



Spatiotemporal trends in reference evapotranspiration over South Korea

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Abstract

The universal phenomena of global warming caused by climate change have direct linkage with different hydro-meteorological variables which in turn affect the evaporative demand of the atmosphere. Therefore, this study evaluated the seasonal and spatial changes in reference crop evapotranspiration (ET_o) during last 4.7 decades and identified the forcing mechanism behind the seasonal changes in ET_o using a stepwise regression equation. To remove the effect of serial correlation, the modified Mann–Kendall test was adopted together with Sen’s slope and linear regression method to identify and compare the spatial and temporal trends between Thornthwaite, Hargreaves and FAO Penman–Monteith (FAO-PM) methods. Results indicate that the annual average ET_o value is higher along the south and east coastal areas and lower along the northwest side of South Korea. The highest number of stations with significant increasing trends was detected in Thornthwaite and significant decreasing trend in FAO-PM method. Spatial and temporal correlation analysis showed the existence of strong correlation between Hargreaves and FAO-PM methods with the Pearson *r* value ranging from 0.84 to 0.98 and *R*² of 0.8. Wind speed is found to be the most influencing climatic variable, especially in autumn, early winter and early summer, and maximum temperature during spring and late summer.

Keywords Modified Mann–Kendall · Sen’s slope · Linear regression · Thornthwaite · Hargreaves · FAO Penman–Monteith

Introduction

It is now accepted worldwide that the climate system is warming in recent decades with the increase in air and ocean temperatures, increase in sea levels and widespread snow melting (Intergovernmental Panel on Climate Change 2007). It is reported that in the late nineteenth century, the earth

temperature has increased about 0.3 and 0.6 °C. Over the past 100 years (1906–2005), the land surface air temperature has increased up to 0.74 °C and expected to increase up to 1.1–6.4 °C by the year 2100 (Intergovernmental Panel on Climate Change 2007). Change in air temperature is directly or indirectly linked with the other climatic variables such as vapor pressure deficit, shortwave radiation, relative humidity, precipitation, wind speed and direction and dew-point temperature (Gao et al. 2006), which in turn affect the evaporation from the surface and transpiration from the plants and lead to sudden changes in evapotranspiration from coupled plant–soil interface. Since evapotranspiration is a nonlinear complex function of many climatic variables, any changes in the variables in conjunction with the air temperature lead to an abrupt increase or decrease in the magnitude and trends of evapotranspiration. Therefore, identifying the reasons of such changes in evapotranspiration is a crucial step to understand the hydrological cycle in the region. However, the quantitative analysis of dominant factors affecting evapotranspiration trends in the South Korea is not addressed so far, although some qualitative argument has been made

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about the relationship between evapotranspiration and climatic variables.

The amount of evaporation that would occur if a sufficient water source was available can be represented as potential evapotranspiration (PET) (Penman 1948; Thornthwaite 1948), and reference evapotranspiration (ET_o) refers to the amount of evaporation and transpiration from a reference vegetation of grass (Hargreaves 1994; Allen et al. 1998; Droogers and Allen 2002). Both the PET and ET_o methods are a complex biophysical process affected by different climatic and environmental parameters. In this study, ET_o is estimated by the temperature-dependent Hargreaves method (Hargreaves 1994) and FAO Penman–Monteith (FAO-PM) method which is dependent on variety of different climatic variables (Allen et al. 1998). Less data-intensive methods such as Hargreaves or Thornthwaite methods are highly recommended in developing countries where limited meteorological stations are available (Singh and Pawar 2011). The Thornthwaite method has previously been recommended for the humid climatic condition such as east central of America and south Florida (Abtew 2007) and thus can successfully be applied in South Korean environment. A theoretical entity more than an operative one, the PET or different types of ET_o is difficult to quantify directly, and so, a variety of different estimation methods have been developed because of the involvement of different climatic variables in each model. Therefore, comparing the performance of each predictive model of evapotranspiration leads to the use of complete set of climatic variables and can produce more convincing estimates of the dynamic of potential evaporation (Donohue et al. 2010).

Overall, the same ET_o method may yield different results under different climatic conditions and geographical environments. The high altitude, changeable weather and complex terrain and even season of the year can be responsible for the changing results of ET_o between the empirical equations, for example (Lang et al. 2017). Differences among methods often reach hundreds of millimeters per growing season (Federer et al. 1996), and accuracy of a given method depends heavily on the climatic conditions of the study site.

Furthermore, many studies have shown the comparison of different PET and ET_o models. For example, Chen et al. (2005) performed comparison of the Thornthwaite method and pan data with the standard Penman–Monteith estimates of reference evapotranspiration in China; results showed that the Thornthwaite method overestimates the ET_o in southeastern part of China and underestimates it in other parts of China in spring, summer and autumn. Hari (2016) compared the four different temperature- and radiation-based and combined parameter-based (FAO-56) modified Penman–Monteith methods; results showed that the highest sums were provided by the Blaney–Criddle, Penman–Monteith-FAO-56, modified Penman methods and Hargrove method, while

the lowest amounts were provided by the modified Penman methods and Hargreaves methods. Zarei et al. (2015) showed that pan evaporation method, Hargreaves–Samani modified and Blaney–Criddle do not have a significant difference ($p < 0.05$ in ANOVA statistics) by Penman–Monteith-FAO-56. However, the Thornthwaite model has the most difference by Penman–Monteith-FAO-56. Ilesanmi et al. (2014) conducted analysis for Onne and Kano states in Nigeria and results showed that the Blaney–Morin–Nigeria method was the best to be used for estimating ET_o as this method showed strong correlation with the Penman–Monteith method. Alexandris et al. (2008) performed the comparison of the ET_o from the surface of rain-fed grass in central Serbia, using six empirical methods against the Penman–Monteith method and results showed that the Turc's and Makkink's methods underestimated results, while the Priestley–Taylor, Hargreaves–Samani and Copais methods performed well for the region and generated results closest to the Penman–Monteith method.

Many researchers have investigated the trends in ET_o, and they yielded diverse results in different regions of the world. For example, in Pisa Italy, Moonen et al. (2002) analyzed the trends over the period of 122 years and found a decrease in minimum temperature, precipitation, maximum temperature and ET_o trend. The ET_o value was calculated based on temperature using the Hargreaves empirical equation (Hargreaves 1994). However, ET_o may show the decreasing trend with the increase in temperature; for example, in northwest and southeast China, ET_o has decreased during 1954–1993 in all the seasons (Thomas 2000). In addition to this, decreasing trends were also observed in Yangtze River basin, Yellow River basin, northern regions and Tibetan Plateau of China (Wang et al. 2007; Zhang et al. 2007, 2010). Decreasing trends in ET_o were observed in India (Bandyopadhyay et al. 2009) and USA (Irmak et al. 2012). A decreasing trend in ET_o shown in above studies is completely opposite to the general perception that the increase in air temperature lead to an increase in actual evaporation, ET_o and PET.

On the other hand, many regions also showed an increasing trend in ET_o. For example, Kaohsiung, south Taiwan, showed an increasing trend in ET_o over the 48-year period (Yu et al. 2002). Northeast arid zone of Nigeria showed an increase in ET_o because of the observed increasing trend in wind speed over the region (Hess 1998). Analysis of the trends in pan evaporation for the Canadian Prairies showed both increasing and decreasing trends during the period of 1971–2000 (Burn and Hesch 2007). They analyzed the influence of climatic parameters on pan evaporation and showed that the wind speed tends to show more decreasing trend and vapor pressure deficit tends to show more increasing trends. In addition to this, semiarid Iran also tend to show more increasing trend in ET_o (Tabari 2010; Tabari and Marofi

2010). One of the major reasons of inconsistent findings in the trends of ETo is the fact that some climate change studies utilize only one kind of empirical equation which uses only few climatic variables (i.e., temperature or radiation) and thus is unable to consider the influence of other critical climatic variables (i.e., wind speed, sunshine hours, relative humidity, atmospheric pressure, etc.). Therefore, comparing the performance of different predictive models can increase the possibility of using more climatic variables and thus potentially more robust and true trends in ETo can be obtained.

Robustness of significance testing for climatic data is getting special concerns in trend analysis studies because of the difficulties in establishing a valid null hypothesis and the impact of long term persistence, as reported in previous literature (Clarke 2010; Serinaldi et al. 2018). These difficulties in trend analysis techniques are because of the reason that the hydro-climatic data are not able to meet the assumptions of statistical testing such as distribution, correlations and stationarity. Many researchers in South Korea have conducted the studies about trend analysis of hydro-climatic variables. For example, Jung et al. (2011) investigated the spatial and temporal variability of precipitation trends over Korea during the years 1973–2005 using the Mann–Kendall test (Mann 1945; Kendall 1975). Some trend analysis studies mainly focused on summer or seasonal precipitating trends (Kwon and Lee 2004; Chang and Kwon 2007; Baek et al. 2017); a very few studies focused on spatial and temporal variation in ETo trends in South Korea (Nam et al. 2015), which is an important component of hydrological cycle over South Korea. In most of the previous studies, trend analysis was performed using nonparametric techniques, especially Mann–Kendall (MK) test, without paying any attention to the existing serial correlation in the climatic data. However, it is well recognized in previous literature that the serial correlation in climate data adversely affects the power of the trend test (Yue et al. 2002). Therefore, a more comprehensive approach based on variance correction, the modified Mann–Kendall (ModMK) proposed by Hamed and Ramachandra Rao (1998), was adopted in this study to remove the effect of serial correlation.

Based on above discussion, the main objectives of this study were: (1) to estimate the monthly and annual ETo using FAO Penman–Monteith (FAO-PM), Hargreaves and Thornthwaite methods and to compare them at both spatial and temporal scales; (2) to detect the monotonic linear trends in the annual and monthly ETo time series considering the effect of serial correlation; (3) to estimate and compare the slopes of trend lines of ETo time series using Theil–Sen’s estimator and linear regression (LR) method; and (4) to identify the most crucial and dominating climatic variables influencing the ETo time series over the region, using multiple (stepwise) regression analysis.

Materials and methods

Study area and data

South Korea is situated in East Asia and has a total area of 100,210 km². Asian monsoon season heavily impacts the climatic patterns over South Korea. Winter is mainly comprised of extremely dry and cold air and summer is comprised of warm and moist air masses coming from Southeastern Asia. The spatial distribution and topographical characteristics of 54 meteorological stations selected in this study are presented in Fig. 1.

Initially, monthly and annual meteorological data were collected from 70 meteorological stations administered by the Korea Meteorological Administration (KMA; Web site: web.kma.go.kr) over South Korea for the period of 1971–2017 (47 years). However, only 54 meteorological stations were selected because of the unavailability sufficient record lengths or missing values of meteorological data at other 16 stations. The climatic variables used in this study to calculate ETo consist of the following: latitude of the sites (Lat, in degrees), monthly total precipitation (P_{pre} , mm), monthly mean daily maximum temperature (T_{max} , °C), monthly mean daily minimum temperature (T_{min} , °C), monthly mean temperature (T_{avg} , °C), monthly mean daily wind speeds at 2 m height (U_2 , m/s), monthly mean daily bright sunshine hours (T_{sun} , hour), monthly mean dew-point temperature (T_{dew} , °C), monthly mean relative humidity (RH, %), monthly mean atmospheric pressure at surface (P , kPa), monthly mean atmospheric pressure at sea level (P_0 , kPa) and elevation of the sites (z , m). Atmospheric pressure was available in Pascal, and the necessary unit corrections were made to convert it to kPa, to confirm its application to evapotranspiration equations. Initially collected data were plotted to visually inspect whether there is any error in the data. If there were any outlier or unusual data points, we then relooked the same data for the nearby stations and corrected the errors accordingly. Furthermore, preliminary analysis was performed to check the quality of initially collected using the double-mass method and the run test to evaluate the homogeneity and randomness of the data, respectively (Adeloye and Montaseri 2003).

Methods for estimating ETo and PET

There are many methodologies proposed for the estimation of ETo and PET. However, their performance varies with the variation of environment because all the equations have different empirical backgrounds. Previous studies have recommended the use of FAO Penman–Monteith

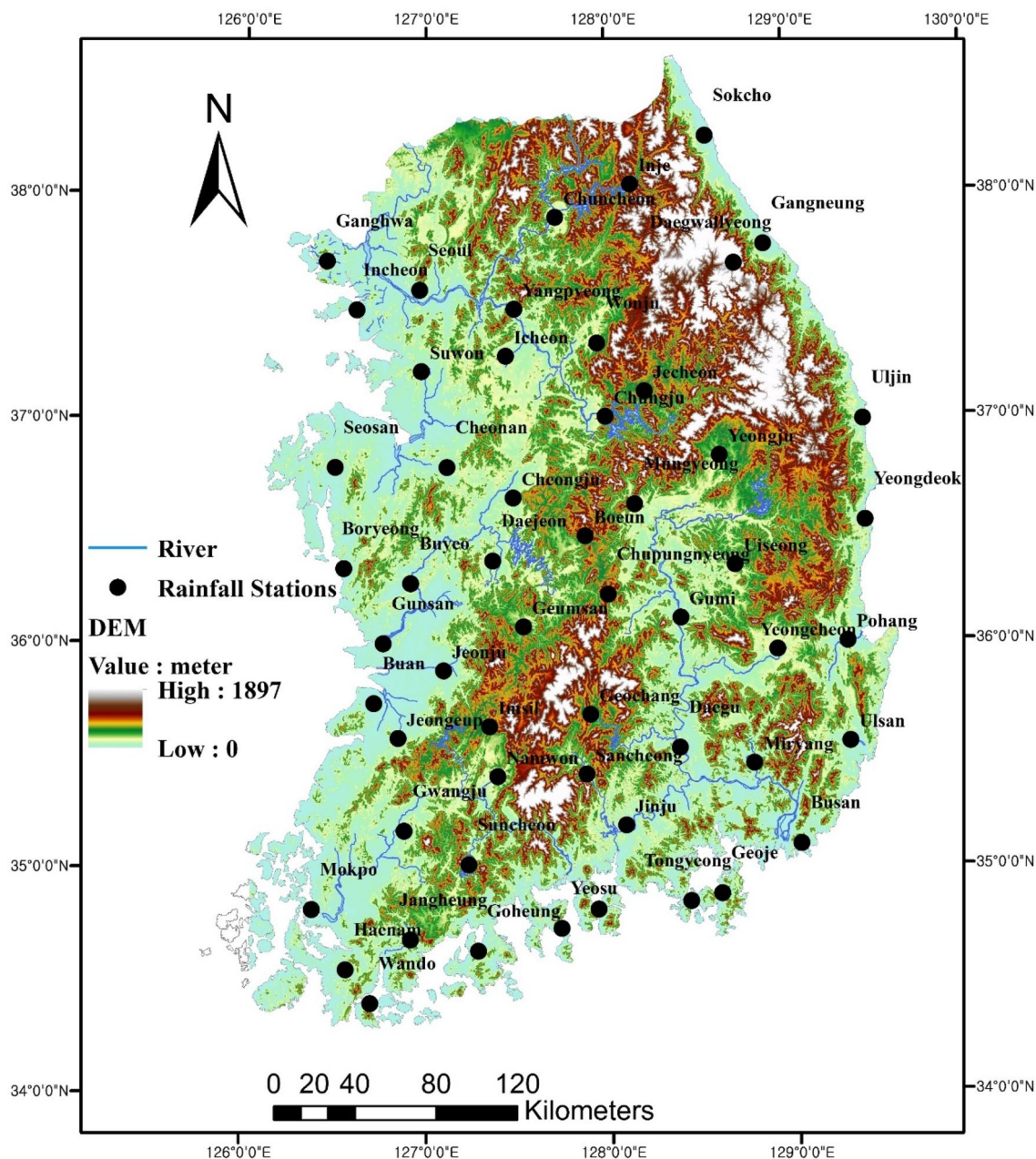


Fig. 1 Spatial distribution and topographical characteristics of 54 meteorological stations (used in this study) in South Korea

method (FAO-PM) for determining E_{To} (Xing et al. 2008); however, following special weather conditions, it might lead to errors (Widmoser 2009). At the places where the substantial inaccuracy existed in large climatic data set, FAO-PM method may lead to uncertainty in calculations. Therefore, alternative methods such as Hargreaves and Thornthwaite were also adopted to compare the performance of different predictive models. The mathematical formulation of above-stated methods of E_{To} and PET is as follows.

FAO Penman–Monteith (FAO-PM) method

The FAO-PM method is recommended by Allen et al. (1998) as the standard method for calculation of E_{To} . This method is able to incorporate a variety of different climatic variables which can be divided into physiological and aerodynamic parameters (Xu et al. 2006). Its accuracy and reliability under different climatic variables have been widely accepted in South Korea (Nam et al. 2015). Following the methodology proposed by Allen et al. (1998), the method was used to calculate the monthly values of E_{To} and annual E_{To} was

estimated by accumulating the monthly ETo. Further details about the computation of climatic parameters, are available in Chapter 3 of the FAO paper 56 (Allen et al. 1998).

Hargreaves method

The original Hargreaves method (Hargreaves 1994) uses only the maximum and minimum temperatures to estimate the ETo, and the mathematical formulation can be expressed as follows:

$$ETo = 0.0023 \times 0.408R'_a (T_{\max} - T_{\min})^{0.5} (T + 17.8) \tag{1}$$

where R'_a is the extraterrestrial solar radiation measured in ($MJm^{-2}d^{-1}$) and T is defined as the average of T_{\max} and T_{\min} . However, Droogers and Allen (2002) proposed the modified Hargreaves method which can give better results with the addition of precipitation factor in the formula, which corrects the ETo by utilizing the amount of rain of each month as a proxy for insolation. In this formula, addition of precipitation data is based on the assumption that it can represent relative levels of humidity. The following mathematical equation can be derived (Droogers and Allen 2002):

$$ETo = 0.0013 \times 0.408R'_a ((T_{\max} - T_{\min}) - 0.0123P)^{0.76} (T + 17.0) \tag{2}$$

Here, P_p indicates the precipitation in mm per month. Therefore, the modified Hargreaves method is adopted in this study because of availability of reliable precipitation in South Korea. Moreover, because of unavailability mean external radiation data, it is estimated using the latitude data and month of the year.

Thornthwaite method

The Thornthwaite method is proposed by Thornthwaite (1948), which consists of average temperature for a given period (T), normal annual temperature (T_a) and number of sunshine hours N . In this study, PET was calculated following the methodology proposed by Thornthwaite:

$$PET_J = 16 \left(\frac{10\bar{T}_J}{I} \right)^{a_{th}} \left(\frac{\overline{hrday}}{12} \right) \left(\frac{daymon}{30} \right) \tag{3}$$

where PET indicates the monthly potential evapotranspiration in mm/month for month J ($J=1, \dots, 12$), \overline{hrday} indicates the mean daily daylight hours during month J , $daymon$ is the number of days in month J , \bar{T}_J is the mean monthly air temperature ($^{\circ}C$) during month J and is the annual heat index. The annual heat index is estimated as the sum of the monthly indices:

$$I = \sum_{j=1}^{12} i_j \tag{4}$$

where $i = \left(\frac{\bar{T}_J}{5} \right)^{1.514}$

$$a_{th} = 0.4924 + 1.79 \times 10^{-2}I - 7.71 \times 10^{-5}I^2 + 6.75 \times 10^{-7}I^3 \tag{5}$$

Trend analysis techniques

Modified Mann–Kendall (ModMK) test

Trend analysis techniques are applied on the basis of assumption that the observed time series is serially independent. However, the data such as mean annual values of climatic variables may show significant correlation. In such situation when the significant autocorrelation is present in the time series, MK test tends to show the significant trends, when no trend exists in reality (von Storch 1995; Yue and Wang 2004). Therefore, the existence of serial correlation primes to an increasing probability of disproportionate rejection of the null hypothesis. To cope with this problem, Hamed and Ramachandra Rao (1998) considered all the significance serial correlation structure existed in the time series of climatic data. This method used the corrected value of the variance

$$V(S)^* = cf * V(S) \tag{6}$$

The positive (negative) value of S shows the upward (downward) trend. The S is assumed as normally distributed if $N \geq 8$, and its mean and variance can be estimated as follows:

$$E[S] = 0 \tag{7}$$

$$var(S) = \frac{[N(N-1)(2N+5) - \sum_{i=1}^n t_i i(i-1)(2i+5)]}{18} \tag{8}$$

where N is the number of observation and t_i are the ties of the sample time series. $V(S)$ depicts the variance value of the MK test statistic, while S shows the original time series and cf is the correction factor as proposed in Hamed and Ramachandra Rao (1998) which can be expressed as follows:

$$cf = 1 + \frac{2}{N(N-1)(N-2)} \sum_{k=1}^{N-1} (N-k)(N-k-1)(N-k-2)r_k^R \tag{9}$$

r_k^R shows the value of serial correlation coefficient for lag- k of the observed climatic time-series data. If the value of Z is positive, then trend is called as increasing and vice versa. In this study, trends were tested at the significance level of $\alpha = 0.05$ and 0.01 .

Theil–Sen estimator

An approach proposed in Theil (1950) and Sen (1968) is utilized to estimate the magnitude of the trends in ETo time series, which can be computed as follows:

$$\beta = \text{Median}[Y_i - Y_j/i - j] \quad \forall j < i \quad (10)$$

where $1 < j < i < n$. If N represents the all possible combination of record pairs for the entire climatic data set, then value of slope can be computed as $n = N(N - 1)/2$, and β indicates the median of these n values.

Linear regression (LR) method

The slope value estimated by the Theil–Sen estimator is compared with the slope value estimated using LR method. The positive slope value calculated by LR shows an increasing trend, while a negative value shows the decreasing trend. The LR line can be estimated as follows:

$$y = a + bx \quad (11)$$

Here, x is an explanatory variable and y is a dependent variable, while b and a indicate the slope and intercept, respectively (Gocic and Trajkovic 2013).

Each regression model is tested for the potential existence of collinearity between independent variables by computing the variance inflation factor (VIF) (Marquardt 1970). Collinearity problem exists when VIF is very large, such as 10 or more. The multicollinearity has been tested in previous studies conducted in Arizona (Wang et al. 2016) and also been used for monthly land-cover-specific evapotranspiration models derived from global eddy flux measurements and remote sensing data (Fang et al. 2016).

Results

Statistical summary of climatic variables

Basic statistical analysis of climatic variables which are used to estimate the value of ETo is crucial because a small change in variables directly affects the value of ETo. Box plot of all climatic variables recorded for the period of 1971–2017 (47 years) at 54 meteorological stations across South Korea is presented in Fig. 2. The line drawn within the rectangle indicates the mean values, while rectangle width in the upper and lower portion shows the 75th and 25th percentile, respectively. The lower end of the line shows the minimum value, and the upper end shows the maximum. It can be seen from the statistical summary of 54 meteorological stations that during summer season (June, July and

August) South Korea has the minimum values of average P and P_0 (nearly 100.5 kPa) as compared to other months of the year (Fig. 2a, b). Apart from outliers, overall, the monthly variation of P and P_0 is quite similar to each other. Similarly, in case of T_{dew} , the mean values started increasing from February (-7°C) and reached the peak in August (22°C) and then started decreasing abruptly till December (Fig. 2c). The monthly variation of T_{max} , T_{min} and T_{avg} is quite similar throughout the year (as shown in Fig. 2d, e, j). An abrupt increase is observed in the ranges of the maximum, minimum, 75th and 25th percentiles of total monthly precipitation in summer (Jun, July, and August) season (Fig. 2f). The possible reason of this increase is the Asian Monsoon system, which brings the majority of summer precipitation in a relatively short period (Chung et al. 2004). In case of RH (Fig. 2g), after the slow decline from January to April, the abrupt increase was observed from April to July and started declining from July onward. In Fig. 2i, the highest (lowest) value of wind speed was observed in April (September), while in Fig. 2i, highest numbers of sunshine hours were recorded in May and lowest in July. Overall, most of the climatic variables showed the significant changes in temporal patterns during summer because of an increase in temperature and effect of Asian monsoon system.

Spatial and temporal distribution of ETo across South Korea

In terms of wet and dry conditions, there is no large climatic difference between the stations, because of the small area of South Korea ($100,210 \text{ km}^2$). Overall, South Korea falls under the category of humid continental/subtropical climate with dry winter. The temperate climate of South Korea contains very wet and humid conditions, especially during summer season due to the influence of the North Pacific high-pressure system and East Asian monsoon. So summer meets the well-watered condition to estimate the value of ETo. In case of winter, the South Korea is topographically influenced by expanding Siberian high-pressure zones which results in predominantly cold, dry northwesterly winds. So concerns might exist about the estimation of ETo in dry weather conditions in winter. In order to cope with dry and wet climatic conditions, in this study, three approaches were compared to check the sensitivity of evapotranspiration data at local conditions.

The contour maps to show spatial distribution of mean annual ETo and PET, during the period of 1971–2017, are presented in Fig. 3, which shows a combined effect of all climatological factors. It can be seen from Fig. 3 that all the three methods showed different values of ETo from one location to another because of different climatic environments. ETo value is relatively higher along the south and east coastal areas and relatively lower along the northwest

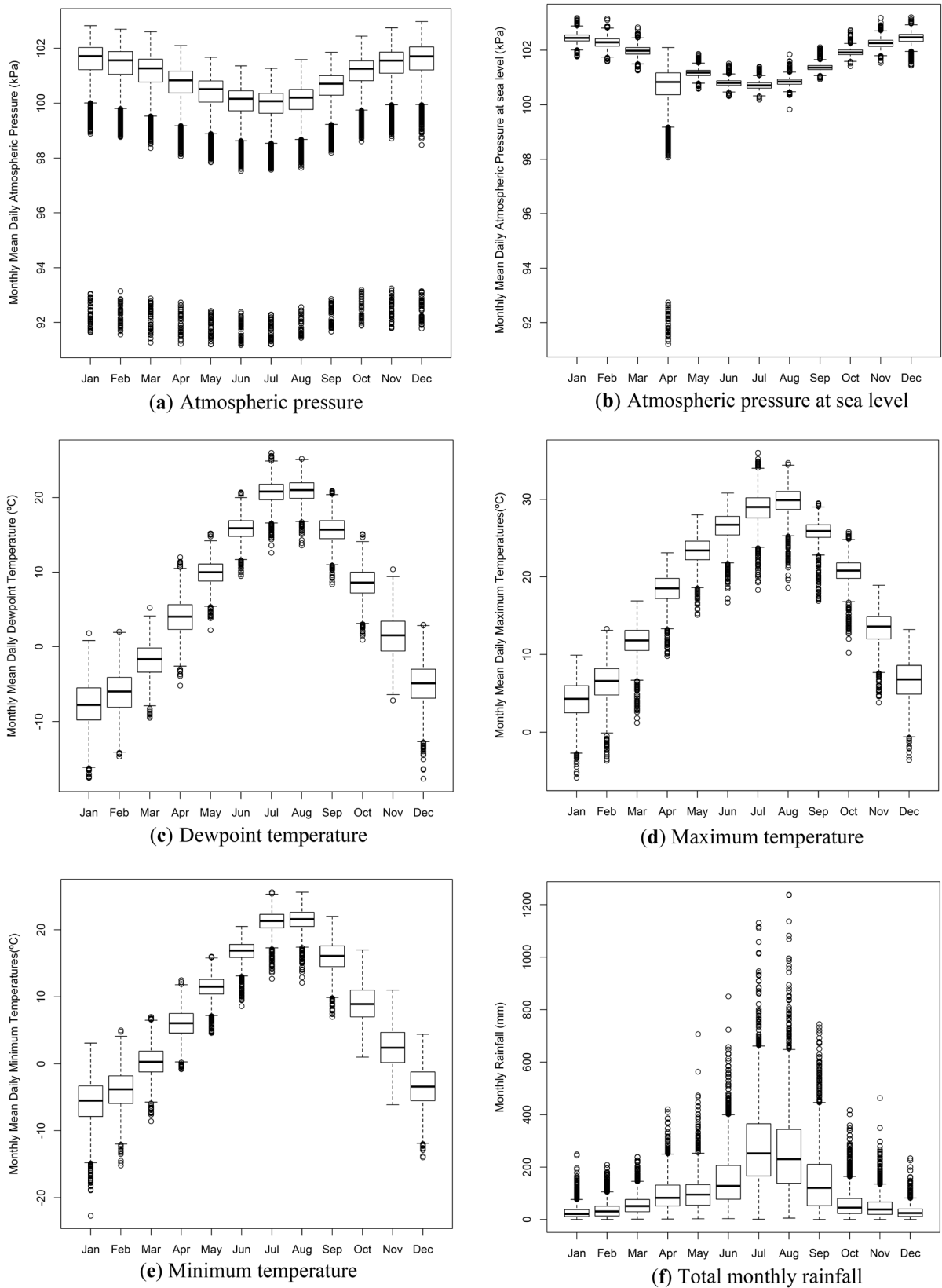


Fig. 2 Box plot showing the monthly variations of the major meteorological variables across South Korea. These variables include: **a** atmospheric pressure (kPa), **b** atmospheric pressure at sea level (kPa),

c dew-point temperature (°C), **d** maximum temperature (°C), **e** minimum temperature (°C), **f** total monthly rainfall (mm), **g** relative humidity (%), **h** wind speed (m/s), **i** sunshine (hour), **j** mean temperature (°C)

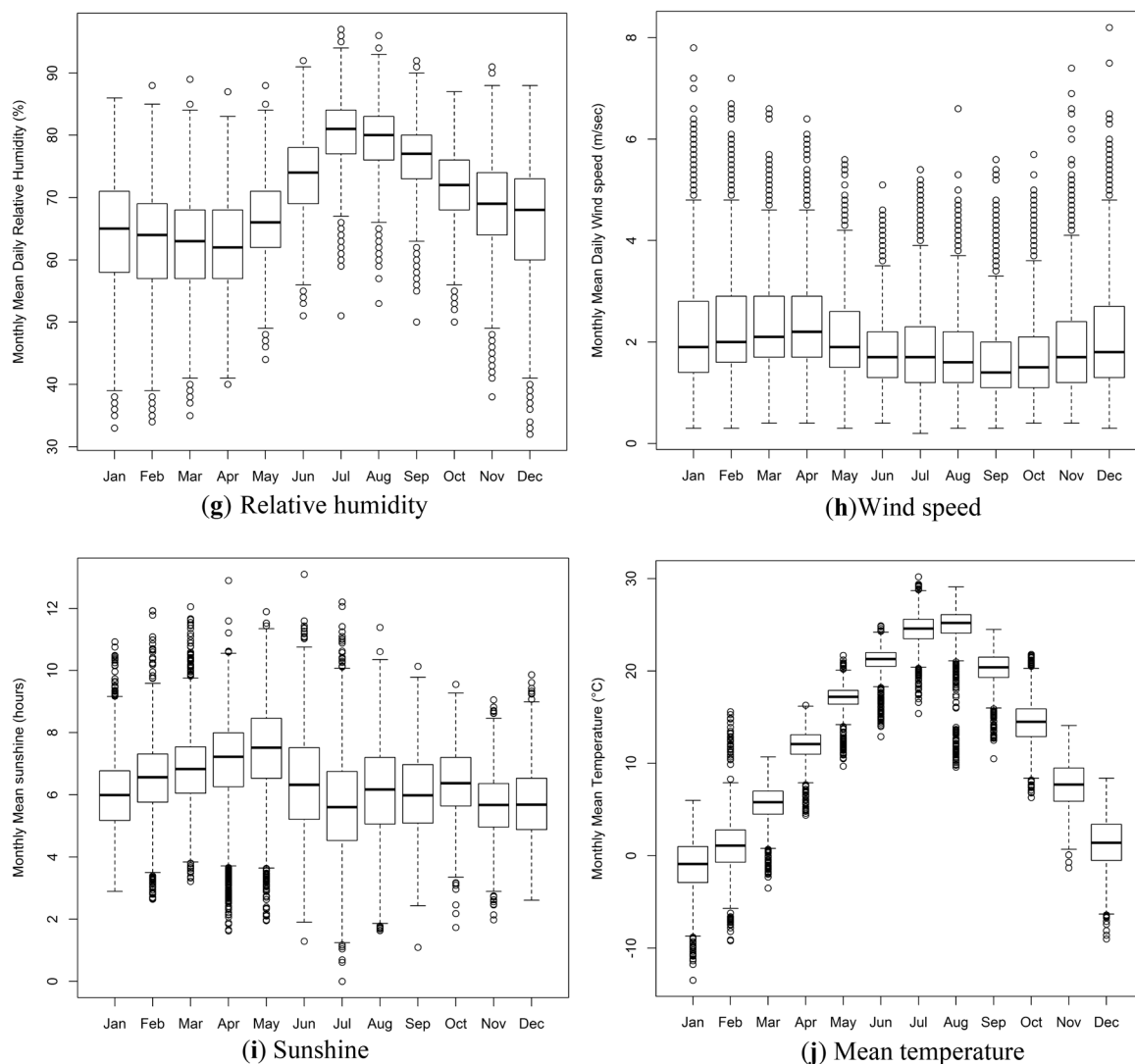


Fig. 2 (continued)

side of South Korea. This is because of the reason that the yearly average, minimum and maximum temperature in South Korea increases from north to southward, and along the east and south coast. This increase in temperature can be reflected in the ETo and PET contour lines of FAO-PM, Hargreaves and Thornthwaite methods. For example, the highest mean annual values of FAO-PM (Fig. 3a) were estimated at the station Daegu (945 mm, located at southeast part), Mokpo (882 mm, located at southwest coast), Sokcho (871 mm, located at northeast coast) and Chupungnyeong (849 mm, located at mid-latitude portion). In case of Hargreaves (Fig. 3b), the annual average values of ETo are significantly higher at all stations as compared to FAO-PM and PET values of Thornthwaite method. This is because of dominant role of T_{max} and T_{min} in the empirical equation used in Hargreaves. The highest values of

Hargreaves were estimated at the stations such as Uiseong (1183 mm), Miryang (1166 mm) and Namwon (1151 mm) located near the south side or coastal part of South Korea, where annual average temperature is relatively higher as compared to other regions. The lowest values of Hargreaves were estimated at Daegwallyeong (843 mm) and Incheon (899 mm) stations located at northern portion of South Korea. The possible reason is that the temperature of South Korea tends to be cooler as moving from south to northward. Thornthwaite ETo calculated based on T_{avg} also showed a similar distribution pattern as that of other two methods as shown in Fig. 3c. The highest mean annual values were estimated at the stations such as Daegu (796 mm), Busan (785 mm) and Pohang (780 mm) located at southern part, whereas the lowest value was estimated at Daegwallyeong (561 mm) located at northern part.

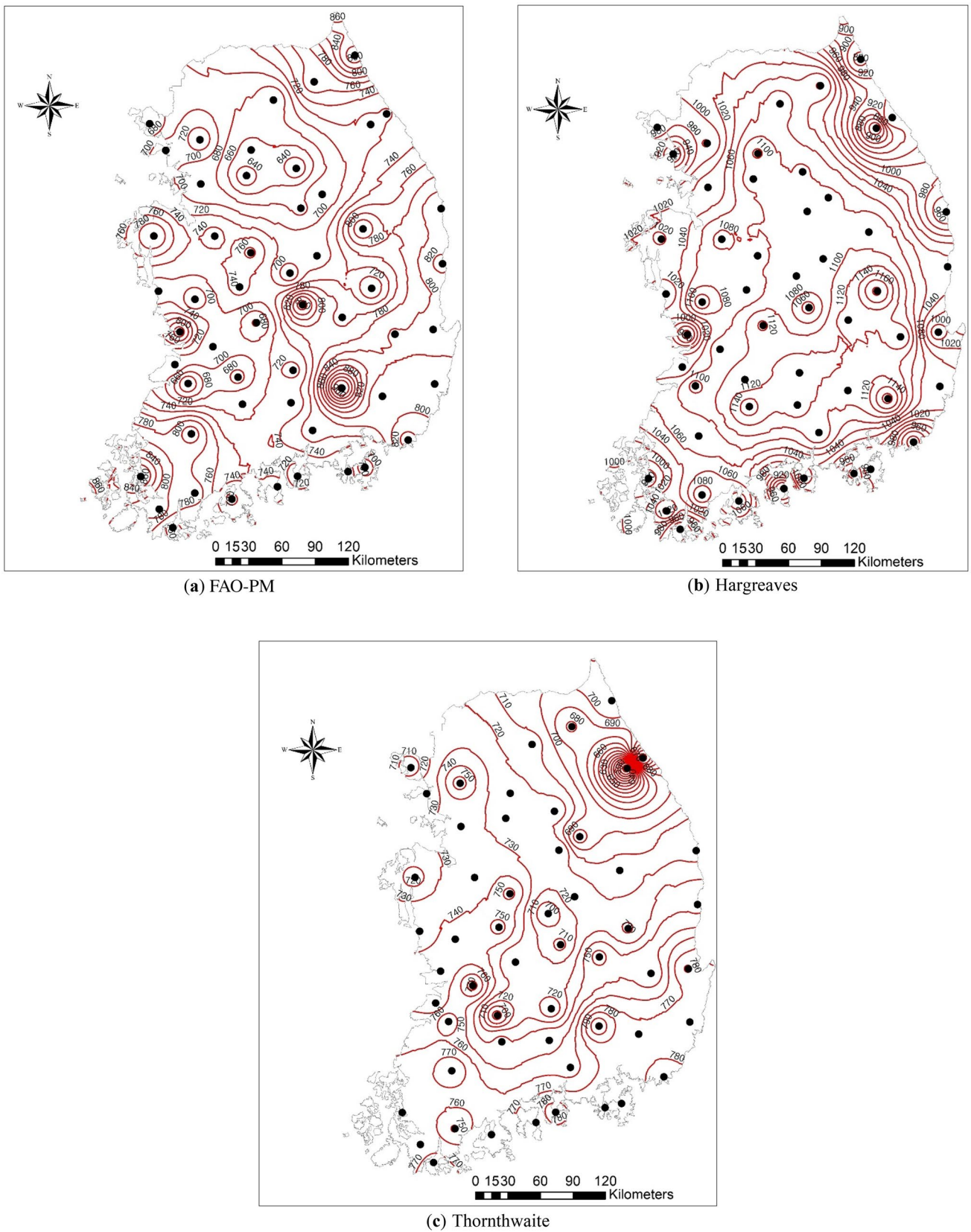


Fig. 3 Spatial distribution of mean annual ET₀ (mm) across South Korea using following methods: **a** FAO-PM, **b** Hargreaves, **c** Thornthwaite

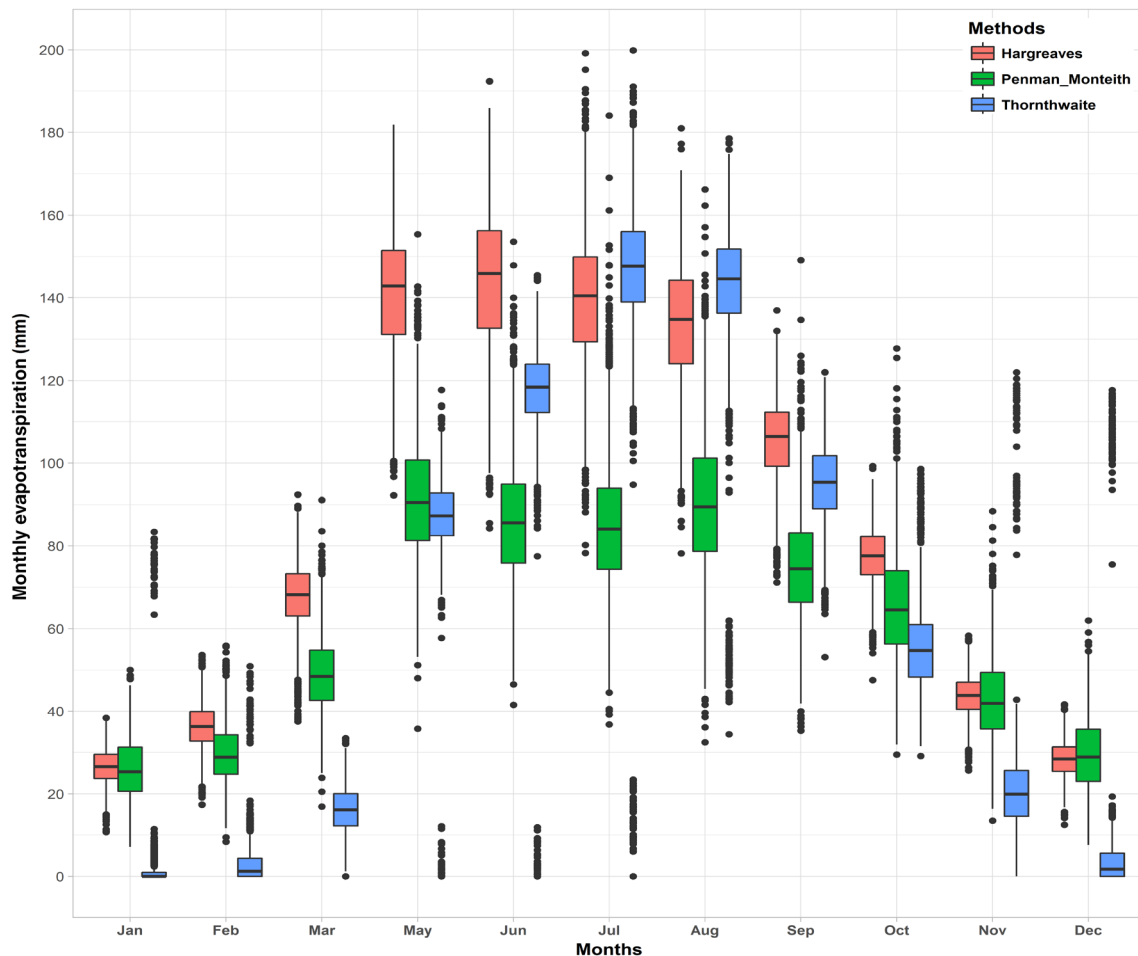


Fig. 4 Temporal distribution of monthly ETo (mm), comparing all methods of evapotranspiration (Thornthwaite, Hargreaves and FAO-PM)

The spatial distribution maps of ETo and PET give a valuable information to water resource engineering for accurate planning and management of water resources in the region, since the changes in annual and seasonal values of ETo and PET are an important driving force which directly affect the hydrological cycle. Furthermore, analyzing the influence of changes in meteorological variables to ETo in different seasons or areas will be likely to have a different effect on the ETo and PET and, in turn, affect the water availability in the region.

The monthly temporal distribution of ETo and PET estimated during 1971–2017 using FAO-PM, Hargreaves and Thornthwaite methods is presented in Fig. 4. It can be seen that, from winter to spring (December–May), the mean, 75th and 25th percentile values of the FAO-PM are higher than those of the Thornthwaite and lower than those of Hargreaves. However, during summer season (June–September) PET estimated by Thornthwaite is significantly higher than the ETo estimated by FAO-PM and lower than the ETo estimated by Hargreaves. During winter season

(December–February), Thornthwaite method has the least values of the mean, 75th and 25th percentile as compared to other two methods because of its heavy dependence on the sole climatic variable (i.e., T_{avg}). Overall, Thornthwaite and Hargreaves methods are more sensitive to seasonal variation of temperature and lead to over prediction as compared to FAO-PM, which is able to consider the collective impact of different climatic variables. Therefore, FAO-PM method shows relatively smooth seasonal deviation, with the gradual increase from January to May and decrease from August onward.

It can be noticed from the Thornthwaite values in Fig. 4, during winter season (December–February) the mean values are nearly zero. This is because below-freezing temperature in winter season is estimated as zero in the parameterization of Thornthwaite method (Van Der Schrier et al. 2011), whereas the parameterization of FAO-PM and Hargreaves methods still estimates some values of ETo.

Temporal trend analysis of monthly and annual ETo and PET across South Korea

The trends in the monthly and annual ETo and PET were analyzed by performing the ModMK test as mentioned in “Theil–Sen’s estimator” section. Z statistics of ModMK are presented in Tables 1, 2 and 3 using Thornthwaite, Hargreaves and FAO-PM, respectively. The value of Z statistics is tested for the significance level of 95% ($\alpha = 0.05$) and 99% ($\alpha = 0.01$) as indicated in bold and asterisk, respectively. Summary graph of the trend analysis using three methods is presented in Fig. 5a–c. In case of Thornthwaite, most of the stations tend to show positive trends in monthly and annual time series; however, the number of stations with significant positive trend varies from one month to another. It can be clearly seen from Table 1 and Fig. 5a that a significant positive trend ($p < 0.05$ or $p < 0.01$) was observed in more than 50% of the stations during February (36), March (43), May (38), June (33), October (42) and November (31), whereas insignificant trends (no trends) were observed in January (50), April (40), July (51), August (44), September (28) and December (47), at 95% and 99% confidence levels. However, none of the station showed a significant negative trend (except one station in January and two stations in August) in monthly and annual time series.

In case of Hargreaves, from January to December (except February) more than 70% of the stations did not show any significant trend ($p > 0.05$), as shown in Table 2 and Fig. 5b. In summer season (June–September), more than 50% of the stations showed a decreasing trend; however, only few stations showed a significant decreasing trend.

As compared to Thornthwaite and Hargreaves methods, the FAO-PM method showed more equally distributed significant increasing and decreasing trends, especially in summer season, as shown in Table 3 and Fig. 5c. However, still more than 50% of the stations fall under the category of insignificant trends ($p > 0.05$) throughout the year.

Thornthwaite method showed the highest number of significant increasing trends after the Hargreaves and FAO-PM, which can be correlated with the effect of parameterization between them. The comparative significant increasing trend of Thornthwaite method is related to the simplicity of its parameterization (Van Der Schrier et al. 2011). In addition to this, the reason of greater number of stations with significant increasing trends in case of Thornthwaite and Hargreaves methods is likely associated with the exclusion of cloud cover and vapor pressure deficit (which relates to the capacity of the air to take up water) in their parameterization, as both parameters tend to suppress high value of ETo estimated by Hargreaves and PET in atmosphere (Van Der Schrier et al. 2011).

The stations having highest value of Z statistics in case of Thornthwaite, Hargreaves and FAO-PM are the Suwon

(8.67), Busan (6.57) and Sancheong (11.78) stations, respectively. Their corresponding annual time series were drawn to check and compare the linear regression slopes at each selected station, as shown in Fig. 6. It can be seen that the annual ETo estimated by Hargreaves method is significantly higher than that estimated by the FAO-PM and Thornthwaite method at all three stations. In case of Suwon station, Thornthwaite has the highest value of slope (2.72) and R^2 (0.5947), following the FAO-PM (slope of 2.48 and R^2 of 0.41) and Hargreaves (slope of 0.67 and R^2 of 0.07) methods. Positive slope of LR observed in all three methods indicates the possibility of existing correlation between them at Suwon station.

Similarly, the slope of LR and R^2 values for Busan and Sancheong stations are shown in Fig. 6b, c, which confirms the increasing trend and presence of correlation between their time series. Furthermore, an abrupt increase in annual ETo and PET was observed in years 1974, 1994 and 2015 at all the 54 meteorological stations using three methods selected in this study. This increase in evaporative demand during 1974, 1994 and 2015 is also mentioned in previous studies (Nam et al. 2015; Azam et al. 2018).

Monthly temporal distribution of the magnitude of the trends detected in monthly ETo (mm) throughout the year estimated by Thornthwaite, Hargreaves and FAO-PM methods is compared using the mean (symbol “x”), 25th, 75th percentiles of the slope b of LR and Sen’s slope, as shown in Fig. 7. It can be seen that the overall seasonal changing patterns of both the LR and the Sen’s slopes are quite similar; for example, an abrupt increase in the range of the maximum, minimum, 75th and 25th percentiles of summer ETo (June, July and August) was observed for LR and the Sen’s slope. However, the monthly magnitude of the trends varies significantly according to the method of estimation of ETo. For example, in case of LR (Fig. 7a), the Thornthwaite has the highest value of 75th percentile and lowest value of mean from May to August as compared to Hargreaves and FAO-PM methods. However, in case of Sen’s slope method (Fig. 7b), the mean, 25th, 75th percentiles of Thornthwaite, Hargreaves and FAO-PM methods are quite comparable throughout the year.

The increase in the magnitude of the trends in summer season can be correlated with the sudden increase in geopotential height at 700 hPa ($\Phi 700$) over mid-latitude Asia in the mid-1970s (Ho et al. 2003). An increase in geopotential height causes stronger northerly wind and produces more evaporation. Furthermore, the increase in evaporative demand during summer is linked with the intensification of the upper-level westerly Jet over Korea and the anomalously warm sea surface temperature (SST) in the western North Pacific region (Baek et al. 2017).

Table 1 Z statistics of modified MK trend tests for the Thornthwaite reference crop evapotranspiration over South Korea

Stations	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Sokcho	1.24	1.52	3.17*	2.39	1.83	2.40	1.61	1.54	2.52	1.59	0.93	-0.83	3.80*
Daegwallyeong	0.95	1.23	2.64*	1.51	3.00*	1.77	1.01	1.72	2.46	3.02*	2.48	1.66	4.26*
Chuncheon	1.21	1.25	2.44	1.23	4.33*	3.61*	1.32	3.32	3.86*	3.16*	1.15	-0.77	4.79*
Gangneung	1.55	2.87*	3.56*	2.11	1.94	2.16*	1.26	1.52	3.83*	4.49*	1.80	0.01	4.15*
Seoul	-1.40	2.14	2.82*	1.87	4.60*	3.22*	1.94	3.61*	4.55*	3.24*	1.24	0.25	5.01*
Incheon	-1.21	2.30	3.98*	2.72*	4.47*	6.03*	1.82	5.83*	4.75*	4.87*	1.81	1.16	5.23*
Wonju	1.65	3.03*	1.92	2.25	4.46*	4.40*	1.94	2.18	3.51*	5.25*	5.40*	2.24	5.59*
Suwon	-1.23	2.33	4.33*	2.83*	5.02*	4.52*	2.52	4.32*	5.15*	4.63*	2.57*	1.46	8.47*
Chungju	1.65	1.60	1.43	0.80	1.95	1.20	0.39	0.69	1.93	3.49*	2.20	0.97	3.03*
Seosan	-1.45	1.89	1.63	0.83	2.60*	2.16	1.19	3.20*	3.00	2.94*	1.07	0.34	2.88*
Ulsan	0.66	1.98	2.57	1.25	0.53	0.74	0.23	-0.44	0.72	1.66	2.12	0.49	1.65
Cheongju	0.77	5.11*	4.87*	2.94*	4.97*	5.25*	2.11	3.87*	4.88*	5.00*	3.14*	2.04	6.14*
Daejeon	-1.03	2.53	4.08*	2.10	4.59*	4.23*	1.51	2.21	3.97*	3.97*	1.97	1.52	5.19*
Chupungnyeong	-2.27*	1.85	2.68*	0.70	2.58*	1.88	0.32	0.28	1.05	1.03	0.81	-0.02	1.56
Pohang	1.74	3.00*	4.35*	3.35*	4.04*	2.98*	1.38	1.52	3.36*	4.31*	2.50	1.25	4.82*
Gunsan	0.46	2.03	2.93*	1.70	4.08*	4.36*	1.47	1.08	1.60	1.55	1.34	0.11	3.01*
Daegu	1.94	3.37*	4.62*	5.04*	5.15*	3.48*	1.38	1.42	3.46*	4.00*	2.54	1.78	5.93*
Jeonju	0.91	3.97*	3.43*	1.32	4.26*	4.15*	1.43	1.38	3.21*	4.45*	2.12	1.35	4.26*
Ulsan	1.87	2.94*	4.03*	3.34*	5.25*	2.72*	1.52	1.06	3.64*	4.38*	2.04	1.14	4.60*
Gwangju	1.74	4.08*	5.35*	2.09	5.72*	5.14*	1.82	1.72	3.56*	4.72*	2.58*	1.33	4.92*
Busan	1.83	2.71*	3.06*	2.56	5.23*	3.62*	1.30	1.44	3.01*	4.90*	1.87	0.80	4.18*
Tongyeong	1.10	2.20	2.94*	1.66	1.85	2.36	0.82	0.92	1.90	3.09*	0.94	0.50	2.57*
Mokpo	-0.09	1.38	1.71	1.08	3.37*	4.11*	1.96	0.83	1.42	1.34	0.26	-0.42	2.11
Yeosu	1.49	2.51	3.24*	1.92	3.79*	3.15*	1.21	1.08	2.69*	4.28*	1.70	1.20	3.79*
Wando	0.29	1.04	1.69	0.63	3.75*	3.65*	1.47	0.46	0.28	1.10	0.60	0.17	2.94*
Jinju	0.03	1.52	1.83	0.66	3.44*	1.77	0.69	0.52	1.38	1.35	0.29	-0.03	2.16
Ganghwa	1.62	1.83	1.41	0.01	0.24	0.87	-0.62	0.39	3.79*	3.45*	2.17	1.34	2.14
Yangpyeong	1.69	2.35	4.58*	1.91	3.50*	3.07*	0.92	1.71	2.93*	4.42*	3.02*	2.17	4.79*
Icheon	1.50	1.94	3.40*	0.94	2.62*	2.10	0.36	-0.27	1.96	2.54	1.90	1.13	4.19*
Inje	1.52	1.81	3.72*	0.57	1.74	1.94	0.09	-0.10	1.87	3.37*	2.09	1.05	3.12*
Jecheon	1.49	0.55	2.19*	-0.06	0.71	0.67	-0.28	-1.83	0.15	1.67	1.37	0.89	0.87
Boeun	1.54	2.29	1.25	0.87	2.93*	1.87	0.35	1.23	1.68	3.05*	3.11*	2.30	3.31*
Cheonan	0.02	2.13	4.81*	1.07	3.15*	2.11	0.23	-0.26	1.58	2.91*	1.96	0.66	3.18*
Boryeong	1.65	2.64*	4.44*	0.63	1.93	2.46	0.71	1.42	2.61*	4.38*	4.27*	2.28	4.11*
Buyeo	-0.49	2.08	2.61*	0.59	2.24	2.21	0.46	0.57	2.94*	2.78*	2.05	1.10	2.92*
Geumsan	0.54	1.89	3.70*	-0.08	1.72	1.18	0.09	-0.95	1.15	2.26	1.69	1.11	2.06
Buan	1.46	3.17*	3.06*	0.91	2.49	2.89*	0.90	0.79	1.84	3.78*	2.97*	1.71	3.69*
Imsil	0.84	1.14	3.94*	-0.41	2.14	1.89	0.86	0.00	1.63	2.87*	2.18	1.44	3.07*
Jeongeup	1.45	2.72*	3.19*	1.08	3.56*	2.25	0.94	0.33	2.91*	3.38*	2.90*	1.40	3.88*
Namwon	-0.29	2.02	1.25	-0.11	2.08	1.49	0.30	-1.56	0.74	1.51	1.40	0.63	1.61
Jangheung	3.17*	2.60	1.33	0.71	2.88*	1.95	0.12	-0.63	1.15	2.74*	2.33	2.09	2.88*
Haenam	0.76	1.91	1.69	-0.31	1.90	2.31	0.61	-0.77	0.53	1.43	1.01	0.50	1.76
Goheung	2.33	2.48	1.42	0.38	0.67	-0.16	-0.56	-2.03	0.43	1.94	1.29	1.80	1.27
Yeongju	1.66	2.40	3.56*	1.11	2.77*	1.37	-0.08	-1.09	1.56	2.77*	2.21	1.65	2.76*
Mungyeong	-0.92	1.62	1.18	-1.00	-0.69	-1.27	-1.60	-3.64*	-1.20	0.55	1.38	1.33	-1.44
Yeongdeok	1.53	2.73*	3.10*	1.35	1.33	1.02	-0.20	-1.41	0.19	2.45	2.19	0.93	2.23
Uiseong	0.00	1.87	3.87*	0.46	1.41	0.72	0.64	-0.46	1.21	2.24	1.60	1.56	2.49
Gumi	1.81	3.78*	4.12*	2.61*	3.15*	2.98	1.35	0.91	2.81*	4.26*	3.12*	2.82*	5.00*
Yeongcheon	1.62	2.92*	3.40*	1.22	1.81	1.55	0.21	-0.68	1.43	3.04*	2.05	1.20	3.15*
Geochang	0.17	2.64*	5.11*	0.72	3.06*	2.29	0.74	-0.13	1.44	2.84*	2.06	1.38	3.01*
Miryang	1.69	3.05*	3.08*	1.71	3.36*	2.58	0.95	0.70	1.99	3.71*	1.89	1.60	3.44*
Sancheong	1.22	2.53	2.47	0.62	2.05	0.90	-0.23	-1.39	0.37	2.48*	2.31	1.52	2.48
Geoje	2.62	3.25	3.74*	1.96	3.06*	1.98	0.56	0.27	1.39	3.66*	2.66*	1.81	3.31*
Namhae	1.92	2.36	2.58*	1.37	2.11	1.26	0.69	0.14	0.84	3.79*	2.28	1.69	3.18*

Bold values indicate the statistically significant trend at the 95% confidence level, * indicates the statistically significant trend at 99% confidence level

Relationship between Thornthwaite, Hargreaves and FAO-PM equations

Because of the difference between the parameterization of temperature-based equations (i.e., Thornthwaite, Hargreaves) and high data-intensive equation (i.e., FAO-PM), it is important to analyze the nature of correlation existed between their ETo time series. Spatial distribution of monthly Pearson's correlations between Thornthwaite–Hargreaves (Thorn–harg), Thornthwaite–FAO-PM (Thorn–Pm) and Hargreaves–FAO-PM (Harg–Pm) and their corresponding relationship were assessed by drawing the linear fit on the scatter plot as shown in Fig. 8. All the three combinations of ETo equations showed close linear correlation ($p < 0.01$). It can be seen that the corresponding R^2 of the linear fit (on right) increases with the increase in the value of Pearson's correlation (left). The monthly values of ETo time series tend to be more concentrated around the linear fit in case of Harg–Pm, with the highest values of R^2 (0.8) and Pearson's r (0.84–0.98) as compared to Thorn–Pm (R^2 0.65 and Pearson's r 0.70–0.92) and Thorn–harg (R^2 0.76 and Pearson's r 0.70–0.92). This seems like linear fit tending to increase with the increase in the value of parameterization from low data-intensive equations to high data-intensive equations. Furthermore, the value of Pearson's correlations decreases with the increase in the value of yearly average values of ETo and PET from north to southward as shown in Figs. 3 and 8. The correlation is relatively low at high-temperature areas along the mid-latitude east coast and south coast and high at low-temperature areas along the north portion and along the west coast. Thus, areas of lower correlation can be associated with the dominate role of temperature in Thornthwaite and Hargreaves methods and the integrated effect of sunshine, wind, temperature and relative humidity, atmospheric pressure in FAO-PM method. This finding matches well with the previous literature (Beguiría et al. 2014). Apart from temperature, precipitation is also an important climatic factor used in the Hargreaves (modified) method which results in a significant reduction in sunshine hours and wind speed as the available energy is the primary driver of ETo, and this fact is also recognized by Irmak et al. (2012). Thus, due to indirect linkage between the parameterization of the Hargreaves and FAO-PM methods, the value of correlation is highest among them.

Apart from the Pearson's r correlation, LR regression equation is utilized to check the nature of linear trend existing between the ETo and PET, estimated by three different methods. It can be noticed from Fig. 8 (right) that all pairs of ETo and PET methods showed an increasing trend, with the Thorn–harg has the highest value of slope b (0.745) following the Harg–Pm (0.532) and Thorn–Pm (0.408). A significant increasing trend detected by the LR method in Fig. 8b matches well with the results of temporal trend analysis

performed separately on the time series of Thornthwaite and Hargreaves methods using modMK test as shown in Tables 1 and 2 and Fig. 5a, b. Therefore, the trends detected by the Z statistics of modMK test are quite comparable with the trends detected by the LR method. The similarity between behavior of the modMK test statistics and LR equation is also observed in the trend analysis of precipitation and temperature (Asfaw et al. 2018) and drought time series (Azam et al. 2018).

In order to check the seasonal changes in correlation between the methods of ETo and PET, the monthly and annual values were drawn in the form of box plot as shown in Fig. 9. It can be clearly seen that Hargreaves–FAO-PM has the highest value of correlation throughout the year, which verifies the results of R^2 value of 0.8, as shown in Fig. 8f. This increase in the correlation is mainly due to stations located near the western coast and near the North Korea (Fig. 8e).

However, smaller correlation in the eastern and southern coastal areas of South Korea is because of the reason that eastern and southern coasts are located in the path of East Korea warm current (EKWC). EKWC is a surface oceanic current located at the sea of Japan. It branches off from the Tsushima Current located at the eastern side of Korea Strait, and it passes along southeastern coast of Korean peninsula toward north (Olesen 2011). In addition to this, east coastal areas of South Korea were also affected by the North Korea cold current (NKCC), especially during winter season. Choi and Zhang (2005) investigated the association of sea and air temperatures in the eastern and southern coastal regions of South Korea, by checking the temporal variation of heat and momentum exchanges which in turn cause the heating and cooling in atmosphere of coastal areas. They concluded that wind speed, surface and air temperature over sea surface can affect the latent heat fluxes in the lower atmosphere of coastal areas.

Influence of climatic variables on ETo changes in South Korea

In case of Thornthwaite and Hargreaves, one can assume that increasing or decreasing are because of atmospheric temperature. This is because of the reason that the temperature is the most important climatic variable in their empirical equations. However, in case of FAO-PM it is difficult to identify the reason of the significant trends detected by the LR, Sen's slope and modMK Z statistics because of the involvement of various climatic variables. Therefore, in order to quantify the influence of each climatic variable which is responsible for the observed increasing trends in monthly values of ETo at various meteorological stations in South Korea, a multiple stepwise regression method was applied on the monthly time series of ETo obtained by FAO-PM. The multiple stepwise regression analysis was

Table 2 Z statistics of modified MK trend tests for Hargreaves reference crop evapotranspiration over South Korea

Stations	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Sokcho	2.05	3.65*	3.85*	3.80*	3.19*	2.93	2.09	2.95*	2.80	3.06	1.78	0.02	5.04*
Daegwallyeong	1.54	3.52*	2.48	1.54	1.05	0.99	-0.37	-0.04	0.43	1.60	1.27	0.15	0.78
Chuncheon	1.06	2.68*	2.71*	0.66	1.82	2.56	-1.56	0.26	0.44	1.73	0.86	-0.68	0.65
Gangneung	1.53	3.04*	2.39	0.13	0.12	0.11	-0.95	-1.00	-1.98	-1.29	-0.26	-0.86	0.07
Seoul	0.33	2.51	1.41	0.22	1.94	1.04	-1.44	0.18	0.44	1.48	0.64	-0.06	0.63
Incheon	1.00	2.75*	2.38	1.15	2.13	1.86	-0.63	0.20	-0.13	0.18	0.29	-0.25	0.96
Wonju	2.04	2.86*	2.46	0.55	2.24	1.52	-1.76	-1.79	-2.38	-0.59	0.28	0.13	0.48
Suwon	0.79	2.62*	2.74*	0.86	2.40	2.52	0.00	0.42	-0.55	0.43	0.11	-0.22	0.97
Chungju	1.80	2.38	2.07	1.21	2.19	2.14	-0.62	-0.40	-0.55	0.79	1.06	0.07	1.04
Seosan	0.55	2.51	2.32	1.36	1.92	0.37	-1.04	-0.51	0.11	1.20	0.55	-0.18	0.85
Ulsjin	0.07	1.66	3.17*	2.21	0.53	-0.03	0.48	-0.72	-0.65	-0.25	1.08	0.40	0.96
Cheongju	0.97	2.59*	2.89*	0.51	1.26	0.34	-1.16	-1.33	-2.09	-1.24	0.23	-0.47	0.14
Daejeon	1.59	3.10*	3.62*	1.17	1.58	0.60	-1.76	-1.42	-1.43	0.00	1.17	0.47	0.39
Chupungnyeong	0.57	2.68*	5.09*	1.13	4.27*	1.18	0.50	0.28	0.55	0.66	0.83	-0.91	1.19
Pohang	-0.47	1.80	1.13	-0.03	-0.79	-1.67	-1.21	-2.34*	-4.29*	-4.64*	-0.40	-1.65	-2.31
Gunsan	2.77*	4.55*	6.76*	5.43*	2.79*	2.99*	0.25	0.78	1.87	2.24	2.73*	0.79	5.63*
Daegu	0.86	2.97*	6.07*	1.05	0.89	0.07	0.70	-0.55	-0.62	-1.28	0.48	-0.72	0.68
Jeonju	0.90	2.88*	3.48*	1.71	3.63*	2.27	0.28	0.29	1.27	0.99	1.05	-0.40	1.67
Ulsan	1.82	2.79*	2.32	1.06	0.38	-0.13	0.10	-0.51	-1.08	-1.40	0.24	-0.89	0.44
Gwangju	0.79	3.05*	5.33*	2.48	2.55	1.36	0.89	-0.29	0.04	0.55	1.16	-0.39	1.48
Busan	1.60	3.17*	3.24*	1.22	1.94	1.41	1.00	0.30	-0.17	0.19	0.82	0.07	6.57*
Tongyeong	1.65	2.92*	2.62*	2.15	1.74	-0.24	-0.15	0.37	0.77	1.59	1.60	0.83	-1.31
Mokpo	-1.55	0.44	0.18	-0.52	0.33	-0.34	-2.08	-0.75	-1.76	-1.14	-1.82	-1.55	-1.20
Yeosu	0.22	2.48	0.66	-0.64	-0.07	-4.13*	-1.71	-2.73*	-4.72*	-1.88	-0.51	-0.55	-4.22*
Wando	0.53	2.18	2.81*	2.52	2.25	1.55	2.09	1.84	1.42	1.76	1.36	-0.71	2.56
Jinju	1.96	3.47*	3.75*	2.37	3.91*	0.86	0.79	1.12	1.98	2.20	1.61	0.31	1.97
Ganghwa	1.47	2.24	2.00	-0.59	-0.54	-1.82	-4.06*	-2.00	-0.02	1.19	0.50	-0.06	-1.20
Yangpyeong	1.67	5.11*	2.48	1.34	2.11	1.19	-2.82*	-1.65	-2.23	-0.45	-0.02	-0.04	0.13
Icheon	2.35	3.80*	5.24*	3.10*	3.87*	2.93*	-0.39	0.97	1.38	2.82*	2.18	0.71	2.31
Inje	1.21	2.92*	2.15	0.65	0.90	2.26	-1.31	-0.44	0.72	1.51	-0.02	-0.62	0.41
Jecheon	1.36	3.31*	3.43*	1.87	1.81	2.73*	-1.03	0.02	-0.33	3.25*	1.03	0.03	1.32
Boeun	2.04	2.88*	4.64*	1.78	1.75	1.51	0.29	-1.58	-1.10	0.63	2.03	0.26	1.14
Cheonan	1.98	3.26*	3.59*	1.97	2.53	1.49	-1.58	-0.93	-0.37	2.31	1.60	0.42	1.34
Boryeong	0.62	1.83	1.56	-0.60	0.12	-1.49	-3.25*	-2.22	-3.19*	-1.92	0.02	-0.37	-2.25
Buyeo	1.89	2.22	3.06*	2.64*	4.51*	1.71	-0.33	-0.48	-0.66	0.36	1.23	0.38	1.65
Geumsan	2.37	2.32	3.25*	1.73	4.48*	2.81*	0.99	0.93	0.23	0.04	1.61	0.44	2.03
Buan	1.23	3.05*	2.86*	2.02	2.07	-0.04	-0.98	-1.23	-0.39	-0.43	1.54	0.22	3.64*
Imsil	1.89	2.59*	3.17*	2.14	3.89*	2.43	0.55	0.07	0.39	0.34	2.11	0.35	2.12
Jeongeup	0.64	1.94	2.35*	1.12	1.52	0.33	-0.90	-1.07	-0.39	-0.70	0.80	-0.57	0.57
Namwon	0.35	1.43	1.47	0.80	3.07*	-0.51	-0.57	-1.75	-1.67	-1.08	0.35	-0.94	-0.22
Jangheung	1.79	2.18	2.53*	2.84*	1.60	-2.44	-1.25	-0.81	-1.52	-0.47	1.08	-0.22	-0.20
Haenam	2.80	2.95	3.89*	3.59*	2.93*	0.26	0.35	0.18	1.90	2.06	2.59*	0.71	5.86*
Goheung	0.42	1.39	0.99	-0.57	-0.08	-2.13	-1.98	-1.85	-2.40	-0.89	0.07	-1.63	-1.92
Yeongju	0.13	1.65	1.48	0.72	1.23	1.50	-0.62	-0.94	-1.03	-0.49	-0.61	-1.58	0.18
Mungyeong	0.57	1.96	1.58	0.40	1.10	0.95	-0.52	-0.94	-1.19	-0.03	-0.02	-0.88	0.19
Yeongdeok	-0.75	3.26*	2.88*	1.01	0.83	2.09	1.10	0.87	-0.85	-1.99	-0.18	-1.82	1.10
Uiseong	1.94	3.49*	3.93*	2.79*	3.24*	2.41	1.91	1.59	0.72	0.06	1.80	0.35	2.27
Gumi	2.24	2.91*	3.12*	1.40	2.72*	1.40	0.79	-0.46	-1.30	-1.19	1.31	0.39	1.46
Yeongcheon	1.94	3.57*	3.82*	2.15	1.67	1.10	1.06	0.70	-0.59	-0.64	2.05	0.35	1.79
Geochang	2.26	3.37*	3.25*	1.55	3.83*	1.34	1.06	0.51	-0.07	0.07	1.93	0.72	1.77
Miryang	1.96	2.44	2.77*	2.29	2.66*	1.93	2.90*	2.56	0.94	-0.11	2.79*	0.39	3.12*
Sancheong	0.95	2.38	1.87	0.77	1.42	-0.81	-0.17	-0.79	-1.12	-1.23	0.83	-1.05	0.22
Geoje	1.67	3.23*	2.81*	1.96	2.24	0.77	0.94	1.20	0.18	-0.10	1.98	0.64	2.31
Namhae	1.54	1.89	1.38	1.64	2.18	-0.04	1.58	0.30	-1.79	-3.13*	-0.75	-1.74	1.08

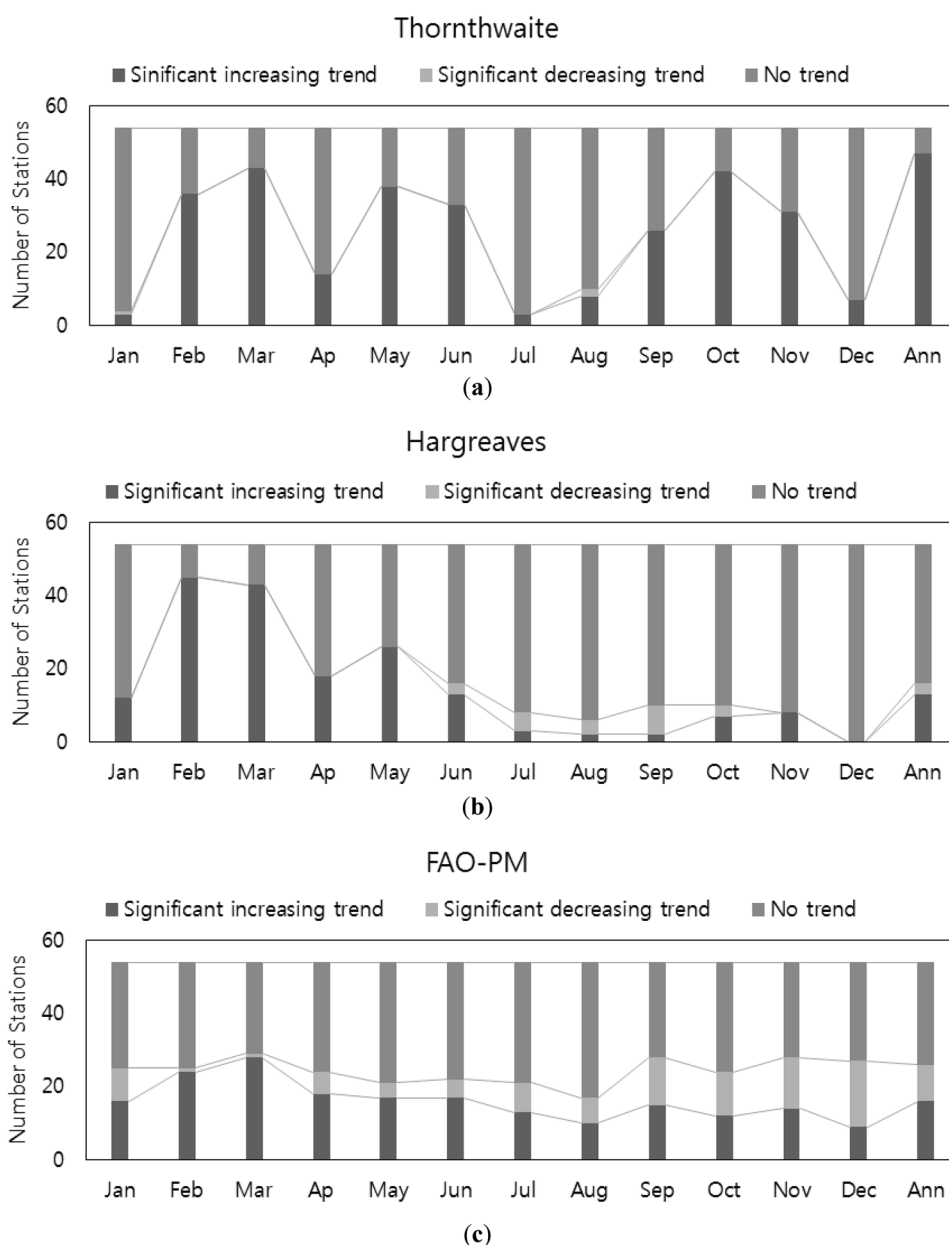
Bold values indicate the statistically significant trend at the 95% confidence level, * indicates the statistically significant trend at 99% confidence level

Table 3 Z statistics of modified MK trend tests for FAO-PM reference crop evapotranspiration over South Korea

Stations	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Sokcho	-1.21	1.83	3.71*	2.70*	0.55	1.52	0.36	-0.11	0.86	-0.11	-0.97	-2.53	1.80
Daegwallyeong	3.39*	3.01*	4.12*	1.47	1.57	1.17	0.48	-0.10	-0.07	0.48	0.99	0.61	2.64*
Chuncheon	-1.64	-2.02	-1.03	-2.60*	-1.94	-0.68	-2.35	-0.59	-1.14	-2.57	-3.21*	-2.50	-2.47
Gangneung	-0.28	1.94	1.15	-1.22	-0.29	0.56	0.09	-0.49	-0.72	-0.99	-1.98	-2.56	-0.39
Seoul	-0.68	1.82	0.46	-0.28	0.71	0.71	-0.46	0.83	0.31	0.72	-0.13	-0.73	-0.06
Incheon	-1.89	0.62	1.17	-0.50	-0.21	-0.61	-2.00	-2.09	-3.16*	-2.68*	-3.58*	-3.28*	-6.07
Wonju	-0.56	1.56	0.75	-0.33	0.23	0.93	-0.70	0.33	0.02	-0.44	-1.02	-2.28	0.15
Suwon	1.10	2.02	2.24	1.39	2.92*	4.05	2.45	3.25	3.76*	2.40	1.80	1.45	4.22*
Chungju	2.20	2.41	2.78*	3.30*	2.85*	5.23	3.93*	3.84	4.12*	2.47	2.03	2.10	2.80*
Seosan	0.94	2.40	1.90	1.28	3.79*	0.44	-1.03	-1.06	-0.25	1.03	0.19	0.27	0.52
Uljin	-0.82	0.99	3.78*	0.34	-0.75	-0.94	0.06	-1.23	-0.60	-0.36	0.00	-1.11	-0.37
Cheongju	-1.00	-0.27	-1.19	-1.86	-1.96	-0.63	-2.41	-1.41	-2.20	-1.97	-2.44	-1.45	-2.01
Daejeon	2.35	2.81	2.16	-0.22	0.77	0.00	-1.67	-0.70	-0.62	0.66	2.49	0.96	0.46
Chupungnyeong	-0.85	1.58	1.93	0.48	0.86	-0.51	-0.35	-1.01	-2.23	-1.76	-0.46	-2.70*	-0.70
Pohang	-3.34*	-1.13	-1.10	-3.62*	-1.97	-2.55	-1.93	-2.85*	-5.72*	-7.00*	-4.00*	-7.92*	-5.04*
Gunsan	-2.46	0.83	3.28*	0.61	0.19	-1.69	-3.41*	-3.92*	-4.77*	-4.24*	-3.49*	-3.03*	-4.55*
Daegu	-2.95*	-0.18	-1.01	-2.10	-2.08	-2.75*	-2.49	-2.26	-5.25*	-3.76*	-3.58*	-3.19*	-3.57*
Jeonju	5.26*	6.11*	5.26*	5.00*	6.85*	3.34*	2.70*	2.79*	4.24*	5.36*	5.91*	4.24*	6.30*
Ulsan	-1.98*	-0.42	0.42	0.37	-0.46	0.13	0.11	-0.36	-0.69	-1.32	-2.26	-5.73*	-0.61
Gwangju	-2.40*	0.11	-0.26	0.00	1.68	0.49	0.79	-0.40	0.09	-1.91	-2.66	-3.57*	-0.04
Busan	-1.10	0.06	-0.05	-0.62	0.36	-0.44	-0.09	-1.50	-2.57	-2.05	-2.51	-2.61*	-1.36
Tongyeong	1.50	1.46	4.64*	-0.26	0.31	-0.26	-0.53	-1.14	2.30	2.13	0.79	1.57	0.89
Mokpo	-1.78	-0.61	-1.89	-1.33	-1.33	-1.85	-2.82*	-3.16*	-3.79*	-2.64*	-2.41	-1.91	-2.01
Yeosu	-0.35	1.26	-0.17	-0.32	0.38	-2.10	-1.03	-1.90	-2.40	-1.91	-0.96	-0.15	-1.27
Wando	3.08*	3.51*	3.33*	2.81	4.93*	2.36	2.73*	3.87*	3.13*	2.80*	1.61	1.43	2.77*
Jinju	-0.56	0.18	0.50	-0.45	0.04	-0.46	-1.25	-1.08	0.37	-0.27	-1.10	-0.98	-0.53
Ganghwa	1.58	3.92*	3.06*	2.04	1.83	2.35	2.17	4.07*	3.75*	6.03*	1.93	0.26	3.41*
Yangpyeong	-0.04	0.88	0.90	-0.28	0.67	2.20	1.23	1.76	0.62	-0.40	-0.32	-1.34	0.55
Icheon	2.55	2.97*	3.31*	3.30*	2.80*	3.58	6.63*	2.77*	2.13	2.89*	2.27	2.89*	3.93*
Inje	-1.61	-0.50	-0.06	-2.28	-1.11	1.12	-1.96	-0.53	0.86	0.22	-2.20	-4.26*	-1.50
Jecheon	4.87*	4.15*	1.91	2.13	1.61	2.57	0.13	0.15	-0.20	1.17	3.04*	3.38*	1.92
Boeun	0.73	1.98	3.98*	1.43	1.80	1.05	0.88	-0.50	-1.30	-2.45	0.57	0.40	0.89
Cheonan	3.03*	4.15*	3.56*	2.86*	2.87*	0.84	1.12	-0.77	0.10	1.52	1.90	2.05	1.94
Boryeong	-2.07	-1.58	-2.31	-3.61*	-2.18	-3.26*	-2.92*	-5.61*	-5.06*	-2.99*	-2.29	-2.40	-4.86*
Buyeo	0.00	0.63	1.76	0.31	2.01	0.81	0.66	-0.23	-0.40	0.50	-0.02	0.49	0.68
Geumsan	-0.93	0.51	0.67	-0.79	0.68	0.22	0.39	-0.64	-0.20	-2.21	-0.73	-1.65	-0.08
Buan	-3.02*	0.75	2.54	0.60	1.55	-0.31	0.64	-0.84	0.40	-0.32	-0.77	-2.38	0.29
Imsil	1.72	2.66*	4.75*	4.20*	4.29*	3.78*	2.15	1.58	2.66*	3.04*	2.92*	0.88	4.47*
Jeongeup	0.17	2.88*	1.97	1.89	3.65*	2.29*	1.67	1.06	1.41	0.72	1.96	0.92	2.19
Namwon	3.10*	1.91	2.75*	4.51*	4.06*	3.22*	3.24*	1.54	5.19	2.57	3.69*	2.31	4.47*
Jangheung	2.62*	2.38	2.73*	5.43*	1.92	-0.38	1.17	0.12	0.49	1.10	1.30	1.52	1.73
Haenam	2.16	2.44	5.76*	4.07*	5.41*	2.82*	2.90*	2.43	3.14*	1.96	1.87	1.35	2.67
Goheung	3.28*	3.45*	2.53	2.11	2.70*	-1.16	-0.57	-2.37	-2.03	0.71	2.05	3.26*	1.48
Yeongju	3.91*	3.25*	4.02*	2.40	3.02*	3.20	2.59	2.15	2.71*	2.80*	2.66*	1.12	3.65*
Mungyeong	2.65*	2.64*	2.86*	1.67	2.04*	2.26	1.61	1.07	1.54	2.02	2.26	1.43	2.75*
Yeongdeok	1.60	3.15*	2.54	4.45*	1.92	3.63*	2.97	2.11	3.23	2.10	2.63*	0.52	3.60*
Uiseong	1.50	2.57*	2.70*	2.75*	1.71	1.54	1.38	0.87	1.96	0.15	1.43	1.52	1.59
Gumi	-3.74*	-1.74	-0.94	-2.66*	-1.19	-0.29	0.59	-0.39	-2.49	-3.25	-3.59*	-3.97*	-2.46
Yeongcheon	2.38	2.88	2.90*	2.72*	4.89*	3.47	4.07*	3.36	4.02*	1.33	2.44	2.05	3.33*
Geochang	1.42	2.92	2.40	1.39	1.84	1.06	1.56	0.29	0.74	0.62	1.87	1.08	1.63
Miryang	-0.73	0.06	-0.43	-0.48	1.63	4.37*	1.83	0.64	0.64	-0.60	-1.55	-2.20	0.97
Sancheong	3.91*	2.64*	2.24	2.51	3.39*	1.89	3.01*	1.59	2.93*	1.34	2.68	2.92*	11.78*
Geoje	-1.05	0.67	0.85	0.72	0.84	-0.33	0.99	0.22	0.07	-0.72	-0.86	-1.74	0.54
Namhae	-2.53*	-0.29	-1.58	-1.47	-0.02	-3.31*	0.15	-0.80	-2.53	-1.75	-1.94	-2.09	-1.99*

Bold values indicate the statistically significant trend at the 95% confidence level, * indicates the statistically significant trend at 99% confidence level

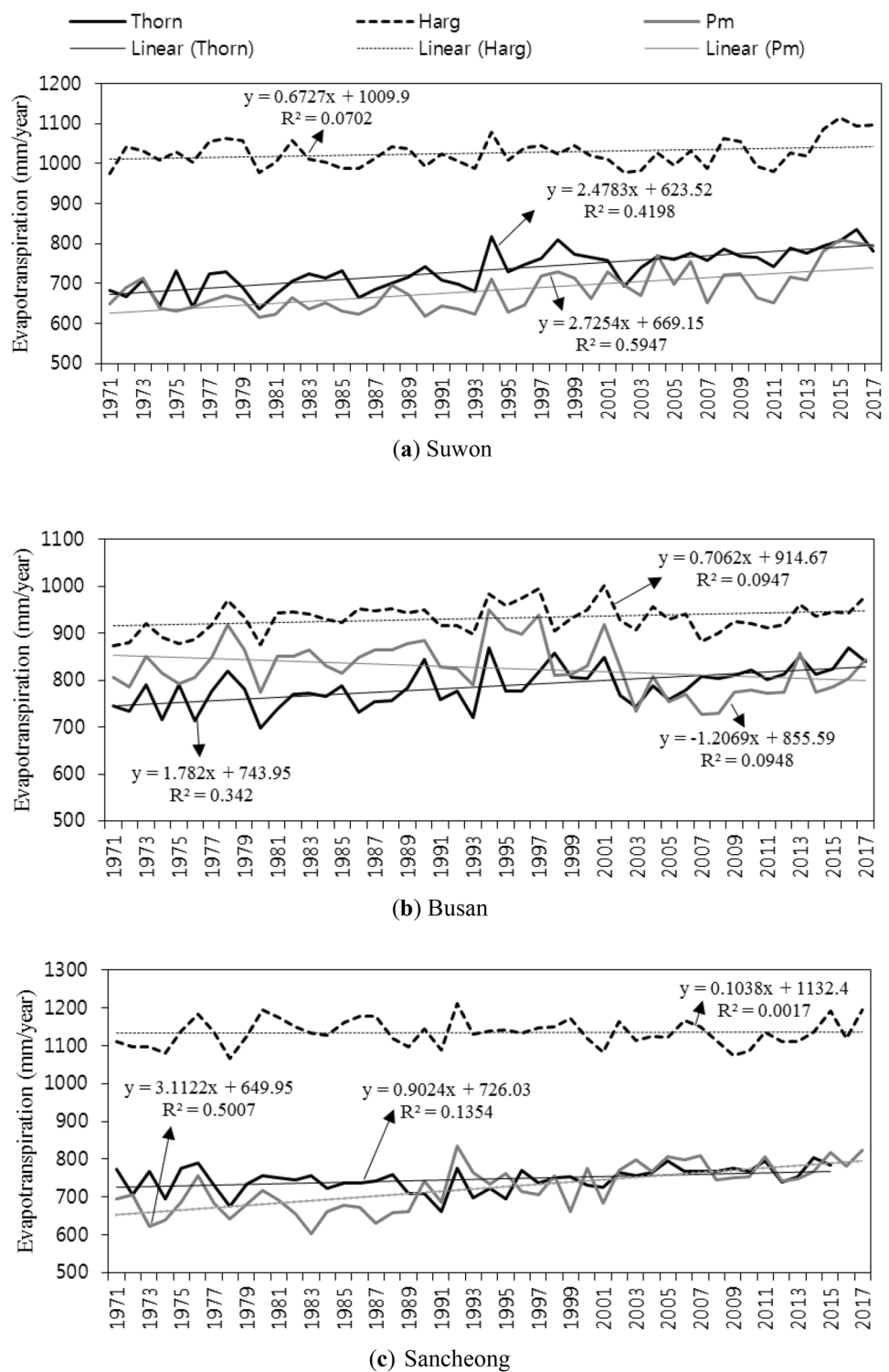
Fig. 5 Summary of ETo and PET trend analysis at 54 meteorological stations across South Korea using three methods: **a** Thornthwaite, **b** Hargreaves, **c** FAO-PM



carried out using R programming package, namely "olsrr" (Hebbali 2017), in which monthly time series of ETo is considered as a dependent variable and eight climatic variables such as T_{\max} , T_{\min} , T_{sun} , T_{dew} , P , P_0 , U_2 and RH are considered as independent variables. The results of multiple stepwise regression model for each month (January–December) are presented in Table 4. It can be noticed that the order of climatic variables is different from one month to another, sorted on the basis of dominance of climatic variable influencing the monthly values of ETo. The climatic variables having lowest value of p and highest value of R^2 are selected in the first step of multiple stepwise regression and considered as the most dominant variable influencing the value of ETo. The results showed that during autumn, early winter

(September–January) and early summer (May–June) wind speed is the most dominant variable influencing ETo at 55 stations across South Korea. The highest values of Pearson's correlation for the wind speed during autumn, early winter and early summer confirm its dominant effect on ETo (Table 5). On the other hand, during spring (February–April) and late summer (July–August), the T_{\max} followed by U_2 is the most dominant climatic variable, using multiple stepwise regression model (Table 4) and Pearson's correlation method (Table 5). The R^2 value varies from 0.754 to 0.901 which showed fairly good agreement of multiple stepwise regression model. Those climatic variables which do not have a significant impact ($p > 0.05$) on ETo were removed in multiple stepwise regression model and

Fig. 6 LR-based trend in annual evapotranspiration at the stations having highest value of Z statistics: **a** Suwon station for Thornthwaite method, **b** Busan station for Hargreaves method, **c** Sancheong station for FAO-PM method

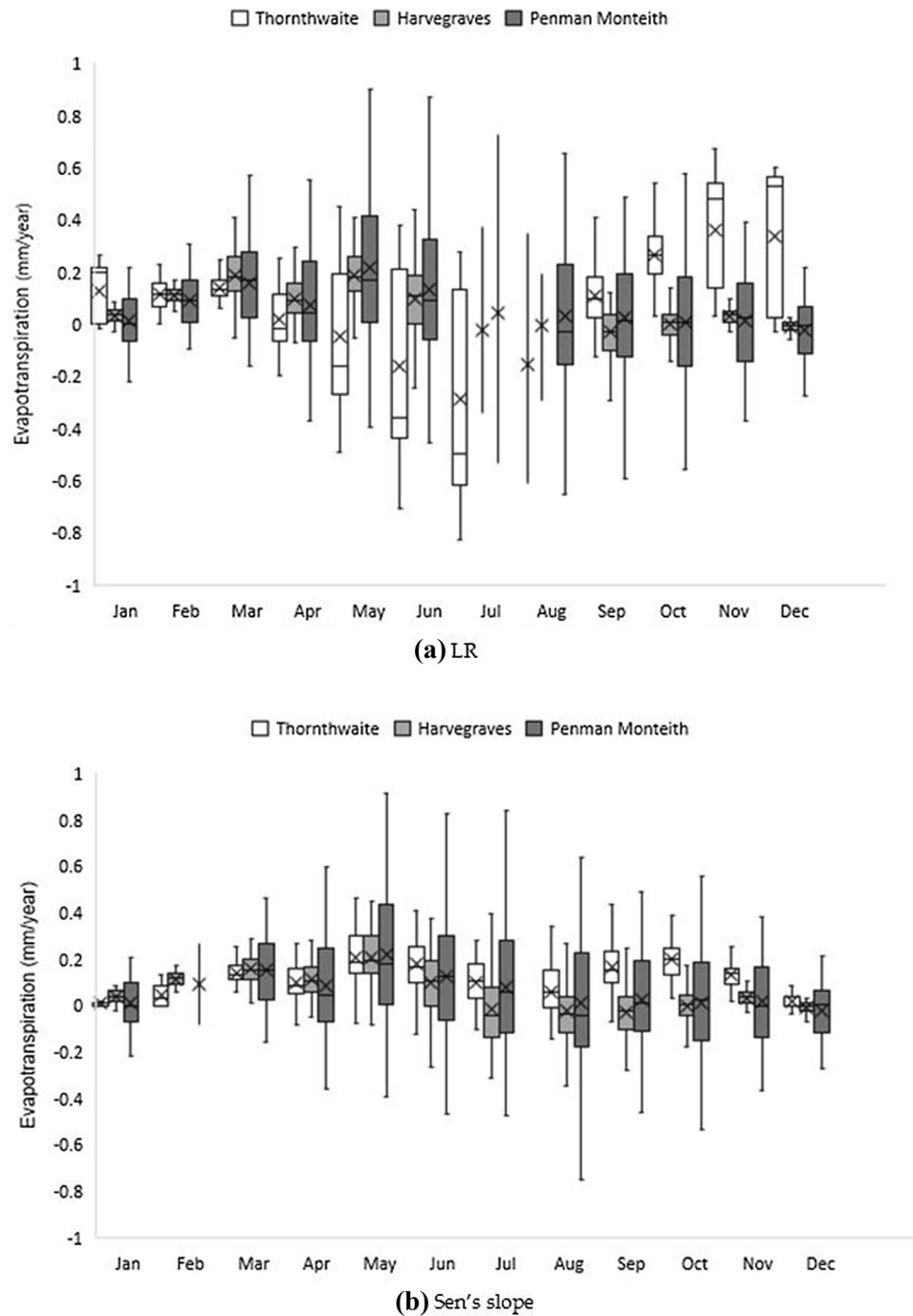


indicated in bold (Table 4). The corresponding values of beta, standard error and *t* statistics for each climatic variable are also shown in Table 4.

The sensitivity and impact of U_2 and T_{max} are higher on the value of ETo as compared to other climatic variables. The higher influence of U_2 during autumn, early winter and

early summer can be because of the fact that the energy associated with the wind speed leads to a rapid change in vapor pressure deficit conditions. Previous studies have shown the impact of wind speed on the magnitude and significance of ETo trends in Australia (Rayner 2007; Roderick et al. 2007), in Tibetan Plateau (Shenbin et al. 2006; Zhang et al.

Fig. 7 Monthly temporal distribution of the magnitude of trends detected in ETo (mm/year) using; **a** the slope b of LR, **b** Sen's slope, using three methods (i.e., Thornthwaite, Hargreaves and FAO-PM)



2007) and in Canada (Burn and Hesch 2007). Furthermore, combination of U_2 and T_{sun} also leads to affect the ETo (Gao et al. 2006; Xu et al. 2006). Irmak et al. (2006) showed that ETo is most sensitive to U_2 at semiarid regions having strong wind. This is because of the reason that an increase in wind speed will lower the aerodynamic resistance which in turn increases the value of ETo. In general, when crops transpire water, the immediate surrounding environment of the crop canopy will be moist. In arid climates, the wind flow is most

likely to replace this moist air with dry air and causes an increase in ETo.

They found that at semiarid regions and island locations ETo is more sensitive to T_{max} than any other climatic variable in summer months, which match well with the results of this study. These findings indicate the importance of each climatic variable in terms of trends and magnitude of ETo and their value changes according to the regional and temporal characteristics. As a result, only one or

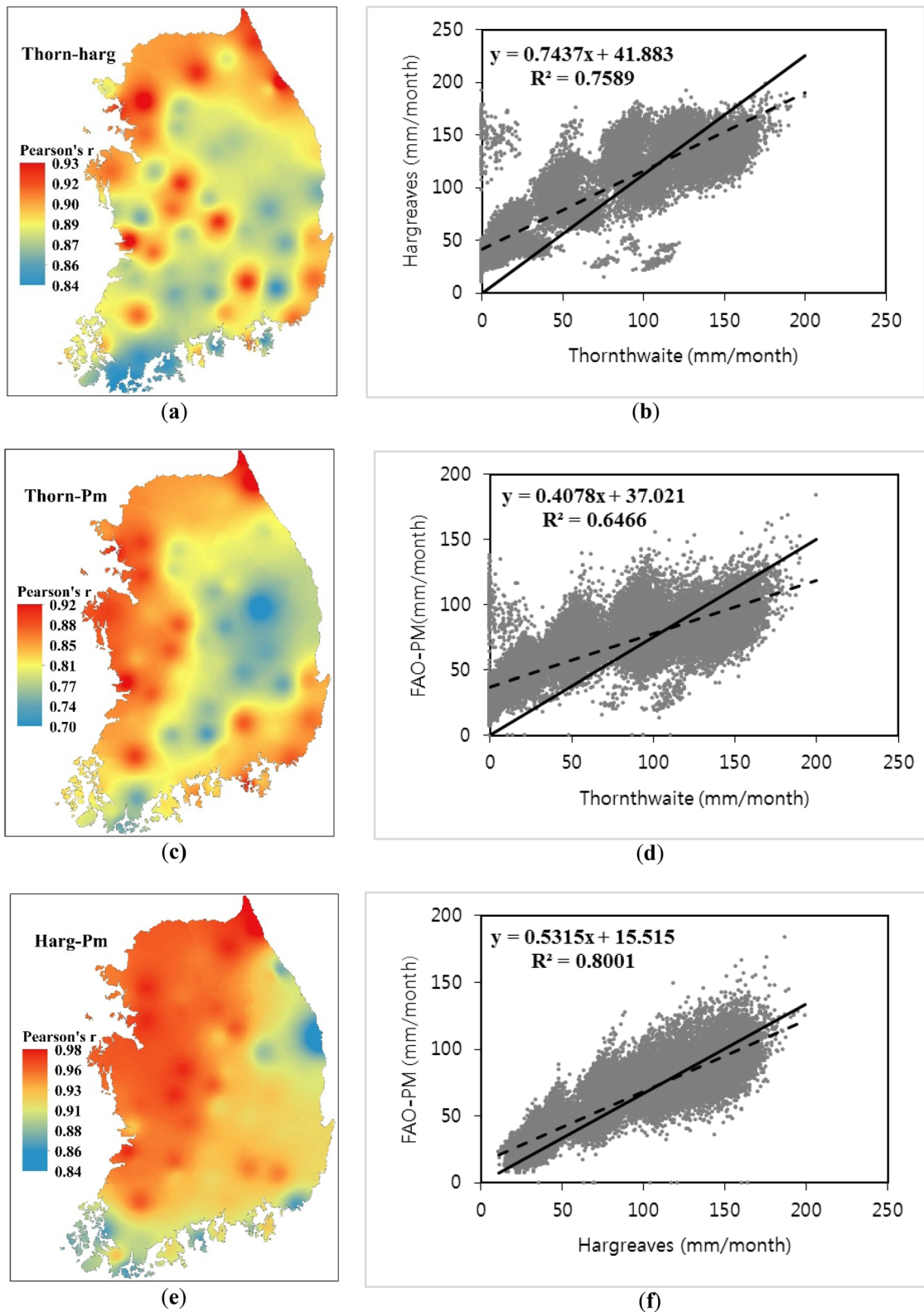
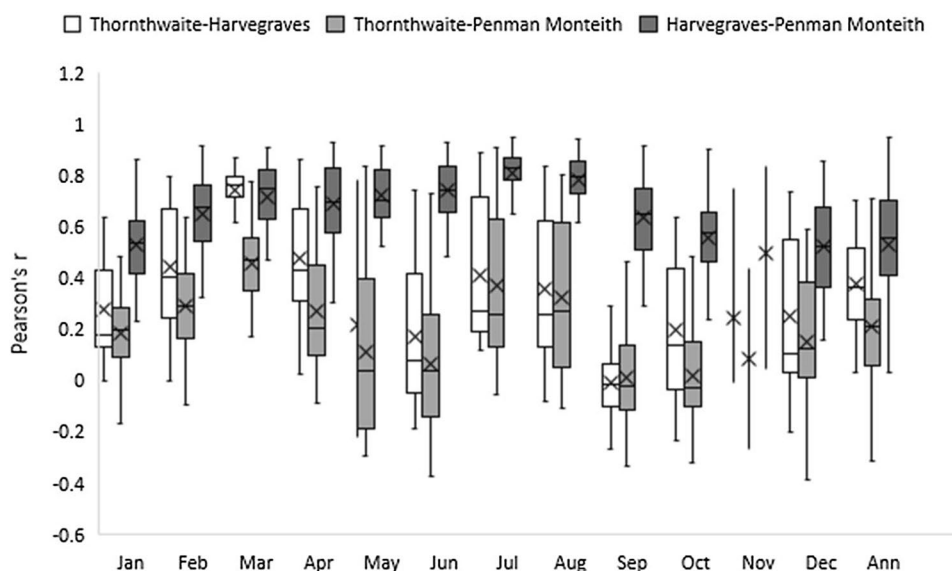


Fig. 8 Spatial distribution of Pearson’s correlations (left) between monthly ETo and PET time series obtained by the Thornthwaite (Th), Hargreaves (Harg) and FAO-PM (Pm) equations at 54 meteorological stations in South Korea. Scatter plot (right) shows the corresponding

relationship of the magnitude of change for different ETo and PET equations; the solid line represents the perfect agreement (1:1) and the dashed line represents a linear fit to the data

Fig. 9 Monthly and annual temporal variation of Pearson's r correlation at 54 meteorological stations across South Korea



two climatic variables are not responsible to the spatial or temporal changes in ETo; therefore, it needed to be collectively estimated by a combination of energy balance equation, rather than relying only on temperature or radiation data.

Multicollinearity diagnosis is performed using the VIF to identify the collinearity problem. VIF values were tested for the ETo obtained by FAO-PM as shown in Table 6. Most of the climatic variables lie between the VIF values of 1 and 6 ($VIF < 10$), thereby indicating that there were no potential multicollinearity problems existed in our dataset.

Conclusions

Since ETo and PET determine the crop water demand and irrigation scheduling across the region, investigating the spatial and temporal trends is a crucial step. In this study, a spatial and temporal trend analysis of monthly and annual ETo was performed, while taking care of serial correlation of time series, using Thornthwaite, Hargreaves and FAO-PM methods. Their results were compared to find more robust trends at 55 meteorological stations throughout the region. A multiple stepwise regression method was used to identify the leading climatic variables influencing the trends in ETo. The following major conclusions can be drawn from this study:

1. Although there is the quantitative difference between the values of PET and ETo estimated by Thornthwaite, Hargreaves and FAO-PM methods, spatial changing pattern of PET and ETo according to the location of meteorological stations is same; for instance, ETo value
2. Trend analysis performed considering the effect of serial correlation using modMK Z statistics showed that the Thornthwaite method tends to show the highest number of stations (most of them located at east and south coast) with a significant increasing trend in monthly and annual time series (except July and August) as compared to Hargreaves and FAO-PM methods, because of its strong association with temperature. However, FAO-PM method showed the larger number of stations (mostly located on mid-latitude areas and south coastal areas) with significant decreasing trends as compared to Thornthwaite and Hargreaves methods, which can be correlated with the impact of the collective involvement of different climatic variables in addition to the atmospheric air temperature. Moreover, the magnitude of the trends detected by the LR and the Sen's slope method is quite comparable with the abrupt increase in summer.
3. Spatial and temporal correlation analysis showed the presence of association ($p < 0.01$) between Thornthwaite, Hargreaves and FAO-PM equations, while the strongest correlation existed between Hargreaves and FAO-PM as it ranged from 0.84 to 0.98 with R^2 value of 0.8. Furthermore, the correlation is relatively lower at high-temperature areas along the mid-latitude east coast and south coast and high at low-temperature areas along the north portion and along the west coast.
4. Various climatic variables evaluated to check their influence on ETo using multiple stepwise regression model showed that the U_2 is the most influencing climatic variable, especially in autumn, early winter and early summer, and T_{max} during spring and late summer.

Table 4 Monthly climatic variables sorted according to value dominance and R^2 in multiple stepwise regression model at 95% confidence level

Month	Variable	Beta	SE	<i>t</i>	<i>p</i>	R^2	R^2 adj	RMSE
January	(Intercept)	35.756	29.948	1.194	0.233	0.897	0.897	2.298
	U_2	4.957	0.056	88.607	0.000			
	T_{max}	2.832	0.049	57.336	0.000			
	T_{min}	-1.645	0.062	-26.473	0.000			
	RH	-0.169	0.023	-7.270	0.000			
	<i>P</i>	0.230	0.038	6.093	0.000			
	T_{dew}	0.372	0.096	3.864	0.000			
	T_{sun}	0.115	0.045	2.576	0.010			
	P_0	-0.510	0.292	-1.749	0.080			
February	(Intercept)	130.791	28.530	4.584	0.000	0.869	0.868	2.550
	T_{max}	2.881	0.058	49.994	0.000			
	U_2	5.105	0.062	82.623	0.000			
	T_{min}	-1.804	0.073	-24.723	0.000			
	RH	-0.216	0.029	-7.494	0.000			
	T_{dew}	0.587	0.119	4.938	0.000			
	T_{sun}	0.220	0.049	4.473	0.000			
	P_0	-1.380	0.281	-4.910	0.000			
	<i>P</i>	0.180	0.041	4.360	0.000			
March	(Intercept)	154.065	42.103	3.659	0.000	0.838	0.837	3.686
	T_{max}	4.600	0.074	61.894	0.000			
	U_2	8.174	0.103	79.619	0.000			
	T_{min}	-2.771	0.089	-31.092	0.000			
	RH	-0.226	0.035	-6.477	0.000			
	<i>P</i>	0.362	0.064	5.663	0.000			
	P_0	-1.970	0.417	-4.723	0.000			
	T_{sun}	0.306	0.065	4.676	0.000			
	T_{dew}	0.503	0.136	3.701	0.000			
April	(Intercept)	128.292	59.667	2.150	0.032	0.804	0.869	5.203
	T_{max}	6.367	0.113	56.121	0.000			
	U_2	12.206	0.163	74.669	0.000			
	T_{min}	-3.622	0.116	-31.217	0.000			
	RH	-0.268	0.054	-5.006	0.000			
	<i>P</i>	0.730	0.089	8.168	0.000			
	T_{sun}	0.500	0.071	7.061	0.000			
	P_0	-2.375	0.588	-4.041	0.000			
	T_{dew}	0.473	0.201	2.350	0.019			
May	(Intercept)	102.993	83.356	1.236	0.217	0.801	0.801	6.546
	U_2	17.000	0.225	75.590	0.000			
	T_{max}	8.273	0.098	84.768	0.000			
	T_{min}	-3.866	0.118	-32.849	0.000			
	T_{sun}	0.921	0.087	10.585	0.000			
	<i>P</i>	1.046	0.130	8.068	0.000			
	P_0	-2.946	0.821	-3.590	0.000			
	T_{dew}	-0.969	0.099	-9.829	0.000			
	RH*	-0.070	0.077	-0.909	0.363			

Table 4 (continued)

Month	Variable	Beta	SE	<i>t</i>	<i>p</i>	<i>R</i> ²	<i>R</i> ² adj	RMSE
June	(Intercept)	131.500	99.581	1.321	0.187	0.781	0.780	6.855
	<i>U</i> ₂	17.409	0.245	71.079	0.000			
	<i>T</i> _{max}	7.773	0.176	44.273	0.000			
	<i>T</i> _{min}	−4.374	0.191	−22.910	0.000			
	<i>T</i> _{sun}	1.128	0.089	12.640	0.000			
	<i>P</i>	0.621	0.132	4.698	0.000			
	<i>P</i> ₀	−2.623	0.990	−2.650	0.008			
	<i>T</i> _{dew} *	−0.573	0.308	−1.864	0.062			
	RH*	−0.080	0.073	−1.100	0.271			
July	(Intercept)	−134.994	13.400	−10.074	0.000	0.790	0.790	7.459
	<i>T</i> _{max}	8.670	0.158	54.703	0.000			
	<i>U</i> ₂	15.562	0.224	69.461	0.000			
	<i>T</i> _{min}	−5.203	0.187	−27.869	0.000			
	<i>T</i> _{sun}	1.637	0.102	16.043	0.000			
	RH	−0.190	0.032	−5.877	0.000			
	<i>P</i>	0.576	0.135	4.277	0.000			
	<i>P</i> ₀ *	−0.882	1.022	−0.862	0.389			
	<i>T</i> _{dew} *	−0.095	0.411	−0.231	0.818			
August	(Intercept)	−146.960	13.938	−10.544	0.000	0.800	0.800	7.608
	<i>T</i> _{max}	8.704	0.153	57.066	0.000			
	<i>U</i> ₂	17.440	0.244	71.461	0.000			
	<i>T</i> _{min}	−5.212	0.173	−30.188	0.000			
	<i>T</i> _{sun}	1.409	0.110	12.812	0.000			
	<i>P</i>	0.589	0.143	4.107	0.000			
	RH	−0.102	0.033	−3.074	0.002			
	<i>T</i> _{dew} *	0.585	0.526	1.112	0.266			
	<i>P</i> ₀ *	−0.844	0.988	−0.854	0.393			
September	(Intercept)	−84.639	13.831	−6.119	0.000	0.754	0.754	6.605
	<i>U</i> ₂	16.289	0.219	74.390	0.000			
	<i>T</i> _{max}	5.911	0.164	35.939	0.000			
	<i>T</i> _{min}	−4.005	0.161	−24.869	0.000			
	<i>T</i> _{sun}	1.094	0.114	9.640	0.000			
	RH	−0.277	0.058	−4.800	0.000			
	<i>P</i>	0.470	0.130	3.619	0.000			
	<i>T</i> _{dew}	0.720	0.246	2.930	0.003			
	<i>P</i> ₀ *	1.686	1.058	1.593	0.111			
October	(Intercept)	−67.316	11.734	−5.737	0.000	0.810	0.809	5.714
	<i>U</i> ₂	15.422	0.188	81.881	0.000			
	<i>T</i> _{max}	5.137	0.120	42.911	0.000			
	<i>T</i> _{min}	−3.559	0.132	−26.885	0.000			
	RH	−0.394	0.049	−8.004	0.000			
	<i>T</i> _{dew}	1.188	0.210	5.652	0.000			
	<i>P</i>	0.468	0.105	4.472	0.000			
	<i>T</i> _{sun}	0.406	0.110	3.696	0.000			
	<i>P</i> ₀ *	−0.074	0.862	−0.086	0.931			

Table 4 (continued)

Month	Variable	Beta	SE	<i>t</i>	<i>p</i>	<i>R</i> ²	<i>R</i> ² adj	RMSE
November	(Intercept)	43.806	44.146	0.992	0.321	0.859	0.858	3.776
	<i>U</i> ₂	9.404	0.105	89.692	0.000			
	<i>T</i> _{max}	4.085	0.065	63.009	0.000			
	<i>T</i> _{min}	−2.389	0.074	−32.174	0.000			
	RH	−0.195	0.025	−7.776	0.000			
	<i>P</i>	0.610	0.065	9.339	0.000			
	<i>T</i> _{dew}	0.377	0.104	3.627	0.000			
	<i>P</i> ₀	−1.143	0.434	−2.635	0.008			
	<i>T</i> _{sun} *	0.052	0.084	0.620	0.535			
December	(Intercept)	76.728	28.205	2.720	0.007	0.901	0.901	2.701
	<i>U</i> ₂	6.280	0.070	90.011	0.000			
	<i>T</i> _{max}	3.188	0.047	68.123	0.000			
	<i>T</i> _{min}	−1.958	0.058	−33.616	0.000			
	RH	−0.170	0.018	−9.222	0.000			
	<i>P</i>	0.555	0.047	11.735	0.000			
	<i>T</i> _{dew}	0.379	0.079	4.831	0.000			
	<i>P</i> ₀	−1.282	0.273	−4.691	0.000			
	<i>T</i> _{sun} *	0.003	0.058	0.048	0.962			

*Indicates the variables which are removed in the stepwise regression model. Only variables significantly related to FAO-PM at 95% level were selected. Moreover, the climatic variables in each matrix are sorted according to the stepwise selection of the variables in stepwise regression model

Table 5 Pearson’s correlation between the climatic variables and ETo from January to December

Month	<i>U</i> ₂	<i>T</i> _{sun}	RH	<i>T</i> _{max}	<i>T</i> _{min}	<i>T</i> _{dew}	<i>P</i>	<i>P</i> ₀
January	0.687	0.155	−0.504	0.602	0.521	0.157	0.011	−0.446
February	0.536	0.125	−0.422	0.598	0.436	0.139	0.048	−0.324
March	0.377	0.174	−0.432	0.568	0.259	−0.025	0.070	−0.257
April	0.231	0.172	−0.386	0.474	−0.036	−0.156	−0.114	−0.176
May	0.269	0.148	−0.488	0.458	−0.081	−0.347	−0.138	−0.115
June	0.251	0.309	−0.483	0.471	−0.070	−0.258	−0.058	−0.066
July	0.342	0.414	−0.317	0.583	0.404	0.278	0.081	0.021
August	0.454	0.446	−0.291	0.561	0.422	0.323	0.170	−0.122
September	0.623	0.266	−0.339	0.219	0.157	0.003	0.179	−0.041
October	0.687	0.273	−0.394	0.288	0.271	0.090	0.055	−0.190
November	0.661	0.312	−0.410	0.472	0.385	0.135	0.048	−0.249
December	0.671	0.246	−0.486	0.616	0.547	0.185	0.047	−0.301

Although this study clearly stated the existence of increasing trends in monthly and annual ETo and identified the wind speed and maximum atmospheric air temperature as the forcing mechanism behind these trends, evaluation of the amount of increase in water demand with the increase in ETo, in various sectors such as agriculture and reservoirs operations is beyond the scope of

this study. The results of this study can be used as a theoretical basis for future water resource planning and management in South Korea. Moreover, ETo changes based on location and time of the year emphasize the seasonal management of reservoirs and hydraulic structures across the country.

Table 6 Seasonal collinearity statistics for the climatic variables in South Korea

Month	U_2	T_{sun}	RH	T_{max}	T_{min}	T_{dew}	P	P_0
January	2.036	1.405	3.044	4.078	5.652	3.012	1.524	1.334
February	1.774	1.453	5.915	4.176	5.520	3.254	1.457	1.222
March	1.897	1.177	3.769	3.271	3.563	5.371	1.622	1.127
April	2.124	1.069	4.846	3.584	2.154	4.723	1.510	1.103
May	2.060	1.076	5.721	3.401	1.352	5.356	1.912	1.066
June	1.677	1.215	2.769	4.670	0.614	4.342	1.729	1.081
July	1.609	1.394	0.780	4.538	4.858	5.564	1.513	1.069
August	1.796	1.514	5.992	4.809	4.380	4.181	1.691	1.044
September	1.958	1.296	5.771	3.651	3.868	2.558	1.796	1.119
October	2.177	1.153	4.769	3.437	4.620	5.011	1.650	1.119
November	2.025	1.413	5.220	4.004	4.129	5.212	1.576	1.153
December	2.131	1.517	1.987	5.625	3.384	5.485	1.714	1.163

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