| Radiation-based | 1 | Makkink | (Makkink 1957) | $T$, $R_s$ |
| | 2 | Turc | (Turc 1961) | $T$, $R_s$, RH |
| | 3 | Jensen-Haise | (Jensen and Haise 1963) | $T$, $R_s$ |
| | 4 | Priestley-Taylor | (Priestley and Taylor 1972) | $T$, $R_s$, RH |
| | 5 | McGuinness-Bordne | (McGuinness and Bordne 1972) | $T$, $R_s$ |
| | 6 | Caprio | (Caprio 1974) | $T$, $R_s$ |
| | 7 | Ritchie | (Jones and Ritchie 1990) | $T_{min}$, $T_{max}$, $R_s$ |
| | 8 | Abtew | (Abtew 1996) | $T$, $R_s$ |
| | 9 | Irmak-Rs | (Irmak et al. 2003) | $T$, $R_s$ |
| | 10 | Irmak-Rn | (Irmak et al. 2003) | $T$, $R_s$, RH |
| Mass transfer-based | 1 | Dalton | (Dalton 1802) | $T$, RH, $u$ |
| | 2 | Trabert | (Trabert 1896) | |

| No | Model | References | Parameter |
|---|---|---|---|
| 3 | Meyer | (Meyer 1926) | |
| 4 | Rohwer | (Rohwer 1931) | |
| 5 | Penman | (Penman 1948) | |
| 6 | Albrecht | (Albrecht 1950) | |
| 7 | Brockamp-Wenner | (Brockamp and Wenner 1963) | |
| 8 | WMO | (Gangopadhyaya 1966) | |
| 9 | Mahringer | (Mahringer 1970) | |
| 10 | Szasz | (Szász 1973) | |

(Note: T: $T_{min}$: minimum temperature (°C), mean temperature (°C), $T_{max}$: maximum temperature (°C), $R_a$: extraterrestrial radiation (MJ/m$^2$/day), $R_s$: solar radiation (MJ/m$^2$/day), $e_s$ is the saturation vapor pressure (hPa), RH: relative humidity (%), u: wind speed at 2 m (m/s)).

# 3.2 Performance evaluation

The KGE was used to evaluate the performance of the 30 ET models at each PGF grid location. The KGE provides an integrated measurement of correlation, bias, and variability (Gupta et al. 2009),

$$KGE = 1 - \sqrt{(r-1)^2 + \left(1 - \frac{\mu_s}{\mu_o}\right)^2 + \left(\frac{\sigma_s/\mu_s}{\sigma_o/\mu_o}\right)^2} \quad (2)$$

where $r$ is Pearson's correlation; $\mu$and $\sigma$represent the mean and standard deviation of the each empirical equation and PM equation as a reference, respectively. The KGE ranges from -∞ to an optimal value of 1. The overall ranking of different ET models over Pakistan was also evaluated using different statistical metrics, including Mean Bias Error (MBE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the coefficient of determination (R2) Nash–Sutcliffe Efficiency coefficient (NSE), Percent Bias (PBIAS), and coefficient of agreement (md), as defined below:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}|S_i - O_i| \tag{3}$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2\right]^{0.5} \tag{4}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(O_i - \bar{O})\,(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\,\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}}\right)^2 \tag{5}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{6}$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(O_i - S_i) * 100}{\sum_{i=1}^{n} O_i}\right] \tag{7}$$

where $O_i$ is the PM ET, $S_i$ is the ET estimated using empirical equations; *n* represents the number of grids, $\bar{O}$ and $\bar{S}$ are the mean ET estimated using PM and empirical equations, respectively.

## 3.3 Multi-criteria group decision-making (MCGDM)

To rank the model for the whole of Pakistan, an MCGDM was implemented. For this purpose, each model is provided with a weight based on the rank achieved by the model at different grid points (n) to calculate an integrated index ($I_x$). The weight of an equation was set as an inverse of the rank. It provides the best model with a weight of 1 (1/1 = 1), the second-best model with a weight of 0.5 (1/2 = 0.5), and the third-best model with a weight of 0.33 (1/3 = 0.33), and so on. The integrated index of a model is estimated as,

$$I_x = \sum_{i=1}^{n}\frac{1}{rank}, for\ the\ top\ 10\ ranks\ only \tag{8}$$

In this process, the model obtained a rank of 10 or higher at a grid point was only considered. Otherwise, it is considered incapable of estimating ET at the grid point and, thus, assigned a zero weight. The $I_x$ value of different models was used to provide a final ranking of the models. A model with higher $I_x$ indicates its better performance in estimating ET for the whole of Pakistan.

# 4. Results

## 4.1. Ranking of ET equations

The ET was estimated using empirical equations in each grid of Pakistan. Estimated ET using different equations (Table 1) was compared with the PM ET using KGE. The ET models were then ranked from 1 to 30 at each grid point based on KGE. Figure 3 shows the top three ET models at each grid point over Pakistan. More than 60% of the grids, mostly located in the middle and south, showed the temperature-based Hamon as the best model, while in the southwest and upper-middle region, mass transfer-based Penman was ranked as the best. Radiation-based Irmak-Rs, Caprio and McGuinness and temperature-based Hargreaves and Kharrufa were ranked first at a few grids in the north, east and southwest regions. Hargreaves was ranked as the 2nd best model at more than 50% of the girds, followed by Penman and Hamon. The Kharrufa was ranked 3rd in many grids in the south region, followed by Penman and Hargreaves.

The present study also individually ranked the temperature, radiation, mass transfer, and combined models for Pakistan to reveal the best models in each category. Figure 4 shows the top three temperature-based ET models at each grid point over Pakistan. Hamon was ranked first in more than 80% of the grids. However, Hargreaves showed the best performance in the east and Kharrufa in the north and southeast regions. The Hargreaves was ranked 2nd in the middle and south, Hamon in the east, while the remaining four temperature-based equations showed better performance in the north. The Kharrufa was ranked 3rd in all regions, except in the east and north, where none of the temperature models showed dominating performance over the whole region.

The performance of three relative humidity-based equations considered in this study is shown in Fig. 5. The Ivanov model showed the best performance at more than 60% of the grids. The Papadakis model showed the best performance in the rest of the grids. However, Ivanov was ranked as the second-best at the grids where the Papadakis was ranked first. In the north, Schendel was ranked as the second-best equation.

The performance of ten radiation-based equations considered in this study is shown in Fig. 6. The McGuinness-Bordne and Caprio models were ranked first in the north, while the Irmak-Rs model was the best in the middle and the Ritchie in the south. The Irmak-Rs was the 2nd best model in the south and the Ritchie in the middle. The Jensen-Haise was the 3rd best model in the north, east and south, while Caprio in the middle and southeast.

Among the mass transfer-based equations, Penman was ranked first over the whole of Pakistan, except at some grids in the north, where WMO was the best equation (Fig. 7). The Szasz was ranked as the 2nd best model in the central and south, while Penman and WMO in the north and east. WMO was ranked as the 3rd best model over most of Pakistan, except the Mahringer in the north, Mayer in the south coastline, and Szasz in the east.

## 4.2 Ranking for the whole of Pakistan

The top three ET models identified by MCGDM suitable for estimating ET for the whole of Pakistan are given in Table 2. The results showed that the Hamon model was ranked first among all ET models considered in this study, with an $I_x$ of 1027.12. Penman ranked second ($I_x$=599.71), followed by HS ($I_x$=528.04). The results indicate a much higher performance of Hamon than other models in terms of $I_x$. Among the RH models, Ivan performed best ($I_x$=147.03), followed by Papa ($I_x$=99.06) and Schen ($I_x$=21.12). In the case of Radiation-based models, IrmakRS performed best ($I_x$=223.72), followed by Capr ($I_x$=129.00) and McGui ($I_x$=84.45). Among the Mass transfer-based equations, Penman performed the best ($I_x$=599.71), followed by Szas ($I_x$=195.69) and WMO ($I_x$=122.72). Overall, the temperature-based model's ranking was much higher than other categories of models. Mass transfer-based models performed better than RH and radiation-based models. The worst performance was shown by RH-based models.

Table 2
Ranking of different categories of ET model for the whole of Pakistan using multi-criteria group decision-making method

| | **1st** | **2nd** | **3rd** |
|---|---|---|---|
| | All equations rank | | |
| Model name | Hamon | Penman | HS |
| MCGDM Index | 1027.12 | 599.71 | 528.04 |
| | Temperature-based equations rank | | |
| Model name | Hamon | HS | Kharu |
| MCGDM Index | 1027.12 | 528.04 | 349.59 |
| | RH-based equations rank | | |
| Model name | Ivan | Papa | Schen |
| MCGDM Index | 147.03 | 99.06 | 21.12 |
| | Radiation-based equations rank | | |
| Model name | IrmakRS | Capr | McGui |
| MCGDM Index | 223.72 | 129.00 | 84.45 |
| | Mass transfer-based equations rank | | |
| Model name | Penman | Szas | WMO |
| MCGDM Index | 599.71 | 195.69 | 112.72 |

## 4.3 Validation of ranking

The ranking of different models to replicate reference ET based on various statistical indices is presented in Fig. 8. The highest rank is presented using the light orange color, while the worst using dark brown in the figure. The intention was to show the capability of the best-ranked model obtained in this study in terms of different statistics. Different indices rank the ET models differently. However, Hamon was the best, followed by Penman, in almost all indices. Priestley-Taylor and Irmak-Rn showed the worst performance in all indices.

## 4.4 Spatial bias in top-ranked models

The spatial distribution of PBIAS, ME and correlation of the top-ranked (Hamon, Penman and HS) is presented in Fig. 9. The intention was to show the error in estimated ET by the models in different regions of Pakistan. The PBIAS of all the models ranged from − 15 to -100, indicating underestimation of ET by all models. The underestimation was more in the north cold region (up to -90%). Overall, Hamon showed the least PBIAS. It was near zero in the west and less than − 50% in most Pakistan. The mean error (ME) in Hamon estimated ET was less than − 4 mm for the whole of Pakistan. The error was nearly zero over a large area in the west. It was high (-3 to -4 mm) only over a small area in the central west. The results indicate that Hamon can estimate ET in most parts of Pakistan with a mean error of less than − 3 mm. The correlation between ET estimated by the top three models and the PM model was above 0.5 for almost all of Pakistan, except in the far north. It should be noted that the correlation coefficient higher than 0.06 is statistically significant at $p < 0.05$ for 69 years of monthly data (828 months). The results indicate the selected models can estimate ET in Pakistan with less bias and high correlation.

# 5. Discussion

The purpose of this research is to evaluate the suitability of various ET models in Pakistan. Numerous studies have been undertaken to assess the ET model's performance in various regions of the world (Nandagiri and Kovoor 2006b; Niaghi et al. 2013; Azhar et al. 2014; Djaman et al. 2015; Hu et al. 2019). Different indices have been used for this purpose. The studies showed different ET models as the best in terms of different statistics (Niaghi et al. 2013). The present study also showed different performances of ET models in terms of different statistical metrics (Fig. 8). This study used an integrated statistical metric, KGE, to assess the performance of ET models at each grid point to avoid contradictory results obtained using different statistical metrics. Making a decision based on different rankings of models at different grid points is a difficult task. This study proposed an MCGDA approach to overcome this drawback. Therefore, it is expected that the rankings obtained in this study are reliable. This is also proved by the performance of the models in terms of an array of statistical metrics. Therefore, it can be remarked without any doubt that Hamon is the best model for estimating ET in Pakistan after the PM method.

Assessment of ET performance revealed different models as the best in reproducing the observed or PM ET. For example, Nandagiri and Kovoor (2006) compared seven commonly used ET equations and

showed Hargreaves as the best at four stations in India. Trajkovic and Kolakovic (2009) evaluated the performance of five ET models in the humid Balkan region and showed the Turc model to perform the best. Similarly, Peng et al., (2017) showed Berti as the best model in mainland China. Niaghi et al., (2013) showed Penman as the closest to PM model in some locations of Iran. The ET models' performance assessment studies are very limited in Pakistan. As reviewed in the Introduction section, the previous studies showed the analysis of only a few ET models at a few stations in the semiarid region of Pakistan. This is the first attempt to evaluate the ET model over Pakistan using robust methods. The study revealed the better performance of temperature-based models in Pakistan. It also established temperature-based Hamon model as the best model for estimating ET in Pakistan.

Shirmohammadi-Aliakbarkhani and Saberali, (2020) evaluated the skill of several ET models at 13 locations in Iran, bordering Pakistan in the east. They also showed better performance of temperature-based models than others. Aparecido et al., (2020) evaluated the performance of 19 ET models in Midwest Brazil and showed better performance of temperature-based models than others. Paparrizos et al., (2017) revealed that temperature-based models are more reliable in estimating ET in different regions of Greece.

Several studies reported Hamon is most reliable in estimating ET in different regions (Federer et al. 1996rösmarty et al. 1998; Lu et al. 2005). Federer et al., (1996) evaluated different ET models globally and reported Hamon as the best for a wide range of climates. Vörösmarty et al., (1998) also evaluated eleven ET methods for a diverse range of climates in the US and showed Haman as the most reliable. Shirmohammadi-Aliakbarkhani and Saberali, (2020) also ranked Hamon as one of the best models for estimating ET in Iran. Askar *et al*., (2015) evaluated seven ET models in peninsular Malaysia and showed Hamon as the most sensitive model. Paparrizos et al., (2017) showed different versions of Hamon as the best model for estimating in different climates of Greece. Singh et al., (2021b) showed the efficiency of Hamon in estimating ET from satellite data in agricultural regions of India. Ansorge and Beran (2019) compared the performance of several temperature-based ET models with observed pan evaporation data and showed higher correlation and least error in Homon estimated ET. However, several studies also showed very poor performance of Hamon (Santos et al. 2017; Zhao et al. 2021). This indicates the need for performance evaluation of ET before their use in an area.

Though Hamon provides the best estimation of ET in Pakistan, it underestimated ET all over the country, except in the far west. McCabe et al., (2015) also showed underestimation of ET using the Hamon method all over the United States, except in the country's southwest. They proposed calibration of the Hamon model for the region of interest to enhance the model performance. This can be recommended as future work.

# 6. Conclusion

This study assessed the performance of 30 empirical ET models for Pakistan, considering PM estimated ET as the reference. The intention was to rank them according to their performance to allow users to

select the most suitable model according to data availability. The PGF daily climate data for 1948–2016 was used for this purpose. The study revealed Hamon as the best model for most of Pakistan, followed by Hargreaves-Samani and Penman models. Hamon uses only mean temperature for the estimation of ET. Therefore, it can be used for a reliable estimate of ET over most of Pakistan using only temperature data. All global climate models simulate temperature for different climate change scenarios. Those simulated data could be used for reliable projection of ET of Pakistan using the Hamon model. However, it should be noted that Hamon estimated ET is prone to an average − 50.2% bias which also varies spatially. Therefore, estimated ET using the Hamon model should be used for practice with caution. The estimated bias in the Hamon and other models presented in this study can be utilized for bias correction of ET before its application. This study considered 30 empirical daily ET estimation models. In the future, more ET models can be considered for performance evaluation, particularly the monthly ET models like Thornwaite, which are widely used for drought estimation.

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### Conflict of interest

The authors declare no conflict of interest.

### Availability of data:

All the data are available in the public domain at the links provided in the texts.

### Availability of code

The codes used for the processing of data can be provided on request to the corresponding author.

### Authors contribution

M.M.H. and N.K. contributed to formal analysis, investigation, methodology, and writing of the original draft. M.M.H., M.K.I.M. and S.S. was involved in data curation, investigation, and resources. M.K.I.M. and S.S. contributed to review and editing. N.K. and S.S. was involved in conceptualization, review, and editing. All authors read and approved the final manuscript.

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# Figures

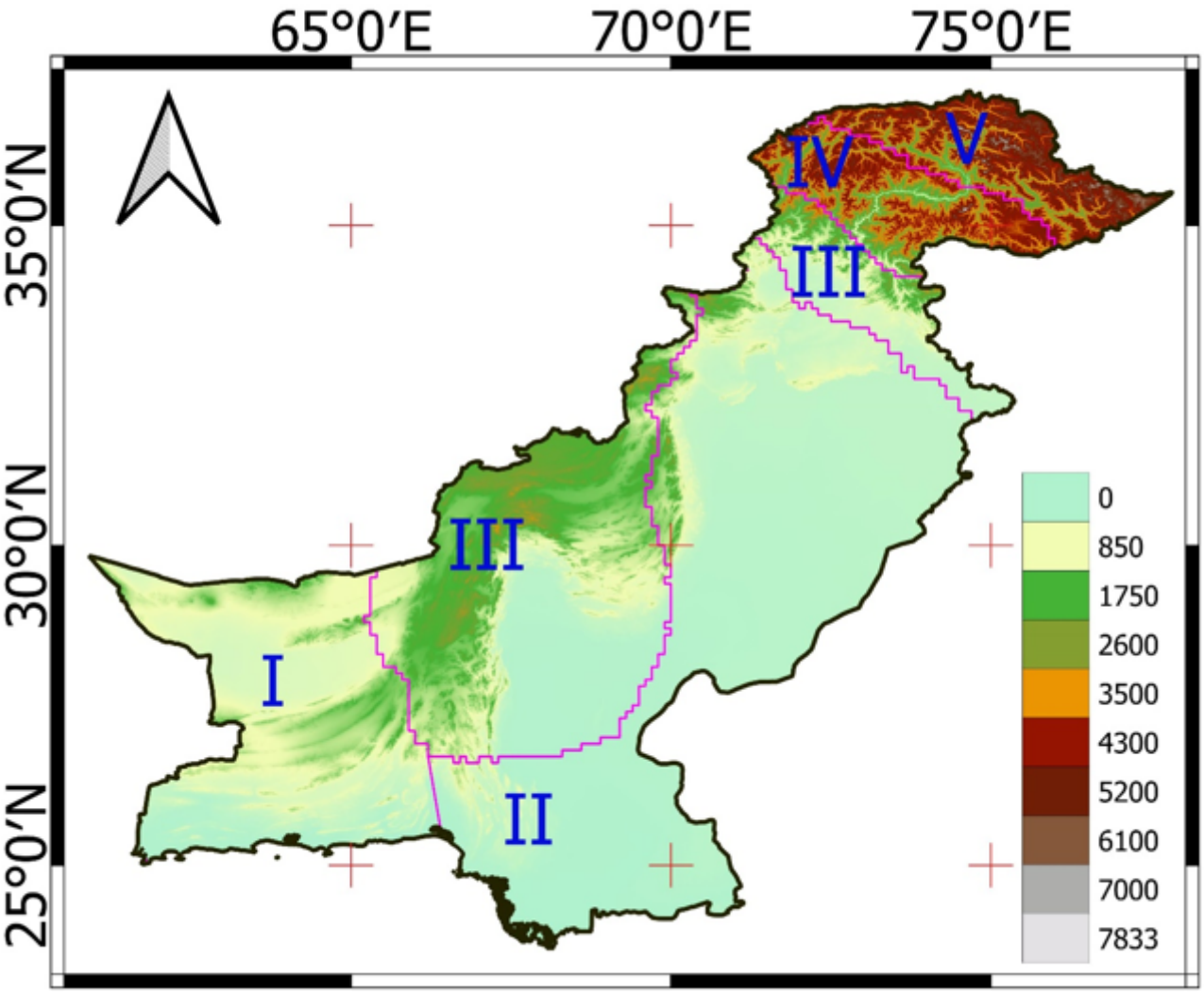



**Figure 1**

Study area location with its topography.

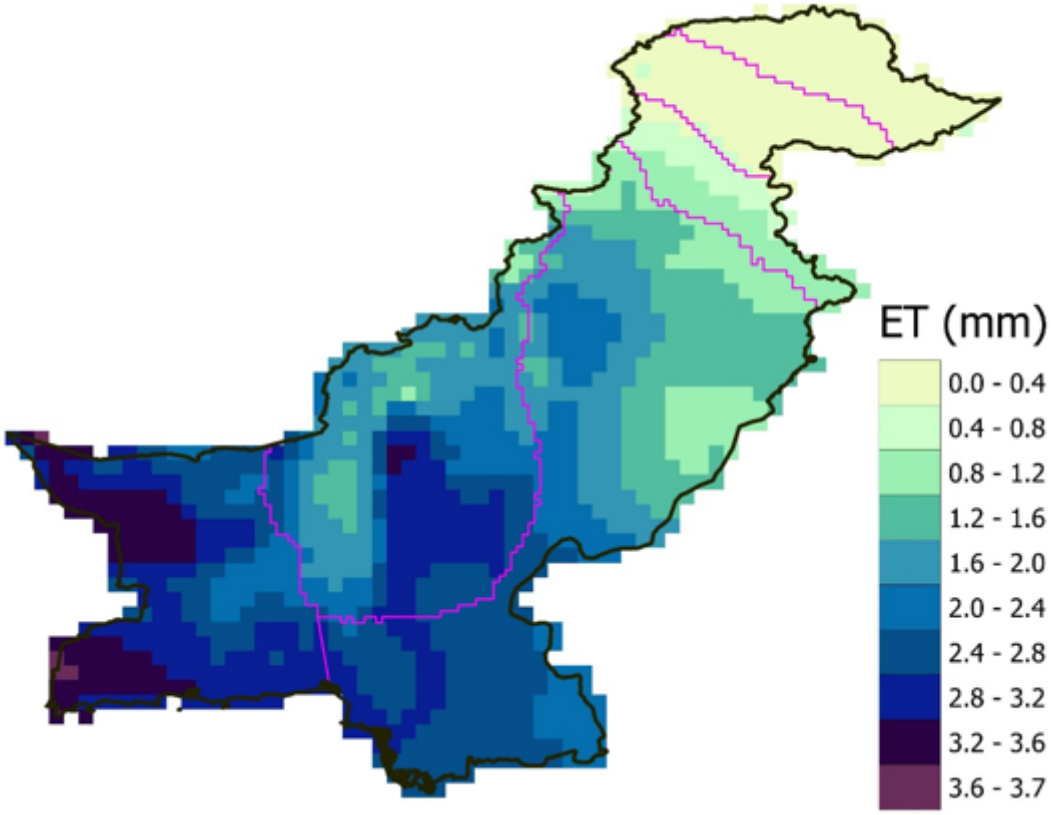



**Figure 2**

Spatial variability of daily mean evapotranspiration (ET) estimated using Penman-Monteith (PM) method for the period 1948–2016.

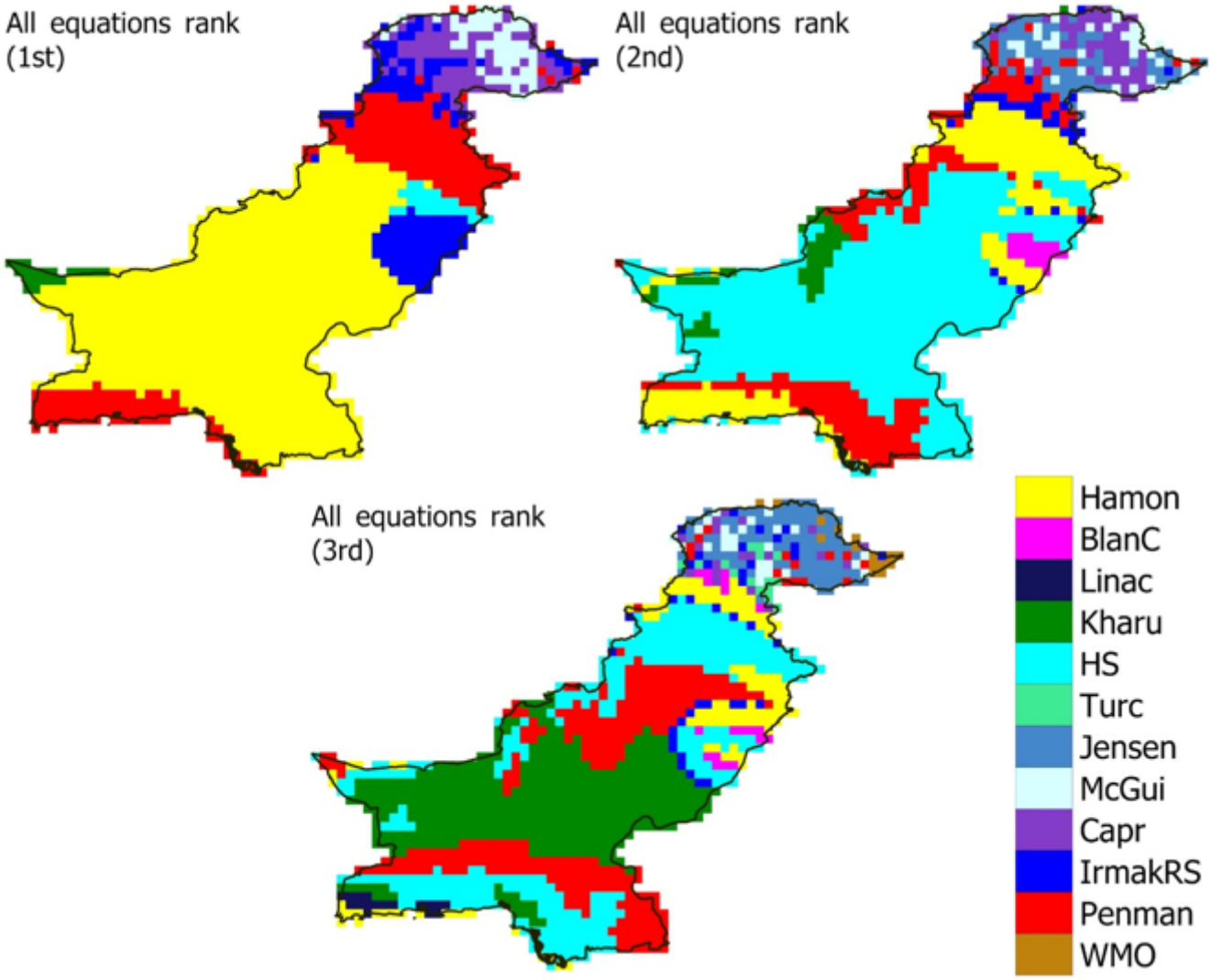



**Figure 3**

Spatial distribution of the top three ET models over Pakistan.

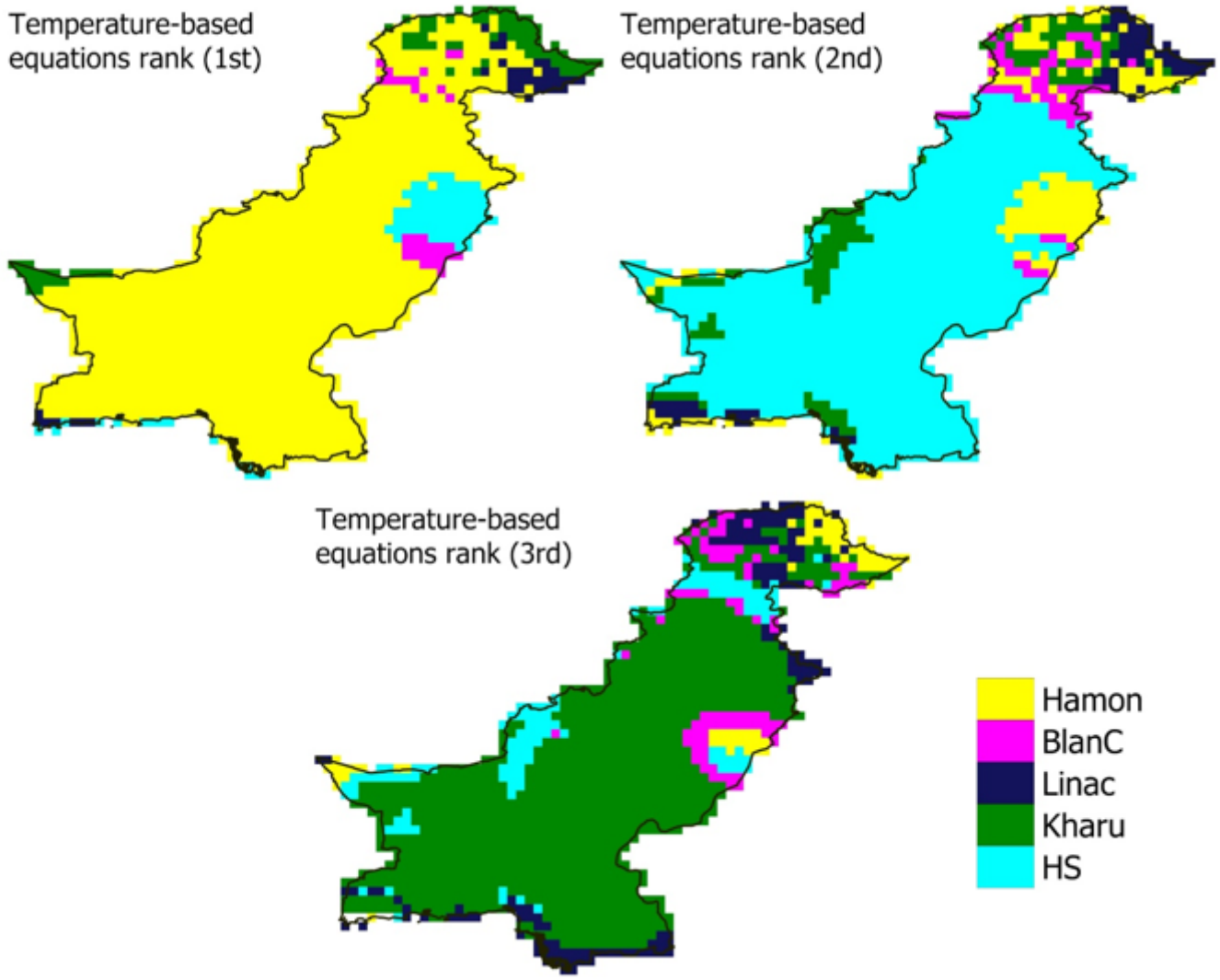
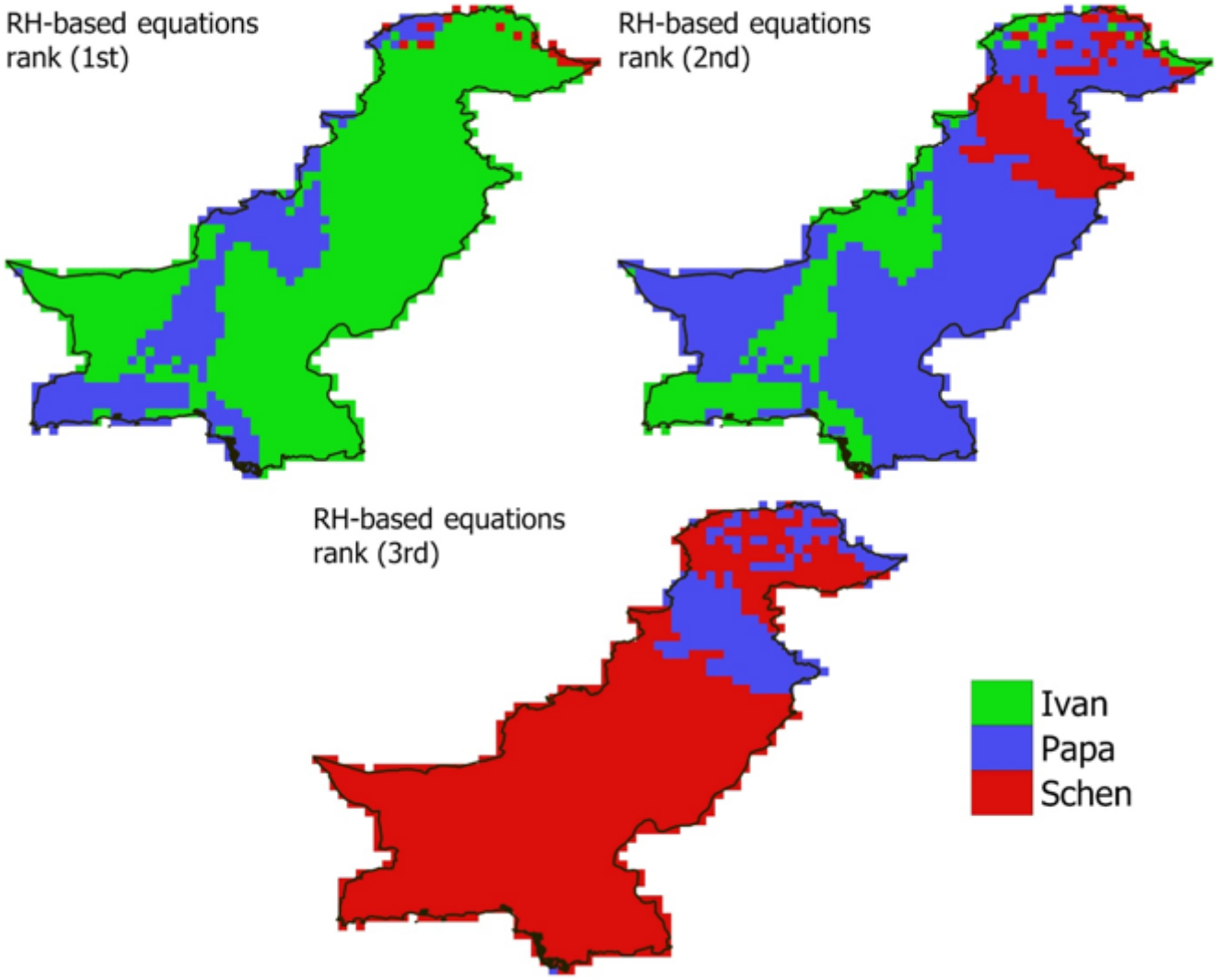



**Figure 4**

Same as Figure 3, but for temperature-based equations




## Figure 5

Same as Figure 3, but for relative humidity-based equations.

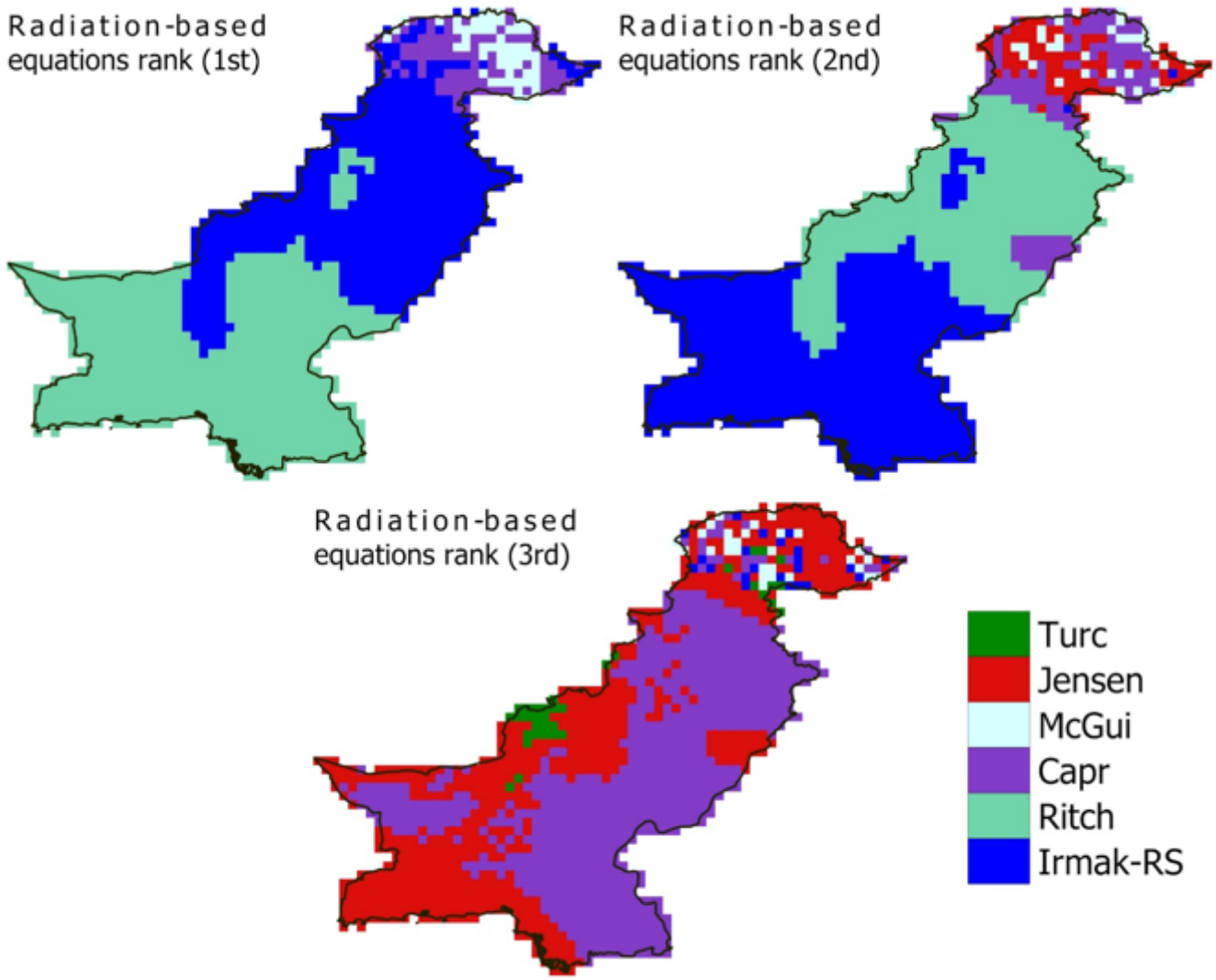



**Figure 6**

Same as Figure 3, but for radiation-based equations.

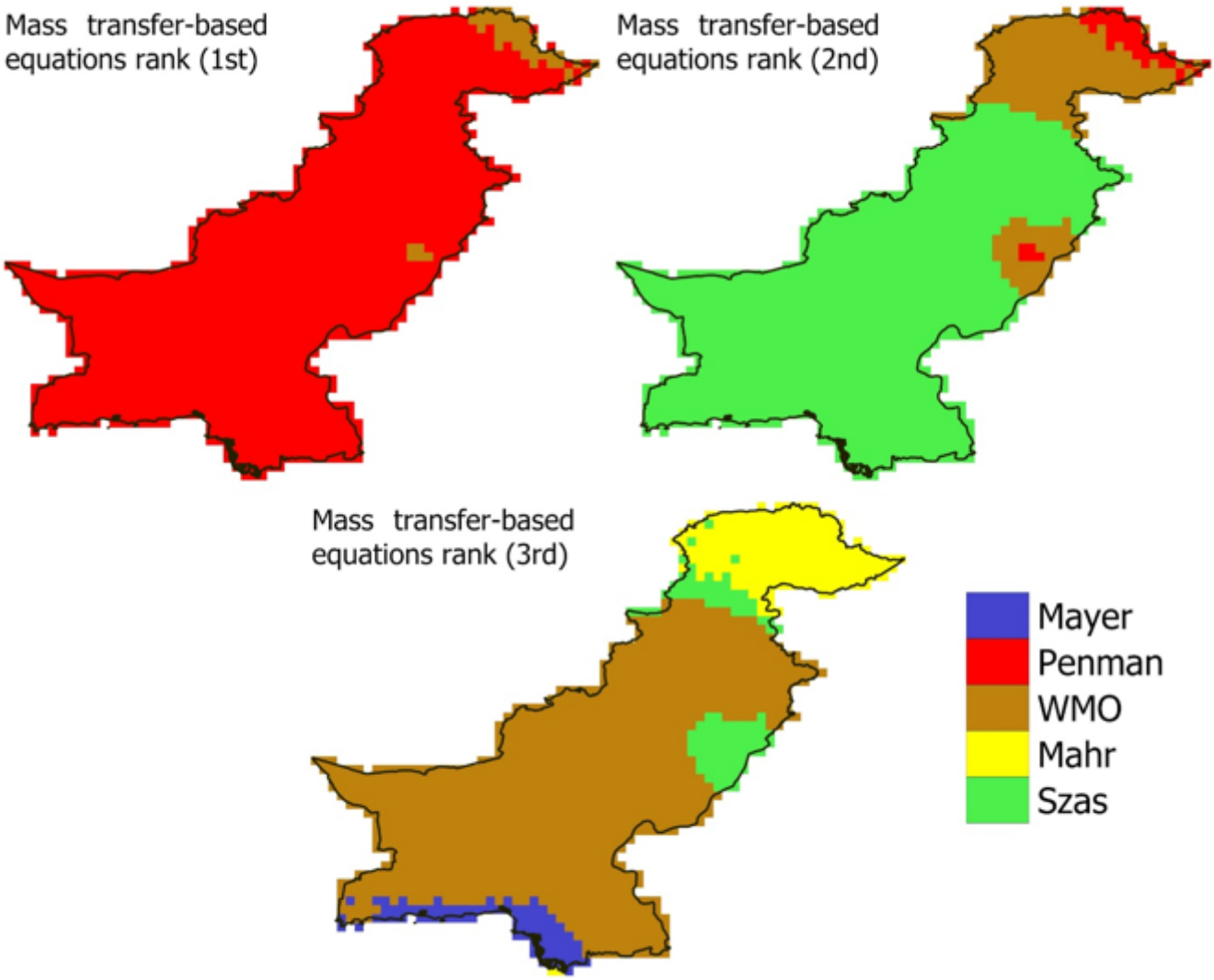
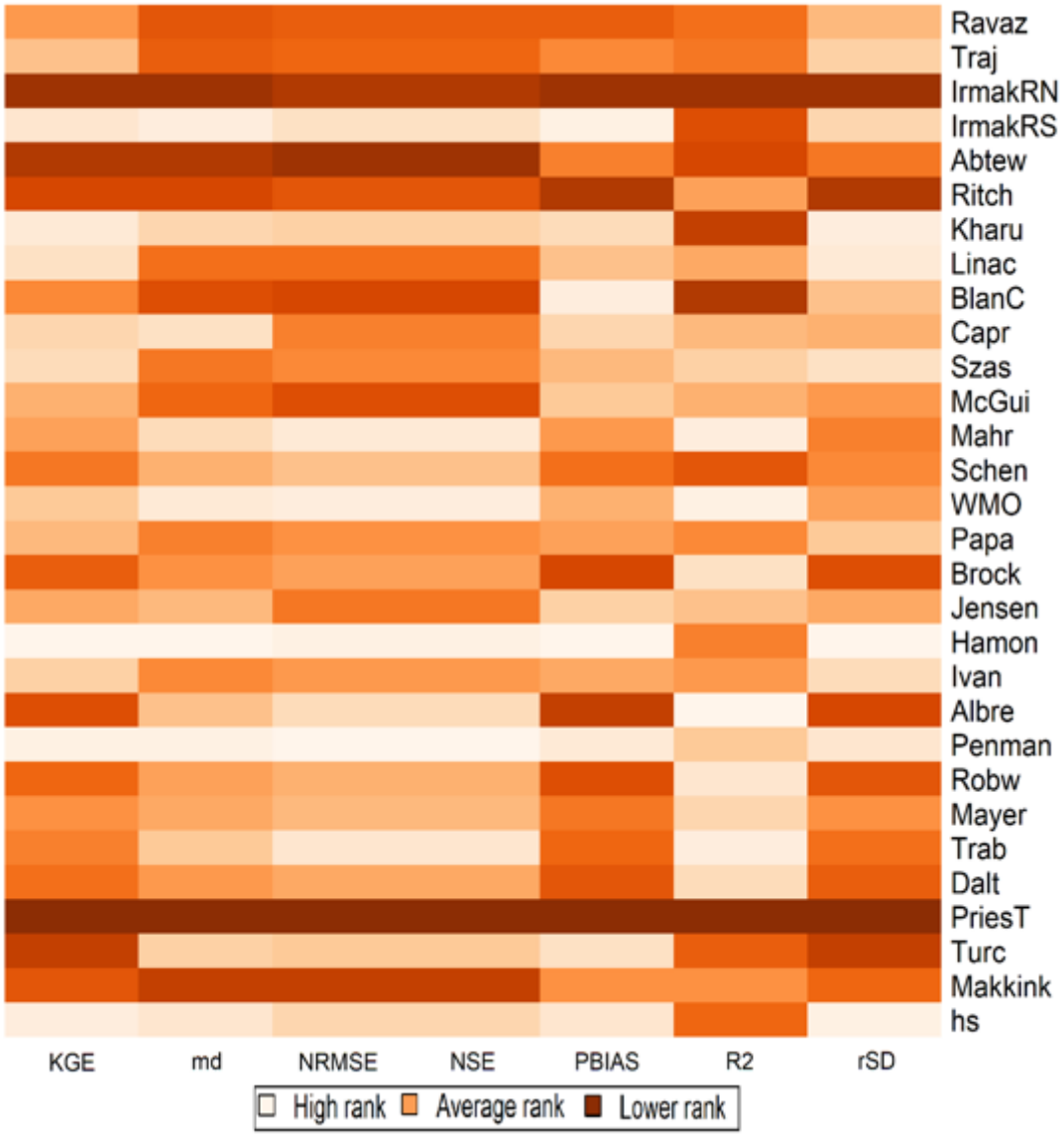



**Figure 7**

Same as Figure 3, but for mass transfer-based equations




## Figure 8

Ranking of ET model based on different statistical indices.

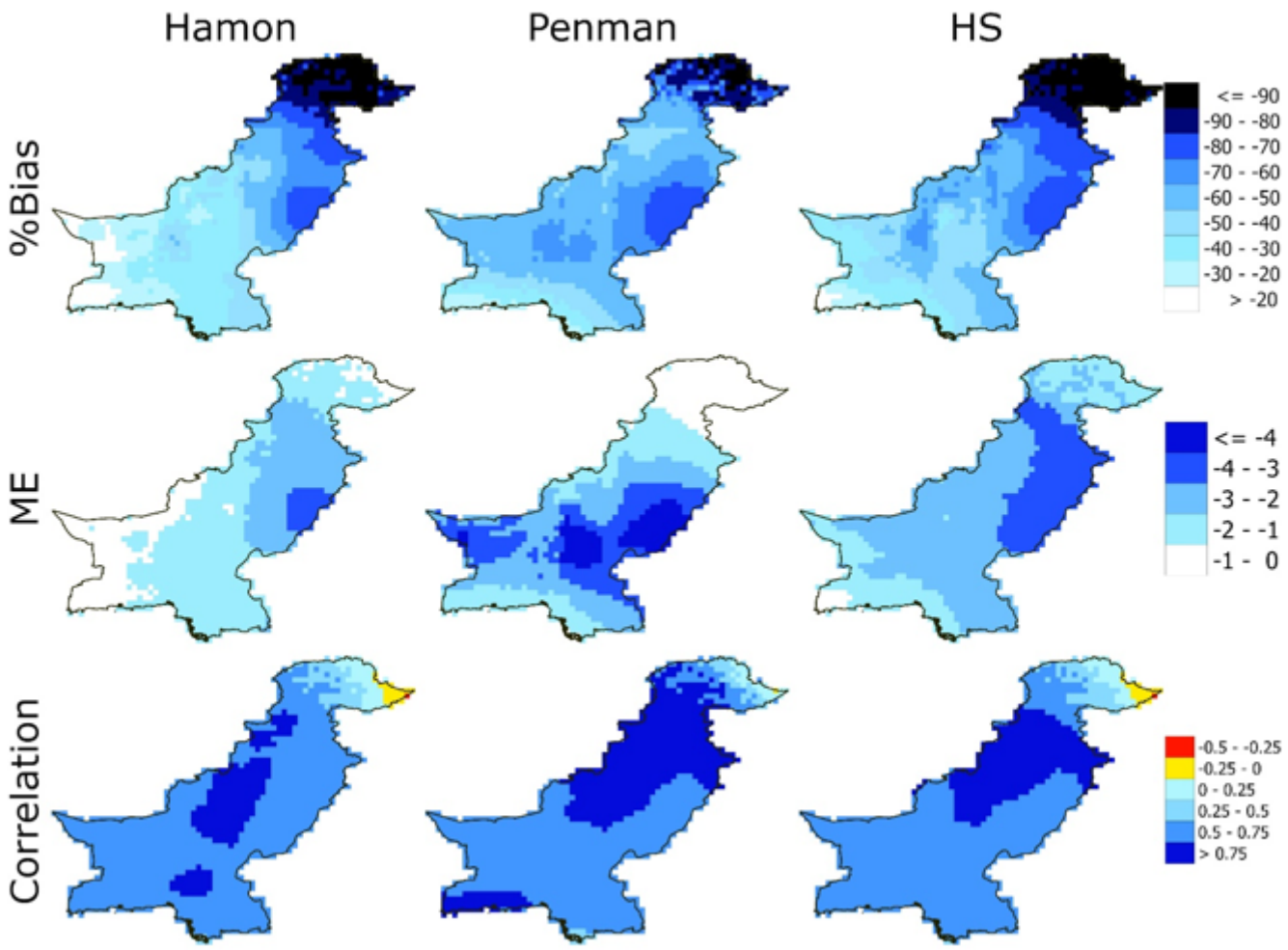



**Figure 9**

Spatial distribution of MAE, ME and correlation for the top three equations

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterials.docx