Future drought analysis of SPI and EDDI considering climate change in South Korea
Jeongeun Won and Sangdan Kim

ABSTRACT
Prediction of drought is important for efficient water management, as the occurrence of droughts affects large areas over a long period. According to various climate change scenarios, it is reported that in the future, Korea’s climate is likely to increase in temperature with increasing rainfall. This increase in temperature will have a big impact on the evapotranspiration. The occurrence of drought begins mainly with two causes: lack of rainfall or an increase in evapotranspiration. Therefore, in this study, the impact of climate change on future droughts is revealed through the standardized precipitation index and the evaporative demand drought index. Two drought indices with different characteristics are used to examine the trend of future drought, and the SDF curve was derived to quantitatively analyze the depth of future drought. Future droughts are projected by applying future climate data generated from various climate models.

Key words | drought, evaporative demand drought index, SDF curve, standardized precipitation index

HIGHLIGHTS
● The future drought in South Korea was analyzed using SPI and EDDI.
● The future drought using SPI would be weakened by future precipitation increases.
● EDDI suggests future drought prospects that have become unrealistically severe.
● Drought monitoring needs to be developed that appropriately reflects the effects of precipitation and evapotranspiration on drought.

INTRODUCTION
The increase in temperature due to climate change is expected to increase severity and frequency of drought. In fact, the Intergovernmental Panel on Climate Change (IPCC) predicted that the annual average temperature of the Korean Peninsula would be about 2–4 °C higher than the present by 2050, resulting in a subtropical climate (IPCC 2014). In addition, as the temperature has risen, the frequency of droughts in Korea has occurred 0.36 times per year by 2000, while it has increased sharply to 0.67 times in the last 15 years. The occurrence of droughts begins with changes in climate variables such as lack of precipitation and increased evapotranspiration. Such a condition is defined as a meteorological drought. When a meteorological drought occurs, depletion of soil moisture causes deterioration of plant growth and crop yield, which is defined as agricultural drought. Hydrological droughts are also defined as depletion of river flow or reservoir levels due to depletion of soil moisture. Drought is caused by natural phenomena such as changes in precipitation and evapotranspiration, and has a great impact on society both economically and environmentally.
In the field of drought monitoring, drought has been numerically interpreted using drought indices to respond to drought, and drought indices based on precipitation have been mainly used. The Standardized Precipitation Index (SPI; Mckee et al. 1993), the most widely known precipitation-based drought index, is an index that uses only precipitation. In many studies on drought, the cause of drought has been interpreted as a lack of precipitation, and SPI has been mainly used, and its utility as a drought index has been verified (Cancelliere et al. 2007; Livada & Assimakopoulos 2007; Naresh Kumar et al. 2009; Sim et al. 2013; Nabaei et al. 2019). In addition, SPI has been used as a comparison target for verification of new drought analysis approaches (Gebrewahid et al. 2017; Fang et al. 2019). As such, although the SPI is a very simple index, it has excellent applicability worldwide, and the Korea Meteorological Administration (KMA) also relies on the SPI to monitor drought (Kim et al. 2012; Ryu et al. 2012). However, since SPI does not take into account changes in other climate variables such as surface air temperature, there is a limitation that does not reflect the effects of climate change at all (Kempes et al. 2008; Zhang & He 2016). In fact, since an abnormal increase in surface air temperature due to climate change has a great influence on the frequency and severity of drought, it may not be reasonable to interpret drought using only precipitation. Accordingly, in the field of drought monitoring, interest in evapotranspiration, an aspect of atmospheric moisture demand, has been increasing, and its importance has been proven through many studies (Vicente-Serrano et al. 2010; Taylor et al. 2012; Teuling et al. 2013; Won et al. 2018). For this reason, Vicente-Serrano et al. (2010) developed the Standardized Precipitation Evapotranspiration Index (SPEI), which analyzes drought by considering both the variability of precipitation and potential evapotranspiration (PET). Recently, Hobbins et al. (2016) developed the Evaporative Demand Drought Index (EDDI), a drought index based on PET. The drought index, based on PET, makes it easy to detect and monitor drought initiation and ongoing drought conditions with virtually no delay. Also, since EDDI considers various climate variables, it can be usefully applied to capture flash drought caused by climate variables that change strongly temporarily. EDDI has verified the reproducibility of the drought events observed in the past in China, and the applicability to the flash drought has been positively evaluated (Yao et al. 2018). Also, Won et al. (2018) compared the performance of SPI and EDDI on the past observed drought in Korea, and reported that EDDI can be sufficiently utilized as a drought index. Therefore, this study aims to analyze future drought through SPI, which is dependent on precipitation, which is the moisture supply side of the atmosphere, and EDDI, which is based on PET, which is the moisture demand aspect of the atmosphere.

In the drought analysis through the drought index, studies have been conducted worldwide to quantify the depth of drought events (Byun & Wilhite 1999; Keyantash & Dracup 2002; Chanda & Maity 2015). The Drought Severity-Duration-Frequency (SDF) curve has been mainly used. Dalezios et al. (2000) created SDF curves to analyze droughts caused by environmental factors in Greece. Shiau & Modarres (2009) created a copula-based SDF curve to analyze the complex correlations of depth, duration and frequency of drought events. Lee & Kim (2013) identified the effects of climate change on droughts by deriving SDF curves in future climates. Current SDF curve analysis studies in Korea have been conducted with frequency analysis using annual maximum drought depth time series (Park et al. 2015; Kim et al. 2016). However, given the nature of the drought, the use of annual maximum time series may be insufficient in interpreting drought. Therefore, this study intends to create a SDF curve by constructing a new drought depth time series considering the characteristics of drought. The six-month timescale SPI and EDDI were used for drought analysis using the SDF curve.

METHODOLOGY AND MATERIALS

Evaporative demand drought index

The EDDI is a new drought index based on the PET ($E_0$). EDDI focuses on $E_0$, which is the moisture demand side of the atmosphere in interpreting the water exchange between surface and atmosphere. The interaction between the $E_0$ and the actual evapotranspiration ($ET$) in the drought onset and the persistent drought condition forms
the physical basis of the EDDI, which can be explained by Figure 1. Figure 1 was modified from Won et al. (2018). At the beginning of the drought, surface moisture changes are a delayed response to changes in meteorological factors, resulting in a slow transition of soil moisture. In this transitional period, sufficient soil moisture for ET is still available, so the ET increases as the $E_0$ increases (arrow 1 in Figure 1). As the dry condition continues, the elevated ET eventually depletes the soil moisture, and therefore, in a continuous drought condition, the ET decreases due to the depleted soil moisture (downward arrow 2 in Figure 1). In this condition, the atmosphere requires more moisture due to the lack of previously moisture demand, which leads to a rise in $E_0$ (upper arrow 2 in Figure 1). In both of these drought conditions, $E_0$ increases, while ET reacts in opposite directions, so it can be seen that $E_0$ is more useful as an indicator of different conditions of drought.

The EDDI was verified by applicability assessment in Korea (Won et al. 2018) and the reproducibility of observed drought events was excellent, and the correlation with SPI was high. In addition, it was concluded that EDDI can be used as a drought index together with SPI and it can properly respond to various meteorological variables. Therefore, in this study, it was determined that EDDI can be utilized as much as the SPI which was used in the past, and it was applied to analyze future drought.

**Derivation of PET**

In this study, the Penman-Monteith method was used to derive PET. The Penman-Monteith method is an improved version of the Penman FAO-24 method by the Food and Agriculture Organization (FAO), it is known to be highly applicable since it can be used under limited meteorological data as well as provides consistent values for crop water requirement worldwide.

The American Society of Civil Engineers (ASCE), and the World Meteorological Organization (WMO) are also recommended for this method. It was studied that this method is more appropriate than the Penman method (Penman 1948) for prediction future PET and for drought indices such as EDDI or SPEI using PET (Dewes et al. 2017). To use this method, meteorological data on surface air temperature, relative humidity, radiation and wind speed are required and the daily PET can be estimated as follows (Allen et al. 1998):

$$ET_{SZ} = \frac{0.408 \Delta (R_n - G) + \frac{C_n}{T + 273} u_2 (e_s - e_a)}{\Delta + \frac{\gamma}{1 + C_d u_2}}$$ (1)

where $ET_{SZ}$ is the standardized reference evapotranspiration (mm day$^{-1}$); $R_n$ is the net radiation (MJ m$^{-2}$ day$^{-1}$); $G$ is the soil heat flux density (MJ m$^{-2}$ day$^{-1}$); $T$ is the surface air temperature (°C); $u_2$ is the wind speed at a 2 m height (m s$^{-1}$); $e_s$ is the saturated vapor pressure (kPa); $e_a$ is the actual vapor pressure (kPa); $\Delta$ is the slope of the vapor pressure-temperature curve (kPa °C$^{-1}$), and $\gamma$ is the psychrometric constant (kPa °C$^{-1}$). $C_n$ and $C_d$ can be determined by the aerodynamic roughness. Since the $G$ is relatively small compared to the $R_n$, the $G$ can be neglected.

In Korea, the observational radiative data for estimating PET is incomplete, so the method of estimating solar radiation data proposed by Allen et al. (1998) was used. This method calculates the solar radiation energy ($R_s$) reaching the earth surface using the difference between the daily maximum temperature and the daily minimum temperature as follows:

$$R_s = k_{rs} \sqrt{T_{max} - T_{min}}$$ (2)
where $R_s$ is the extraterrestrial radiation which changes with respect to the location and date of the observation site. The $T_{\text{max}}$ is the daily maximum air temperature (°C), $T_{\text{min}}$ is the daily minimum air temperature (°C), and $k_{rs}$ is the empirical coefficient, which can be calculated as follows:

$$k_{rs} = k_{r0} \left( \frac{P}{P_0} \right)^{0.5}$$

(3)

where $P$ is the mean atmospheric pressure (kPa); $P_0$ is the mean atmospheric pressure at sea level (101.3 kPa); $k_{r0}$ is an adjustment factor and has a value of 0.17 in inland and 0.20 in coastal areas. Once the solar radiation data is constructed, the net radiation can be obtained using the method proposed by Allen et al. (1998).

### Drought index formulation

The calculations for both SPI and EDDI were based on the SPI estimation formula developed by McKee et al. (1993). SPI is simple since this index only uses precipitation, and is now mainly used by KMA. SPI and EDDI are calculated using moving-averaged monthly precipitation or PET for a given time-scale. The optimal probability density function for each month of the moving-averaged monthly time series is estimated, and is applied to the moving-averaged monthly time series to construct its monthly cumulative probability time series. The drought index is the value obtained by applying the monthly cumulative probability time series inversely to the standard normal distribution. The probability distribution used is a two-parameter Gamma distribution, and its probability density function is given by

$$f(x) = \frac{1}{\alpha^\beta \Gamma(\beta)} x^{\beta - 1} e^{-x/\alpha}$$

(4)

where $x$ is the moving-averaged monthly precipitation or PET; $\alpha$ is the scale parameter; and $\beta$ is the shape parameter. The parameters $\alpha$ and $\beta$ are estimated for each month using the method of probability weighted moments. Table 1 shows the drought classification according to the SPI and EDDI.

The above drought index calculation method is to express the drought in the region as a relative value of each month time series. However, since the drought index for the future period should be calculated based on the amount of change in the future compared to the present, the method of calculating the drought index based on the observational data cannot be equally applied. The future drought index $Z_f$ can be estimated as follows based on the relative amount of precipitation or evapotranspiration over the current period.

$$Z_f = G^{-1}(F_p(x_f))$$

(5)

where $x_f$ is the moving-averaged data of the future period; $F_p$ is the Gamma cumulative distribution function of the present data; $G^{-1}$ is the standard normal inverse cumulative distribution.

Climate data simulated from GCMs or RCMs should be bias-corrected since there are biases with observations. Quantile Mapping (QM), one of the commonly used bias-correction methods, is a method of mapping the probability distribution of simulation data to the probability distribution of observation data by using the cumulative probability distribution of observation data and simulated data from climate models (Hashino et al. 2006). However, the relative ranking of climate model simulated data remains unchanged after the bias correction using QM. In other words, since the drought index is estimated as the relative value of each data, there is no significant difference in the drought index with or without bias correction. As a representative example, the data simulated by MM5 RCM driven by MPI-ESM-LR GCM was used to compare each drought index before and after bias correction (Figure 2). Figure 2 shows that the

| Moisture condition and drought classification according to the index |
|--------------------------|--------------------------|
| **Index Range** | **SPI** | **EDDI** |
| More than 2.00 | Extreme Wet | Extreme Dry |
| 1.50 ~ 1.99 | Very Wet | Severely Dry |
| 1.00 ~ 1.49 | Moderately Wet | Moderately Dry |
| 0.99 ~ 0.99 | Near Normal | Near Normal |
| 1.49 ~ 1.00 | Moderately Dry | Moderately Wet |
| 1.99 ~ 1.50 | Severely Dry | Very Wet |
| Less than –2.00 | Extreme Dry | Extreme Wet |

Table 1
correction of climate model data is unnecessary in the calculating the drought index. In this study, bias correction is performed in the SDF curve derivation process described in Section 2.5. For reference, the time-scale of the two drought indices in Figure 2 is 6-month.

Data and study area

This study was conducted in South Korea. Korea is located in the mid-latitude temperate climate zone, and therefore has distinct seasonal climate characteristics. The seasonality in Korea is a major feature of the monsoon climate. In particular, due to the East Asian monsoon, the seasonal distribution of rainfall in Korea is not uniform, and the rainy season and the dry season are distinguished. Since most of the annual precipitation is concentrated in summer and rainfall during winter is very low, it is very important to understand Korea’s climate patterns for water resource management. In the case of Korea, secondary damage such as floods and landslides are occurring due to
the increase in torrential rains, and the frequency of droughts is also increasing. Korea’s abnormal rainfall patterns and increased incidence of drought are related to climate change (Nam et al. 2015; Choi et al. 2019; Lee et al. 2020). In other words, it is very essential to understand the impact of climate change using reliable future climate data to prepare for natural disasters in Korea. In this study, as shown in Figure 4, we analyzed the future droughts at six major sites in Korea. These sites represent six administrative districts in Korea, and each site has various land use and climate characteristics.

Meteorological data from 6 sites of ASOS (Automated Synoptic Observing System) operated by the KMA was used. Data for a period of 30 years from 1981 to 2010 were used, and the used climate variables were the daily averaged surface air temperature, maximum and minimum surface air temperature, wind speed, relative humidity and precipitation. In addition, future climate change scenario data was used for future drought analysis. Future climate data was simulated using Global Climate Models (GCMs) and Regional Climate Model (RCMs). Since data generated from GCMs has limitations due to low resolution and relatively simple physics, more accurate and more detailed climate data are required and such data can be obtained by using RCM that can simulate detailed regional characteristics. Therefore, a total of 8 model combinations were used in this study, applying 2 GCMs of HadGEM2-AO (Hadley Center Global Environment Model version 2 - Coupled Atmosphere-Ocean model) and MPI-ESM-LR (Max Planck Institute Earth System Model-Low Resolution) and 4 RCMs of MM5, RegCM, RSM, and WRF. In addition, by applying the RCP 4.5 and RCP 8.5 scenarios for each of the 8 model combinations, a total of 16 combination scenarios are used. Future climate data consists of present data for the period 1981–2010 and future data for the period 2021–2050.

Severity-Duration-Frequency (SDF) curve

The SDF curve replaces rainfall intensity with drought severity in the Rainfall Intensity-Duration-Frequency (IDF) curve used in flood analysis and is a useful tool for determining drought characteristics for the region (Park et al. 2015). In order to derive SDF curves, the annual maximum drought severity time series of each drought index should be constructed. However, unlike rainfall, droughts do not occur on a yearly basis, and long-term droughts continue into the next year, so the annual maximum time series may not be suitable for drought frequency analysis. Therefore, this study constructed the drought severity time series by applying the Peak-Over-Threshold (POT) concept. First, we set the threshold to identify the drought events, define the start of the drought event when the drought severity of each drought index exceeds the threshold, and define the end of the drought event when it falls below the threshold. The identified drought events consisted of drought severity and drought duration as shown in Figure 3. In many studies using SDF curves, a drought severity time series has been constructed by extracting drought severity and drought duration from drought event as shown in Figure 3 (Kim et al. 2011; Janga Reddy & Ganguli 2012; Lee & Kim 2013; Sung & Chung 2014; Halwatura et al. 2015). In this study, the average drought severity during duration of each drought event was calculated to construct a drought severity time series. Based on the constructed drought severity series, the frequency analysis was conducted and the SDF curve was derived for various durations and return periods. Frequency analysis was conducted by selecting the optimal distribution through the K-S test and χ²-test for the drought severity time series data. However, there are biases in SDF curves of observed and climate model data. In order to overcome this problem, the bias correction using QM was performed for the drought severity time series of the climate model data.

![Figure 3](http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2020.209/737172/ws2020209.pdf)
RESULTS AND DISCUSSION

Drought index time series and future trends

Drought indices such as SPI and EDDI can be estimated using a variety of time-scales, and only by selecting a time-scale that reflects the hydrologic climatic characteristics of the region can well represent the droughts in that region. In this study, EDDI (EDDI6) and SPI (SPI6) were calculated for 6-month time-scale and analyzed drought events for 6 sites in Korea (Figure 4). Figure 5 shows the results of the SPI6 and EDDI6 time series for the present period (1981–2010) and future period (2021–2050) derived from the combination of the MPI-ESM-LR and MM5 climate models. For the comparison between the drought indices, SPI represent the converted value, so a large positive value indicates a severe drought condition.

As shown in Figure 5, in the case of SPI6, the drought in the future period is similar to or mitigated as the present, while EDDI6 intensifies drought. Climate change scenarios mainly project increases in precipitation, so precipitation-dependent SPIs tend to result in lessening future droughts. On the other hand, in the case of EDDI, the increase in temperature under climate change scenarios resulted in an increase and intensification of future droughts. The future drought trends of the two drought indices can be clearly identified at Seoul site in Figure 5(f). In RCP4.5 and RCP8.5, the SPI is not expected to cause severe droughts above –2, while EDDI6 is expected to undergo several extreme droughts. At Busan site, the future SPI6 projects three extreme droughts, but all are short-term drought events with short drought duration. In addition, the future SPI6 of Chuncheon site predicts a number of severe droughts from 2021 to 2041, but there will be no severe droughts over the next 10 years.

The change rate of future drought experience probability was compared to identify the change in future drought occurrence. For each drought index, the number of droughts experienced in the present and future periods was calculated, and the rate of change in the probability of future drought experience compared to the present was calculated through Equation (6). The reference index for drought
Figure 5 | Comparisons of time series of SPI6 and EDDI6 using climate change scenarios in 6 sites. (a) Busan. (b) Chuncheon. (c) Daegu. (d) Daejeon. (e) Gwangju. (f) Seoul.
events was set at a value greater than 1.0 for EDDI and less than −1.0 for SPI.

\[ CP(\%) = \frac{N_f}{N_p} \times 100 \]  \hspace{1cm} (6)

where \( N_f \) is the number of drought events in the future, \( N_p \) is the number of drought events in the present, and \( CP \) is the percentage of change in the probability of future drought experience. The calculated rate of change is divided into RCP scenarios and is shown in Figure 6. If the rate of change exceeds 100%, the probability of future drought experience is increased, and if it is less than 100%, the probability of future drought experience is less than the present. In the case of SPI, drought experience is likely to decrease at most of the six sites, with the exception of some model combinations. In particular, the Seoul site is likely to reduce the probability of future drought experiences in all future ensembles. EDDI has shown an increased probability of future drought experience at all future climate ensembles at all sites, and projects a rate of change of at least 200%. This means that in the future, the probability of experiencing a drought is at least twice that of the present. In RCP8.5 scenario, where a relatively higher surface air temperature is projected, a rate of change of more than 500% may occur at the four sites except Daegu and Daejeon sites. However, the Gwangju site shows a rate of change of about 250%, indicating that the difference between climate model combinations is relatively large. In summary, the SPI is generally expected to reduce the probability of future droughts, but some climate model combinations show an increased chance of droughts, and thus no clear change in the pattern of drought occurrences could be identified. On the other hand, EDDI has shown that the probability of occurrence of future drought increases relatively clearly, but it can be seen that the uncertainty is very large.

**SDF curves**

In this section, the SDF curve is used to quantitatively analyze changes in the severity of future droughts. The future drought severity time series was constructed using the number of observed drought severity time series. First, drought events were extracted by setting threshold to 0 in the observed drought index time series. Present and future drought events were extracted by setting a threshold equal to the number of observed drought events from the present and future time series of drought indices. The drought severity time series was constructed by estimating the maximum mean drought severity for various durations (1-month to 6-month) from the constructed drought events. A bias correction was performed by comparing the observed drought severity time series with the present period drought severity time series. As a result of the goodness-of-fit test, the Gumbel distribution was adopted as the optimal probability density function of the drought severity time series. The bias-corrected SDF curves of the present period simulated by climate models are shown in Figure 7 compared with the SDF curves of the observed data. Figure 7 compares the SDF curves at Chuncheon and Seoul sites, but similar results were obtained at the other sites. The present SDF curves well represent the corresponding observed SDF curves.

Figure 8 shows the present and future SDF curves using SPI6. SPI6 projected from most future climate ensembles reveals that the severity of future droughts is likely to be less than the present severity. Especially at Daegu and Gwangju.
sites, it was projected that for all durations under RCP 4.5 scenario, the severity of future droughts would be greatly reduced in all eight future climate ensembles. In some ensembles, the future drought severity is intensified over the present severity under RCP 8.5 scenario, but for most ensembles, the future drought severity is projected to be similar to or less than the present severity. Other sites were also projected that future drought severity under RCP 4.5 scenario would likely be significantly less than present severity, with RCP 8.5 scenario showing greater uncertainty among ensembles.

**Figure 9** shows the present and future SDF curves using EDDI6. Future drought severity by EDDI6 is projected to deepen significantly in all future climate ensembles. This trend was found at all sites. In particular, the strongest drought severity increase at Daegu site was projected. It can be seen that the severity of the drought, which corresponds to return period of 10-year and duration of 1-month, is 4 or more. This drought severity is equivalent to return period of 30-year at Gwangju site. Daegu site is projected to experience more severe droughts than other sites in the future. However, future droughts estimated by EDDI6 raise the disadvantage that the deviations between future climate ensembles are very large. The high uncertainty of the future EDDI appears to be a result of the overlap of uncertainties caused by each of the numerous climate variables required for PET estimation. It is also true that doubts are raised that future drought severity will increase to that extent.

The future trends of SPI and EDDI are due to the future behavior of the climate variables (i.e., precipitation and PET) on which the indices depend, respectively. The drastically different trends of two drought indices projecting future droughts using the same future climate ensembles at the same sites will have a significant impact on which drought index will be applied to future projections of future droughts.

**CONCLUSIONS**

In the future, rainfall is likely to increase due to climate change. Nevertheless, there is also the possibility that the
Figure 8 | SDF Curves of SPI6. (a) Busan. (b) Chuncheon. (c) Daegu. (d) Daejeon. (e) Gwangju. (f) Seoul.
Figure 9 | SDF Curves of EDDI6. (a) Busan, (b) Chuncheon, (c) Daegu, (d) Daejeon, (e) Gwangju, (f) Seoul.
drought will intensify due to the increase in temperature. Since SPI, which has been mainly used for drought analysis, is calculated only by considering precipitation, there is a limit to applying SPI to the establishment of drought adaptation measures that reflect the effects of global warming. Therefore, this study analyzes future droughts by adding EDDI that can reflect changes in various climate variables caused by climate change in addition to SPI. The analysis shows that future droughts projected by EDDI are likely to be much worse than present droughts. However, in the case of SPI, future droughts do not differ much from present droughts or rather tend to be relaxed. Drought frequency analysis using SDF curves shows that future droughts calculated by EDDI will be very severe, but very high uncertainties are found. Future droughts, calculated by the SPI, are projected to be less likely than present droughts.

Future droughts using two drought indices calculated using different climate variables yielded very different results. The future drought caused by the SPI is not projected to be significantly worsened even in RCP8.5, a scenario in which greenhouse gases are emitted as of the current trend. Rather, there were future climate ensemble results that could potentially mitigate drought severity. The overall drought relief prospects of future climate ensembles may be very embarrassing for establishing future drought adaptation measures. In the future, droughts will be weakened, so it may seem unnecessary to take any countermeasures. Some are suggesting alternatives to these embarrassing prospects, and adopting future worst-case climate ensembles separately to establish future drought adaptation measures for the worst drought scenarios. However, these alternatives are incomplete since they are not based on scientific evidence and will eventually lose public confidence.

Future droughts by EDDI have resulted in all future climate ensembles that droughts will be very severe in the future. In a sense, it can be misleading as it can be a very good result for establishing future drought adaptation measures. However, the uncertainty between future climate ensembles was also very large since future outputs of various climate variables were used in the calculation of EDDI. Some climate model ensembles have exposed projections of extreme droughts that would destroy humanity so unrealistically. Because of these limitations, future drought adaptation measures based on prospects for future drought from EDDI will be difficult to gain public confidence.

The results of this study show that future precipitation and evapotranspiration should be taken into account when establishing drought adaptation measures for future climate change. In the journey of climate change adaptation policy to drought to gain public confidence, the findings of this study suggest that there is a need for studies on alternatives to complement the problems exposed in SPI and EDDI. In light of these needs, the development of new drought indices that reflect various future climate variables, including precipitation, or the development of combined drought indices that can incorporate various currently used drought indices based on different meteorological variables will be a prerequisite for establishing climate change drought adaptation measures.

**ACKNOWLEDGEMENTS**

This work was supported by Korea Environment Industry & Technology Institute (KEITI) through Smart Water City Research Program, funded by Korea Ministry of Environment (MOE) (2019002950004). The authors also acknowledge that this work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2019R1A2C1003114).

**DATA AVAILABILITY STATEMENT**

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

**REFERENCES**

Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. 1998 Crop evapotranspiration-Guidelines for computing crop water requirements-FAO irrigation and drainage paper 56. *Fao, Rome* 300 (9), D05109.

Byun, H. R. & Wilhite, D. A. 1999 Objective quantification of drought severity and duration. *Journal of Climate* 12 (9), 2747–2756.
Cancelliere, A., Di Mauro, G., Bonaccorso, B. & Rossi, G. 2007 Drought forecasting using the standardized precipitation index. *Water Resources Management* **21** (5), 801–819.

Chanda, K. & Maity, R. 2015 Meteorological drought quantification with standardized precipitation anomaly index for the regions with strongly seasonal and periodic precipitation. *Journal of Hydrologic Engineering* **20** (12), 06015007.

Choi, J., Lee, O., Jang, J., Jang, S. & Kim, S. 2019 Future intensity-depth-frequency curves estimation in Korea under representative concentration pathway scenarios of fifth assessment report using scale-invariance method. *International Journal of Climatology* **39** (2), 887–900.

Dalezios, N. R., Loukas, A., Vasilides, L. & Liakopoulos, E. 2000 Severity-duration-frequency analysis of droughts and wet periods in Greece. *Hydrological Sciences Journal* **45** (5), 751–769.

Dewes, C. F., Rangwala, I., Barsugli, J. J., Hobbins, M. T. & Kumar, S. 2017 Drought risk assessment under climate change is sensitive to methodological choices for the estimation of evaporative demand. *PloS one* **12** (3), e0174045.

Fang, W., Huang, S., Huang, G., Wang, H., Leng, G., Guo, Y. 2019 Probabilistic assessment of remote sensing-based terrestrial vegetation vulnerability to drought stress of the Loess Plateau in China. *Remote Sensing of Environment* **232**, 111290.

Gebrewahid, M. G., Kasa, A. K., Gebrehiwot, K. A. & Adane, G. B. 2017 Analyzing drought conditions, interventions and mapping of vulnerable areas using ndvi and spi indices in eastern ethiopia, somali region. *Ethiopian Journal of Environmental Studies & Management* **10** (9), 1137–1150.

Halwatura, D., Lechner, A. M. & Arnold, S. 2015 Drought severity-duration-frequency curves: a foundation for risk assessment and planning tool for ecosystem establishment in post-mining landscapes. *Hydrology & Earth System Sciences* **19** (2), 1069–1091.

Hashino, T., Bradley, A. A. & Schwartz, S. S. 2006 Evaluation of bias-correction methods for ensemble streamflow volume forecasts. *Hydrology and Earth System Sciences Discussions* **3** (2), 561–594.

Hobbins, M. T., Wood, A., McEvoy, D. J., Huntington, J. L., Morton, C., Anderson, M. & Hain, C. 2016 The evaporative demand drought index. Part I: linking drought evolution to variations in evaporative demand. *Journal of Hydrometeorology* **17** (6), 1745–1761.

Intergovernmental Panel on Climate Change (IPCC) 2014 Climate Change 2014: Synthesis Report. Contribution of Working Groups I,II and III to the Fifth Assessment Report og the Intergovernmental Panel on Climate Change, IPCC, Geneva, Switzerland.

Janga Reddy, M. & Ganguli, P. 2012 Application of copulas for derivation of drought severity-duration-frequency curves. *Hydrological Processes* **26** (11), 1672–1685.

Kempes, C. P., Myers, O. B., Breshears, D. D. & Ebersole, J. J. 2008 Comparing response of Pinus edulis tree-ring growth to five alternate moisture indices using historic meteorological data. *Journal of Arid Environments* **72** (4), 350–357.

Keyantash, J. & Dracup, J. A. 2000 The quantification of drought: an evaluation of drought indices. *Bulletin of the American Meteorological Society* **81** (8), 1167–1180.

Kim, S., Kim, B., Ahn, T. J. & Kim, H. S. 2011 Spatio-temporal characterization of Korean drought using severity-area-duration curve analysis. *Water and Environment Journal* **25**, 22–30.

Kim, S., Ryu, J., Oh, K. & Jeong, S. 2012 An application of copulas-based joint drought index for determining comprehensive drought conditions. *Korean Society of Hazard Mitigation* **12** (1), 223–230.

Kim, J., Lee, J., Park, M. & Joo, J. 2016 Effect of climate change scenarios and climate models on the drought severity-duration-frequency analysis. *Korean Society of Hazard Mitigation* **16** (2), 351–361.

Lee, J. H. & Kim, C. J. 2013 A multimodel assessment of the climate change effect on the drought severity-duration-frequency relationship. *Hydrological Processes* **27** (19), 2800–2813.

Lee, O., Kim, H. & Kim, S. 2020 Hydrological simple water balance modeling for increasing geographically isolated doline wetland functions and its application to climate change. *Ecological Engineering* **149**, 105812. https://doi.org/10.1016/j.ecoleng.2020.105812.

Livada, I. & Assimakopoulos, V. D. 2007 Spatial and temporal analysis of drought in Greece using the Standardized Precipitation Index (SPI). *Theoretical and Applied Climatology* **89**, 143–153.

McKee, T., Doesken, N. & Kleist, J. 1993 The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology*, Vol. 17, 22, pp. 179–185.

Nabaei, S., Sharafati, A., Yaseen, Z. M. & Shahid, S. 2019 Copula based assessment of meteorological drought characteristics: regional investigation of Iran. *Agricultural and Forest Meteorology* **276–277**, 107611. https://doi.org/10.1016/j.agrformet.2019.06.010.

Nam, W., Hayes, M., Svoboda, M. D., Tadesse, T. & Wilhite, D. 2015 Drought hazard assessment in the context of climate change for South Korea. *Agricultural Water Management* **160**, 106–117.

Naresh Kumar, M., Murthy, C. S., Seshai Sai, M. V. R. & Roy, P. S. 2009 On the use of Standardized Precipitation Index (SPI) for drought intensity assessment. *Meteorological Applications: A Journal of Forecasting, Practical Applications, Training Techniques and Modelling* **16** (3), 381–389.

Park, M., Sim, H., Park, Y. & Kim, S. 2015 Drought severity-duration-frequency analysis based on KMA 1-km resolution RCP scenario. *Korean Society of Hazard Mitigation* **15** (3), 347–355.

Penman, H. L. 1948 Natural evaporation from open water, bare soil and grass. *Proceedings of the Royal Society of London. Series A* **19** (1032), 120–145.
Ryu, J., Ahn, J. & Kim, S. 2012 An application of drought severity-area-duration curves using copulas-based joint drought index. *Journal of Korea Water Resources Association* 45 (10), 1043–1050.

Shiau, J. T. & Modarres, R. 2009 Copula-based drought severity-duration-frequency analysis in Iran. *Meteorological Applications: A Journal of Forecasting, Practical Applications, Training Techniques and Modelling* 16 (4), 481–489.

Sim, H., Ryu, J., Ahn, J. & Kim, S. 2013 Real-time drought index for determining drought conditions in natural water supply system communities. *Korean Society of Hazard Mitigation* 13 (5), 365–373.

Sung, J. H. & Chung, E. S. 2014 Development of streamflow drought severity-duration-frequency curves using the threshold level method. *Hydrology and Earth System Sciences* 18 (9), 3341.

Taylor, C. M., de Jeu, R. A., Guichard, F., Harris, P. P. & Dorigo, W. A. 2012 Afternoon rain more likely over drier soils. *Nature* 489, 423–426.

Teuling, A. J., Van Loon, A. F., Seneviratne, S. I., Lehner, I., Aubinet, M., Heinesch, B. & Spank, U. 2013 Evapotranspiration amplifies European summer drought. *Geophysical Research Letters* 40 (10), 2071–2075.

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. 2010 A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of Climate* 23 (7), 1696–1718.

Won, J., Jang, S., Kim, K. & Kim, S. 2018 Applicability of the evaporative demand drought index. *Korean Society of Hazard Mitigation* 18 (6), 431–442.

Yao, N., Li, Y., Lei, T. & Peng, L. 2018 Drought evolution, severity and trends in mainland China over 1961–2013. *Science of the Total Environment* 616, 73–89.

Zhang, B. & He, C. 2016 A modified water demand estimation method for drought identification over arid and semiarid regions. *Agricultural and Forest Meteorology* 230, 58–66.

First received 27 May 2020; accepted in revised form 18 August 2020. Available online 4 September 2020.