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Spatial-temporal variability of climate indices in Chungcheong provinces of Korea: Application of graphical innovative methods for trend analysis

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ABSTRACT

Climate change causes unprecedented damage in form of climate extreme events such as floods and drought, especially in the agricultural sector. Understanding the variations and trends of climate characteristics is a step toward mitigating climate-related disasters. This study investigates the annual and seasonal spatial-temporal variability of UNEP and De Martonne climate indices from 10 synoptic stations distributed homogeneously over the Chungcheong Provinces in Korea from 1974 to 2019. The spatial assessment of the variability of climate indices was conducted using the inverse distance weighting (IDW) interpolation method. The annual and seasonal trends were assessed using innovative trend analysis (ITA), while a further trend assessment on a seasonal scale was conducted using innovative polygon trend analysis (IPTA) to reveal periodic features and trend transitions. The results of the ITA were compared to the classical Mann-Kendall (MK) and Modified Mann-Kendall (MMK) trend methods. The findings revealed that the Chungcheong Provinces is a wet climate dominance on an annual scale, with a high occurrence frequency of humid to extreme humid climates. However, there are variations in the climatic classes of UNEP and De Martonne indices on the seasonal timescale and across the stations. The spatial assessment indicated the dominance of moderate climatic conditions, while the heavy climatic condition is consistent at the far-end northeast. The ITA shows significant (95% confidence level) upward trends on an annual scale at 50 and 60% of the stations in UNEP and De Martonne indices, respectively. Moreover, an increasingly significant trend dominated the summer and autumn, while spring and winter seasons exhibited significant decreasing trends. The IPTA shows a dominant transition from the increasing area in autumn to decreasing area in winter, while summer consistently transited in the increasing region at almost all the stations. Both climate indices demonstrate homogeneous and isotropic behaviors and nearly stable conditions. Furthermore, ITA and MK trend statistics indicate a good positive correlation ($r > 0.50$). The findings of this study are important for the ongoing climate-change-related policy in the agricultural sector in Korea.

1. Introduction

The impacts of climate change such as floods and droughts have become increasingly popular in many regions of the world due to the frequency of climate extremes. While direct or indirect human activities over a long period are attributed to climate variability (United Nations, 1992), the abrupt changes are becoming significant and are expected to be more frequent in the future (Izzo et al., 2021; Wang et al., 2017b). Intrinsically, adequate monitoring of the climatic variables is critical to keep track of climate change to address its foreseeable impacts. To this end, trend detection is recognized as an important technique to analyze the change in magnitude of both temporal and spatial distribution of climate variables and the associated climate change impacts in climate change studies (Anghileri et al., 2014). Moreover, identifying trend patterns and variability in the climate variables could provide informed strategies to reduce the risks of climate change impacts and improve sustainable human activities in a region (Izzo et al., 2021; Pingale et al., 2014).

Several studies have been conducted to investigate the trends of climate variables and their impacts on climate change globally (Ahmad

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et al., 2018; Jung et al., 2011; Kumar and Kumar, 2020; Li et al., 2018; Pingale et al., 2014; Quan et al., 2021; Wazneh et al., 2017). Among these variables, precipitation and temperature are the most considered in the literature due to their relative importance in ecological change, food security, water resources management, and climate change assessment (de Lima et al., 2013; Dinpashoh et al., 2014; Odey et al., 2022; Shiru et al., 2019; Tsiotas et al., 2021). In Korea, 17 temperature and precipitation based-indices were used to analyze the trend of extreme climate indices in the upper Geum River Basin based on climate data series from 5 stations covering 1988 to 2020 (Felix et al., 2021). The authors observed an increase in temperature and precipitation intensities with a prolonged summer season and precipitation shifts under seasonal and monthly timescales. Similarly, the spatial and temporal variability of precipitation were investigated for the whole country using weather data of 183 stations from 1973 to 2005 based on 16 precipitation indices (Jung et al., 2011). The results showed a significant positive trend in annual precipitation and a strong spatial variability that is likely to cause an increase in flood and drought risks due to an increase in frequency and intensity of precipitation during the summer season. Another study analyzed the spatial characteristics of temporal trends for the precipitation and severity of drought based on data from 55 weather stations covering 1980 to 2015 (Azam et al., 2018). The results indicated significant trends in precipitation for summer, winter, and late spring along the south coast of the country, and in drought severity on the northeast coast. However, annual precipitation showed no significant trend. Bae et al. investigated the long-term trend of spatial and temporal variations of precipitation and runoff for 139 river basins from 1968 to 2001 (Bae et al., 2008). Results showed increasing annual precipitation and runoff in the northern part of the country while the southern part showed decreasing trend, with strong to moderate positive autocorrelation in the regional patterns of precipitation; thus, suggesting a high potential of spring drought and summer flooding in some parts of the country in the future.

Many of these studies used a single climate variable to investigate the trend analysis. However, a single climate variable might not capture the dynamics that signify the true change in the climate required to plan for the anticipated impacts such as flood and drought events. Moreover, studies have shown an unexpected lack of significant change in trend when using a single variable like precipitation, either at global or regional scales (Wen et al., 2018). Climate indices, which combine two or more climate variables reflect more comprehensive climatic characteristics of a region (Wen et al., 2018). Besides, climate indices that considered more climatic variables like temperature, precipitation, and evapotranspiration produce more realistic results of change in climatic conditions of an area (Wang et al., 2017a). Further, climate indices provide good insights and also serve as an important metric to assess the potential climate change impact of a specific region or local conditions (Zhang et al., 2011). The United Nations Environment Program (UNEP) and De Martonne climate indices are among the popular and highly used indices with two or more climatic variables, including precipitation and temperature to assess and classify the climatic conditions of different regions and countries (Bahmani et al., 2021; Passarella et al., 2020; Sadeqi and Kahya, 2021; Şarlak and Mahmood Agha, 2018; Tsiros et al., 2020; Ullah et al., 2022; Zarei et al., 2019; Zarei and Mahmoudi, 2021). However, there are limited studies that investigated the trends of climate indices, particularly in Korea. Meanwhile, Korea is one of the countries characterized by variable climate conditions, thereby making it vulnerable to climate extreme events (KMA, 2021). Moreover, there has been an emphasis on the need for local and regional studies on climate trends due to the relative impacts of local conditions and regional specificities, especially in regions with variable climatic conditions (de Lima et al., 2013; Izzo et al., 2021).

New graphical methods such as innovative trend analysis (ITA) and the most recent innovative polygon trend analysis (IPTA) have been proposed to identify the trends in climatic variables using visual monotonic and non-monotonic trend identifications (Şen, 2012; Şen et al., 2019). Several studies have been conducted using ITA and IPTA to detect trends in hydrological, meteorological, and environmental variables in different regions of the world (Ahmed et al., 2022b; Akçay et al., 2022; Caloiero et al., 2018; Gedefaw et al., 2018; Praveen et al., 2020; Şan et al., 2021; Wang et al., 2020; Wu and Qian, 2017). Wu and Qian (2017) assessed the annual and seasonal trends of rainfall and their extreme values in the Shaanxi province of China using the ITA approach. Ay and Kisi (2015) investigated the trend of monthly precipitation in six provinces of Turkey using the ITA method. Ahmad et al. (2018) applied the ITA method to investigate the variability of annual and seasonal precipitation in the upper Indus basin in Pakistan. The trend of monthly precipitation was examined for the 25 weather stations in Algeria using the ITA method (Elouissi et al., 2016). The variability of annual, seasonal, and extreme precipitation in the Han River Basin of Korea was investigated using the ITA method (Shah et al., 2022). The results showed significant variability in summer precipitation with an indication of possible extreme floods during the summer and drought severity during the fall and winter. Şan et al. (2021) applied both ITA and IPTA methods to assess the monthly rainfall trends of 15 stations in Vietnam, while the obtained results were also compared to the Mann-Kendall, a classical method of trend analysis. The results showed that nearly 90% of all the months indicated trends with significant tests compared to the Mann-Kendal method, where only 23% of the months showed a significant trend. Ceribasi et al. analyzed the trends of temperature data from the Susurluk Basin in Turkey using IPTA (Ceribasi et al., 2021). The trend of changes in monthly streamflow in the Hindukush–Karakoram–Himalaya Region of Pakistan was conducted using IPTA (Ahmed et al., 2022b).

These studies demonstrated universal applicability of the graphical methods of trend analysis and have been adjudged as better alternatives due to the non-requirement of statistical assumptions such as serial correlation, sample numbers, and non-normality relating to the classical statistical parametric and non-parametric trend tests like linear regression, Mann Kendall, Theil-Sen, and Spearman's rho methods (Ahmad et al., 2018; Ay and Kisi, 2015; Dabanlı et al., 2016; Güçlü, 2018). Moreover, the graphical method is believed to be more practical than the classical method in detecting trends of hydrological, meteorological, and environmental variables (Dabanlı et al., 2016). Further, graphical methods have been found to detect the hidden significant sub-trends that are critical for the assessment of extreme climate events (Mandal et al., 2021; Wang et al., 2020; Wu and Qian, 2017).

Therefore, this study analyzes the variability and trends of climate indices to assess the annual and seasonal changes in climatic conditions in Chungcheong Provinces of Korea. Specifically, the UNEP and De Martonne climate indices in combination with the graphical innovative methods of ITA and IPTA, and the Inverse Distance Weighting (IDW) spatial interpolation method are used to investigate the spatial-temporal variability and trends of climatic conditions in Chungcheong Provinces, Korea. Further, the climate indices are classified based on percentile to analyze the extreme climate events of floods and droughts for which the study area is susceptible. To the best of our knowledge, this is the first study that investigates the trend of climate indices using the graphical innovative trend methods.

2. Materials and methods

2.1. Study area

The study area, Chungcheong Provinces, is located in the west-central of Korea and on the east end of the Asian continent between Latitude 35°58′ N - 36°00′ N and Longitude 127°38′ E - 125°32′ E, covering a total area of about 16,642 km^2 (Fig. 1). Geographically, it consists of mountainous terrain in the east, while the west is flatter and lower, with about 65.7% of the total land area <100 m above sea level and with a slope of fewer than 5 degrees (KOSIS, 2022). The climate is classified as a continental climate and part of the temperate monsoon

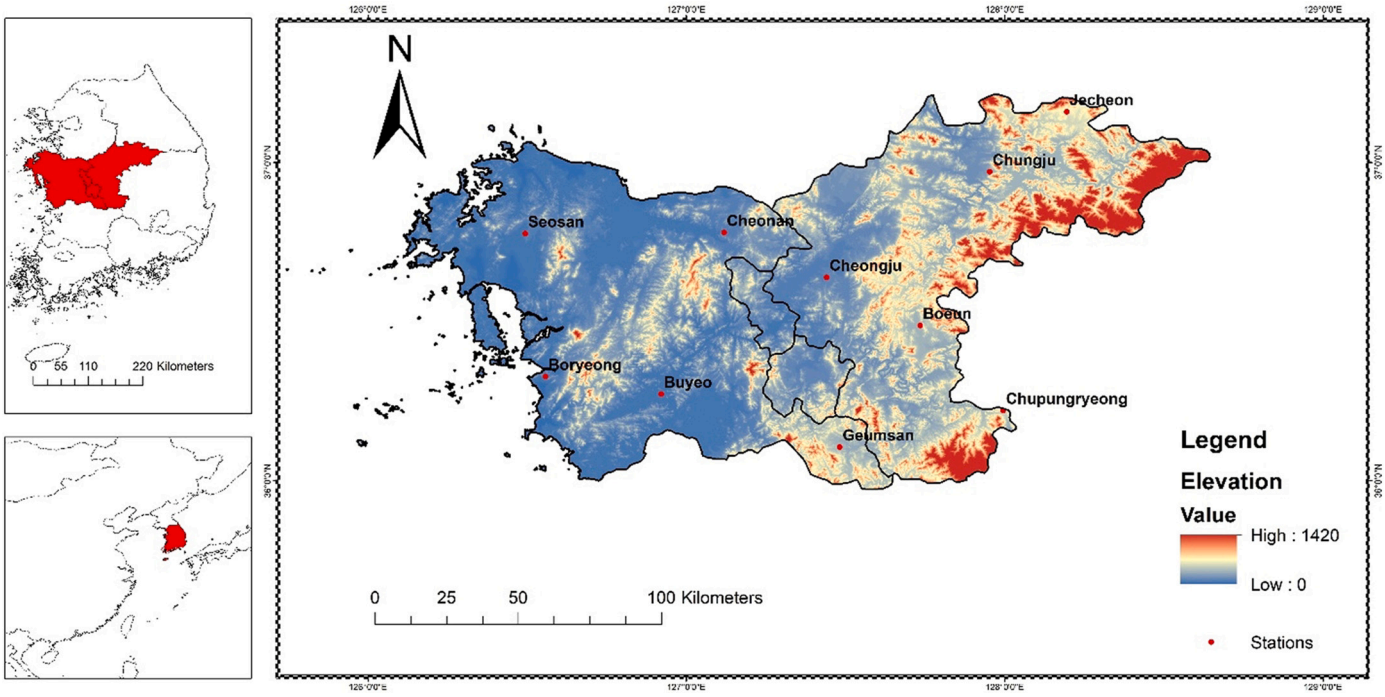


Fig. 1. Study area map showing the elevation and locations of the Synoptic stations within South Korea.

climate zone with four distinct seasons, which are defined as spring (March to May), summer (June to August), autumn (September to November), and winter (December to February). The mean annual temperature and precipitation are about 11.7 °C and 1239.7 mm, respectively, with about 56% of the annual precipitation occurring during the summer season (May to September) and <10% in the winter (December to March) (Table 1).

Chungcheong Provinces have been reported to be vulnerable to the hydrological disasters of climate extreme events, particularly floods and droughts due to their location in the region with variable and extreme weather conditions, and differential altitudes (Jeong, 2020; Kim et al., 2021). Further, it is also an active and one of the major agricultural-based areas in Korea, which climate extreme events could cause overarching impacts; thus, necessitating an investigation of its climate trend and variability.

2.2. Data and analysis

The daily data of hydro-meteorological variables, including precipitation, temperature, wind speed, and relative humidity of 10 synoptic stations (5 each from the North Chungcheongbuk-do Province and South Chungcheongnam-do Province in Korea) from 1974 to 2019, was obtained from the Korean Meteorological Administration, a reputable institution in charge of the collection and maintenance of the stations while the quality compliance of the meteorological data is ensured by the Korea Water Resources Corporation (KMA, 2022; KWRC, 2022). The daily obtained data was subsequently converted to monthly, seasonal, and annual average values. The selected stations were based on the completeness of data records and the statistical homogeneity of the time series data to ensure adequate data quality required for the climate change study. The homogeneity of the data was assessed using the standard normal homogeneity test (Alexandersson, 1986), von Neumann ratio test (von Neumann, 1941), and Buishand range test (Buishand, 1982) at a 95% confidence level. Moreover, the mean distance between these stations is approximately 12 km (Jung et al., 2011), which considered the stations to be neighbors since the distance was <20 km (Mainuddin et al., 2022). Previous studies also acknowledged the consistency and qualitative representation of these data for studying climate variability and trend after examining the homogeneity for each station using various methods, including the Worsley likelihood ratio, cumulative deviations method, and Bayesian procedures (Chang and Kwon, 2007; Jung et al., 2011).

2.3. Climate indices

The annual and seasonal climatic conditions were assessed using UNEP and De Martonne climate indices. These indices allow the assessment and classification of climatic conditions of an area or region

Table 1
Geographical information of synoptic stations and average annual precipitation and temperature.

Station name	Code	Latitude (°N)	Longitude (°E)	Elevation (m)	Mean annual precipitation (mm)	Mean annual temperature (°C)
Chungju	B127	36.97	127.95	115.1	1189.62	11.5
Seosan	N129	36.78	126.49	28.9	1228.97	11.9
Cheongju	B131	36.64	127.44	57.2	1219.41	12.5
Chupungryeong	B135	36.22	127.99	244.7	1165.97	11.7
Jecheon	B221	37.16	128.19	263.6	1326.39	10.2
Boeun	B226	36.49	127.73	175.0	1274.13	11.0
Cheonan	N232	36.78	127.12	21.3	1214.08	11.8
Boryeong	N235	36.33	126.56	15.5	1199.93	12.4
Buyeo	N236	36.27	126.92	11.3	1313.82	12.2
Geumsan	N238	36.11	127.48	170.4	1264.62	11.6

with variable and extreme weather conditions that could lead to extreme events of floods and drought. The classification of climatic conditions for both UNEP and De Martonne indices is presented in Table 2. The high values of both UNEP and De Martonne climate indices indicate a wet condition and the low values signify a dry condition. For easy comparison of the two indices, the calculated UNEP and De Martonne climate indices were further classified into five percentile categories of climatic conditions (Table 2), to assess the extreme events associated with drought (<10th percentile) and flood (> 90th percentile) (Ahmad et al., 2018; Shah et al., 2022).

2.3.1. UNEP climate index

The UNEP climate index, originally developed by UNEP (UNEP, 1992), was calculated using the ratio of precipitation and potential evapotranspiration for annual and seasonal timescales (Eq. (1)).

$$AI_{UNEP} = \frac{P}{PET} \tag{1}$$

Where AI_{UNEP} is the UNEP climate index for the annual or seasonal climatic condition of a region, is the annual or seasonal precipitation in mm, and PET is the annual or seasonal potential evapotranspiration in mm.

The FAO-56 Penman-Monteith equation was used to estimate the PET (Allen et al., 1998). This equation has been widely used to calculate potential evapotranspiration under various climatic conditions, especially when it comes to agricultural water resources management.

2.3.2. De Martonne climate index

De Martonne's climate index was first introduced by De Martonne (de Martonne, 1926) and the index combined both precipitation and temperature, the two important climatic variables for assessing and classifying climatic conditions of areas and regions. The annual and seasonal De Martonne climate index are calculated using Eqs. (2) and (3).

$$I_{DM_a} = \frac{P_a}{T_a + 10} \tag{2}$$

Where I_{DM_a} is the De Martonne annual climate index, P_a is the annual amount of precipitation in mm, T_a is the mean annual air temperature (°C).

$$I_{DM_s} = \frac{4P_s}{T_s + 10} \tag{3}$$

Where I_{DM_s} is the De Martonne seasonal climate index, P_s is the seasonal amount of precipitation in mm, T_s is the mean seasonal air temperature (°C).

Table 2
Climatic classification of UNEP and De Martonne climate indices for annual and seasonal, and percentile classification.

UNEP climate index		De Martonne climate index		Percentile classification	
Climate condition	Value range	Climate condition	Value range	Class	Value range
Hyper-arid	<0.05	Arid	<10	Light	0 - 10th
Arid	0.05–0.20	Semi-arid	$10 \leq I_{DM} < 20$	Low	10th - 40th
Semi-arid	0.20–0.50	Mediterranean	$20 \leq I_{DM} < 24$	Moderate	40th - 60th
Semi-humid	0.50–0.65	Semi-humid	$24 \leq I_{DM} < 28$	High	60th - 90th
Humid	>0.65	Humid	$28 \leq I_{DM} < 35$	Heavy	90th - 100th
		Very humid	$35 \leq I_{DM} \leq 55$		
		Extremely humid	>55		

2.4. Spatial interpolation

Spatial patterns of the variability and change in annual and seasonal climate indices based on the six percentile categories were created using the Inverse Distance Weighting (IDW) interpolation technique in QGIS software (Version 3.24.1). Previous studies have demonstrated the accuracy and the ease of use of the IDW interpolation technique (Fung et al., 2022; Jo et al., 2018; Kim et al., 2014; Pingale et al., 2014; Zhou et al., 2020). Besides, among the essential features of the IDW include the ability to estimate extreme changes in different terrains and well interpolation of close data points as obtained for the considered stations in this study, while also providing the least root square mean error (Fung et al., 2022). The underline assumption of IDW is that the weight decreases exponentially with respect to an increase in the distance between the unobserved points and the neighboring observation points (Jo et al., 2018). The IDW interpolation is generally computed by averaging the weight of the observation values followed by the identification of the neighbors of the interpolated points using Eqs. (4) and (5).

$$w(x,y) = \sum_{i=1}^{N} \lambda_i w_i \tag{4}$$

$$\lambda_i = \frac{d_i^{-p}}{\sum_{i=1}^{N} d_i^{-p}} \tag{5}$$

Where $w(x,y)$ is the interpolated value at a position (x,y), N is the number of nearest observation points surrounding (x,y), λ_i is the weight of each observation point w_i located at (x_i,y_i), d_i is the Euclidean distance between (x_i,y_i) and (x,y), p is the degree of change in weight according to the Euclidean distance (p was set as 2 in this study as recommended by previous studies (Fung et al., 2022; Kim et al., 2014)).

2.5. Trend analysis

Trend analysis is an important aspect of climate change study. In this regard, the two graphical innovative methods i.e., ITA and IPTA were used to analyze the trends in annual and seasonal climate indices in this study. Specifically, the ITA method was first used for the annual and seasonal trend analysis; and to understand the periodical features of seasonal trend behaviors, which ITA is currently lacking, the IPTA method was further used for the seasonal trend analysis. These two graphical trend methods were then compared to the Mann-Kendall and Modified Mann-Kendall, two prominent classical trend test methods.

2.5.1. Innovative trend analysis method

The ITA method, a non-parametric graphical trend method proposed by Sen (Şen, 2012) and with a statistical significance test by Şen (Şen, 2017) was applied to the annual data series of the climate indices. The trend analysis was conducted by dividing the calculated time series of annual climate indices into two halves, and then re-arrange each obtained sub-series in ascending order separately. The first sub-series $(x_i : i = 1, 2, \ldots, n/2)$ is placed on the horizontal axis (X-axis) and the second sub-series $(y_i : j = n/2 + 1, n/2 + 2, \ldots, n)$ is on the vertical axis (Y-axis) of the two-dimensional Cartesian coordinate system as shown in Fig. 2(a). The data clustering on the 1:1 (45°) line of the coordinate system indicates no trend, as this separates the decreasing and increasing trends. Conversely, the data points in the triangular area above the 1:1 line indicate an increasing trend while the data points below the 1:1 line signify decreasing trend, which is regarded as a monotonic trend due to the clear distinction in the trend locations (Şen, 2012). Further, there could also be a non-monotonic increasing or decreasing trend, which comprises different trends in the time series (Güçlü, 2018).

The trend slope and indicator of the ITA are calculated using Eqs. (6) and (7).

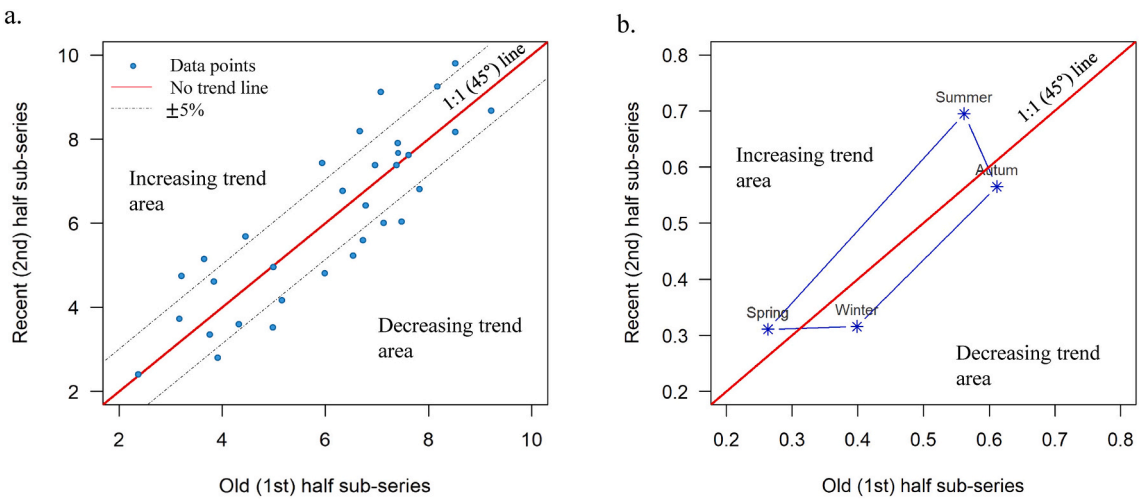


Fig. 2. (a) Illustration of trends regions in ITA method **(b)** Hypothetical innovative polygon trend method for seasonal data.

$$s = \frac{2(\bar{x} - \bar{y})}{n} \tag{6}$$

Where, s is the trend slope, n is the number of data, $\bar{x}$ and $\bar{y}$ are the mean values of the first sub-series and second sub-series, respectively.

$$D = \frac{1}{n}\sum_{i=1}^{n}\frac{10(y_i - x_i)}{\bar{x}} \tag{7}$$

Where D is the trend indicator (a positive value indicating an upward trend and a negative value signifying a downward trend), n is the number of data in each sub-series, is the mean value of the first sub-series, and x_i and y_i observed data values in the first and second sub-series, respectively.

The significance of the ITA is estimated using the probability distribution function such that when the confidence interval of a standard normal distribution function with zero mean and standard deviation of ITA trend slope (σ_s) at a significance level of α, the confidence limit of trend slope (CL) is calculated using Eq. (8).

$$CL_{(1-\alpha)} = 0 \pm s_{\sigma_s} \tag{8}$$

The null hypothesis of no slope is rejected when the estimated ITA trend slope, s is greater than the critical value. The slope, s of the data series is, thus, considered statistically significant if the data points fall outside the stated confidence limit. In this study, a 95% confidence level is considered and the ITA was performed using the "trend change" package in the R environment (Patakamuri and Das, 2019). The details about the ITA can be found in Şen (Şen, 2017).

2.5.2. Innovative polygon trend analysis method

The IPTA, which was recently proposed by Şen et al. (Şen et al., 2019) as an advancement of the ITA to reveal the underline periodical features of trend transition between successive seasons was applied to the seasonal data series of the climate indices. Just like the ITA, the seasonal time series data are divided into two halves for the IPTA. The basic statistics, including mean and standard deviation for each seasonal period, are calculated in both sub-series. The first and second sub-series are placed on the horizontal axis (X-axis) and vertical axis (Y-axis) of the two-dimensional Cartesian coordinate system, respectively. Similar to the ITA, the data points above or below the 1:1 indicate an increasing or decreasing trend, accordingly. The points of consecutive seasons are then connected by straight lines to form a polygon (Fig. 2(b)**).** Lastly, the slope and size of the line between consecutive points are estimated to form trend slope and slope length, respectively, using Eqs. (9) and (10).

$$s = \frac{y_2 - x_2}{y_1 - x_1} \tag{9}$$

$$|AB| = \sqrt{\left((x_2 - x_1)^2 + (y_2 - y_1)^2\right)} \tag{10}$$

Where, s is the trend slope of each straight line, and $|AB|$ is the length of the straight line between two points, A (x_1, y_1) and B (x_2, y_2). Further information about the IPTA can be found in Şen et al. (Şen et al., 2019).

2.5.3. Mann-Kendall trend analysis method

Mann-Kendall (MK) trend test is one of the classical non-parametric tests that is often used to detect trends in a time series of hydro-meteorological data (Kendall, 1975; Mann, 1945). The MK trend test is known for assessing the monotonic trends such that the standardized MK test statistic (Z_{MK}) with positive (negative) values indicate increasing (decreasing) trends. The MK trend test is computed using Eqs. (11)–(14).

$$S = \sum_{k=1}^{n=1}\sum_{j=k+1}^{n} sgn(x_j - x_k) \tag{11}$$

$$sgn(x_j - x_k) = \begin{Bmatrix} +1 \; if \; (x_j - x_k) \rangle 0 \\ 0 \; if \; (x_j - x_k) = 0 \\ -1 \; if \; (x_j - x_k) \rangle 0 \end{Bmatrix} \tag{12}$$

$$V(s) = \frac{n(n-1)(2n+5)}{18} \tag{13}$$

$$Z_{MK} = \begin{Bmatrix} \frac{S-1}{V(S)} \; for \; S > 0 \\ 0 \; for \; S = 0 \\ \frac{S+1}{V(S)} \; for \; S < \end{Bmatrix} \tag{14}$$

Where n denotes the number of observations in the dataset, x_j and x_k are the time series values at times j and k, respectively, from a given time series with n observations, sgn represents the sign function with the values 1, 0, or − 1, if $x_j > x_k$, $x_j = x_k$, or $x_j < x_k$, respectively. S denotes the Kendall sum statistic, and $V(S)$ is the variance.

The significance of the trends is based on the different levels of confidence such as very high (99%), high (95%), moderate (90%), and low (80%), for $Z_{MK} \geq Z_{\alpha/2} = |\pm 2.576|$, $Z_{MK} \geq Z_{\alpha/2} = |\pm 1.96|$, $Z_{MK} \geq Z_{\alpha/2} = |\pm 1.645|$,and $Z_{MK} \geq Z_{\alpha/2} = |\pm 1.282|$, respectively. The magnitude of the MK trends was further estimated using Theil-Sen's slope approach (Sen, 1968).

2.5.4. Modified Mann-Kendall trend analysis method

Due to the possible autocorrelation, which hydro-meteorological variables are known to sometimes exhibit, a bias-corrected pre-whitening technique is, thus, used following the procedures proposed by Hamed (Hamed, 2009). This Modified Mann-Kendall (MMK) procedures employ the ordinary least square method to simultaneously estimate the lag-1 serial correlation coefficient and trend of the slope, after which the lag-1 serial correlation coefficient is bias corrected. The details about the Modified Mann-Kendall test using bias-corrected pre-whitening can be found in Hamed (Hamed, 2009).

3. Results and discussion

3.1. Annual and seasonal variability analysis of climate indices

The variability analysis of climate indices, which combines two or more climate variables is an important step toward mitigating the clime extreme events. The annual and seasonal variation characteristics of climatic conditions for Chungcheong Provinces in Korea from 10 synoptic stations covering 1974 to 2019 were analyzed using both the UNEP and De Martonne climate indices. The results of temporal variations in the annual and seasonal average of the climate indices at 10 different stations are presented in Figs. 3 and 5.

Generally, the annual climate condition of the Chungcheong Provinces can be classified as a wet climate season since the UNEP climate index values at all the stations are above 0.65 (indicating humid climate), while the De Martonne index average values range from 35.3 (humid climate) to 85.9 (extremely humid) (Fig. 3a), according to the climatic classification of both indices (Table 2). There is a clear indication of seasonal variability in the climate conditions, with the summer season having the high average value of UNEP and De Martonne climate indices (Fig. 3a). Further assessment of the long-term (annual) and short-time (seasonal) timescale analyses could provide the detailed variation characteristics of the climate conditions.

3.1.1. Annual variability of climate indices

The annual average values of the UNEP climate index ranged from 1.20 to 1.55 at Chupungryeong and Jecheon stations, respectively, while the lowest and highest values of the De Martonne climate index were 42.53 and 65.70 at Geumsan and Jecheon stations, respectively (Fig. 3b). The Jecheon station having the highest average values of both indices can be attributed to its location with high altitude (263 m) compared to others, while also receiving relatively abundant precipitation and low average temperature. The UNEP climate index shows that the entire study area exhibits a humid climate. However, based on the climate classification of the De Martonne climate index, 60% of the considered stations, including Chungju, Seosan, Jecheon, Boeun, Cheonan, and Buyeo stations, were extremely humid, while stations like Cheongju, Chupungryeong, Boryeong, and Geumsan fall under a very humid climate condition.

Previous studies have also reported that many cities in Korea are characterized by long-term increase in precipitation amount and intensity, which are sometimes followed by dry days without precipitation in some regions (Chang and Kwon, 2007; Choi, 2004; Chung et al., 2004; Felix et al., 2021), which could have influenced the humid climatic condition in the Chungcheong Provinces. It has also been reported that the two climate change regimes of the past 25 years (1959–1983) and recent 25 years (1984–2008) are reflected by a change in average precipitation intensities of 14.2 mm/day and 15.9 mm/day followed by dry days of 28 and 31 days, respectively (Min et al., 2015). The implication of these changes has often resulted in flooding and drought in some areas like Jecheon, Cheongju, Chungju, and Boeun, all within the Chungcheong Provinces (Boram, 2020; Maeng et al., 2017).

The frequency of occurrence distribution of the UNEP climate index classes indicates a 100% humid climate condition at all the 10 stations on a long-term timescale (Fig. 4a). Conversely, for the De Martonne climate index, the highest and lowest occurrence frequency of extremely humid climate occurred at Jecheon (70%) and Chupungryeong (45%) stations, respectively, with other stations having >50% of the occurrence frequency, except for Seosan station (45%) (Fig. 4b). Similarly, a very humid condition of the De Martonne climate index was the second dominated climate condition, with Seosan and Jecheon stations having 51% (highest) and 30% (lowest) of the occurrence frequency, respectively. None of the stations had any occurrence of arid climate conditions for both climate indices on the annual timescale.

These results further demonstrate the variability of the climatic conditions of the study area at different stations, especially based on the De Martonne climate index, which all indicates wet conditions on an annual timescale, as also shown by the UNEP climate index.

3.1.2. Seasonal variability of climate indices

The average values of UNEP and De Martonne climate indices showing the seasonal variability of the climate indices are presented in Fig. 5. The average climate indices vary across the seasons and among the stations with the summer season having the highest values of 4.73 and 199.79 at Boeun and Buyeo stations for UNEP and De Martonne

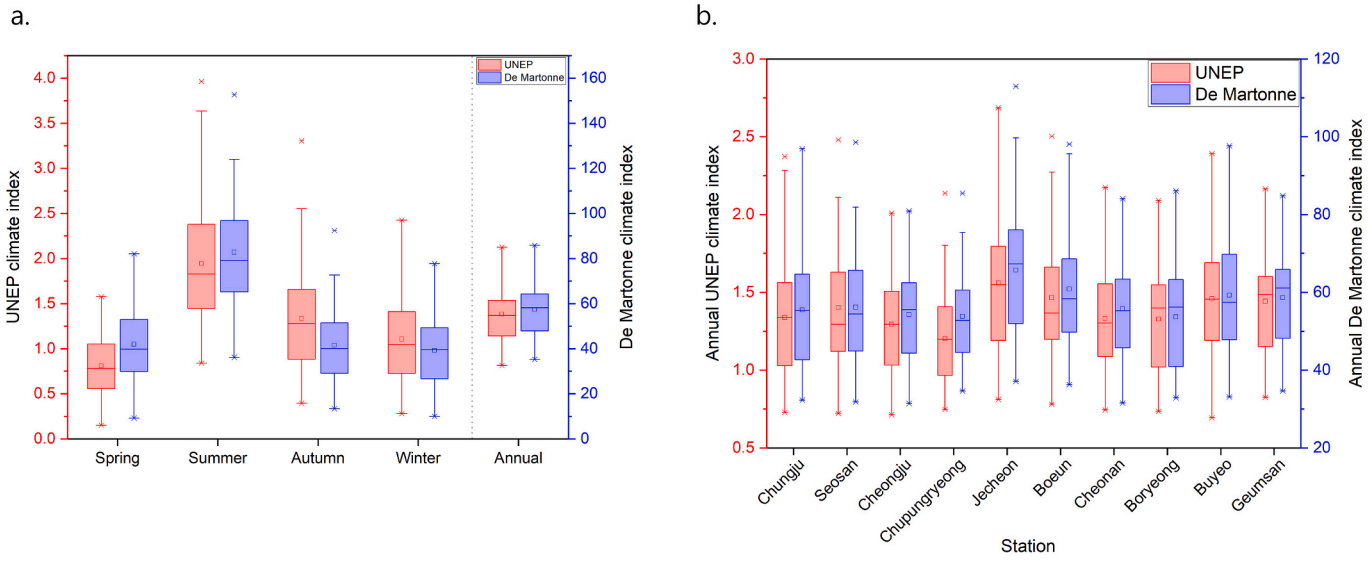


Fig. 3. Average values of annual and seasonal UNEP and De Martonne climate indices at different stations in the Chungcheong Provinces, Korea.

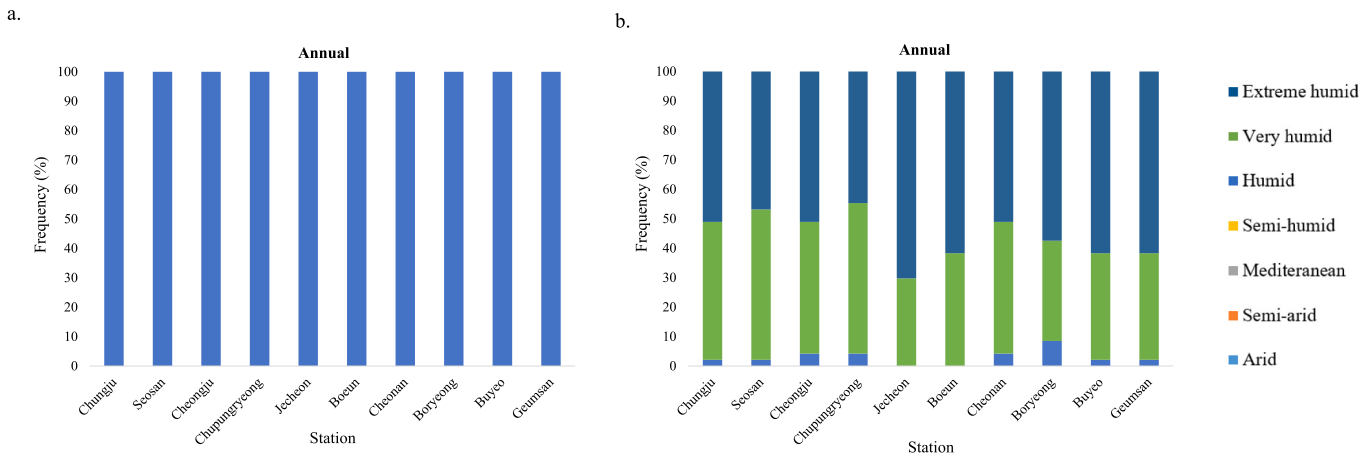


Fig. 4. Frequency of occurrence distribution of climatic conditions on the annual scale for **(a)** UNEP climate index, and **(b)** De Martonne climate index.

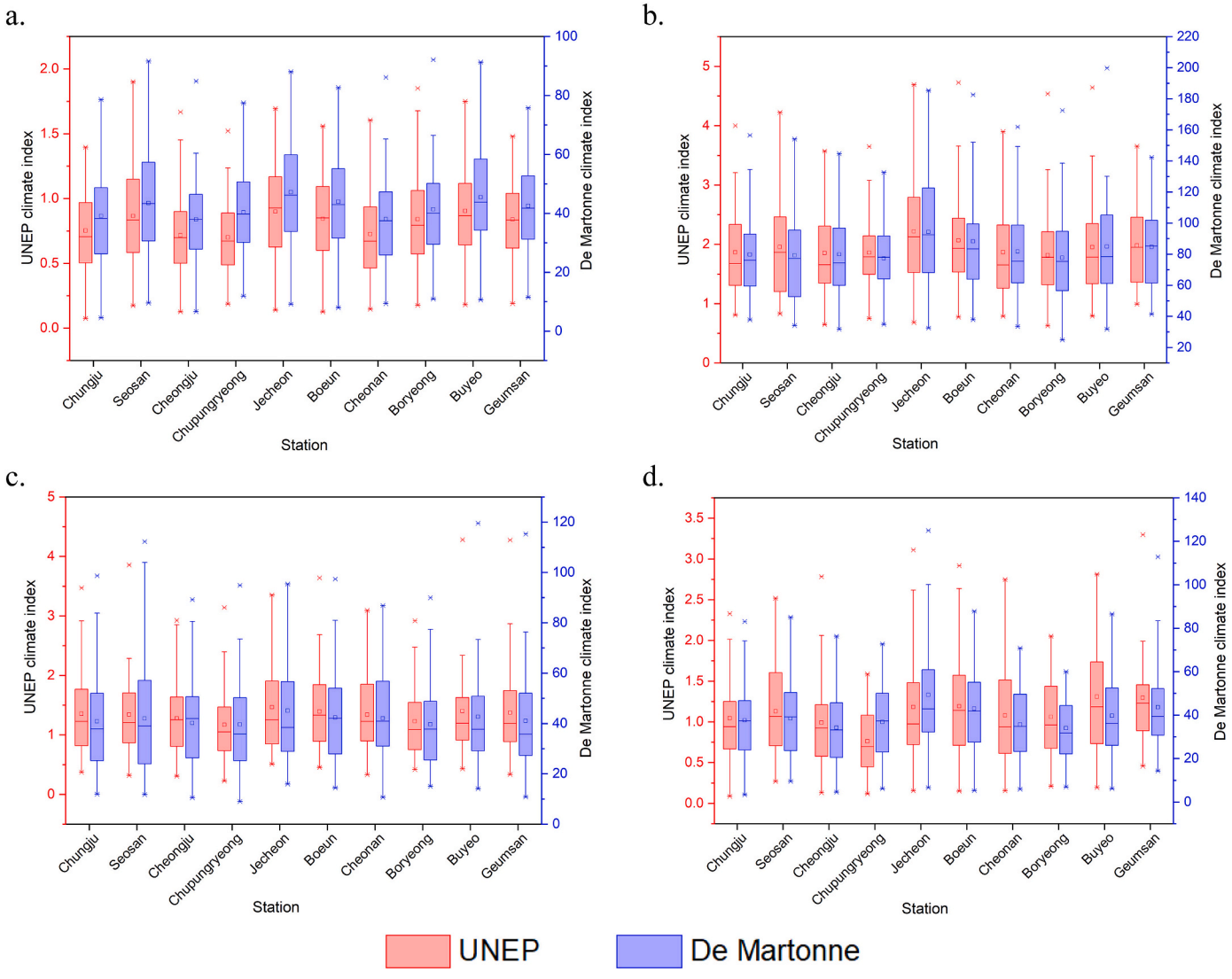


Fig. 5. Average values of UNEP and De Martonne climate indices in **(a)** spring **(b)** summer **(c)** autumn, and **(d)** winter at different stations in the Chungcheong Provinces, Korea.

climate indices, respectively. Similarly, the least average climate indices of 1.40 and 60.02 occurred in the spring and winter seasons at Chungju and Boryeong stations for UNEP and De Martonne climate indices, respectively. Considering the location of the study area at the east end of the Asian continent, the influence of the East Asian monsoon contributes to the uneven distribution of precipitation, one of the important climate

variables in the two considered climate indices, ranging from 74 to 95 mm at Chungju and Buyeo stations, respectively, in winter, and 637 to 727 mm at Chupungryeong and Boeun stations, respectively in summer. Similarly, the average temperature was found to vary among the seasons and across the stations ranging from −3.4 to 0.58 °C at Jecheon and Boryeong stations, respectively, in winter, and 22.7 to 24.7 °C at Jecheon and Cheongju stations, respectively in summer. These two variables are considered to cause variations in the climate indices at different stations due to their relative seasonal dependence.

The distribution of occurrence frequency of different climatic conditions at a seasonal timescale indicates that humid climate occurred most frequently ranging from 55 to 100% in all the four seasons and across all the 10 stations in the UNEP climate index (Fig. 6a). In the summer season, it was shown that all the stations exhibited a 100% humid climate condition except for Cheongju and Boryeong stations which indicated an occurrence frequency of a 2 and 4% semi-humid condition, respectively. The existence of arid classes of climate conditions can be observed in the spring, autumn, and winter seasons. Cheonan station showed the highest occurrence frequency of arid climate in the spring season ranging from 35% (semi-arid) to 2% (arid), while Seosan and Buyeo had an 11% occurrence frequency of arid climate. For the winter season, the highest occurrence frequency of arid conditions was demonstrated at Chupungryeong station with 26% semi-arid and 2% arid conditions.

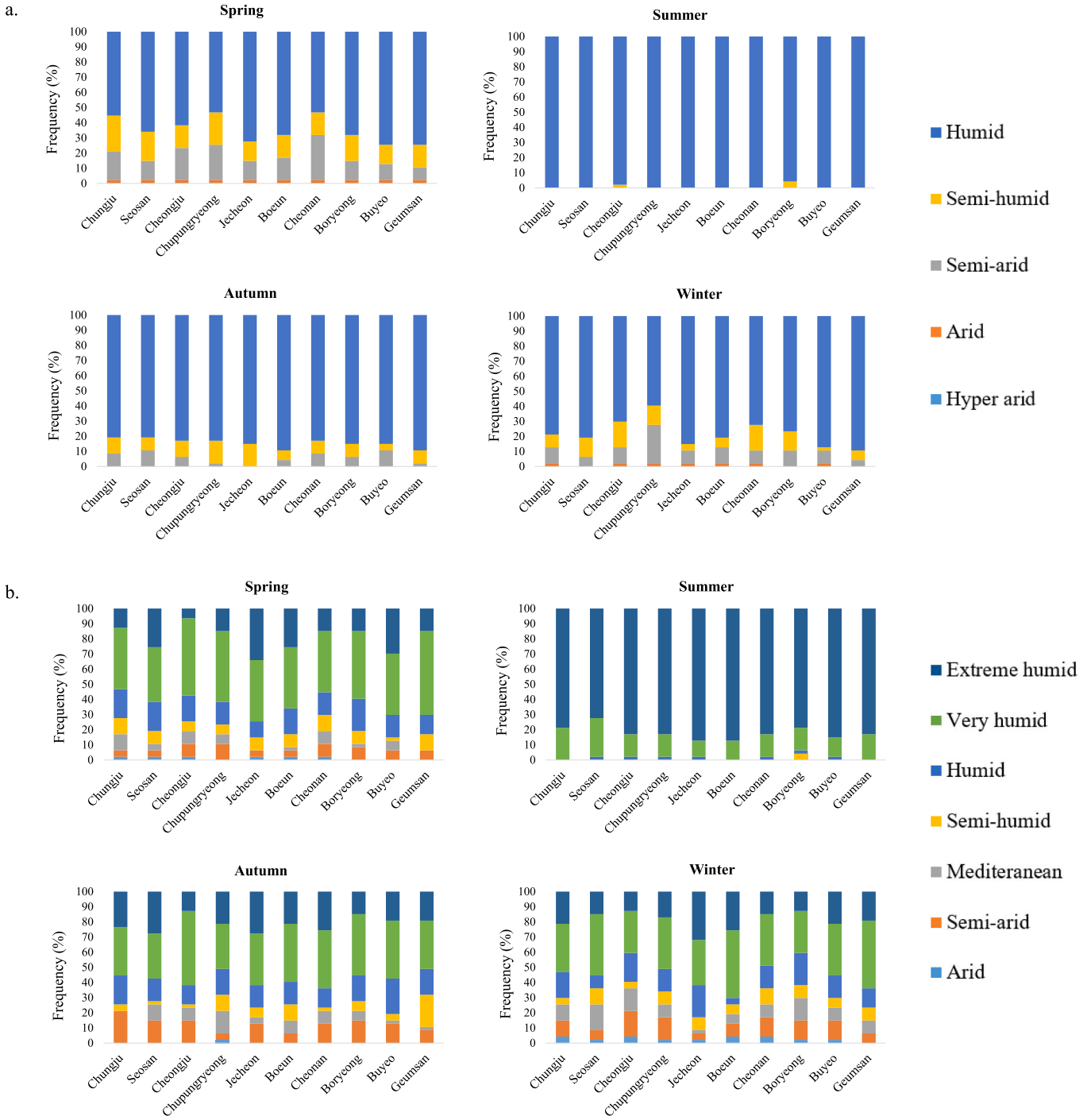


Fig. 6. Frequency of occurrence distribution of climatic conditions on the seasonal scale for (a) UNEP climate index, and (b) De Martonne climate index.

For the De Martonne climate index, highly variable distribution of occurrence frequency of climate condition classes can be observed in the four seasons and at the 10 stations compared to the UNEP index (Fig. 6b). Similar to the UNEP index, the summer season showed no presence of arid classes of climate condition in the De Martonne climate index, while an extreme humid condition dominated with the frequency of occurrence ranging from 72% (at Seosan station) to 87% (at Jecheon and Boeun stations). Spring, autumn, and winter seasons showed the presence of arid classes (semi-arid and arid) of climate conditions, with the highest occurrence frequency of 11% (at Chupungryeong station) for semi-arid climate and 2% (at Chungju, Seosan, Cheongju, Jecheon, Boeun, and Cheonan stations) for arid climate, 21% (at Chungju station) for semi-arid climate and 2% (at Chupungryeong station) for arid climate, and 17% (at Cheongju station) for semi-arid climate and 4% (at Chungju, Cheongju, Boeun, and Cheonan stations) for arid climate, respectively. Similarly, the Mediterranean class of climate conditions can also be observed in the spring, autumn, and winter seasons with Chungju (11%), Chupungryeong (15%), and Seosan (17%) stations having the highest percentage occurrence frequency, respectively.

3.1.3. Spatial variability of climates indices

The spatial distributions of the UNEP and De Martonne climate indices using IDW, and based on the five percentile categories of light, low, moderate, high, and heavy climatic conditions, which were computed using the average values at each station are shown in Figs. 7 and 8. Notably, the De Martonne climate index showed greater variability of the climate conditions in four of the percentile categories than the UNEP index, while both indices showed a similar pattern and variation characteristic of heavy climatic conditions (> 90th percentile) on an annual timescale. Unlike the UNEP index that indicates a moderate climate condition (40th to 60th percentile) in the larger area of Chungcheong Provinces, four climatic conditions are highly represented in the De Martonne climate index, which includes a high climatic condition (60th to 90th percentile) around Seosan, Boeun, Buyeo, and Chungju stations. Further, regions around Geumsan, Boryeong, Cheongju, and Chupungryeong stations range from light (< 10th percentile) to low (10th to 40th percentile) climatic conditions. The region with an annual heavy climatic condition (> 90th percentile) in the Chungcheong Province was at the far-end northeast around Jecheon station, which also recorded the highest average precipitation of 1326 mm and the lowest average temperature of 10.2 °C, as the two major climatic variables in the two indices (Fig. 7a and b). This is an attestation to the frequently occurring flood events around this region (Boram, 2020). Besides, due to the influence of local convection and orographic effect, different precipitation amounts and intensity occur in adjacent weather stations in the mountainous terrain that exists in Chungcheong Provinces (Jung et al., 2011). It has been previously reported that high climate indices such as UNEP and De Martonne could result in extreme climate events (Wang et al., 2020).

The spatial distribution by percentile showed variable patterns in all four seasons and between the two indices. For instance, the heavy climate condition occurred at the far-end northeast of the study area around Jecheon station during the summer and autumn seasons for the UNEP climate index. However, the down south area around Geumsan station during the spring and winter seasons and at the far-end northeast area around Jecheon station in the summer and autumn seasons exhibited a heavy climate condition for the De Martonne climate index. In general, the western region showed relatively uniform and lower climatic conditions ranging from moderate to light for both climate indices, except for the spring season in the UNEP index which indicated a high climatic condition. Besides, a moderate climatic condition dominated in all the four seasons for the UNEP climate index, while only the autumn season indicated a relatively large area of moderate climatic with a high climatic condition relatively dominated in the winter season for the De Martonne climate index. The observed differences in the variability of the climatic conditions between UNEP and De Martonne indices can be attributed to different climate variables that constituted these indices. Considering that the Chungcheong region is prominent for its agricultural activities, the extreme climate events aided by climate change would continue to have an adverse impact on the agricultural activities in this region. However, a shift in agricultural activities in terms of cultivating appropriate crops that support the climatic conditions at different seasons could sustain the agricultural activities in this region. Besides this, there is a need for an adequate monitoring system for the extreme climate events like floods and drought that have continued to severely impact the Chungcheong Provinces and many other regions in the country.

3.2. Trend analysis of climate indices

The trend analysis at annual and seasonal scales was performed for both UNEP and De Martonne climate indices using the ITA method. To further investigate the periodical characteristics of the seasonal trend behaviors, the IPTA was applied to the seasonal UNEP and De Martonne climate indices.

3.2.1. Annual trend

The results of the ITA method with significance tests for the UNEP and De Martonne climate indices on an annual timescale are presented in Table 3 and Fig. 9. Generally, both indices are dominated by upward

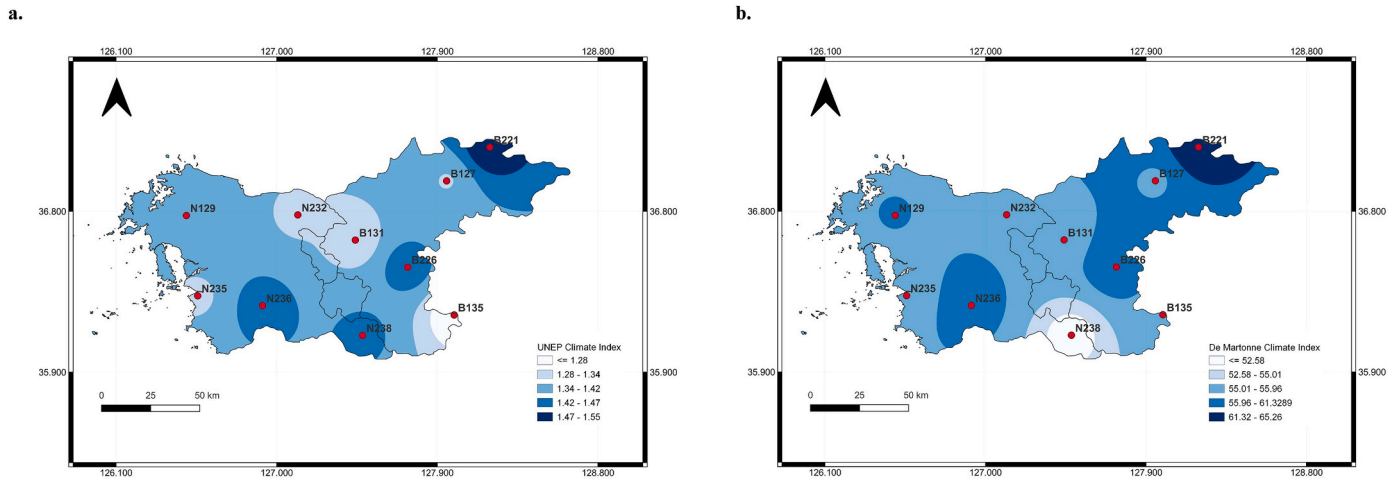


Fig. 7. Spatial distribution of annual climate indices (a) UNEP, and (b) De Martonne, with percentile classifications as indicated in Table 2.

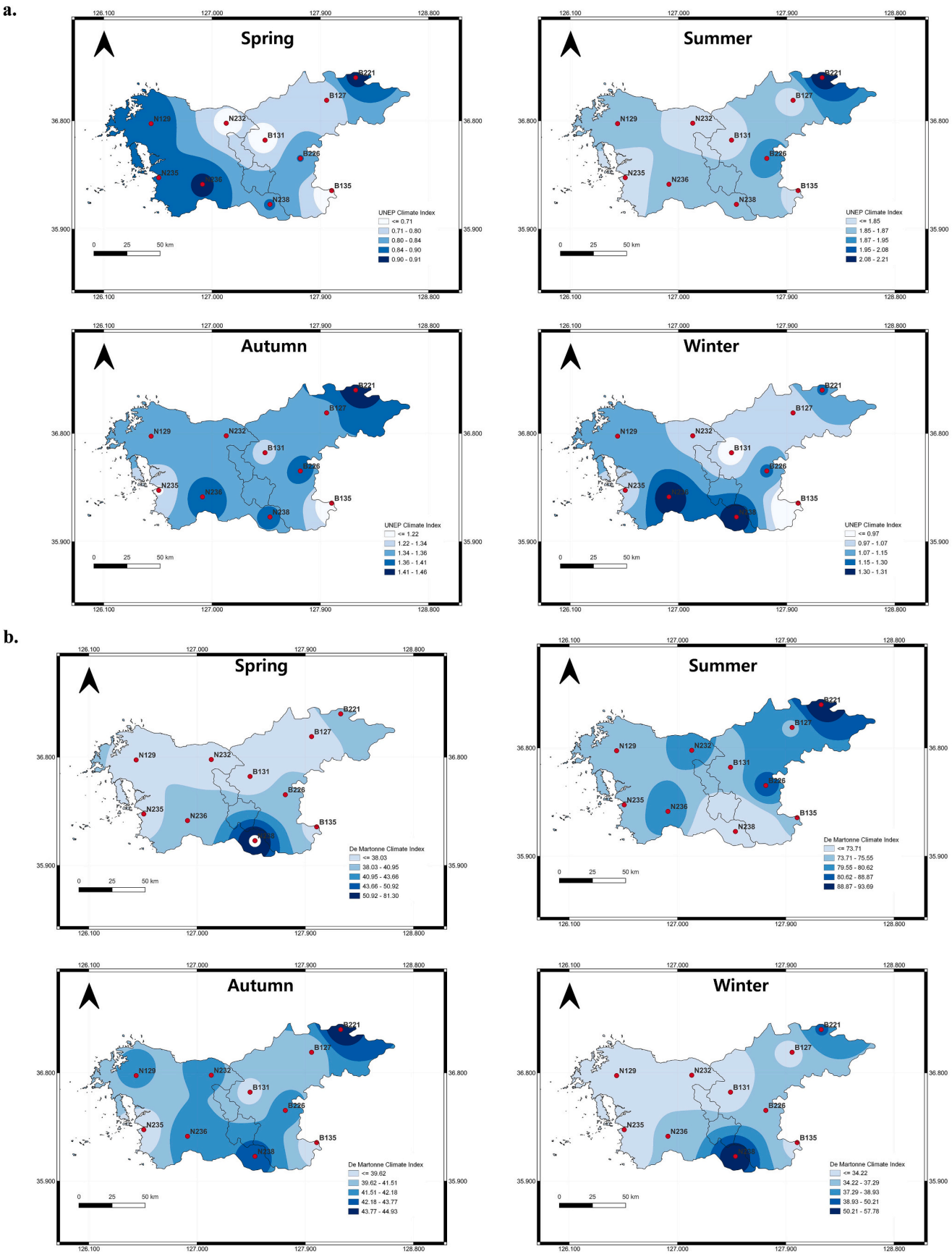


Fig. 8. Spatial distribution of seasonal climate indices (a) UNEP, and (b) De Martonne, with percentile classifications as indicated in Table 2.

Table 3
Results of innovative trend slope and trend indicator for Annual UNEP and De Martonne climate indices in the Chungcheong provinces.

Station	UNEP Climate Index				De Martonne Climate Index			
	Trend slope, s	Trend indicator, D	Slope standard deviation, σ_s	Significance level of 95%	Trend slope, s	Trend indicator, D	Slope standard deviation, σ_s	Significance level of 95%
Chungju	0.0001	0.0101	0.0004	±0.0007	0.0548	0.2329*	0.0157	±0.0309
Seosan	0.0023	0.3827*	0.0006	±0.0011	0.1164	0.4961*	0.0190	±0.0372
Cheongju	−0.0003	−0.0546	0.0004	±0.0009	−0.0112	−0.0478	0.0229	±0.0449
Chupungryeong	0.0024	0.4767*	0.0004	±0.0008	0.1235	0.5540*	0.0116	±0.0228
Jecheon	0.0006	0.0945	0.0005	±0.0009	0.1528	0.5570*	0.0224	±0.0439
Boeun	0.0060	1.0137*	0.0004	±0.0008	0.2384	0.9604*	0.0152	±0.0297
Cheonan	−0.0003	−0.0443	0.0005	±0.0009	−0.0052	−0.0216	0.0194	±0.0381
Boryeong	−0.0019	−0.3295*	0.0005	±0.0010	−0.1387	−0.5847*	0.0168	±0.0329
Buyeo	0.0049	0.8099*	0.0006	±0.0012	0.0417	0.1657	0.0261	±0.0513
Geumsan	0.0043	0.7188*	0.0006	±0.0011	0.1660	0.6845*	0.0177	±0.0347

* represents a 95% significance level.

trends (70%) as shown by the positive values of trend indicator *D*, while 60% and 70% of the stations exhibited significant trends at the 95% confidence level for the UNEP climate index and De Martonne climate index, respectively, as indicated by the trend slope, *s* (Table 3). However, there are slight variations in the level of significance among the stations between the two indices. For instance, the upward trends were significant for the De Martonne index at Chungju and Jecheon stations, while the UNEP index only indicate upward trends that were not significant at the 95% confidence level at the same stations. Similarly, the upward trend of the UNEP climate index was significant at the Buyeo station unlike the trend of the De Martonne index which only showed an insignificant upward trend. Nevertheless, the indicators of upward and downward trends were the same for both indices at all the 10 stations. The same patterns of increasing trends can be observed in Fig. 9, where the data points of most stations are clustered in the triangular area above the 1:1 line of the Cartesian coordinate system, which is very distinctive at each station.

The trends at Boeun, Buyeo, and Geumsan stations (for UNEP climate index), and at Chupungryeong, Boeun, Boryeong, and Geumsan stations (for De Martonne climate index) exhibit monotonic trends due to the clear distinction in the trend locations. Among these stations, only the Boryeong station indicated a downward trend for the De Martonne climate index, where data points clustered below the 1:1 line of the Cartesian coordinate system, while other stations showed upward trends. The trends in other stations are inconsistent (non-monotonic trend) as the data points of climate indices showed combined increasing and decreasing trends, with some data points falling within the confidence interval bands of ±5%. For instance, at Seosan station, the UNEP index values between 0.9 and 1.2 indicate a decreasing trend, index value points between 1.2 and 1.5 shows no trend, while values above 1.5 clearly show an increasing trend. Similarly, at Cheongju station, the De Martonne index values below 52 indicate a decreasing trend, while index value points between 52 and 70 show no trend, and values above 70 indicate an increasing trend. It can be noted that both indices indicated significant increasing trends at 5 stations comprising Seosan, Boeun, Jecheon, Buyeo, and Geumsan with slope values of 0.002, 0.002, 0.006, and 0.004 for the UNEP index and 0.0016, 0.124, 0.238, and 0.166 for the De Martonne index, respectively, compared to only Boryeong station with the significant decreasing trend and with slope values of 0.0023 and 0.166, respectively.

Compared with the classical trend tests, ITA showed a similar pattern of trend direction (upward and downward trends) with MK and MMK trend tests, except at Chungju and Seosan stations for the UNEP climate index and including Buyeo for the De Martonne climate index where a contrary trend direction was observed. While ITA revealed a 95% significant trend level at 60 and 70% of the stations for the UNEP and De Martonne climate indices, respectively, the MMK detected a significant trend (90% significant level) at only one station and MK detected none (Table 4). Thus, demonstrating the capability of the ITA to detect hidden significant trends (Ahmed et al., 2022a).

Although this is the first study that investigated the trend of the climate indices using the ITA, the previous study also reported a significant increasing trend in annual maximum rainfall in Jecheon station using the Mann-Kendall test and suggested the vulnerability of Jecheon to flood and drought (Seo et al., 2012). The superiority of ITA in identifying hidden trends in time series data over other methods like Mann-Kendall has been well documented (Shah et al., 2022; Wang et al., 2020). The obtained results revealed significant increasing trends at Seosan, Boeun, and Geumsan, which also receive >1200 mm of average precipitation annually. Meanwhile, Geumsan station showed a significant decreasing trend of both climate indices with <1200 mm average annual precipitation and an average annual temperature of 12.4 °C. These two opposing events could have some serious consequences on the agricultural activities in terms of flood risks and water resources availability, which would require serious attention if the same trends continue in the future in the Chungcheong Provinces of Korea.

3.2.2. Seasonal trend

The results of the seasonal trends of the UNEP and De Martonne climate indices based on the ITA are presented in Table 5 and Figs. S1 to S4**,** while the IPTA results are presented in Figs. 10 and 11. The trend slope values for both climate indices are positive with a significance level of 95% in all the stations except Boryeong station (for UNEP index) and Buyeo (for De Martonne index), which both indicated non-significant downward and upward trends, respectively, during the summer season **(**Table 5**)**. However, the slope, s values of the UNEP index in all the stations during the spring and winter seasons are negative with 60% and 100% of them significant at a 95% level, respectively. Both UNEP and De Martonne climate indices showed the high variable characteristic of trend slopes among the four seasons and across the stations. While the slope values of the De Martonne index are non-significant positive at Chupungryeong, Boeun, and Geumsan stations, they are all negative for the UNEP index during the same spring season. The variation in trend characteristics between the two indices is more pronounced in the spring season compared to other seasons. In general, more stations (above 50%) exhibit significant (at 95% level) positive trends in the summer and autumn seasons for both climate indices, while negative significant trends dominated (above 60%) in spring (for the UNEP index) and winter (both indices) seasons. A previous study using the precipitation-intensity-based index also showed a significant decreasing trend during the spring season at Geumsan station (Felix et al., 2021). The graphical illustration of the ITA results for the two climate indices in the four seasons is presented in **Fig. S1** to **Fig. S4.** More stations indicate clear monotonic increasing trends in the summer season, these include Buyeo station (UNEP index), Jecheon and Boeun stations (De Martonne index), and Seosan and Geumsan (both indices). Similar trend patterns to the ITA were also shown by the MK and MMK classical trend methods in the spring season for the UNEP climate index

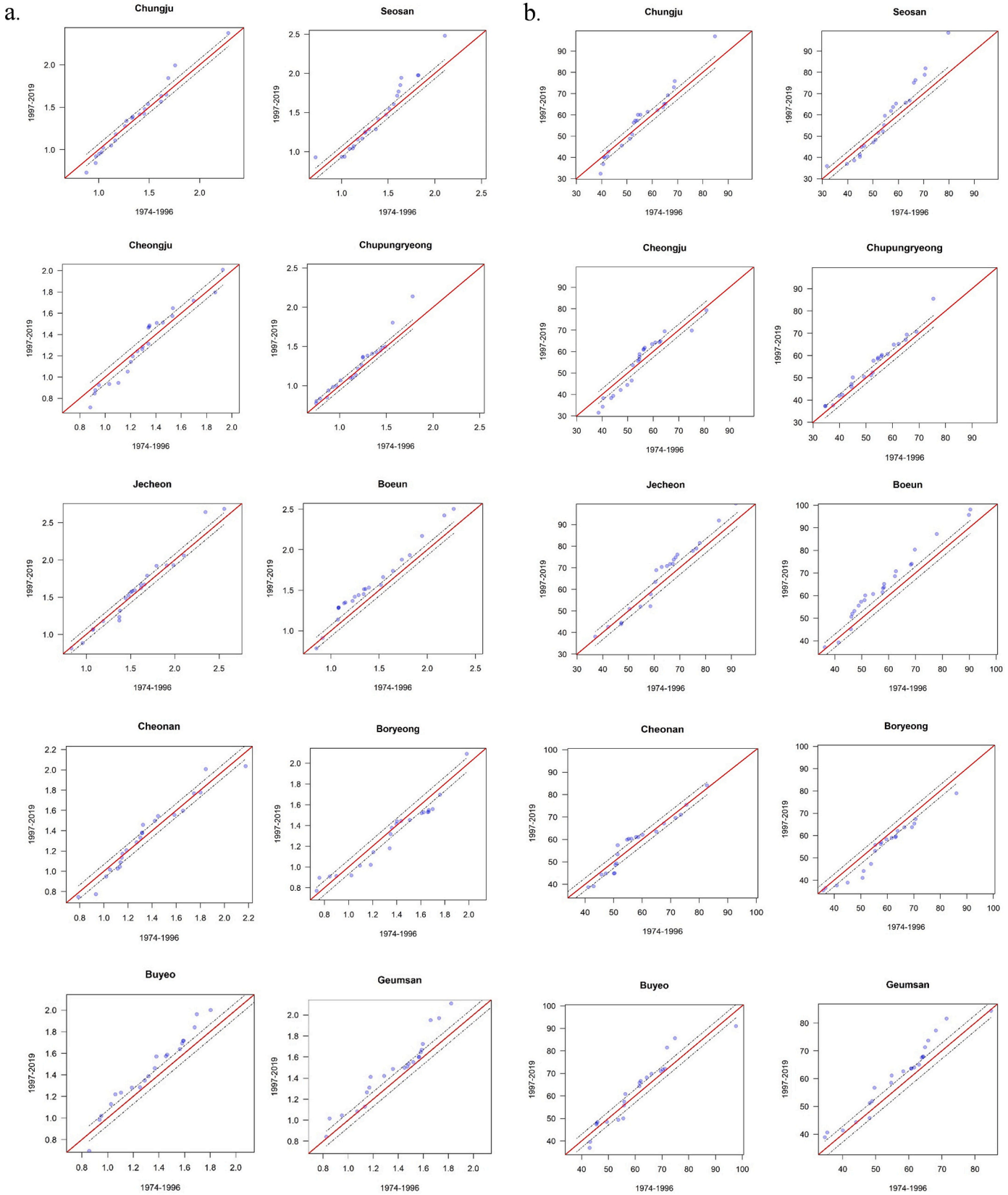


Fig. 9. Innovative trend analysis of **(a)** UNEP climate index, and **(b)** De Martonne climate index for annual timescale at the 10 stations in the Chungcheong Provinces, Korea.

Table 4
Results of Mann-Kendall and Modified Mann-Kendall standardized statistics (Z_{MK} and Z_{MMK}) and their respective Sen's slopes for Annual UNEP and De Martonne climate indices in the Chungcheong provinces.

Station	UNEP Climate Index				De Martonne Climate Index			
	Z_{MK}	Sen's slope	Z_{MMK}	Sen's slope	Z_{MK}	Sen's slope	Z_{MMK}	Sen's slope
Chungju	−0.495	−0.002	−0.928	−0.003	−0.257	−0.031	−0.701	−0.108
Seosan	−0.440	−0.002	−0.739	−0.004	−0.183	−0.046	−0.606	−0.084
Cheongju	−0.770	−0.002	−1.041	−0.004	−0.220	−0.028	−0.625	−0.095
Chupungryeong	0.000	0.000	−0.379	−0.001	0.257	0.036	−0.076	−0.018
Jecheon	0.495	0.002	−0.265	−0.002	0.770	0.148	−0.095	−0.023
Boeun	0.935	0.003	0.417	0.002	0.514	0.080	0.057	0.008
Cheonan	−0.569	−0.002	−0.663	−0.002	−0.679	−0.087	−0.720	−0.099
Boryeong	−0.532	−0.003	−0.928	−0.004	−1.174	−0.165	−1.477**	−0.214
Buyeo	0.550	0.002	0.227	0.001	−0.110	−0.014	−0.568	−0.094
Geumsan	0.312	0.001	0.227	0.001	0.037	0.004	−0.133	−0.018

** represents a 90% significance level.

Table 5
Results of innovative trend slopes, *s* for UNEP and De Martonne climate indices at the seasonal timescale.

Station	Spring		Summer		Autumn		Winter	
	UNEP	De Martonne	UNEP	De Martonne	UNEP	De Martonne	UNEP	De Martonne
Chungju	−0.0024*	−0.0251	0.0066*	0.1267*	0.0015	0.1362*	−0.0066*	−0.0114
Seosan	−0.0006	−0.0222	0.0108*	0.3864*	−0.0028*	−0.0503*	−0.0029*	−0.0501*
Cheongju	−0.0032*	−0.1459*	0.0045*	0.1557*	0.0027*	0.1089*	−0.0100*	−0.3220*
Chupungryeong	−0.0004	0.0225	0.0048*	0.1736*	0.0086*	0.2831*	−0.0016*	−0.0335
Jecheon	−0.0032*	−0.0291	0.0072*	0.3975*	0.0018	−0.2786*	−0.0117*	0.1447*
Boeun	−0.0005	0.0047	0.0168*	0.5962*	0.0067*	0.2044*	−0.0086*	−0.1773*
Cheonan	−0.0047*	−0.1987*	0.0086*	0.1399*	0.0015	0.0984*	−0.0147*	−0.2310*
Boryeong	−0.0017*	−0.1216*	−0.0008	−0.2723*	0.0020	0.0724	−0.0052*	−0.1016*
Buyeo	−0.0001	−0.0925*	0.0103*	0.0702	0.0095*	0.2026*	−0.0034*	0.0029
Geumsan	−0.0011*	0.0085	0.0137*	0.4496*	0.0023	0.0726	−0.0096*	−0.2714*

* represents a 95% significance level.

as indicated by the decreasing trends across all the stations (Table 6 and Table S3). However, in terms of significant trend level, only Cheonan exhibits a moderate significant (90%) trend level while Chungju and Cheongju stations show a weak significant (80%) trend level compared to the ITA method where 60% of the stations exhibit significant trend at the 95% confidence level. There are slightly varied results in terms of trend patterns (increasing and decreasing trend) and level of significance among the ITA, MK, and MMK trend methods in the summer, autumn, and winter seasons.

The periodic feature of the seasonal UNEP climate index indicates a sharp transition from a no-trend line at Chupungryeong, Boeun, and Buyeo stations, and a low decreasing trend area at Chungju, Seosan, Cheongju, Jecheon, Cheonan, Geumsan stations in the spring season to increasing trends in summer season for the arithmetic mean graph (Fig. 10). Similarly, a transition from an increasing trend in autumn to a decreasing trend in winter was also observed in all the stations, except at Seosan station where it transited within the low decreasing trend area. However, the standard deviation graph showed somewhat transitional variations at different stations. For instance, while the values of the standard deviation of the UNEP climate index transited to an increasing trend area in the autumn season at Cheongju, Seosan, Cheonan, Boryeong, and Buyeo stations, the opposite (decreasing trend) was observed at Chungju, Chupungryeong, Jecheon, Boeun, and Geumsan stations. Besides, there are strong decreasing trends in the winter season at 70% of the stations. The mean (standard deviation) values for trend length ranged from 0.007 to 1.90 (0.073 to 0.83) in winter and spring (summer and spring), and at Chupungryeong and Jecheon stations (Seosan and Jecheon stations), respectively. Similarly, for the slope length, the mean (standard deviation) ranged from −4.86 to 13.68 (−8.46 to 3.76) both in autumn (both in autumn) and at Buyeo and Boeun stations (Boeun and Jecheon stations), respectively. Overall, the UNEP climate index demonstrates homogeneous and isotropic behaviors and nearly stable conditions as indicated by the narrowness of the polygons and systematic shift from one season to another (Şen et al., 2019).

For the periodic feature of the seasonal De Martonne climate index, the IPTA shows a sharp transition from increasing tread area to decreasing trend area in winter at Cheongju, Jecheon, Boeun, Cheonan, Boryeong, and Geumsan stations, while the climate index indicates an increasing trend in summer at all the stations except Boryeong station for arithmetic mean graph (Fig. 11). While the mean of the trend polygons mostly occurred in the no-trend line and increasing trend area, the standard deviation graph showed a distinct different periodic feature such that more transitions occurred from increasing area to decreasing area. A decreasing trend was observed at Chungju, Chupungryeong, Boeun, and Geumsan in the autumn season, at Seosan, Cheongju, Boeun, Cheonan, Boryeong, and Buyeo in spring, and Cheongju, Chupungryeong, Boeun, Cheonan, Boryeong, Buyeo, and Geumsan stations in winter. The maximum trend length is observed within the spring to summer transition for both mean and standard deviation graphs in all the stations except in Jecheon, Buyeo, Geumsan, Boryeong, Boeun, Chupungryeong, and Seosan stations, where the summer to autumn transition is observed as the maximum trend length for the mean graph. The mean (standard deviation) values for trend length ranged from 3.32 to 71.57 (0.54 to 26.22) in winter and summer (winter and spring), and at Chungju and Jecheon stations (Cheonan and Jecheon stations), respectively. Similarly, for the slope length, the mean (standard deviation) ranged from −8.41 to 13.25 (−3.37 to 39.84) in winter and autumn (both in autumn) and at Boeun and Cheongju stations (Cheongju and Buyeo stations), respectively. The De Martonne climate index demonstrates homogeneous and isotropic behaviors and nearly stable conditions as indicated by the narrowness of the polygons and systematic shift from one season to another, which is very similar to the UNEP climate index (Şen et al., 2019).

The significant decreasing trend at the majority of the stations with moderate to low climatic conditions as indicated by both the UNEP and De Martonne climate indices during the spring and winter could impact

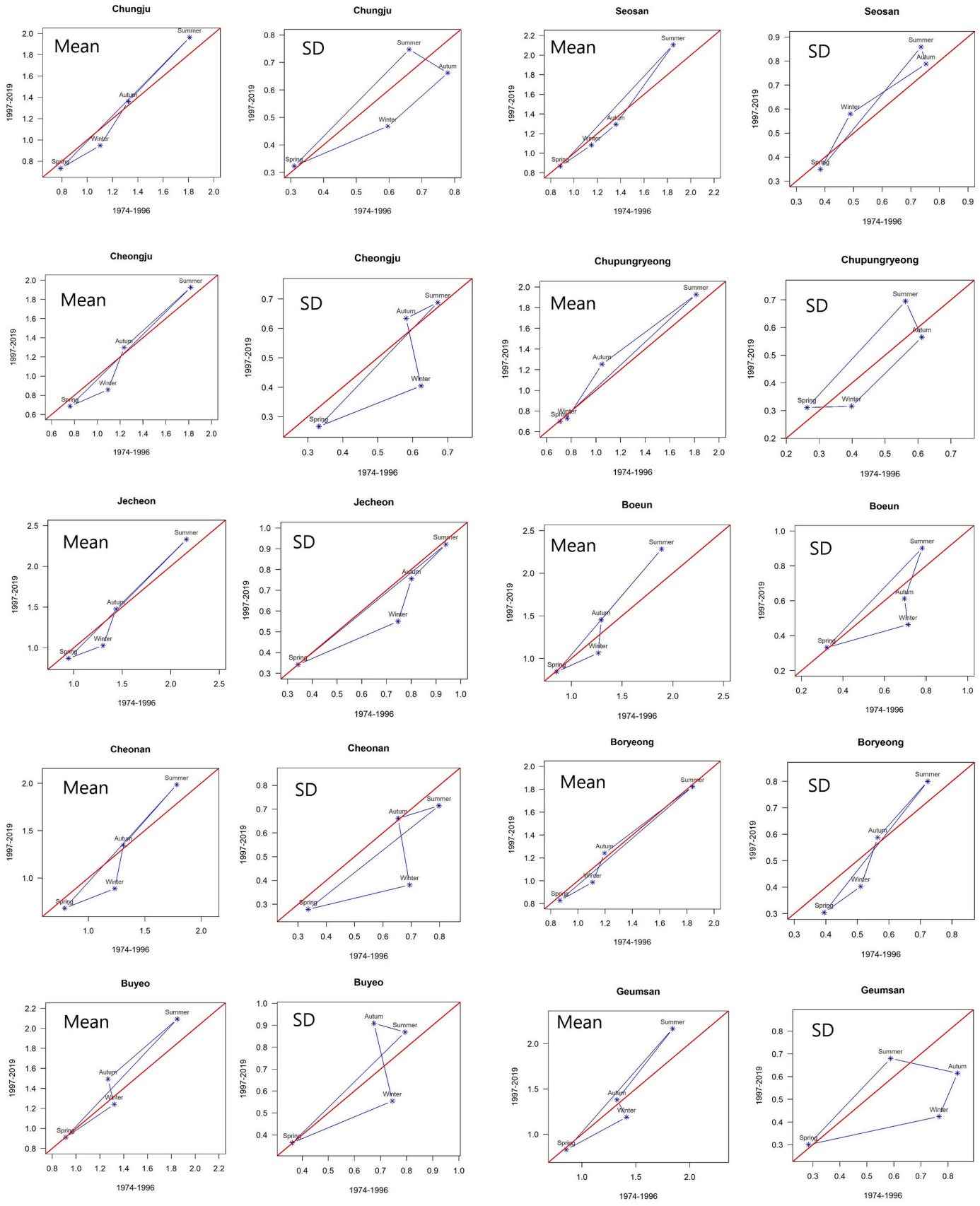


Fig. 10. Innovative polygon trend analysis of seasonal changes in the mean and standard deviation of the UNEP climate index for each station.

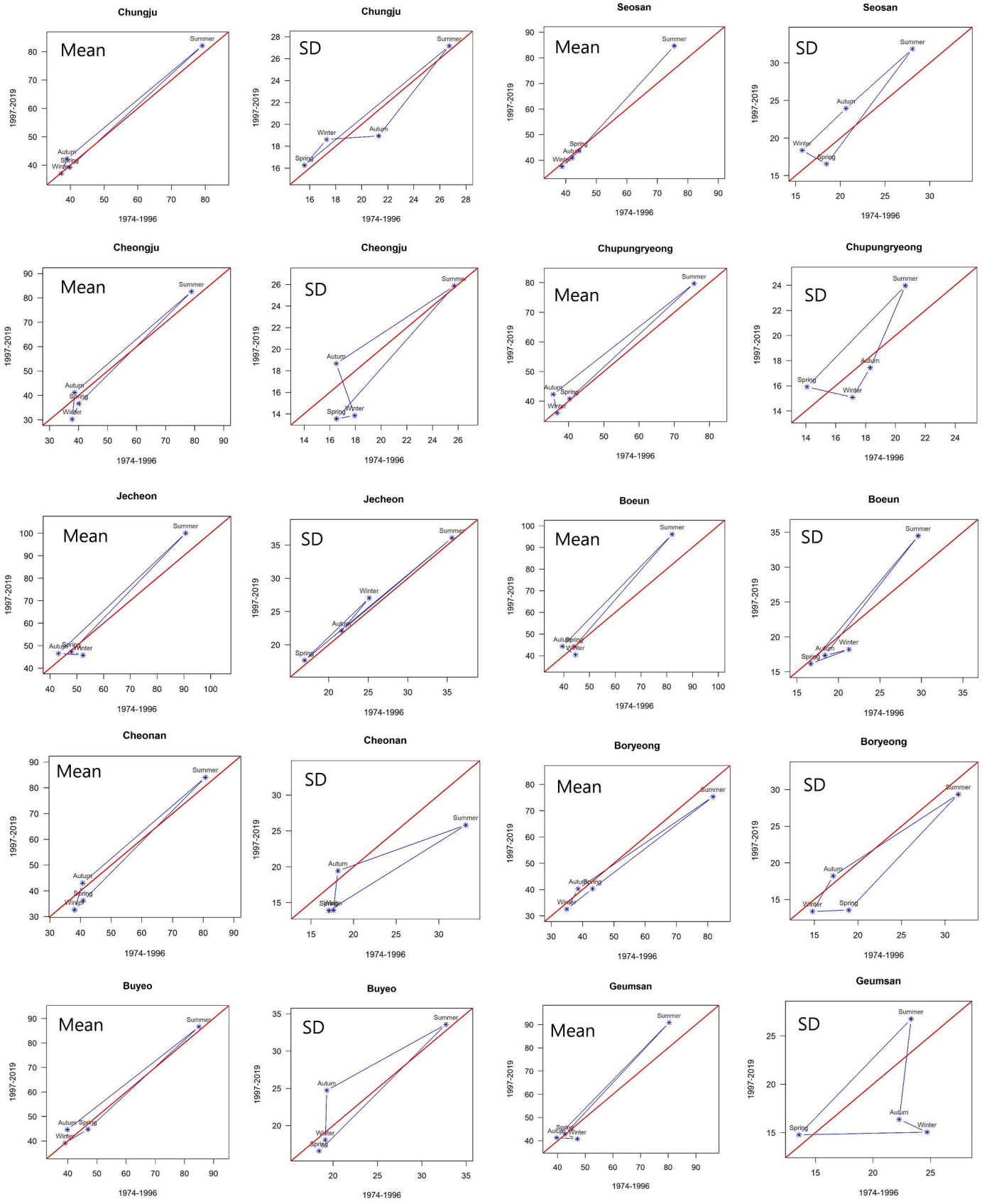


Fig. 11. Innovative polygon trend analysis of seasonal changes in the mean and standard deviation of the De Martonne climate index for each station.

Table 6
Results of Sen's slope (MK) for UNEP and De Martonne climate indices at the seasonal timescale.

Station	Spring		Summer		Autumn		Winter	
	UNEP	De Martonne	UNEP	De Martonne	UNEP	De Martonne	UNEP	De Martonne
Chungju	−0.005***	−0.168	−0.001	−0.075	0.005	0.188	−0.003	−0.050
Seosan	−0.004	−0.164	0.003	0.085	0.003	0.120	0.000	−0.003
Cheongju	−0.005***	−0.190	0.000	0.030	0.002	0.077	−0.005	−0.165
Chupungryeong	−0.003	−0.123	−0.001	−0.056	0.008*	0.265***	0.000	0.007
Jecheon	−0.005	−0.181	0.008	0.311	0.007	0.213	−0.003	−0.185
Boeun	−0.004	−0.123	0.008	0.176	0.013**	0.283***	−0.003	−0.058
Cheonan	−0.007*	−0.314**	0.005	0.046	0.003	0.055	−0.008	−0.139
Boryeong	−0.003	−0.184	−0.006	−0.359	0.006	0.158	−0.001	−0.037
Buyeo	−0.003	−0.238	0.007	−0.040	0.011**	0.232	0.002	0.099
Geumsan	−0.005	−0.174	0.005	0.096	0.005	0.136	−0.002	−0.164

*, **, *** represent 95%, 90%, 80% significance levels, respectively.

negatively on agricultural production, especially during the lull period of precipitation in the summer. The information on the crop water requirements and the provision of alternative water supply that could aid agricultural production should be part of the climate change policy to avoid the risk of aridity in the agricultural areas.

Comparing the significant statistics of the graphical trend test results with selected popular traditional methods, the ITA results showed a good correlation with MK test results as indicated by the Pearson's correlation values of 0.66 and 0.70 for UNEP and De Martonne climate indices, respectively (Fig. 12). However, a moderate correlation was observed between ITA statistic trend results and MMK results with Pearson's correlation values of 0.50 and 0.57 for UNEP and De Martonne climate indices, respectively.

Previous studies that compared the ITA results with other popular classical trend tests such as linear regression, MK, MMK, and Spearman's Rho, also concluded on the superior performance of the graphical innovative trend test (ITA) to reveal underline and significant trends in hydro-meteorological data (Ahmed et al., 2022a; Shah et al., 2022; Wang et al., 2020). Ahmed et al. (2022a, 2022b) also observed a very high correlation between ITA and MK than other traditional methods like MMK and Bootstrapped MK tests in their study (Ahmed et al., 2022a).

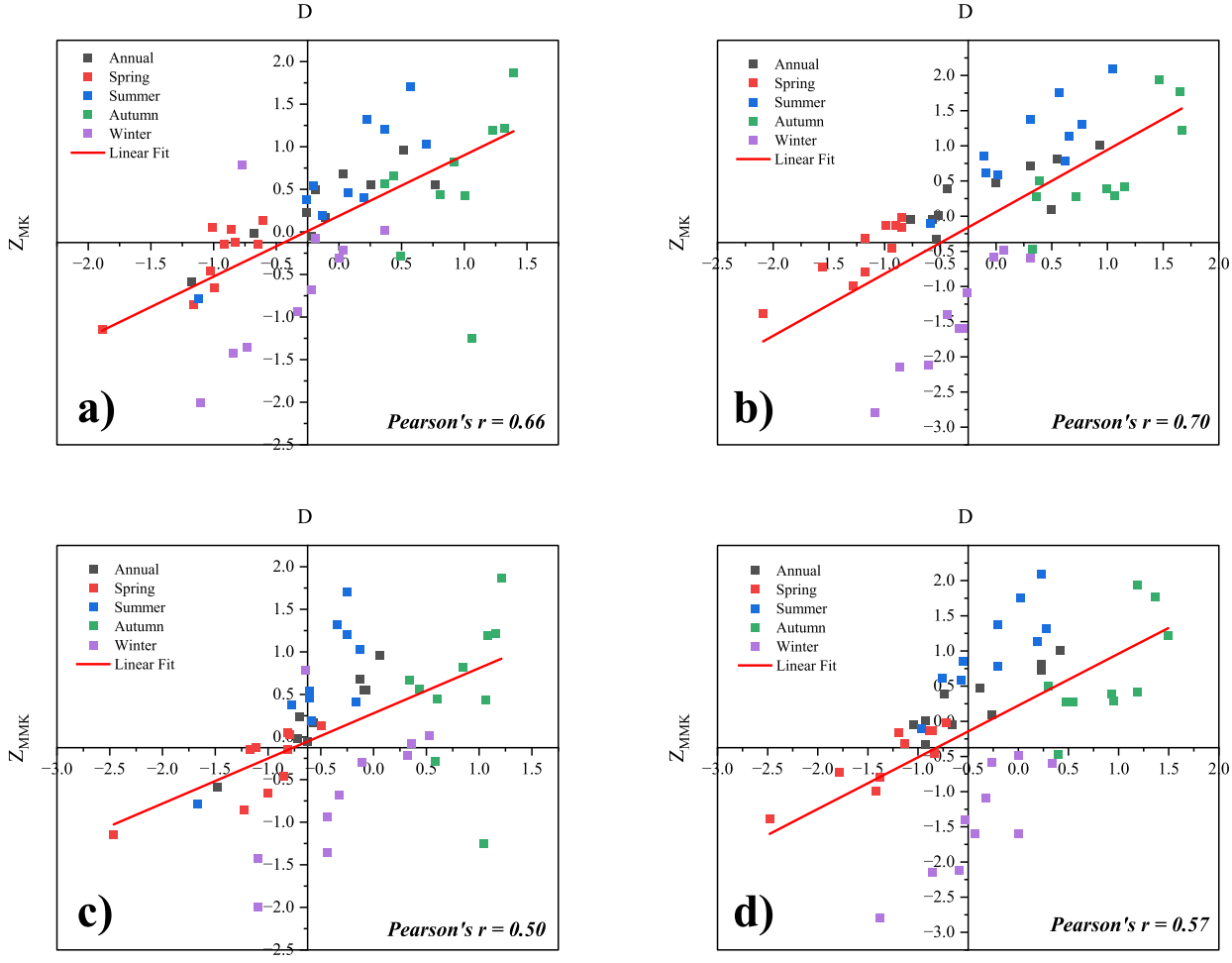


Fig. 12. Correlation and scatter plots between ITA and (a) MK for UNEP climate index (b) MK for De Martonne climate index (c) MMK for UNEP climate index, and (d) MMK for De Martonne climate index.

4. Conclusions

In this study, the annual and seasonal variations of UNEP and De Martonne climate indices in Chungcheong Provinces of Korea from 1974 to 2019 were investigated. The IDW interpolation approach and graphical innovative trend methods consisting of ITA and IPTA were employed to assess the spatial and temporal patterns of annual and seasonal variation characteristics of the climate indices. Specifically, the annual and seasonal trend assessment was first conducted using the ITA, while a further trend assessment on seasonal climate indices was explored using IPTA.

The two climate indices classified the annual climate condition of the Chungcheong provinces as humid to extremely humid climates, which indicate a wet climate season. At the seasonal scale, however, there is significant variability of climate classes in the four seasons and across the stations between the two indices, with high average values of UNEP and De Martonne climate indices in summer. The frequency of arid climate conditions is more pronounced in spring and winter for both climate indices, while the frequency of extreme wet climate dominated in the summer season. Although the De Martonne index shows higher variability of climate conditions, the spatial distribution of a heavy climatic condition (> 90th percentile) at the far-end northeast in summer and autumn is similar for both indices, with a moderate climatic condition (40th to 60th percentile) dominated the largest area of Chungcheong Provinces. Further, only regions around Geumsan, Boryeong, Cheongju, and Chupungryeong stations indicate light (< 10th percentile) to low (10th to 40th percentile) climatic conditions.

For the trend analysis on the annual scale, the ITA shows significant (95% confidence level) upward trends at 50 and 60% of the stations for UNEP and De Martonne indices, respectively. Moreover, an increasingly significant trend dominated the summer and autumn, while spring and winter seasons exhibited significant decreasing trends. The two indices showed an increasing trend in summer at the Jecheon station located around the far-end northeast with the heavy climatic condition, suggesting special attention in this region. The IPTA shows a dominant transition from the increasing area in autumn to decreasing area in winter, while summer consistently transited in the increasing region at almost all the stations. Both climate indices demonstrate homogeneous and isotropic behaviors and nearly stable conditions as indicated by the narrowness of the polygons and systematic shift from one season to another. The ITA statistics showed a high to moderate correlation with classical MK and MMK trend methods, respectively.

The variations in the UNEP and De Martonne climate indices can be attributed to the differences in their constituted variables. Nevertheless, the two indices indicated important temporal changes and variations in Chungcheong Provinces at annual and seasonal scales from 1974 to 2019. A further investigation of the roles of the climate variables on the UNEP and De Martonne climate indices is essential to discern the influencing variables.

CRediT authorship contribution statement

Bashir Adelodun: Conceptualization, Investigation, Formal analysis, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Golden Odey:** Investigation, Methodology, Visualization, Formal analysis. **Hyungon Cho:** Investigation, Formal analysis, Data curation, Visualization. **Seulgi Lee:** Investigation, Visualization. **Khalid Adeola Adeyemi:** Investigation, Methodology, Data curation, Visualization. **Kyung Sook Choi:** Visualization, Resources, Funding acquisition, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosres.2022.106420.

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