Journal of
Water & Climate Change

 Journal of Water and Climate Change Vol 15 No 2, 554 doi: 10.2166/wcc.2023.485

Analyzing the relationship between meteorological changes and evapotranspiration trends in Gia Lai province, Central Highlands of Vietnam

Phan Thi Ha [a], Le Minh Hai [b], Nguyen Duy Liem [a], Nguyen Le Tan Dat [c], Nguyen Thi Huyen [a], Nguyen Ngoc Thuy [d] and Nguyen Kim Loi [a,*]

[a] Research Center for Climate Change, Nong Lam University, Ho Chi Minh City, Vietnam
[b] Institute for Environment and Resources, Vietnam National University, Ho Chi Minh City, Vietnam
[c] Faculty of Management Sciences, Thu Dau Mot University, Thu Dau Mot City, Binh Duong Province, Vietnam
[d] Faculty of Economics, Nong Lam University, Ho Chi Minh City, Vietnam
*Corresponding author. E-mail: ngkloi@hcmuaf.edu.vn

PTH, 0009-0009-5421-1990; NDL, 0000-0001-5151-4560; NLTD, 0000-0002-4645-7810; NTH, 0000-0003-1032-9697; NNT, 0000-0002-0793-3239; NKL, 0000-0002-3063-6910

ABSTRACT

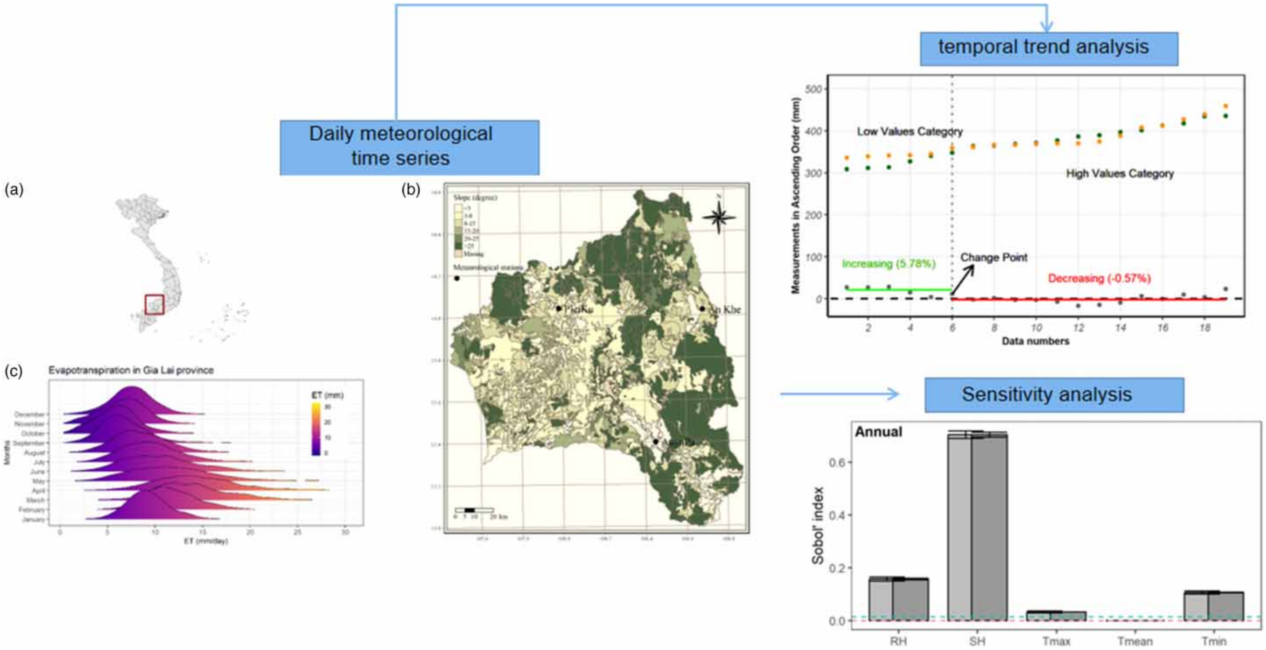
This study aims to analyze the historical trends of evapotranspiration at annual and seasonal scales and assess the sensitivity to various meteorological factors in Gia Lai province from 1980 to 2019. The modified innovative-Şen trend method and Sobol analysis are employed for trend identification and sensitivity assessment, respectively. The results obtained indicate significant downward trends using both the innovative-Şen trend analysis and the improved version of the innovative trend analysis method across different stations and time scales. Furthermore, in the low-value subgroups of the rainy season at Pleiku and An Khe stations, there were notable increasing trends with quantitative values of approximately 6%. Sensitivity analysis reveals that evapotranspiration is most sensitive to sunshine duration across most stations on annual and seasonal time scales, followed by relative humidity and minimum temperature. Overall, this research provides valuable insights into the relationship between evapotranspiration and relevant climate variables, contributing to the assessment of water demand for agricultural irrigation.

Key words: evapotranspiration, Central Highlands of Vietnam, Gia Lai province, modification of Innovative-Şen trend analysis, sensitivity analysis, Sobol indices

HIGHLIGHTS

- The tendency rate of historical evapotranspiration data was evaluated in the Gia Lai province from 1980 to 2019 in this study.
- The improved visualization trend analysis known as the non-parametric detection test was explored, which was proposed to identify the percentage of the fluctuations.
- The temporal characteristics of the sensitivity coefficients between evapotranspiration and key climatic parameters across Gia Lai province were determined.

GRAPHICAL ABSTRACT



INTRODUCTION

Evapotranspiration (ET) plays a significant role in the hydrological cycle as well as the surface energy balance (Beštáková *et al.* 2023). It contributes to two-thirds of land-surface precipitation and is an important factor for agricultural yield (Nhamo *et al.* 2016). Changes in climatic parameters resulting from global warming can affect ET and crop-water requirements (Gerten *et al.* 2004), as well as future planning and management of water resources (Hulme *et al.* 1999; Trinh *et al.* 2022) Therefore, it is crucial to have a comprehensive understanding of temporal trends of ET and its sensitivity to meteorological factors for effective water resource management (Kropf *et al.* 2022), particularly in areas where water availability is limited.

There are various approaches available in the literature for analyzing trends in hydro-climate variables over space and time (Almazroui & Şen 2020). These methods can be divided into two groups: parametric methods, such as simple linear regression, and non-parametric methods, such as Kendall rank correlation, Spearman's rho, Mann–Kendall (MK), the modified MK, and Thiel–Şen slope (Esterby 1996; Şen 2017a). Each of these approaches has specific assumptions that need to be satisfied based on historical records (Şen 2017b). Parametric methods like linear regression require independent and normally distributed data (Almazroui & Şen 2020), whereas non-parametric trend tests only require independent data and can tolerate outliers (Ali *et al.* 2004). To ensure the desired independence structure, researchers have suggested and applied pre-whitening procedures (Şen 2017b). In addition, various applications combine different classical trend analysis methods using MK statistics to address these assumptions. The power of these tests depends on factors such as sample size, trend slope, and the type of probability distribution function (Hussain *et al.* 2022).

For example, Ishida *et al.* (2017) explored the precipitation trend using the dynamically downscaled CMIP5 future climate projections over northern California for 94 years from 2006 to 2100. The results of these trend analyses were quantified by integrating the least-squares regression method and the MK trend test (Ishida *et al.* 2017). The trend and change of sediment for the 2006–2012 period from 45 gauging stations are significantly determined for the rivers in the Mediterranean region of Turkey (Burgan 2022). Innovative trend analysis (ITA), MK, correlated MK, and seasonal MK trend analyses are used in the study. Buyukyildiz (2023) analyzed the temporal variability of the precipitation data for the period 1965–2020 in Turkey by using innovative graphical and statistical trend approaches, including classical MK test, Şen ITA (Şen-ITA), Onyutha trend test, and trend analysis with combination of Wilcoxon test and scatter diagram. The highlight of the above research studies is the strong consistency shown with the results of the combination of diverse methods that can be used as an alternative to the widely used Şen-ITA and the modification of Şen-ITA versions.

Trend analysis has now become a consistent focus of research and application, leading to the development of innovative methodologies and modifications of existing approaches for efficient trend analysis in practical studies (Şen 2017c; Wang *et al.* 2019; Güçlü 2020; Alashan 2022; Buyukyildiz 2023). Alashan (2018) proposed the ITA–change boxes (ITA-CB) method to enhance the visual aspect of the ITA method for better interpretations and detailed classification of trend possibilities for temperature, rainfall, and stream-flow data from different regions that demonstrated the effectiveness of the ITA-CB method. One such adaptation is the improved visualization ITA (IITA) proposed by Güçlü (2020), which belongs to the Innovative-Şen Trend Analysis approach. The IITA approach stands out for its ability to directly apply quantitative trend analysis in various domains, such as energy, water and climate change, and the flow of polluted rivers. Importantly, it is free from assumptions regarding sample size, non-normality, and serial correlation, reinforcing its strengths and credibility (Acar *et al.* 2023).

In the realm of sensitivity analysis, different approaches have been explored, including local sensitivity analysis (LSA) and global sensitivity analysis (GSA) (Saltelli & Annoni 2011). However, LSA has limitations as it provides only a localized view of the problem space, particularly when investigating parameter importance in mathematical modeling (Saltelli *et al.* 2008). To overcome these limitations, GSA has gained recognition. It takes into account the entire range of variation in meteorological time series data inputs and is not constrained by linearity, normality assumptions, or local variations. Among the existing GSA methods, such as variance-based indices, density-based measures, and entropy-based sensitivity measures (Yu *et al.* 2023), the Sobol indices (SIs) are assessed as versatile (Owen 2014). They enable the exploration of sensitivity in complex models with multiple parameters, both simultaneously and over time, producing comparable results (Ferretti *et al.* 2016; Luo *et al.* 2023). The SIs have gained popularity and proven helpful in hydro-meteorological applications (Pianosi *et al.* 2016; Abate *et al.* 2023).

In recent years, several authors have employed trend analysis methods and sensitivity approaches to evaluate the impact of climate change on ET (Luo *et al.* 2023). These studies have yielded effective results in identifying trends and exploring the relationship between climate factors (Iooss & Lemaître 2015; Aschale *et al.* 2023). For instance, Patle *et al.* (2020) conducted an analysis of historical ET changes and their correlation with meteorological parameters in India. They observed an increasing trend in minimum and mean temperature values, while mean relative humidity (RH) and sunshine duration exhibited significant downward trends. To estimate ET for the study area, the authors applied a sensitivity coefficient derived from observed data spanning from 1985 to 2013. These findings emphasized the need for sensitivity analysis in understanding meteorological systems, particularly in elucidating the physical significance of different parameters used to estimate ET.

Ndiaye *et al.* (2020) employed daily meteorological data from the NASA Langley Research Center (LaRC) to analyze ET trends in the Senegal River Basin, on a West Africa scale, spanning from 1984 to 2017. The study revealed a notable upward trend in ET for 32% of the watershed area, while less than 1% of the basin area exhibited a downward trend on an annual scale. The research highlighted temperature as a key climatic parameter explaining variations in ET within the Senegal River Basin, utilizing the sensitivity coefficient method. Furthermore, the works of Obada *et al.* (2017) in Africa, Yang *et al.* (2019) in China, Patle *et al.* (2020) in India, and Aschale *et al.* (2023) in Italy have demonstrated the significance of both trend analysis and relative changes in climatic variables (such as temperature, wind speed, humidity, and solar radiation) on ET.

In Vietnam, previous studies have indicated significant trends in climate (Endo *et al.* 2009; Ngo-Thanh *et al.* 2018; Khoi *et al.* 2021). For instance, Kien *et al.* (2019) employed spatial interpolation techniques in conjunction with the classical MK test and Şen's slope estimator to generate spatial distribution maps depicting temperature and rainfall trends in Vietnam from 1975 to 2014. Building on this, Khoi *et al.* (2021) utilized MK statistical techniques and Şen's estimator to assess the magnitude of trends in extreme indices in Ho Chi Minh City. The findings revealed a rising trend in most extreme indices for future periods. In the Central Highlands, Phuong *et al.* (2022) investigated potential non-monotonic trend components in heavy rainfall events using the Şen-ITA method and well-defined extreme rainfall indices. Furthermore, there is a scarcity of research on sensitivity analysis for ET under climate parameters in the Central Highlands, particularly in the Gia Lai province, which plays a vital role in industrial crop production in Vietnam.

Given this context, the aim of this study is to examine the temporal trends of ET and its responsiveness to climate variables in the Gia Lai province from 1980 to 2019. The objectives of the research are as follows: (i) to quantify the value of trend analysis in ET by modifying the Şen-ITA method (Güçlü 2020); and (ii) to explore the sensitivity of ET to climatic factors (maximum temperature, minimum temperature, RH, and solar radiation) using a state-of-the-art variance-based approach widely employed for hydro-meteorological data characteristics (Song *et al.* 2015; Puy *et al.* 2021).

STUDY AREA AND DATA

The study area selected for this research is Gia Lai province, located in the Central Highlands of Vietnam. The province spans approximately 15,536.9 km^2 and is situated between latitudes 12° 58′20″ N–14°36′30″ N and longitudes 107° 27′23″ E–108° 54′40″ E. The average elevation in the area ranges from 800 to 900 m above mean sea level, with varying soil slopes ranging from 3° to 25° (Figure 1(b)). Gia Lai exhibits a complex topography, characterized by diverse and distinct climate and soil features.

Preliminary analysis of daily rainfall and temperature records reveals that Gia Lai experiences average annual temperatures of approximately 22–25 °C. The coldest month is typically March, with an average maximum daytime temperature of 24 °C, while the warmest month is usually August, with an average maximum temperature of 31 °C. The region receives an annual rainfall total ranging from around 2,100 to 2,200 mm, predominantly occurring during the rainy season (May–October). The annual air humidity in Gia Lai is approximately 80%–83%.

ET in the region varies seasonally and is influenced by the terrain, with higher levels observed in areas with elevated profiles. The annual average ET ranges from less than 800 mm in the high mountains to over 1,400 mm in the lowland valleys. In addition, ET exhibits seasonal variations due to factors such as air temperature, evaporation rates, wind speed, cloud cover, and precipitation patterns. In the dry season, evaporation is greater than during the rainy months. The average monthly ET during the dry season typically exceeds 100 mm, with the highest values occurring in March, April, or June (Figure 1(c)). In contrast, the average monthly ET during the rainy season is generally below 100 mm, with certain locations experiencing ET as low as 35–50 mm in some months.

From an administrative perspective, Gia Lai province had a population of approximately 1.3 million people in 2022, comprising 34 ethnic groups living together. This makes Gia Lai strategically important for national defense, security, and socio-economic development. The province's climate and fertile land make it suitable for agricultural development, resulting in high economic efficiency. However, the region is faced with a significant natural hazard: drought. With the increasing demand for water resources, drought has become a serious concern. In 2021, drought led to agricultural losses spanning over 2,000 ha. The highest estimated economic damage in a district amounted to about 6 million US dollars (Ministry of Planning and Investment 2022). Consequently, establishing the relationships between hydro-meteorological variables will provide valuable insights for integrated water resource management in the agricultural industry of Gia Lai province.

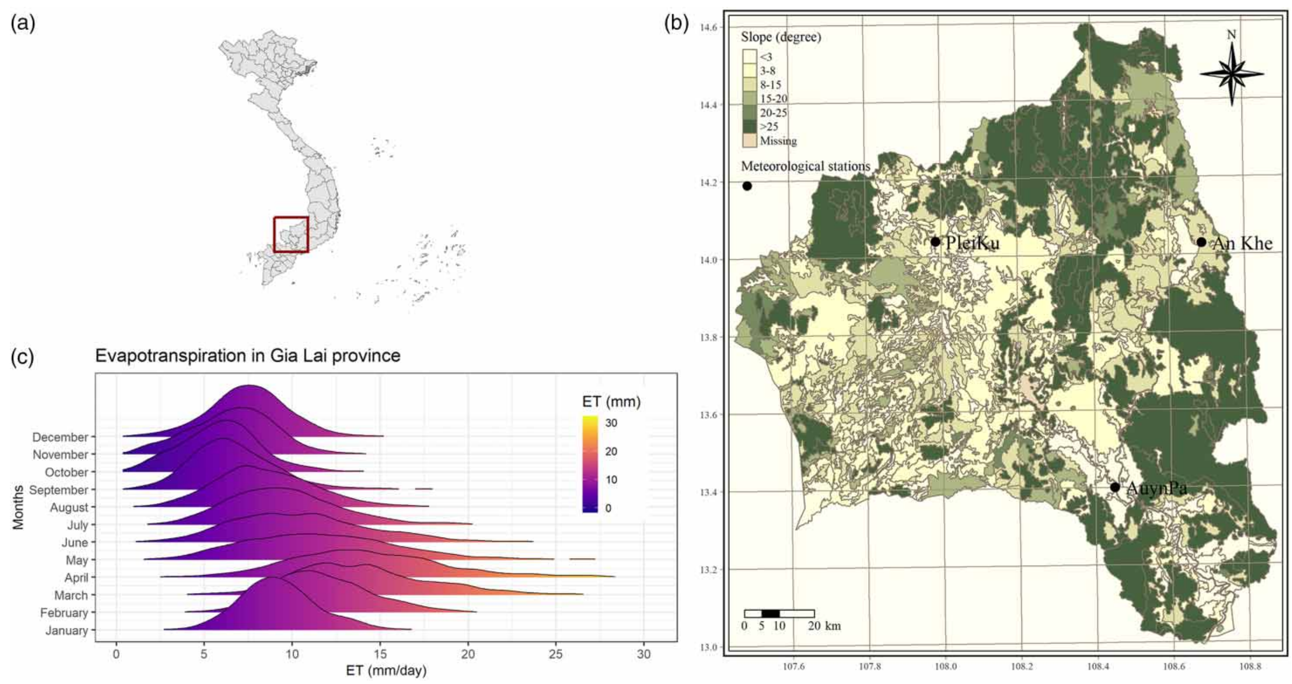


Figure 1 | (a, b) Geographical location and (c) the monthly long-term mean values at three meteorological stations in Gia Lai province.

The observed daily ET, RH, solar hours, maximum temperature (Tmax), minimum temperature (Tmin), and mean temperature (Tmean) datasets from three meteorological stations (Pleiku, An Khe, Ayun Pa), as illustrated in Figure 1(b), were provided by the Mid-Central Regional Hydro-Meteorological Centre for the period 1980–2019 (Table 1).

METHODS

Figure 2 depicts a brief description of the methodology employed in the present study. First, hydro-meteorological records were collected to provide screening analysis. As for trend analysis, integration of statistical approaches, including the ITA and improved visualization of ITA (IITA) were applied to determine overall and partial trend patterns. For the sake of sensitivity analysis, the variance-based sensitivity technique, known as the Sobol method, employed the first-order and total-order indices that reflected the sensitivity of ET to changes in climate variables.

Modification of Şen-ITA (IITA)

There are various statistical techniques available for detecting trends in time series data, including simple linear regression analysis, Şen's slope estimator, MK, modified MK, and Şen-ITA. Each technique has its strengths and weaknesses in trend

Table 1 | Descriptive statistics of climate variables in three stations of Gia Lai province

	Pleiku station			Ayun Pa station			An Khe station		
Climate variables	**Mean**	**SD**	**CV**	**Mean**	**SD**	**CV**	**Mean**	**SD**	**CV**
Minimum temperature (°C)	18.51	2.68	14.51	22.21	2.71	12.21	20.56	2.53	12.31
Maximum temperature (°C)	27.81	2.70	9.71	31.68	3.21	10.13	28.62	3.70	12.95
Mean temperature (°C)	22.05	2.08	9.45	25.94	2.49	9.61	23.65	2.66	11.24
Solar hours (h)	6.58	3.31	50.37	6.62	3.33	50.26	6.67	3.59	12.30
RH (%)	82.87	8.67	10.46	78.95	7.60	9.62	82.83	12.10	7.20
ET (mm)	2.57	1.45	56.71	3.68	1.88	51.11	3.40	1.79	52.88

Note: SD is the standard deviation; CV (%) is the coefficient of variation. These basic statistics were computed from observed daily data for the period 1980–2019.

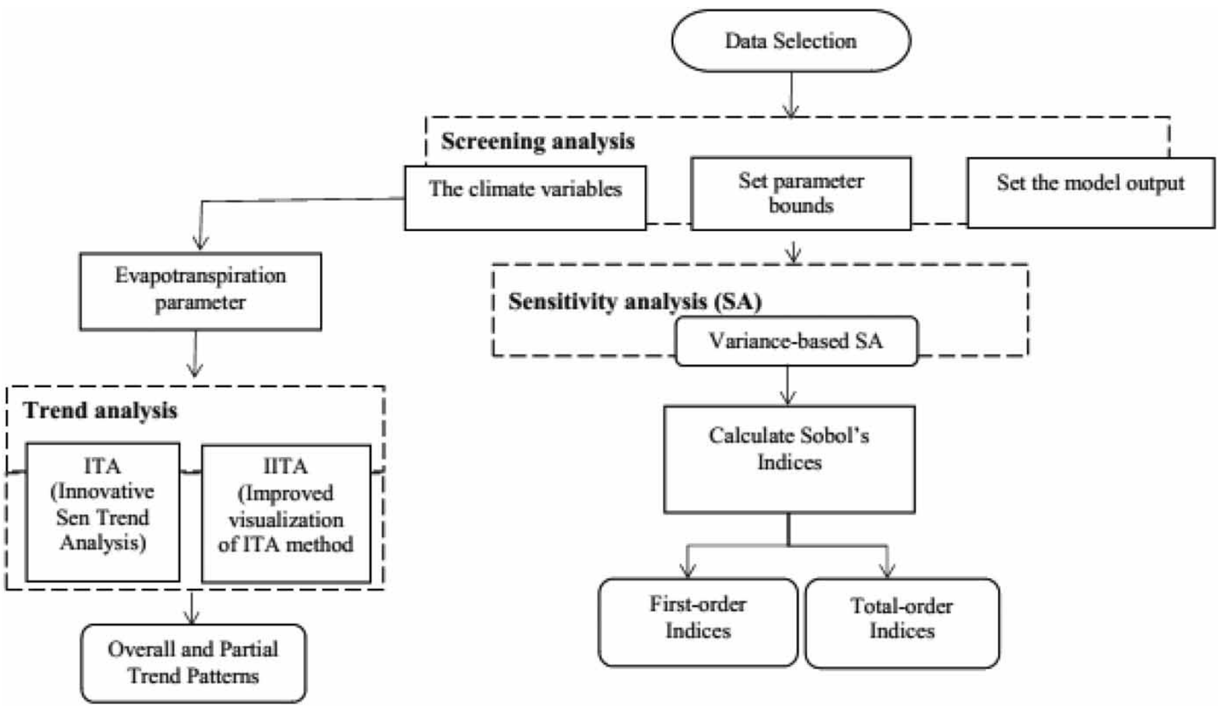


Figure 2 | Schematic framework of research methodology.

detection. However, these techniques often have restrictive requirements such as normal distribution, independence from auto-correlation, and a specific length of data. To overcome these limitations, the ITA proposes the use of graphs as templates, eliminating the need for strict assumptions. ITA has gained recognition through different versions, with the improved visualization for trend analysis (IITA) method developed by Güçlü standing out. The advantage of IITA is its ability to numerically represent the slope and intercept of trends. It also provides more detailed information about overall and partial trends through deliberate categorization.

The IITA approach is based on the original Şen-ITA (Şen 2012) that consists of splitting a time series into two halves of equal sub-series and plotting in a two-dimensional Cartesian coordinate system. Practically, Güçlü (2020) proposed the IITA version that not only demonstrates the types of trends but also depicts the dimension or number of observed data and is highly capable of identifying quantification trends for sub-categories by detecting change points.

In this research, ET is specifically divided into two halves in the coordinate system with the horizontal axis (x-axis) representing the number of observed data and the vertical axis (y-axis) representing the values of given data. An increasing (decreasing) trend is indicated if the values fall above (below) the horizontal line ($y = 0$) significantly. In addition, the quantification of ET trends is determined by comparing the differences between the two halves using the Pettitt test (Pettitt 1979) that calculates the change point and the percentage of change in subgroups (low and high values), and also performance for the numbers belonging to each tendency. The Pettitt test was developed by Pettitt in 1979 and is expressed by:

$$K_T = \max |U_{t,T}| \tag{1}$$

where K_T is the change point location, and $U_{t,T}$ is equivalent to a Mann–Whitney statistic for the testing of the two halves.

Variance-based sensitivity analysis

The need to assess the impact of input factors on output parameters is a recommended course of action (Saltelli *et al.* 2008). The variance-based approach offers a factor-based decomposition of output variance, assuming that this moment is sufficient to describe output variability (Saltelli 2002). In 1990, Sobol published a theorem proving the general variance decomposition scheme and introduced SIs (Sobol 1990). The pioneering work of Cukier *et al.* (1978) considered conditional variance as a measure of model sensitivity, while Hora & Iman (1986) analyzed variance in cases where one parameter is related to another. Sobol subsequently derived a numerical estimation of sensitivity indices using Monte Carlo methods (Sobol 2001), which encompasses both a parameter's direct influence and the interaction with others through covariance (Saltelli *et al.* 2010). In recent years, Sobol's method has gained recognition in sensitivity analysis for ET (Guo *et al.* 2016; Zhang *et al.* 2020) and hydro-meteorological studies (Abate *et al.* 2023).

In the study, Sobol's method (Sobol 2001) was explored to investigate the interaction of climatic variables (maximum temperature, minimum temperature, RH, and solar radiation) with ET. The outputs from Sobol's analysis include the first-order (S_i) and total sensitivity indices ($S_{\mathrm{T}i}$) and are given as Equations (2) and (3), respectively. The first-order indices quantify the direct individual interaction of each meteorological input with ET, while the total indices account for the variance components of each input variable, including its effects and interactions with other variables, in relation to the total variance of the ET model.

$$S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y/X_i))}{V(Y)}, \tag{2}$$

$$S_{\mathrm{T}i} = \frac{E_{X_{\sim i}}(V_{X_i}(Y/X_{\sim i}))}{V(Y)} = 1 - \frac{V_{X_{\sim i}}(E_{X_i}(Y/X_{\sim i}))}{V(Y)}. \tag{3}$$

RESULTS AND DISCUSSION

ET trend analysis results

The improved visualization innovative trend analysis (IITA) concept principles were applied to three hydro-meteorological daily records from different locations in Gia Lai province: Pleiku, An Khe, and Ayun Pa stations. These stations provided long ET records spanning from 1980 to 2019. The locations of each station can be seen in Figure 1(c).

Figures 3–5(b) present the outputs of the IITA for Pleiku, An Khe, and Ayun Pa stations. The graphics indicate the trends at annual and seasonal scales. It is observed that while the rainy season shows a transition from an increasing trend to a decreasing trend at Pleiku and An Khe stations, both the annual and dry seasons exhibit a decreasing trend in both low and high categories. Notably, the quantitative trends are distinct for each tendency, expressed through the amount or percentage of the 'low' and 'high' subgroups.

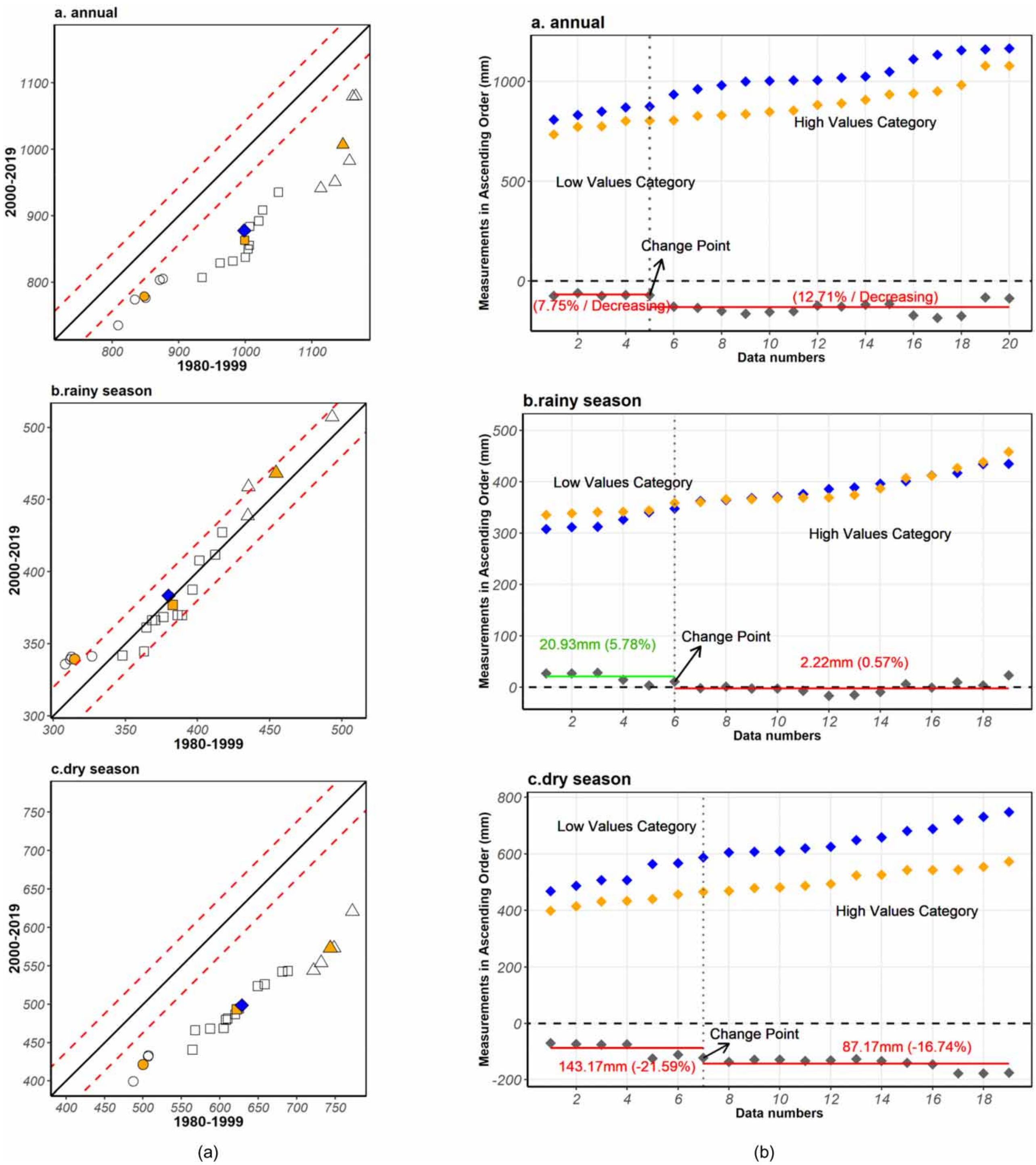


Figure 3 | Annual and seasonal trend results of (a) ITA and (b) IITA methods for Pleiku station.

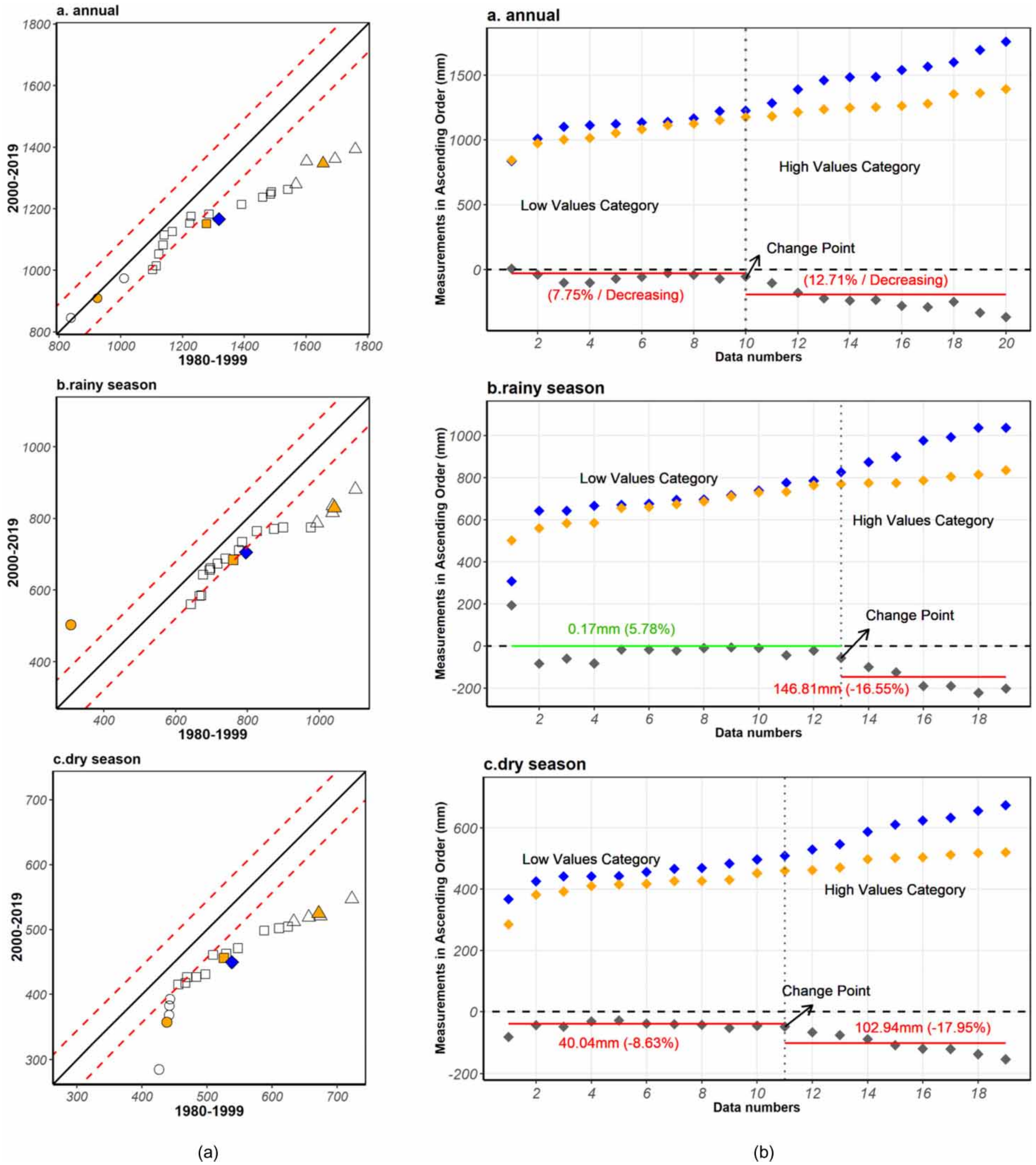


Figure 4 | Annual and seasonal trend results of (a) ITA and (b) IITA methods for An Khe station.

Upon visual interpretation, it becomes evident that in all the downward trends of ET time series at annual and dry-season scales, the high group displays a higher trend rate compared with the low group. Specifically, at Pleiku station, the annual (dry season) values show a decrease of approximately 7.75% and 12.7% (21.59% and 16.74%) in the low and high groups, respectively. Similarly, at the An Khe station, the annual (dry season) graphs exhibit a decrease of around 7.75% and 12.71% (8.63% and 17.95%) in the low and high zones of ET. In the Ayun Pa station, the ET values fall below the horizontal axis ($y = 0$ line),

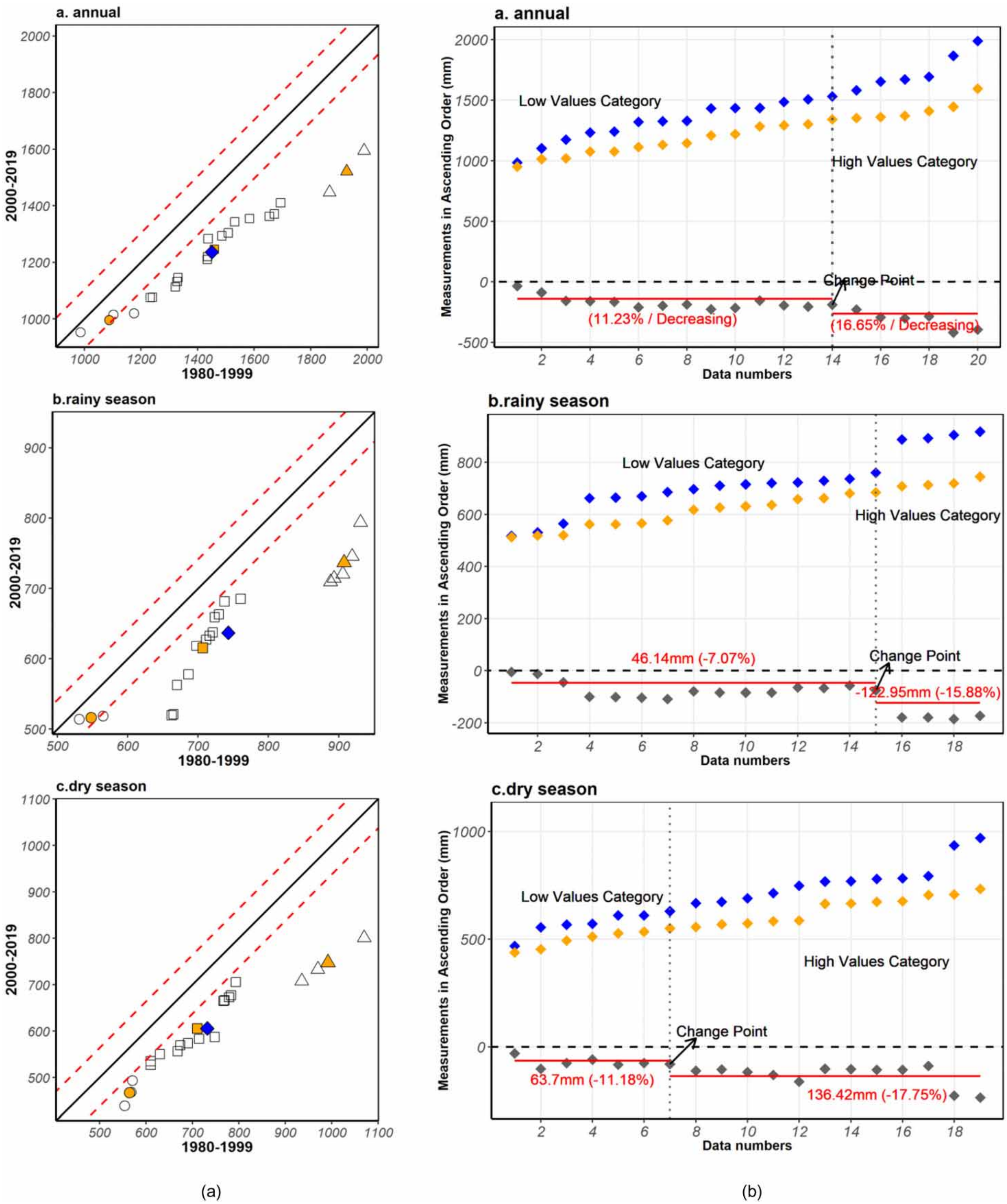


Figure 5 | Annual and seasonal trend results of (a) ITA and (b) IITA methods for Ayun Pa station.

resembling the classical 1:1 straight line. Specifically, for the annual ET, the low and high sub-categories show a downward trend of 11.23% and 16.65%, while the rainy (dry) season shows decreases of 7.07% and 15.88% (11.18% and 17.75%) for the two groups, respectively.

The Ayun Pa station exhibits decreasing trends in both the low- and high-value subgroups during the rainy season. On the other hand, the Pleiku and An Khe stations demonstrate significant declines in the high ET cluster, while the low ET cluster shows a slight upward trend of approximately 20.93 and 0.17 mm, respectively. Therefore, the IITA method effectively captures the slight movement in ET trends without strong fluctuations. Specifically, a positive trend of 20.93 mm is observed at the Pleiku station, while the An Khe station shows a trend of 0.17 mm. Moreover, the change points determined by the Pettitt test in the new type of ITA reveal differences in the number of 'low' and 'high' values. Each change point represents the number of years within each category and indicates the years when significant changes occur. In the case of the Pleiku station, abrupt changes in the ET series are successfully identified at positions 5, 6, and 7 for the annual, rainy, and dry seasons, respectively. Figure 3(b) provides detailed information on the magnitude of changes in the groups and the corresponding change points.

Comparing the results of ITA and IITA, Figures 3–5(a) indicate that the low-, medium-, and high-value subgroups of the annual, dry, and rainy seasons exhibited mostly trend-less or decreasing behaviors. However, Figures 3–5(b) revealed the presence of an increasing trend, specifically in the rainy season, with a calculated value of approximately 20.93 mm. These findings emphasize the significance of quantitative trend detection, not only in ET but also in the assessment of hydro-meteorological parameters.

Recognizing the influence of temperature, RH, solar radiation, and wind on ET, it is important to conduct a sensitivity analysis to examine how the interactions among these variables contribute to temporal changes in ET.

Variance-based sensitivity analysis results

The SIs provide a quantitative measure of the relative importance of each climate variable in relation to ET. Figure 6 illustrates the first-order and total SIs for ET and their interactions with the four climate variables at the annual and seasonal scales (dry and rainy). The first-order indices are plotted against the baseline levels of each climate variable to assess the impact of baseline climate conditions. To facilitate presentation, the baseline levels represent the ranking of the baseline annual and seasonal average values of each climate variable, rather than their absolute levels across the stations.

For Pleiku station, Figure 6(a) displays the SIs, indicating that solar radiation (SH) is generally the most influential variable for ET, with index values ranging from 0.42 to 0.48. These results align with the Sobol first-order indices, suggesting that

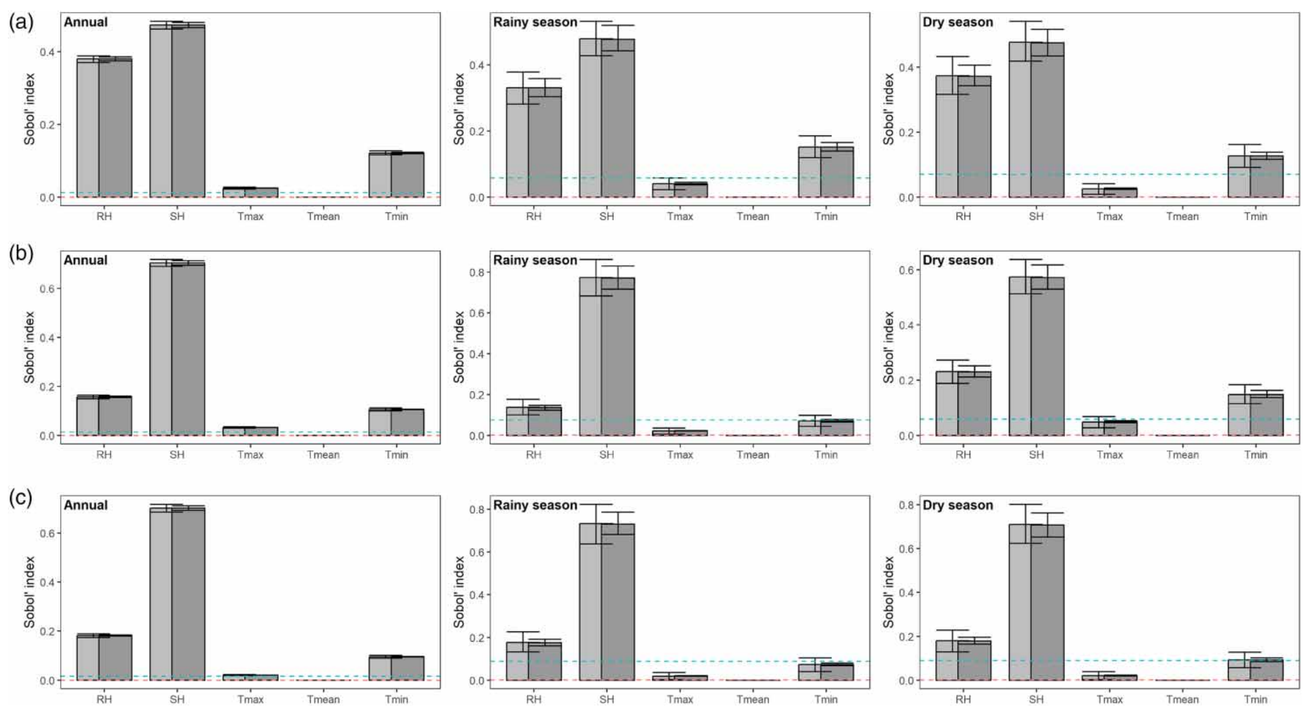


Figure 6 | The SIs for (a) Pleiku, (b) An Khe and (c) Ayun Pa stations (the first-order and total SIs represented by the light- and dark-shaded bars, respectively).

changes in SH contribute to approximately 45% of the observed variation in ET. RH also plays a significant role, being the second-most important variable (with SIs up to 0.35–0.38). Temperature indices (Tmin, Tmax, and Tmean) generally exhibit lower SIs, with the largest contribution (up to 18%) observed for minimum temperature during the dry season (Figure 6(a)).

The Sobol sensitivity indices for An Khe and Ayun Pa stations are presented in Figure 6(b) and 6(c), respectively. Similar to Pleiku station, SH demonstrates the highest sensitivity scores in most cases, ranging from 0.6 to 0.8. Conversely, temperatures have a comparatively minor influence (with SIs ranging from 0.02 to 0.15), as shown in the demonstration for Pleiku station.

These findings provide insights into the relative importance of climate variables in driving ET, with SH and RH playing prominent roles, while temperature variables contribute to a lesser extent.

Analyzing ET sensitivity at a monthly scale allows for a more detailed exploration of the influence of climate variables on ET over time. Figures 7–9 present the results obtained through Sobol sensitivity analysis using the R programming language, providing insights into the relationship between climate variables and monthly ET time series. These figures illustrate the first-order effects of each input parameter on ET across the three stations.

Upon examining Figures 7–9, it becomes apparent that the five parameters exhibit slightly different effects on ET compared with the findings at the annual and seasonal scales presented in Figure 6. The month-to-month variations in the sensitivity of ET to the input parameters can be observed through these figures.

In the monthly time series of Pleiku station, it is evident that SH (solar radiation) has the most significant impact, as indicated by both the first-order and total index effect values, which are approximately 0.47. It is followed by RH, minimum

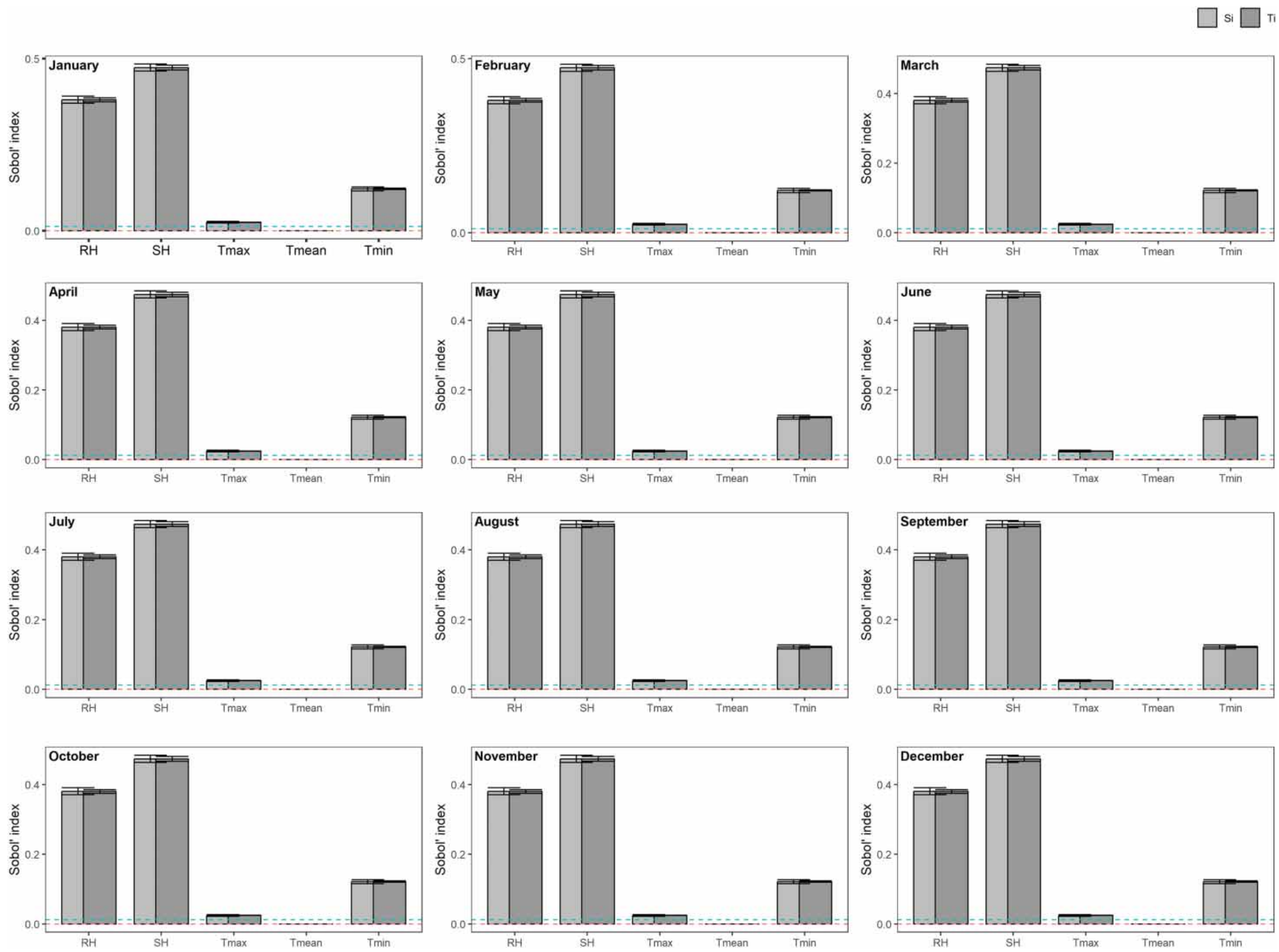


Figure 7 | Monthly sensitivity analysis results for Pleiku station.

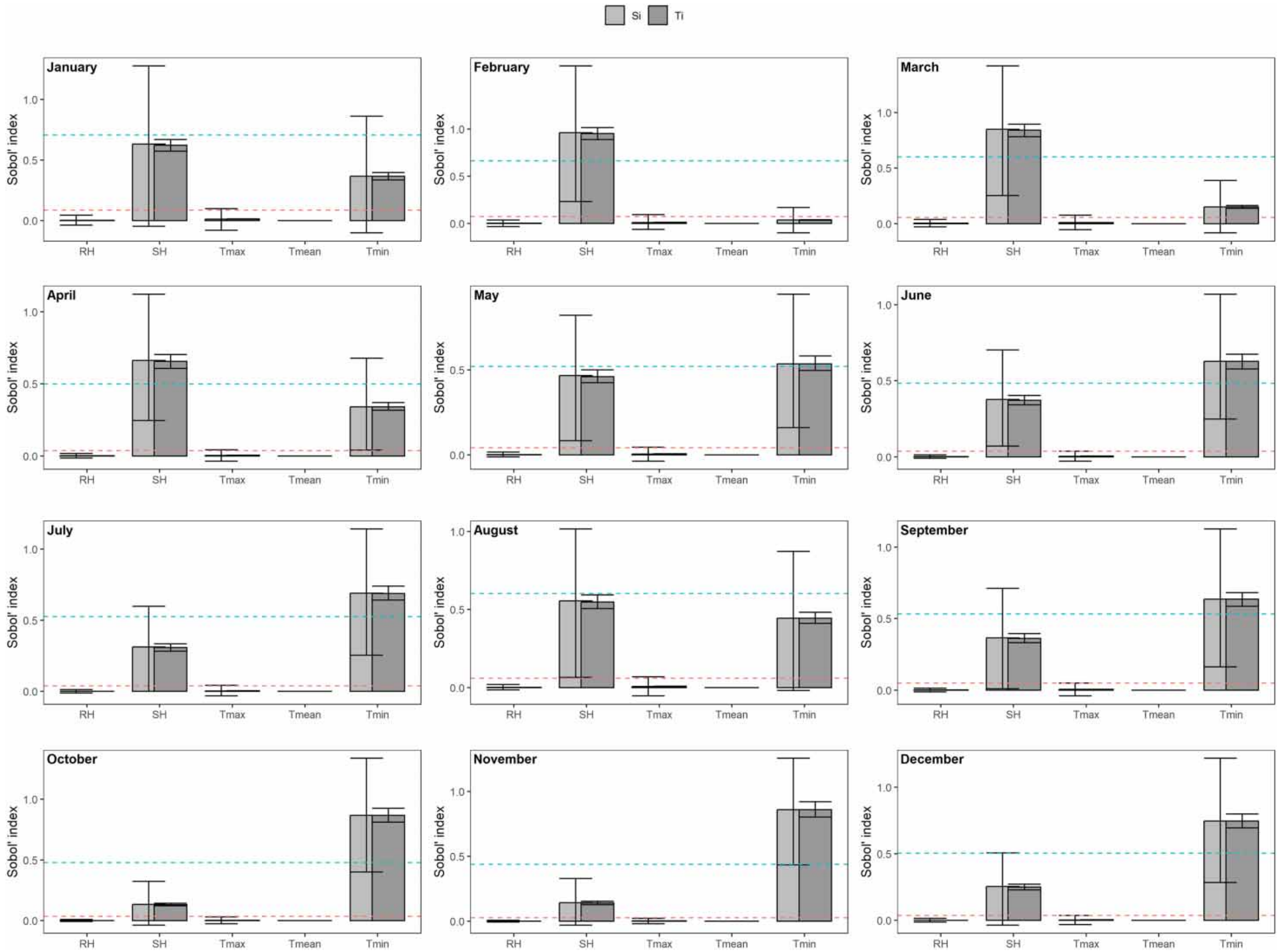


Figure 8 | Monthly sensitivity analysis results for An Khe station.

temperature, and maximum temperature. Among these variables, maximum temperature has the least impact, with a first-order index value of 0.005.

However, the sensitivity analysis results for An Khe and Ayun Pa stations suggest variations in the relative importance of different climate variables compared with Pleiku. Figure 8 illustrates that SH is the dominant variable influencing ET positively in January, February, March, April, and August, with first-order index values ranging from 0.5 to 0.8. On the other hand, Tmin has the highest SIs for the remaining months, contributing fractions of 0.6–0.7 in terms of the interaction effects.

Regarding the Ayun Pa station, it is noteworthy that the minimum temperature also exhibits a strong sensitivity response, contributing to at least 50% of both the first-order and total indices in August, September, October, November, and December. In addition, solar radiation (SH) continues to have a substantial impact, accounting for up to 90% of the overall variability in ET responses in January and February (Figure 9).

CONCLUSIONS

Exploring ET is a crucial task in hydrology and climatology, as it provides valuable insights for a better understanding of water resources management. This study aimed to estimate the sensitivity and contribution rates of meteorological variables to ET trends using data collected from three stations in Gia Lai province over the period 1980–2019. The variables considered were RH, maximum temperature, minimum temperature, average temperature, and sunshine duration.

The results of the ITA test revealed significant decreasing trends in ET at the annual and seasonal time scales. The application of the IITA method provided additional insights, showing negative trends in ET ranging from 7% to 16% over the 40-year period across the three stations. However, the IITA method also indicated a slight increasing trend of about 6%

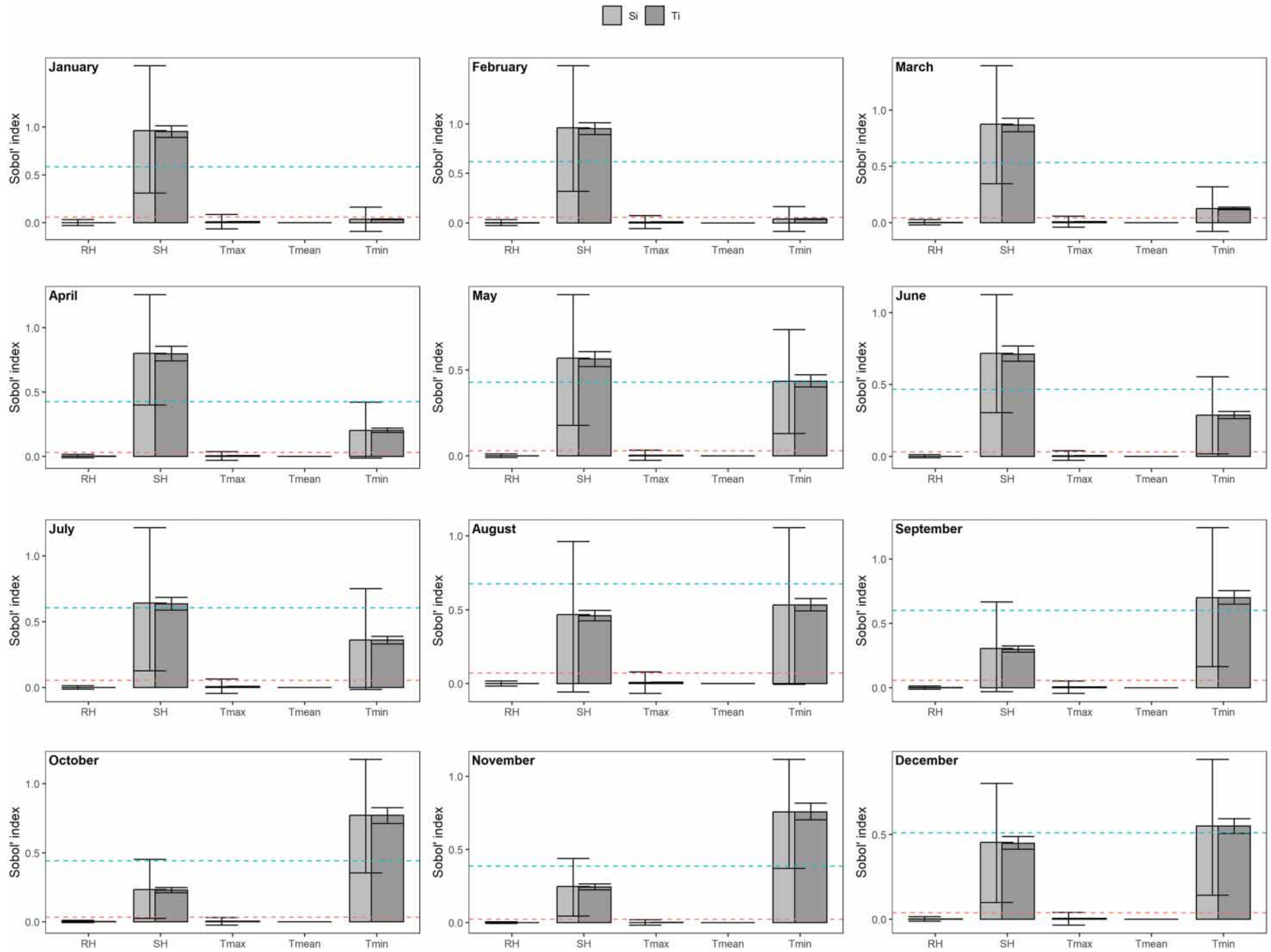


Figure 9 | Monthly sensitivity analysis results for Ayun Pa station.

corresponding to 20.93 and 0.17 mm in the rainy season for the Pleiku and An Khe stations, respectively. As expected, these findings are completely consistent with the trend identification results obtained through the modified ITA method.

In addition, the application of the Sobol method highlighted the significant influence of solar radiation and humidity on ET, with index values ranging from 0.6 to 0.8 and 0.35, respectively. At the monthly scale, minimum temperature emerged as a positive contributor, indicating the high sensitivity of ET to temperature in May, June, July, September, October, November, and December, contributing fractions of 0.6–0.7 in terms of the interaction effects. This suggests that ET will be greatly impacted by climate change in the future.

While this research is based on a 39-year dataset including humidity, sunshine duration, and temperature variables, further studies could enhance the significance of sensitivity assessments by incorporating additional parameters, such as wind speed. Moreover, investigations can be extended to other areas where relevant data are available, allowing for a more comprehensive analysis by applying the IITA and Sobol methods to a larger region across Vietnam with different time scales.

ACKNOWLEDGEMENTS

The authors thank the editor and reviewers for their constructive comments as well as supportive suggestions.

AUTHOR CONTRIBUTIONS

Conceptualization: All authors; Methodology: PTH, LMH, NDL, NLTD, NKL; Formal analysis and investigation: PTH, NLTD, LMH, NDL, NNT, NTH, NKL; Writing – original draft preparation: PTH, NKL; Writing – review and editing: PTH, LMH, NLTD, NDL, NNT, NKL; Supervision: NNT, NKL.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Abate, B. Z., Assefa, T. T., Tigabu, T. B., Abebe, W. B. & He, L. 2023 Hydrological modeling of the Kobo-Golina River in the data-scarce Upper Danakil Basin, Ethiopia. *Sustainability* **15**, 3337. https://doi.org/10.3390/su15043337.

Acar, E., Akpinar, A., Kankal, M. & Amarouche, K. 2023 Increasing trends in spectral peak energy and period in a semi-closed sea. *Renew. Energy* **205**, 1092–1104. https://doi.org/10.1016/j.renene.2023.02.007.

Alashan, S. 2018 An improved version of innovative trend analyses. *Arab. J. Geosci.* **11**, 50. https://doi.org/10.1007/s12517-018-3393-x.

Alashan, S. 2022 Comparison of sub-series with different lengths using Şen-innovative trend analysis. *Acta Geophysica* **71**, 373–383. https://doi.org/10.1007/s11600-022-00869-6.

Ali, M. H., Amin, M. G. M. & Islam, A. K. M. R. 2004 Comparison of various methods for estimating reference crop evapotranspiration. *J. Bangladesh Agric. Univ.* **2**, 313–324.

Almazroui, M. & Şen, Z. 2020 Trend analyses methodologies in hydro-meteorological records. *Earth Syst. Environ.* **4**, 713–738. https://doi.org/10.1007/s41748-020-00190-6.

Aschale, T. M., Peres, D. J., Gullotta, A., Sciuto, G. & Cancelliere, A. 2023 Trend analysis and identification of the meteorological factors influencing reference evapotranspiration. *Water* **15**, 470. https://doi.org/10.3390/w15030470.

Beštáková, Z., Strnad, F., Vargas Godoy, M. R., Singh, U., Markonis, Y., Hanel, M., Máca, P. & Kyselý, J. 2023 Changes of the aridity index in Europe from 1950 to 2019. *Theor. Appl. Climatol.* **151**, 587–601. https://doi.org/10.1007/s00704-022-04266-3.

Burgan, H. I. 2022 The short-term and seasonal trend detection of sediment discharges in Turkish rivers. *Rocz. Ochr. Śr.* **24**, 214–230. https://doi.org/10.54740/ros.2022.016.

Buyukyildiz, M. 2023 Evaluation of annual total precipitation in the transboundary Euphrates–Tigris River Basin of Türkiye using innovative graphical and statistical trend approaches. *Appl. Water Sci.* **13**, 38. https://doi.org/10.1007/s13201-022-01845-7.

Cukier, R. I., Levine, H. B. & Shuler, K. E. 1978 Nonlinear sensitivity analysis of multiparameter model systems. *J. Comput. Phys.* **26**, 1–42. https://doi.org/10.1016/0021-9991(78)90097-9.

Endo, N., Matsumoto, J. & Lwin, T. 2009 Trends in precipitation extremes over Southeast Asia. *Sci. Online Lett. Atmos.* **5**, 168–171. https://doi.org/10.2151/sola.2009-043.

Esterby, S. R. 1996 Review of methods for the detection and estimation of trends with emphasis on water quality applications. *Hydrol. Process.* **10**, 127–149. https://doi.org/10.1002/(SICI)1099-1085(199602)10:2<127::AID-HYP354>3.0.CO;2-8.

Ferretti, F., Saltelli, A. & Tarantola, S. 2016 Trends in sensitivity analysis practice in the last decade. *Sci. Total Environ.* **568**, 666–670. https://doi.org/10.1016/j.scitotenv.2016.02.133.

Gerten, D., Schaphoff, S., Haberlandt, U., Lucht, W. & Sitch, S. 2004 Terrestrial vegetation and water balance – hydrological evaluation of a dynamic global vegetation model. *J. Hydrol.* **286**, 249–270. https://doi.org/10.1016/j.jhydrol.2003.09.029.

Güçlü, Y. S. 2020 Improved visualization for trend analysis by comparing with classical Mann–Kendall test and ITA. *J. Hydrol.* **584**, 124674. https://doi.org/10.1016/j.jhydrol.2020.124674.

Guo, D., Westra, S. & Maier, H. R. 2016 Sensitivity of potential evapotranspiration to changes in climate variables for different climatic zones. *Hydrol. Earth Syst. Sci. Discuss.*. https://doi.org/10.5194/hess-2016-441.

Hora, S. C. & Iman, R. L. 1986 *Comparison of Maximus/Bounding and Bayes/Monte Carlo for Fault Tree Uncertainty Analysis* (SAND85–2839). Sandia National Laboratories, Albuquerque, NM, USA. https://doi.org/10.2172/5824798.

Hulme, M., Barrow, E. M., Arnell, N. W., Harrison, P. A., Johns, T. C. & Downing, T. E. 1999 Relative impacts of human-induced climate change and natural climate variability. *Nature* **397**, 688–691.

Hussain, F., Ceribasi, G., Ceyhunlu, A. I., Wu, R.-S., Cheema, M. J. M., Noor, R.-S., Anjum, M. N., Azam, M. & Afzal, A. 2022 Analysis of precipitation data using innovative trend pivot analysis method and trend polygon star concept: a case study of Soan River Basin, Potohar Pakistan. *J. Appl. Meteorol. Climatol.* **61**, 1861–1880. https://doi.org/10.1175/JAMC-D-22-0081.1.

Iooss, B. & Lemaître, P. 2015 A review on global sensitivity analysis methods. In: *Uncertainty Management in Simulation-Optimization of Complex Systems: Algorithms and Applications* (Dellino, G. & Meloni, C., eds), Springer, New York, USA. pp. 101–122. https://doi.org/10.1007/978-1-4899-7547-8_5.

Ishida, K., Gorguner, M., Ercan, A., Trinh, T. & Kavvas, M. L. 2017 Trend analysis of watershed-scale precipitation over Northern California by means of dynamically-downscaled CMIP5 future climate projections. *Sci. Total Environ.* **592**, 12–24. https://doi.org/10.1016/j.scitotenv.2017.03.086.

Khoi, D. N., Quan, N. T., Nhi, P. T. T. & Nguyen, V. T. 2021 Impact of climate change on precipitation extremes over Ho Chi Minh City, Vietnam. *Water* **13**, 120. https://doi.org/10.3390/w13020120.

Kien, N. D., Ancev, T. & Randall, A. 2019 Evidence of climatic change in Vietnam: some implications for agricultural production. *J. Environ. Manage.* **231**, 524–545. https://doi.org/10.1016/j.jenvman.2018.10.011.

Kropf, C. M., Ciullo, A., Otth, L., Meiler, S., Rana, A., Schmid, E., McCaughey, J. W. & Bresch, D. N. 2022 Uncertainty and sensitivity analysis for probabilistic weather and climate-risk modelling: an implementation in CLIMADA v.3.1.0. *Geosci. Model Dev.* **15**, 7177–7201. https://doi.org/10.5194/gmd-15-7177-2022.

Luo, S., Yong, S., Ng, J. L., Huang, Y. F., Ang, C. K., Mirzaei, M. & Ahmed, A. N. 2023 Local and global sensitivity analysis and its contributing factors in reference crop evapotranspiration. *Water Supply* **23** (4), 1672–1683. https://doi.org/10.2166/ws.2023.086.

Ministry of Planning and Investment 2022 *Socio-economic Situation Report in Second Quarter and Six Months of 2022* (138/BC-TCTK). General Statistics Office, Ministry of Planning and Investment, Hanoi, Vietnam.

Ndiaye, P. M., Bodian, A., Diop, L., Deme, A., Dezetter, A., Djaman, K. & Ogilvie, A. 2020 Trend and sensitivity analysis of reference evapotranspiration in the Senegal River basin using NASA meteorological data. *Water* **12**, 1957. https://doi.org/10.3390/w12071957.

Ngo-Thanh, H., Ngo-Duc, T., Nguyen-Hong, H., Baker, P. & Phan-Van, T. 2018 A distinction between summer rainy season and summer monsoon season over the Central Highlands of Vietnam. *Theor. Appl. Climatol.* **132**, 1237–1246. https://doi.org/10.1007/s00704-017-2178-6.

Nhamo, L., Mabhaudhi, T. & Magombeyi, M. 2016 Improving water sustainability and food security through increased crop water productivity in Malawi. *Water* **8**, 411. https://doi.org/10.3390/w8090411.

Obada, E., Alamou, E. A., Chabi, A., Zandagba, J. & Afouda, A. 2017 Trends and changes in recent and future Penman–Monteith potential evapotranspiration in Benin (West Africa). *Hydrology* **4**, 38. https://doi.org/10.3390/hydrology4030038.

Owen, A. B. 2014 Sobol' indices and Shapley value. *SIAM/ASA J. Uncertainty Quantif.* **2**, 245–251. https://doi.org/10.1137/130936233.

Patle, G. T., Sengdo, D. & Tapak, M. 2020 Trends in major climatic parameters and sensitivity of evapotranspiration to climatic parameters in the eastern Himalayan region of Sikkim, India. *J. Water Clim. Change* **11**, 491–502. https://doi.org/10.2166/wcc.2019.121.

Pettitt, A. N. 1979 A non-parametric approach to the change-point problem. *Appl. Stat.* **28**, 126–135.

Phuong, D. N. D., Huyen, N. T., Liem, N. D., Hong, N. T., Cuong, D. K. & Loi, N. K. 2022 On the use of an innovative trend analysis methodology for temporal trend identification in extreme rainfall indices over the Central Highlands, Vietnam. *Theor. Appl. Climatol.* **147**, 835–852.

Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B. & Wagener, T. 2016 Sensitivity analysis of environmental models: a systematic review with practical workflow. *Environ. Model. Softw.* **79**, 214–232. https://doi.org/10.1016/j.envsoft.2016.02.008.

Puy, A., Piano, S. L., Saltelli, A. & Levin, S. A. 2021 sensobol: An R package to compute variance-based sensitivity indices. *Journal of Statistical Software* **102** (5), https://doi.org/10.18637/jss.v102.i05.

Saltelli, A. 2002 Sensitivity analysis for importance assessment. *Risk Analysis.* **22**, 579–590. https://doi.org/10.1111/0272-4332.00040.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M. & Tarantola, S. 2008 *Global Sensitivity Analysis. The Primer*. Wiley, Chichester, UK.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M. & Tarantola, S. 2010 Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. *Comput. Phys. Commun.* **181**, 259–270. https://doi.org/10.1016/j.cpc.2009.09.018.

Saltelli, A. & Annoni, P. 2011 Sensitivity analysis. In: *International Encyclopedia of Statistical Science* (Lovric, M., ed.), Springer, Berlin, Germany, pp. 1298–1301. https://doi.org/10.1007/978-3-642-04898-2_509.

Şen, Z. 2012 Innovative trend analysis methodology. *J. Hydrol. Eng.* **17**, 1042–1046. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000556.

Şen, Z. 2017a *Innovative Trend Methodologies in Science and Engineering*. Springer, Cham, Switzerland. https://doi.org/10.1007/978-3-319-52338-5.

Şen, Z. 2017b Hydrological trend analysis with innovative and over-whitening procedures. *Hydrol. Sci. J.* **62**, 294–305. https://doi.org/10.1080/02626667.2016.1222533.

Şen, Z. 2017c Global warming quantification by innovative trend template method. *Int. J. Glob. Warm.* **12**, 499–512. https://doi.org/10.1504/IJGW.2017.084783.

Sobol, I. M. 1990 On sensitivity estimation for nonlinear mathematical models. *Matematicheskoe Modelirovanie* **2** (1), 112–118.

Sobol, I. M. 2001 Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Math. Comput. Simul.* **55**, 271–280. https://doi.org/10.1016/S0378-4754(00)00270-6.

Song, X., Zhang, J., Zhan, C., Xuan, Y., Ye, M. & Xu, C. 2015 Global sensitivity analysis in hydrological modeling: review of concepts, methods, theoretical framework, and applications. *J. Hydrol.* **523**, 739–757. https://doi.org/10.1016/j.jhydrol.2015.02.013.

Trinh, T., Diaz, A., Iseri, Y., Snider, E., Anderson, M. L., Carr, K. J. & Kavvas, M. L. 2022 A numerical coupled atmospheric–hydrologic modeling system for probable maximum flood estimation with application to California's southern Sierra Nevada foothills watersheds. *J. Flood Risk Manage.* **15**, e12809. https://doi.org/10.1111/jfr3.12809.

Wang, W., Zhu, Y., Liu, B., Chen, Y. & Zhao, X. 2019 Innovative variance corrected Sen's trend test on persistent hydrometeorological data. *Water* **11**, 2119. https://doi.org/10.3390/w11102119.

Yang, Y., Chen, R., Song, Y., Han, C., Liu, J. & Liu, Z. 2019 Sensitivity of potential evapotranspiration to meteorological factors and their elevational gradients in the Qilian Mountains, northwestern China. *J. Hydrol.* **568**, 147–159. https://doi.org/10.1016/j.jhydrol.2018.10.069.

Yu, X., Zeng, X., Gui, D., Li, X., Gou, Q., Wang, D. & Wu, J. 2023 Projection of flash droughts in the headstream area of Tarim River Basin under climate change through Bayesian uncertainty analysis. *JGR Atmospheres* **128**, e2022JD037634. https://doi.org/10.1029/2022JD037634.

Zhang, R., Chen, T. & Chi, D. 2020 Global sensitivity analysis of the Standardized Precipitation Evapotranspiration Index at different time scales in Jilin Province, China. *Sustainability* **12**, 1713. https://doi.org/10.3390/su12051713.

First received 30 August 2023; accepted in revised form 11 December 2023. Available online 20 December 2023