Thesis for the Degree of Master of Engineering

Development of Copula-based joint drought index using precipitation and climate variables and its application for future drought projection

by

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Division of Earth Environmental System Science

(Major of Environmental Engineering)

The Graduate School

Pukyong National University

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(강수량과 기후변수들을 이용한 Copula 기반의 결합가뭄지수 개발 및 미래 가뭄 전망을 위한 적용)

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List of Contents

List of Figures

List of Tables

강수량과 기후변수들을 이용한 Copula 기반의 결합가뭄지수 개발 및 미래 가뭄 전망을 위한 적용

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요　약

가뭄 모니터링 분야에서는 가뭄을 강수의 부족으로 해석하고 주로 강수량에 기반을 두는 가뭄지수들을 이용해왔다. 하지만 이러한 가뭄지수는 기후변화로 인한 기온의 상승과 같은 다양한 기상변수에 의한 가뭄은 전혀 반영하지 못하는 한계가 존재한다. 이와 같은 이유로 대기의 수분수요 측면인 잠재증발산량에 대한 관심이 증가하고 있으며 잠재증발산 기반의 가뭄지수가 개발되었다. 그러나 강수량이나 잠재증발산만을 고려하는 단일 가뭄지수는 다양한 기후 요인들에 의해 발생하는 가뭄을 종합적으로 해석하기에는 어렵다. 이에 따라 본 연구는 가뭄이 강수량 부족 또는 증발산의 증가만으로도 발생 가능한 것으로 해석하고, 두 가지의 기상변수를 함께 고려하는 가뭄 모니터링 방법을 제안하고자 한다. 이를 위해 강수량만을 고려하는 표준강수지수(Standard Precipitation Index, SPI)와 잠재증발산 기반의 증발수요 가뭄지수(Evaporative Demand Drought Index, EDDI)를 결합한 Copula 기반의 결합가뭄지수(Copula-based Joint Drought Index, CJDI)가 개발된다. Copula를 적용한 CJDI는 두 가뭄지수 사이의 상관성을 반영하여 보다 객관적이고 종합적인 가뭄 모니터링이 가능할 것임을 제시한다. 본 연구의 목적은 새롭게 제안된 CJDI를 기존의 가뭄지수들과 비교하여 CJDI의 적용성을 평가하고, 기후변화 시나리오를 적용하여 기후변화가 미래 가뭄에 미치는 영향을 살펴보는 것이다. 이를 위해 SDF(Drought Severity -Duration-Frequency) 곡선을 유도하여 각 가뭄지수가 전망하는 미래 가뭄의 정량적인 변화를 확인하고자 한다.

Ⅰ. Introduction

Drought affects socially, economically and environmentally, depending on the soil moisture deficiency, duration and area of droughts. Drought is caused by changes in meteorological variables, such as precipitation deficiency or increase in evapotranspiration, and can sometimes evolve into extreme events, becoming a serious disaster that can have a significant impact on communities and society, such as water resources, environment, and ecology(Sönmez et al., 2005). Also, because droughts are difficult to predict, among natural disasters, beginning and end(Mckee et al., 1993), water management and drought monitoring are very important to cope with droughts. In other words, in order to effectively cope with droughts, it is very important to have a system for determining drought conditions by continuously monitoring various climate variables related to drought(Moon and Lee, 2012).

In the field of drought monitoring, the drought index is used to determine the status of drought, and various drought indices have been developed and used worldwide. Drought index is a quantitative indicator of the severity and progress of drought(Kang and Moon, 2014). Drought indices based on rainfall have been mainly used in analyzing droughts(Smakhtin and Hughes, 2007). This is based on the concept of defining droughts as an abnormally persistent shortage of precipitation, and in fact many studies of droughts are interpreting droughts based on the precipitation deficiency(Heim, 2000; Wilhite et al., 2000; Rossi and Cancelliere, 2002; Cancelliere et al., 2007). The standard precipitation index(SPI; Mckee et al., 1993), a drought index mainly used in these studies, has the advantage of simplicity in calculating because it uses only precipitation, and SPI is now one of the most widely used drought indexes. Livada et al. (2007) interpreted the causes of drought as a lack of precipitation over a period of time and used the SPI to study droughts across Greece. Naresh Kumar et al. (2009) also judged the rainfall deficiency as the main cause of meteorological droughts, and used SPI to assess droughts in two regions where rainfall patterns were contrasted. Smakhtin and Hughes (2007) also developed software to calculate various rainfall-based indicators, including SPI, for quantitative assessment of meteorological droughts. Currently, Korea Meteorological Administration (KMA) relies heavily on SPI to monitor drought.

As such, in the field of drought monitoring, droughts have been expressed mainly by focusing on rainfall, which is the moisture supply side of the atmosphere. However, like the SPI, the drought index using only rainfall has a limit that cannot reflect the drought generated and progressed by various climate variables such as an increase temperature due to climate change(Mavromatis, 2007; Kempes et al., 2008; Vicente-Serrano et al., 2010a; Taylor et al., 2012; Teuling et al., 2013; Zhang and He, 2016). In fact, since there have been many flash droughts resulting from abnormal rises in temperature, interpreting drought using only precipitation is unlikely to be a reasonable approach in the climate change. Therefore, in the field of drought monitoring, interest in potential evapotranspiration (E_o), which is the moisture demand side of the atmosphere, has increased recently, and many studies have demonstrated the importance of the evaporation demand of atmosphere in the process of drought occurrence and deepening(Ciais et al. 2005; Otkin et al. 2016). To reflect the effects of climate change, Vicente-Serrano et al. (2010b) has developed the Standardized Precipitation Evapotranspiration Index (SPEI) to monitor droughts based on differences in precipitation and E_o, and Hobbins et al. (2016) has developed a new E_o-baased drought index, the Evaporative Demand Drought Index (EDDI). EDDI, which is based on E_o, does not need to analyse the water availability of the surface separately, and has the advantage that it is easy to detect the onset of drought with almost no delay. Therefore, EDDI can be useful for capturing flash drought caused by meteorological variables that are temporarily changing strongly. If the flash drought occurs without any portents, early detection of flash drought is critical because there is insufficient time to respond to drought(Otkin et al., 2015). Yao et al. (2018) compared the performance of SPI, SPEI, and EDDI in terms of identifying past droughts, and positively assessed the applicability of EDDI to flash drought in China. They suggested that early warning of the onset of drought, which SPI and SPEI do not indicate, is possible with EDDI. Won et al. (2018) also compared the performance of SPI and EDDI using Korea's observed data and concluded that EDDI was adequately applicable in dertermining drought onset and continuous drought conditions.

However, such a drought index using only one clmate variable is difficult to describe all of the complex drought evolution processes caused by various climate factors(Mo, 2008). In fact, because droughts are caused by a complex interaction of various meteorological factors, a simple drought index is not sufficient to characterize such effects(Hao and Singh, 2015). In this study, we interpreted droughts as being likely to occur only with precipitation deficiency or an increase in E_o, and suggested a new method of drought monitoring that considers the two climate variables. In other words, we developed a Copula-based Joint Drought Index (CJDI) combining SPI and EDDI, which are representative drought indices based on different meteorological variables.

Many studies have been conducted to apply copula in drought analysis, and in particular, a multivariate drought frequency analysis with copula has been conducted(Shiau, 2006; Shiau et al., 2007). This is because copula well reflects the correlation between hydrologic variables(Ryu et al., 2012). Shiau and Modarres (2009) proposed a drought severity-duration-frequency (SDF) curve using copula to correlate drought depth, duration, and frequency. Mirabbasi et al. (2012) selected the most suitable copula among various copula functions to construct the joint distribution of drought severity and duration. Song and Singh (2009) constructed a joint distribution of drought severity, duration, and time interval of drought using elliptical copula, and Xu et al. (2015) analyzed past drought events spatiotemporally by performing copula-based trivariate frequency analysis based on drought severity, duration, and area of drought. In Korea, a number of bivariate frequency analyses using copula were performed for drought depth and duration(Lee and Son, 2016; Yu et al., 2016; Yu et al., 2017However, the results of studies conducted in Korea have exposed the limitations of presenting unrealistic results that give excessive return period to past droughts. Chun et al. (2015) performed a copula-based bivariate drought frequency analysis using meteorological data over a 30-year period to evaluate severity and duration of drought, but it was analyzed that in past droughts, the return period exceeded 5,000 years. Kwon et al. (2018) also conducted the study by comparing the bivariate frequency analysis using drought severity and duration with the bivariate frequency analysis using drought severity and low precipitation, but the results showed that past droughts had too high return period, as in Chun et al. (2015). In order to use Copula, the number of data should be large enough. However, these studies showed unrealistic result because they used less than 30 droughts. That is, the observation period of the data is not sufficient to apply Copula.

This study is similar to the above studies in terms of using copula. However, we do not perform multivariate drought frequency analysis using copula to combine drought characteristics data such as drought severity and duration. Instead, we will develop a new drought index that combines two individual drought indices using copula. Individual drought indices were expected to be sufficient for the application of copula because they have a large enough number of data. Recently, a study has been conducted to determine drought in various sides by combining drought indices similar to those proposed in this study. Svoboda et al. (2002) proposed a drought monitoring across the United States by incorporating various drought information, and Kao and Govindaraju (2010) applied copula to express the complex dependence between drought-related variables, showing in more consistent results by combining SPIs of various durations. As such, the development of new drought indices using various climate variables is a research area of great interest. Nevertheless, many studies still need to be conducted against various climate conditions. The CJDI suggested in this study is a new joint drought index that combines SPI describing the moisture supply side of the atmosphere and EDDI describing the moisture demand side of the atmosphere using copula. It is expected that it will be possible to monitor droughts by integrating drought information expressed by two drought indices. In other words, by combining two drought indices with different characteristics, the drought conditions expressed by each drought index could be combined to obtain complementary information. Therefore, this study attempted to confirm the reproducibility of past drought events using the CJDI, and to examine the effects of climate change on drought. Since the impact of climate change has a significant impact on future water resources worldwide (Mishra and Singh, 2009; Sivakumar, 2011;

Yang and Yang, 2012), It is essential to see how the newly proposed drought index explains the impact of climate change.

To analyze future droughts, it is important to identify quantitative changes in droughts. Drought frequency analysis can be interpreted by quantifying the drought severity, duration, and return period. Therefore, in order to quantitatively compare current and future droughts, this study tried to use SDF curves. In the case of drought analysis, it is very important to consider the duration so that the PDS proposed by Stall (1964) is used to construct the drought severity time series for frequency analysis and to derive SDF curves.

The purpose of this study is to evaluate the applicability of CJDI by comparing with the existing drought indices SPI, EDDI, and SPEI, and to evaluate and judge various drought conditions using CJDI. In addition, we will examine the effects of climate change on future droughts by applying climate change scenarios generated from various climate models. For this purpose, the SDF curve is derived using PDS to quantitatively analyze how each drought index represents future drought.

Ⅱ. Method and Material

2.1 Derivation of PET

The method of estimating potential evapotranspiration(PET, E_o) has been suggested by many studies, simple Thornthwaite method(Thornthwaite, 1948), Penman method(Penman, 1948), Penman-Monteith method(Allet et al., 1998) and Hargreaves-Samani method(Hargreaves and Samani, 1985). In this study, we used Penman-Monteith(PM) method known as the most accurate and excellent model for climate conditions around the world by worldwide studies(Xing et al., 2008; Trajkovic and Kolakovic, 2009; Martinez and Thepadia, 2010; Azhar and Perera, 2011). The PM method has been studied to estimate future E_o and to be appropriate for drought indices such as EDDI or SPEI using E_o(Dewes et al., 2017). The PM method requires meteorological data on temperature, humidity, radiation, and wind speed, and the following equation can be used to calculate daily E_o.

$$E_o = \frac{0.408\triangle(R_n - G) + \gamma\frac{C_n}{T+273}u_2(e_s - e_a)}{\triangle + \gamma(1 + C_d u_2)} \quad \cdots\cdots (1)$$

In equation (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 mean daily air temperature (°C), u_2 is the mean daily wind speed at 2-m height (m s^{-1}), e_s is the saturation vapor pressure(kPa), e_a is the actual vapor pressure(kPa), $\triangle$ is the slope of the saturation vapor pressure-temperature curve (kPa ℃$^{-1}$), and γ is the psychrometric constant(kPa ℃$^{-1}$). Also, the value 0.408 used in this equation is a unit conversion factor for converting MJ m^{-2} day^{-1} into mm day^{-1}. C_d and C_n can be determined by the unit of time and aerodynamic roughness. In this study, values of 900 and 0.34 were used. The soil heat flux density(G) is relatively small compared to the net radiation, so the daily G is negligible.

In case of Korea Meteorological Administration, there are limitations in using the PM method due to the large missing data of the observed radiation. Allen et al. (1998) proposed a methodology for estimating the necessary meteorological data using more common variables such as minimum and maximum temperatures. Kwon and Choi (2011) estimated the radiation data using the methodology and evaluated the applicability in Korea. In addition, the PM method was suggested that it can be reasonably estimated in Korea where data is limited. Therefore, in this study, we estimated the radiation by the method proposed Allen et al. (1998). This method estimates the solar radiation energy(R_s) reaching the ground surface using the difference in temperature. R_s is calculated in the following.

$$R_s = k_{rs}\sqrt{T_{\max} - T_{\min}}\,R_a \quad \cdots\cdots (2)$$

where, R_a is the extraterrestrial radiation, which is a well behaved function of the day of the year, time of day, and latitude. $T_{\max}$ is the daily maximum air temperature (℃), $T_{\min}$ is the daily minimum air temperature (℃), and k_{rs} is the empirical coefficient, which can be calculated as follows:

$$k_{rs} = k_{r0}(\frac{P}{P_0})^{0.5} \quad (3)$$

In equation (3), P is the mean atmospheric pressure of the site (kPa), P_0 is the mean atmospheric pressure at sea level (101.3 kPa), and k_{r0} is the empirical coefficient equal to 0.17 for interior regions and equal to 0.20 for coastal regions. Once solar radiation is estimated, the net radiation can be obtained in the method proposed by Allen et al. (1998).

2.2 Drought indices

SPI, EDDI, SPEI and CJDI are used in this study. SPI and EDDI are calculated using the same calculation method. First, the moving average monthly precipitation or E_o data is constructed by duration and the optimal probability distribution of the monthly time series is estimated. To estimate the SPI and EDDI, we estimate the Bivariate Gamma distribution with the optimal probability distribution. The estimated probability distribution is used to calculate the cumulative probability value of the given monthly data, and the value obtained by applying this cumulative probability value to the standard normal distribution is the drought index. The values represented by the SPI and EDDI thus calculated represent conceptually opposite moisture states. Negative values of SPI indicate precipitation deficiency, and positive values of EDDI indicate excessive increase in E_o. Therefore, it can be understood that as the SPI has a large negative value and the EDDI has a large positive value, the drought is intensified. The drought classification according to drought index is shown in Table 2.1.

Table 2.1 Moisture condition and drought classification

Index Range	Drought classifacation			
	SPI	SPEI	EDDI	CJDI
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	

SPEI has the same estimation procedure as the SPI, but with different probability distributions. Because SPEI uses the difference from precipitation and E_o, negative data exists. Since the lower limit of the variable to apply to the bivariate Gamma distribution is 0, the monthly time series constructed according to the difference between precipitation and E_o cannot be applied to the bivariate Gamma distribution. Therefore, Gumbel distribution was selected as the optimal probability distribution for estimating SPEI through χ^2 and K-S goodness-of-fit tests. SPEI is a measure of drought based on the amount of moisture retained, which is the difference between precipitation and evapotranspiration. A negative value of SPEI indicates a dry state. Therefore SPEI has the same drought classification as SPI.

The newly proposed CJDI applies the copula theory as a drought index that combines SPI and EDDI. Although many drought analyzes using copula have been performed, few studies have combined the different drought indices as suggested in this study. In Korea, Kim et al. (2012) studied the joint drought index to simultaneously consider the SPI of the various durations. In this study, we applied the empirical copula proposed by Nelsen (2006). If the sample size is large enough, empirical copula can be used to construct a joint probability distribution. The d-dimensional empirical copula with sample size n for each variable X_j is defined by equation (4).

$$C_n\left(\frac{k_1}{n}, \frac{k_2}{n}, \ldots, \frac{k_3}{n}\right) = \frac{a}{n} \quad \cdots\cdots (4)$$

Where k_i is the i-th rank(in ascending order) of X_j, $X_{j(k_i)}$ is the value of X_j corresponding to the i-th rank, and a is the number of $\{X_1, \ldots, X_d\}$ that simultaneously satisfy $X_1 \leq X_{1(k_1)}, \ldots, X_d \leq X_{d(k_d)}$ in time series of $\{X_1,\ldots,X_d\}$. By applying copula with SPI and EDDI as variables, the correlation between two drought indices can be constructed. The empirical Kendall distribution function (K_C) is used to calculate the probability measure of the correlation structure.

$$C_n(\frac{k_1}{n},\frac{k_2}{n},\ldots,\frac{k_3}{n}) = \frac{a}{n} \quad \cdots\cdots (5)$$

Where b is the number of samples $\{X_1,\ldots,X_d\}$ with $C_n(k_1/n,\ldots,k_d/n) \leq l/n$. The Kendall distribution function can be used to estimate the value of the cumulative probability for a comprehensive drought condition that takes into account a number of variables(Kim et al., 2012). The value obtained by applying this cumulative probability inversely to the standard normal distribution can be finally expressed in CJDI. SPI and EDDI, which are used as variables in estimating CJDI, should express the same drought condition for any value. Therefore, CJDI follows EDDI's drought classification because CJDI was calculated using negative in SPI and EDDI.

2.3 Partial Duration Series

In the case of drought analysis, it is very important to consider the duration. Accordingly, this study analyzed drought with various durations from 1-month to 12-months. Also, unlike rainfall analysis using annual maximum time series, frequency analysis was performed using PDS. For this purpose, PDS by various durations were constructed from the time series of the drought index using the method proposed by Stall (1964), which is applied to the flow frequency analysis of reservoirs. To create a PDS, we first obtain a moving-averaged time series of monthly drought index time series by durations. Among them, the most severe value of drought (SPI and SPEI are the smallest values, EDDI and CJDI are the largest values) was selected as the 1st priority, and a new time series is constructed that eliminates the number of duration month before and after from the original series including this value. In the new time series, the most severe value of drought is selected as the second rank, and the new time series is formed by deleting the value before and after the number of months. PDS is created by repeating the same process. The number of PDS cannot exceed the observed years, and if a value of PDS less than zero is selected, the iteration process is stopped. That is, the maximum number of PDS is the number of years of observation, and in the case of a long duration, the number of PDS may be smaller than the number of years of observation. In the frequency analysis using the annual maximum time series, since the same number of data is obtained for each duration, a separate process is not performed. However, when using the PDS, the number of data must be taken into account when calculating the return period of the drought severity. Therefore, in this study, the return period of drought severity s and duration d in the process of frequency analysis was calculated as follows.

$$T_r(s,d) = \frac{1}{\lambda\{1 - F(s)\}} \quad \cdots\cdots (6)$$

Where λ is the probability of occurrence of PDS, that is, the number of PDS divided by the number of observed years, and $F(s)$ is the cumulative probability density function of PDS.

2.4 Data

Observation data and future climate change scenario were used in this study. The climate variables used are mean temperature, maximum and minimum temperature, wind speed, relative humidity for E_o calculation and precipitation. Observation data was used for the 1973-2018 period at 56 sites of the KMA's Automated Synoptic Observing System(ASOS). Future data are simulated and generated using the Global Climate Model(GCM) and the Regional Climate Model(RCM). Because data generated from GCM has limited data usage due to low resolution and simple physical process, more detailed climate data from RCM are needed. Therefore, in this study, we used data from the 2 GCMs(HadGEM2-AO (Hadley Centre Global Environment Model version 2 - Coupled Atmosphere-Ocean model) and MPI-ESM-LR(Max Planck Institute Earth System Model- Low Resolution)) and 4 RCMs(MM5, RegCM, RSM, and

WRF) as future climate data. In addition, a total of 16 scenarios were used by applying RCP4.5 and RCP8.5 scenarios for each of the eight models. Climate model data includes present data from 1981-2010 and future data of RCP4.5 and RCP8.5 from 2021-2050. For future climate data, bias corrections must be performed because bias with observed data clearly exists. In general, Quantile Mapping (QM) is used to calibrate climate model data. QM is a method of mapping the probability distribution of climate model data to the observation data by using the cumulative probability distribution of observation data and climate model data(Hashino, 2007). In this study, QM was performed in the SDF curve derivation process in order to reduce the bias of the SDF curve between the observation and present data of the climate model. Bias correction was performed for the PDS constructed from observation and climate model data, and future SDF curves were derived using the corrected PDS.

Ⅲ. Results and Discussion

3.1 Temporal variation of dought indices

This section examined the applicability of SPI, EDDI, SPEI and CJDI in Korea. All of these droughts can be calculated from various durations, which can be useful to indicate droughts in the region if appropriate duration is selected considering local characteristics. In this study, we calculated EDDI(EDDI6), SPEI(SPEI6), and CJDI(CJDI6) of the same duration as the 6-month SPI(SPI6), which is currently used mainly by the KMA for drought forecasting and warning. In order to evaluate the reproducibility of past observed droughts of each drought index, Korea was analyzed by dividing into six areas by administrative region, such as Fig. 3.1. The 56 meteorological sites under the KMA, which were applied to calculate the drought index of each region, are shown together, and the Thiessen method is applied to derive the spatial average of each region.

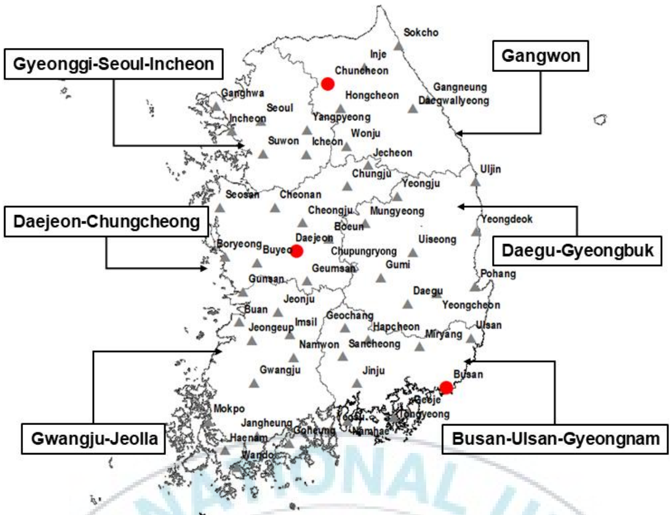

Fig. 3.1 Location of six region and meteorological stations used in this study.

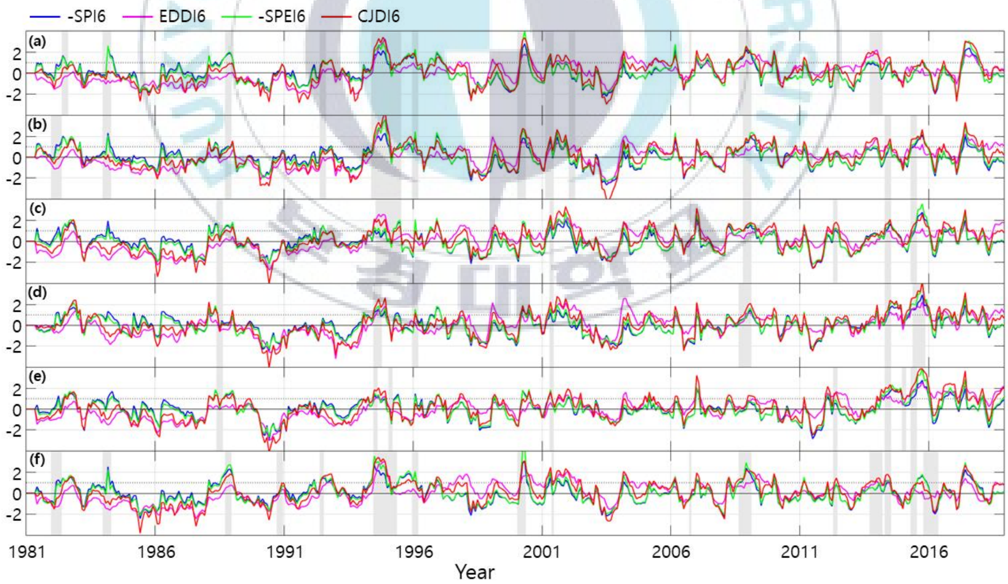

Fig. 3.2 The temporal variations of 6-month SPI, EDDI, SPEI and CJDI over 1981-2018. (a) Busan-Ulsan-Gyeongnam, (b) Daegu-Gyeongbuk, (c) Daejeon-Chungcheong, (d) Gangwon, (e) Gyeonggi-Seoul-Incheon, (f) Gwangju-Jeolla.

In Fig. 3.2, the drought events during the 1981-2018 period in each region and the temporal behavior of the drought indices were compared. Negative SPI6 and SPEI6 are shown be convenient to compare with EDDI6 and CJDI6, and this means that the larger the positive value, the worse the drought. SPI6 and SPEI6 have very similar time series, but SPEI6 shows more severe drought conditions than SPI6. This case occurs during the 1994-1995 period in Fig. 3.2(a), (b) and (f). The period was a year of historic heat wave as well as long-term shortages of rainfall across the country, with the high E_o, which led to a severe drought. It can be seen that SPEI6 was affected by excessive increase in E_o, resulting in more severe drought than SPI6. However, SPEI6 is not always affected by E_o. This can be seen by the fact that SPEI6 does not express drought at all even when the E_o-based EDDI6 increases rapidly. In the 2013 drought event of Fig. 3.2(a), the SPEI6 is the value of about 1 indicating a weak drought with SPI6, although EDDI6 reached a severe drought(the value of 2). Also, in 1997-1998 in the rest of the world except Gyeonggi-Seoul-Incheon(Fig. 3.2(e)), EDDI6 shows a drought extreme, but SPEI6 shows no drought at all. SPEI6 shows similar behavior to SPI6, which is mainly influenced by precipitation, and the effect of E_o is small. That is, it can be seen that even though EDDI6 is extremely dry as E_o increases, SPEI6 does not show drought because it does not properly reflect information of E_o, a variable related to temperature.

On the other hand, CJDI6 comprehensively reflects the information on precipitation and E_o. The CJDI is not simply a mean of the two drought indices, but is influenced by the correlation between the drought indices, so it is possible to comprehensively judge the drought situation represented by each drought index. If SPI6 and EDDI6 together represent a drought, CJDI6 represents a more severe drought reflecting both drought conditions. For example, SPI6 and EDDI6 have shown high values due to the past severe drought event in 1994 in the three regions of Fig. 3.2(a), (b) and (f). As a result, CJDI6 was regarded as a severe drought condition with a precipitation deficiency and an excessive increase in E_o. In the same period, drought event in the Gyeonggi-Seoul-Incheon region(Fig. 3.2(e)) show that SPI6 and EDDI6 are close to 1. CJDI6 indicates extreme drought that exceed the value of 2 as both drought indices indicate drought together. In addition, CJDI6 showed a high value as both SPI6 and EDDI6 expressed droughts in spring drought in southern Korea in 2000(Fig. 3.2 (a), (b) and (f)). However, even if the two drought indices fail to express the drought together, CJDI6 can properly show the drought. In the case of Gangwon region(Fig. 3.2 (d)), in the drought event in 1996, SPI6 exceeded the drought reference value of 1, while EDDI6 showed a value near 0 indicating normal moisture state. In this situation, CJDI6 can detect abnormal moisture supply of atmosphere according to SPI6 and indicate drought condition. In addition, in the 1988 drought in Fig. 3.2(f), EDDI6 did not detect drought, while SPI6 showed extreme droughts of over 2. During the period, the drought was caused by precipitation deficiency, and CJDI6 determined the drought situation through SPI6's information. The advantages of CJDI6 can be seen in Figs. 3.3–3.4. Fig. 3.3–3.4 show two representative drought events in the Daejeon–Chuncheong region and the time series of each drought index.

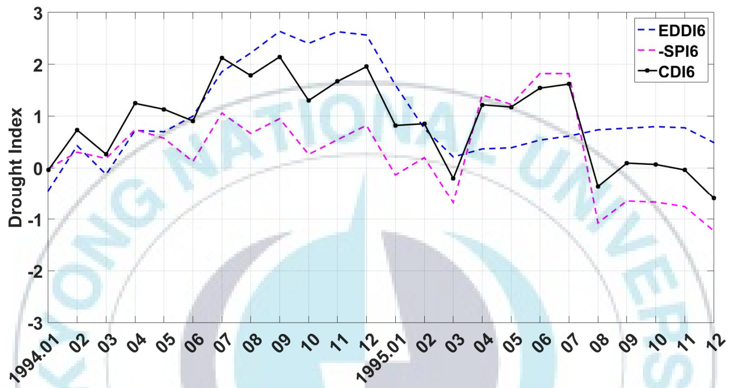

Fig. 3.3 The temporal variations of 6–month SPI, EDDI, CJDI at Daejeon – Chungcheong for 1994 and 1995.

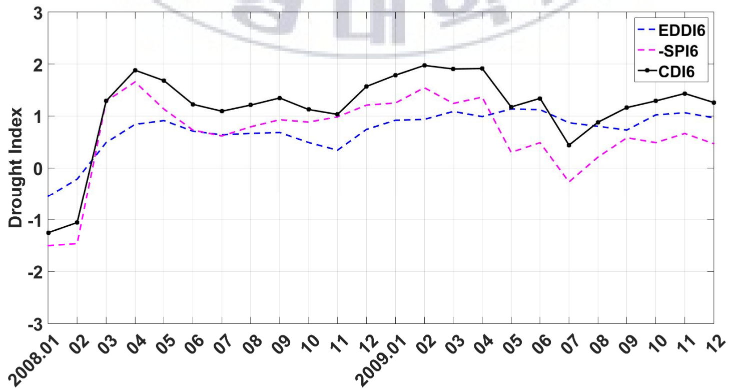

Fig. 3.4 The temporal variations of 6–month SPI, EDDI, CJDI at Daejeon – Chungcheong for 2008 and 2009.

Fig. 3.3 shows the time series of each drought index for drought events in 1994 to 1995. EDDI6 has been detecting drought since July 1994, while SPI6 is above the value of 1, alternating between weak drought and normal state. CJDI6 reflects the extreme drought condition of EDDI6 and shows a continuous drought. However, the drought of CJDI6 was ended by EDDI6, which has declined sharply since January 1995, but CJDI6 has indicated immediately drought by the rising SPI6.

Fig. 3.4 shows the drought event from the end of 2008 to the beginning of 2009. SPI6 expresses the drought that EDDI6 did not detect. Accordingly, CJDI6 also reflects drought information of SPI6, indicating drought. As such, CJDI6 can properly represent droughts in situations where drought indices suggest different drought conditions. However, CJDI6 does not always make the right decision under the conflicting drought indices. This is clear from the drought events in the southern region of Korea in the 1980s. SPI6 reproduces the droughts that occurred in the 1980s, while EDDI6 did not detect drought at all. In this case, CJDI6 is affected by EDDI6, not SPI6, and thus shows no drought. Nevertheless, CJDI6 still shows relatively high observed drought reproducibility compared to other drought indices. In order to confirm this quantitatively, the hit ratio of drought index to observed drought is shown in Table 3.1. Hit ratio was estimated that the value of the drought index indicated the drought during the actual drought events occurring in each region. The reference value for drought is more than 1.0 for EDDI6 and

CJDI6 and less than -1.0 for SPI6 and SPEI6. The hit rate was calculated as a percentage of the number of months the drought index hit during the drought period for the total number of months in which actual drought events occurred by region.

Table 3.1 Hit ratio of drought indices in six region

	SPI6	EDDI6	SPEI6	CJDI6
Busan-Ulsan-Gyeongnam	50.0	40.7	55.6	51.9
Daegu-Gyeongbuk	50.9	30.2	45.3	47.2
Daejeon-Chungcheong	47.6	38.0	66.7	76.2
Gangwon	55.6	59.3	59.3	77.9
Gyeonggi-Seoul-Incheon	52.6	47.4	52.6	68.4
Gwangju-Jeolla	43.8	21.9	45.3	51.6

CJDI6 has the highest hit ratio in four regions except Busan-Ulsan-Gyeongnam and Daegu-gyeongbuk. This is confirmed by the fact that CJDI6 also had a lower hit rate as EDDI6 could not catch the drought of the 1980s in the southern region. However, CJDI6 has a particularly good hit ratio in Daejeon-Chuncheong and Gangwon. EDDI6 has a relatively low hit rate compared to other drought indices. However, in most regions, SPEI6 has a higher hit ratio than SPI6 and CJDI6's excellent hit rate suggests that E_o plays an important role in drought analysis. In other words, it is clear that drought monitoring is important for analysis including E_o.

3.2 SDF curves

In this section, we derives and analyzes the observed SDF curve of each drought index. SDF curves were derived at three sites in Korea(Busan, Chuncheon, and Daejeon), shown in red circles in Fig. 3.1. A total of 46 years of observed data from 1973 to 2018 was used to extract PDS by sites for the frequency analysis of four drought indices. PDS results of Chuncheon site is shown in Fig. 3.5.

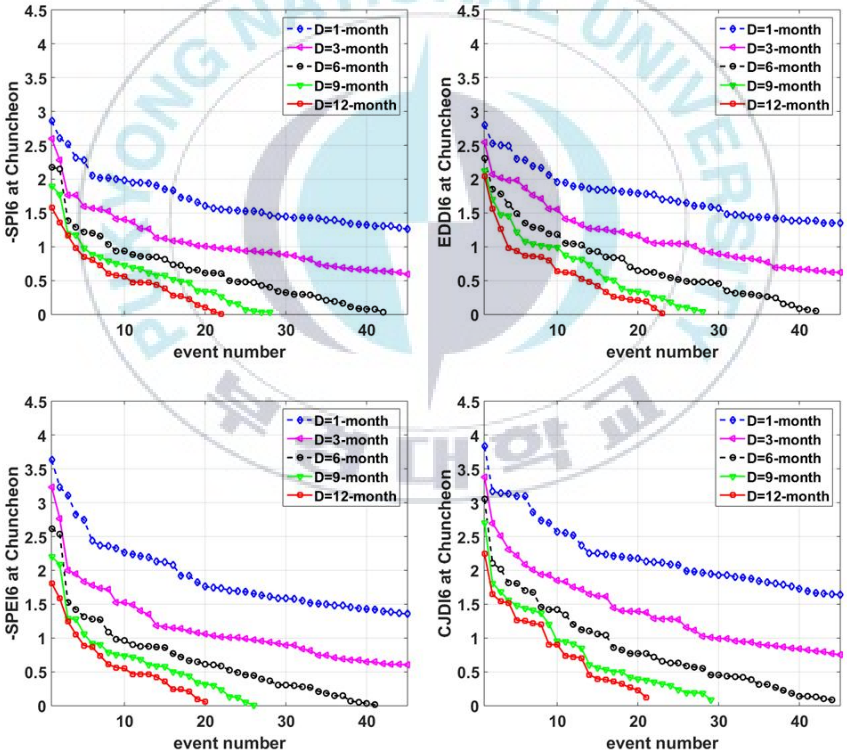

Fig. 3.5 Partial duration series of drought indices using observation data(1973-2018) at Chuncheon site.

In general, PDS is less numerous and lower drought severity with longer duration. Fig. 3.5 shows that CJDI6 constitutes a higher PDS than other drought indices. This is because, as previously analyzed, CJDI6 has characteristics that indicate higher values when SPI6 and EDDI6 express drought together. Similarly, SPEI6 has a PDS similar to SPI6 because it has a time series similar to that of SPI6, but has a higher drought severity than SPI6 under the influence of E_o. This characteristic of drought indices can also be clearly seen in the SDF curve. Figs. 3.6-3.9 show the observed SDF curves for three sites of each drought index and were derived for various durations and return periods. The SDF curve is a curve representing the relationship between drought severity, duration, and frequency, which enables quantitative assessment of drought and can be a useful tool for determining drought characteristics by regions.

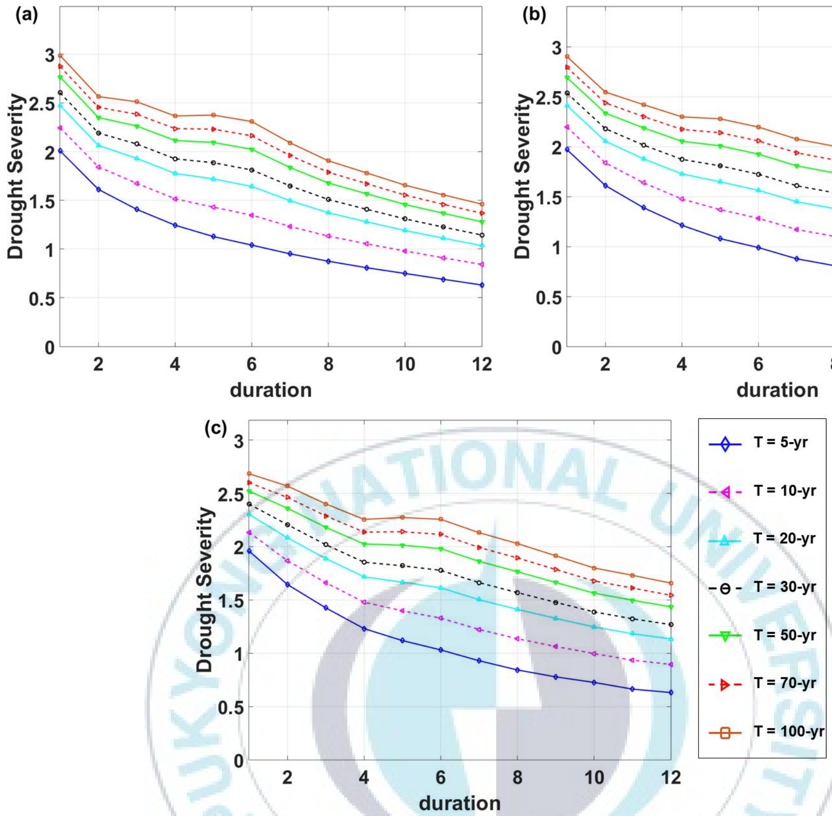

Fig. 3.6 SDF curves of -SPI6 derived from the observation data(1973-2018) at (a) Busan, (b) Chuncheon, (c) Daejeon.

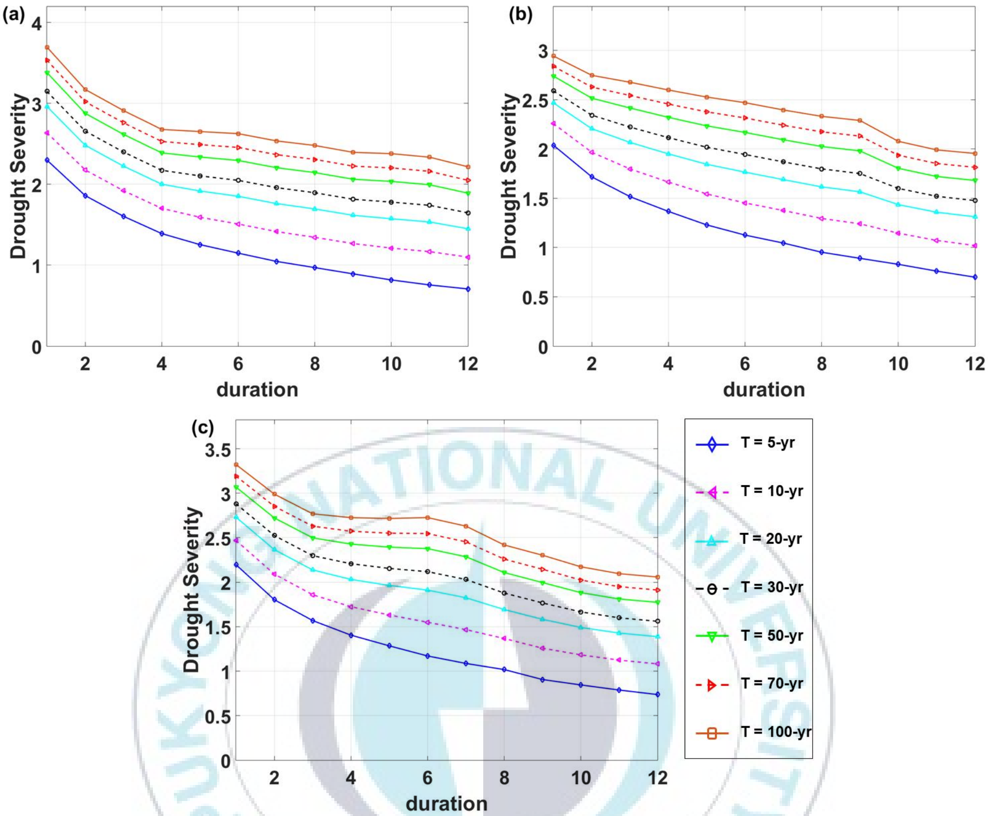

Fig. 3.7 SDF curves of EDDI6 derived from the observation data(1973-2018) at (a) Busan, (b) Chuncheon, (c) Daejeon.

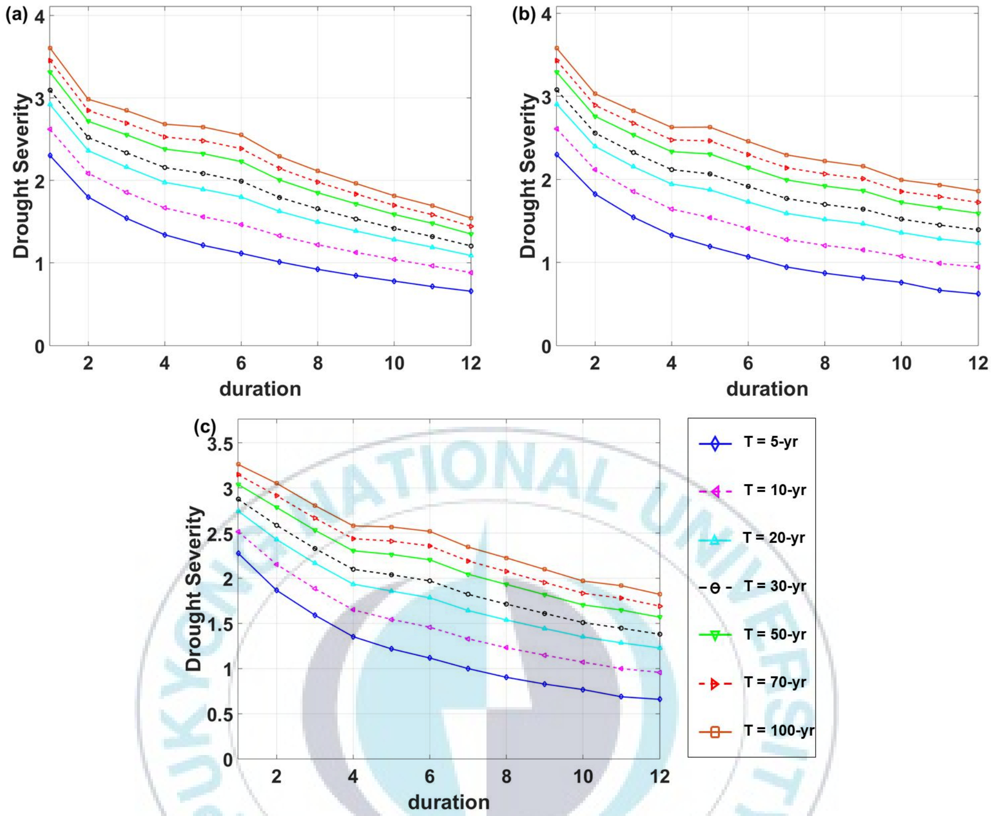

Fig. 3.8 SDF curves of -SPEI6 derived from the observation data(1973-2018) at (a) Busan, (b) Chuncheon, (c) Daejeon.

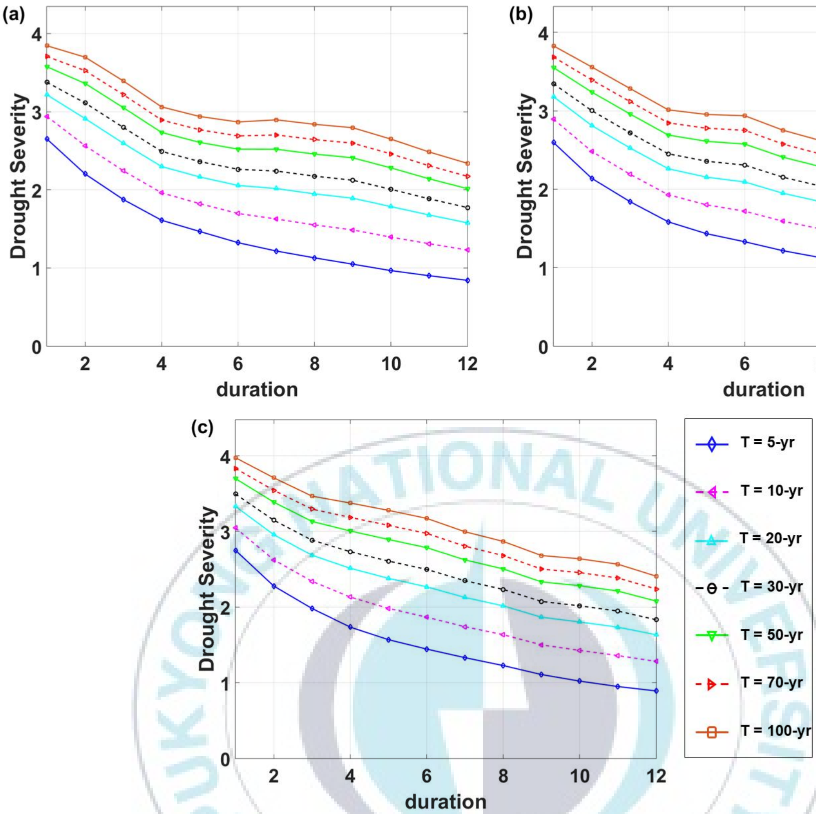

Fig. 3.9 SDF curves of CJDI6 derived from the observation data(1973-2018) at (a) Busan, (b) Chuncheon, (c) Daejeon.

The SDF curve is a common form in which drought severity decreases with longer duration. However, the SDF curve derived from this study has some inversion at high return period. In constructing a PDS, there may be a value that is greater than or nearly similar to a short duration time series in a long duration time series. In this case, the long-duration time series has a relatively larger variance, and the probability drought severity of long-duration at the same return period is higher than the short-duration, depending on the upper tail characteristic of the cumulative probability distribution.

SPEI6 represent an SDF curves similar to that of SPI6, but with a more severe drought severity. SPEI6 is an index for expressing drought based on the moisture retention estimated by the difference between precipitation and E_o. It can express more intensive than SPI6 due to the influence of E_o. CJDI6 also has a higher drought depth than other drought indices because it can express severe droughts by reflecting droughts of SPI6 and EDDI6. Observed SDF curves represent different probability drought severity by the drought index at the same site. Since different SDF curves may appear at the same site according to the characteristics of each region and the drought index, it is important to select the appropriate drought index for each region to understand the drought characteristics of the region.

3.3 Change in future drought

The four drought indices examined in the observed SDF curves have different probability drought severity at the same site, depending on their characteristics. Therefore, in order to forecast and prepare for future droughts, it is necessary to quantitatively understand the changes in future droughts represented by each drought index. In this section, future SDF curves are derived using climate change scenario data generated from various climate models.

To derive the future SDF curve, the bias correction was performed by comparing the PDS of the present data with that of the observed data. To confirm the bias correction results, the bias (%) of the present SDF curves corrected for the observed SDF curves is shown in Fig. 3.10. The bias was calculated as the difference between the probability drought severity of the present and observed SDF curve by return periods and durations. In Fig. 3.10, the results of the Chuncheon site are representatively shown, and the results of eight models by return period and duration are shown as box plots.

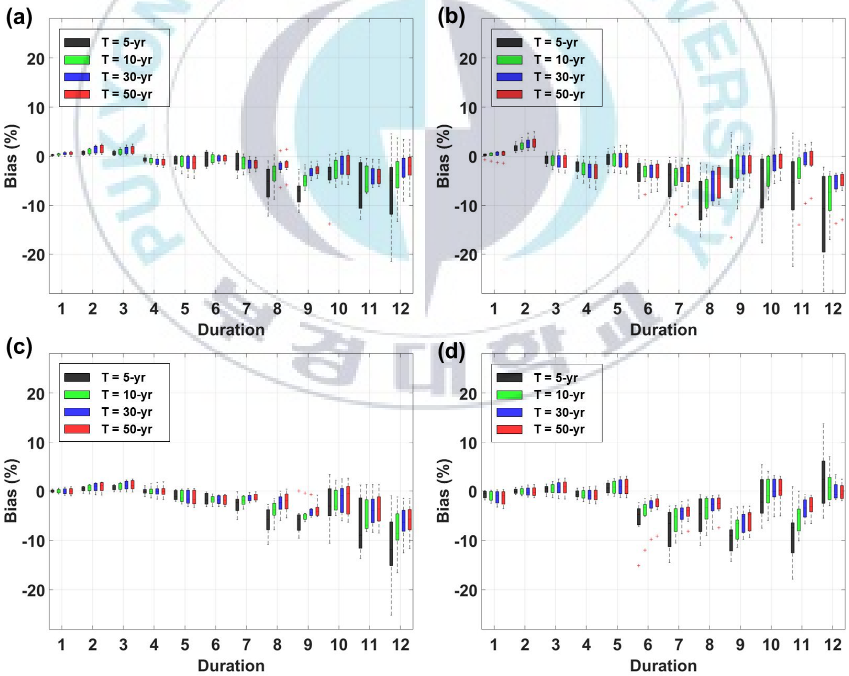

Fig. 3.10 Bias of the SDF curves derived from the corrected present data for the observed SDF curves at Chuncheon site. (a) -SPI, (b) EDDI, (c) -SPEI, (d) CJDI.

The present SDF curves at short-term duration show a bias close to 0 %, indicating that the bias correction is well performed. However, the long-term duration has a relatively high bias (%), and some models have more than 20%. For long durations, the number of PDS data is varied. In order to take into account the difference in the number of data, the process of Equation (6) in Section 2.3 is used and the corrected return period is used instead of the same return period. Therefore, the observed and present drought severity may be different. However, most of the bias (%) is within 10%, it can be confirmed that the bias correction is performed well. Although the results of Chuncheon of the three sites were presented, it was confirmed that the bias correction was well performed at the other sites.

The future SDF curve was derived using the future data corrected with the present data, and the rate of change in future drought severity was analyzed to identify the quantitative change in future drought. The rate of change was calculated as the change of the future drought severity of the RCP4.5 and RCP8.5 scenarios for the present severity by durations for each of the eight models. The rate of change is based on 0%, the higher the value means the increase of the drought severity, the lower the value means the decrease. Fig. 3.11 shows the rate of change of future probable drought severity for each sites of SPI6. The results of eight models of RCP4.5 and RCP8.5 are shown in a box plot.

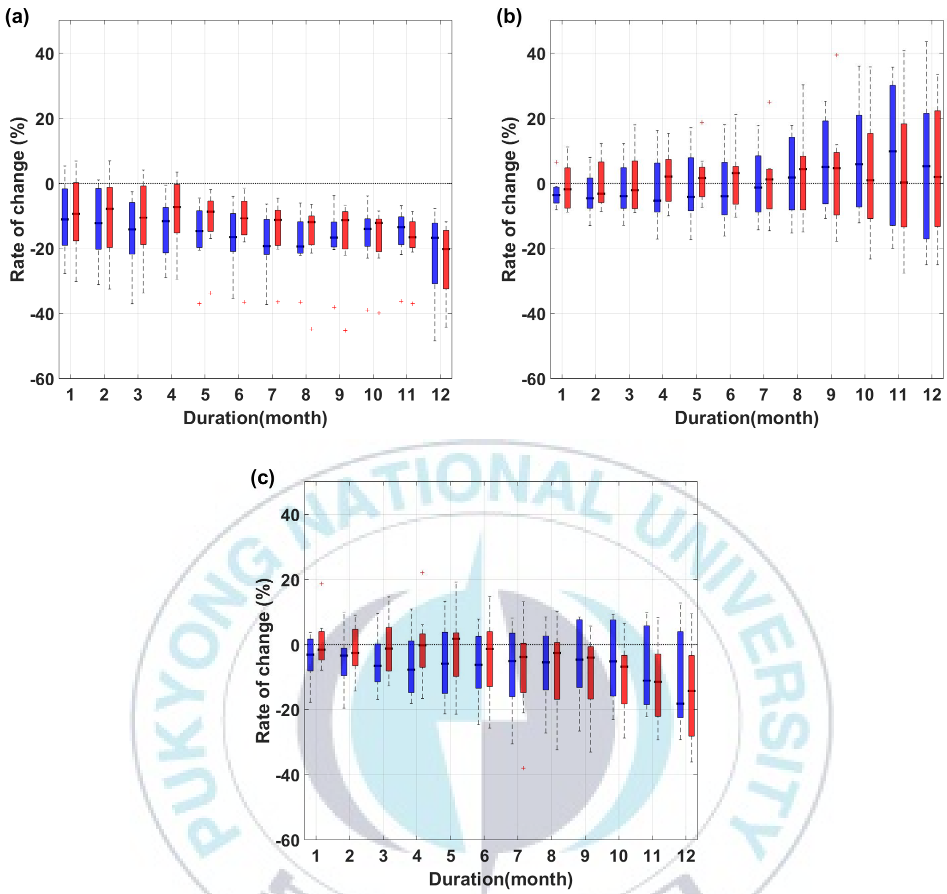

Fig. 3.11 Rate of change in future SDF curves of - SPI6 by RCP4.5(blue box plot) and RCP 8.5(red box plot) scenario at (a) Busan, (b) Chuncheon, (c) Daejeon.

SPI6 represents a different future drought prospect for three sites. Future droughts at the Busan site(Fig. 3.11(a)) are expected to be less than present. The results of some models suggest that future drought severity may be reduced by about 40% from the present. Also at the Daejeon site(Fig. 3.11(c)), most models insist on mitigating future droughts. On the other hand, at the Chuncheon site(Fig. 3.11(b)), various drought projection results are shown for each model, and there are many models that expect the future drought to intensify. Eight models suggest drought mitigation and deepening. Since the eight models represent a wide range of different rates of change, there is a great deal of uncertainty between the climate models. The SPI6 at the Chuncheon shows different prospects for future droughts by model, so we cannot be sure of the future drought. As such, future droughts through SPI6 show some uncertainty, but most are expected to mitigate. This is because it is predicted that the occurrence of extreme rainfall events will increase in the climate change scenarios.

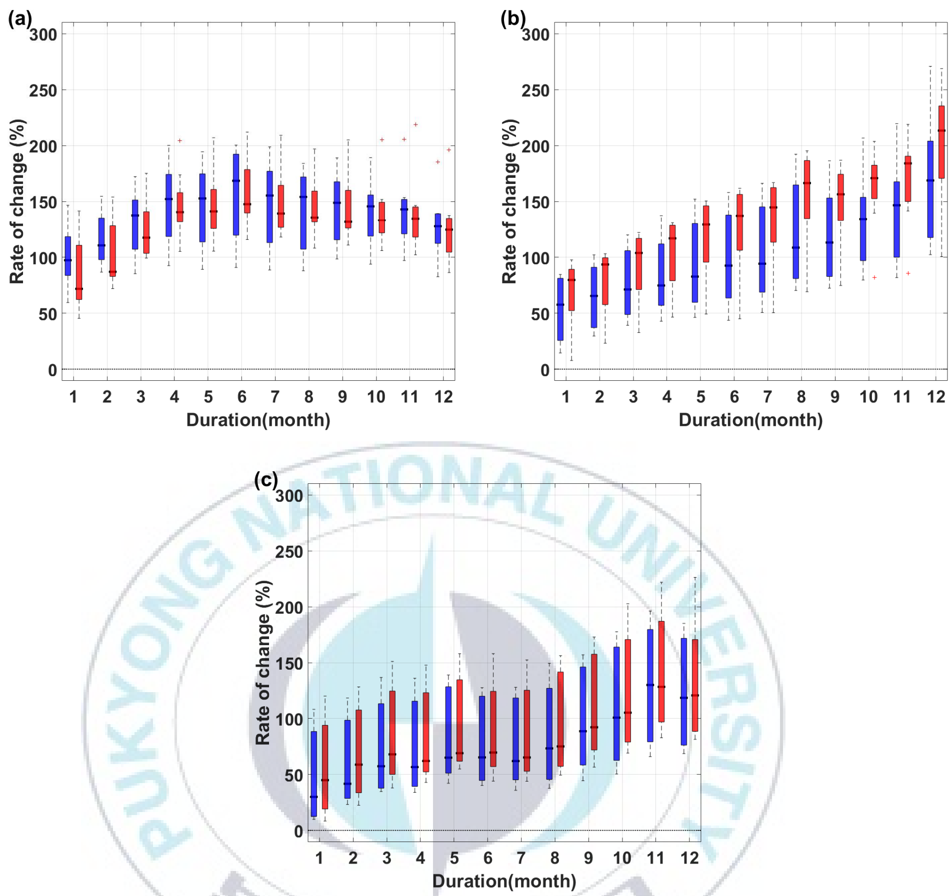

Fig. 3.12 Rate of change in future SDF curves of EDDI6 by RCP4.5(blue box plot) and RCP 8.5(red box plot) scenario at (a) Busan, (b) Chuncheon, (c) Daejeon.

EDDI6, on the other hand, is confident that future droughts will intensify. As shown in Fig. 3.12, EDDI6 shows the result that the future drought is intensified in contrast to SPI6, and none of the eight models alleviates the future drought. EDDI6 in all climate models suggests a moere sever future drought, which covers all three sites. A change rate of more than 100 % is present, and some models are well over 200%. In other words, some models predict that future droughts can be three times more severe than today. EDDI6 predicted that the future drought would be deepen for all climate models, but there is a problem with the large variation between models. The high uncertainty of the future EDDI6 is due to the estimation of E_o using various climate variables. E_o estimated by various climate variables has caused high uncertainty among climate models because the variables produced in the climate models have each uncertainty. EDDI6 also simulates the future drought so severely that doubts arise about whether it is a reasonable drought prospect.

As such, future droughts analyzed from two different sides using SPI6 and EDDI6 show opposite trends. Since precipitation and E_o are major climate variables affecting drought, it is important to consider two climate variables together rather than one to analyze future droughts.

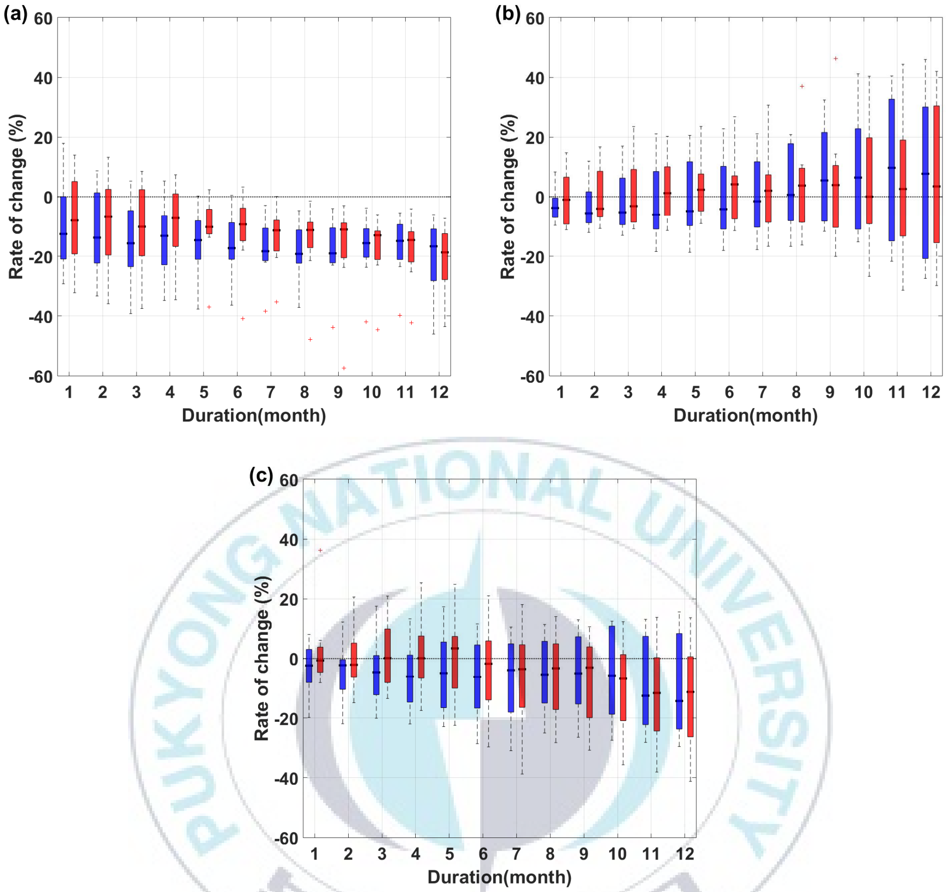

Fig. 3.13 Rate of change in future SDF curves of −SPEI6 by RCP4.5(blue box plot) and RCP 8.5(red box plot) scenario at (a) Busan, (b) Chuncheon, (c) Daejeon.

Fig. 3.13 is an analysis of future drought changes in SPEI6 that consider both climate variables together. However, SPEI6, which is affected by E_o, appears to mitigate future droughts, mostly similar to SPI6. In case of the Busan(Fig. 3.13(a)) and Daejeon(Fig. 3.13(c)), most models show a lowwer future drought severity than the present. In the Chuncheon(Fig. 3.13(b)), there is a contradictory future projection between the models, which is similar to SPI6. However, as with SPI6, the results of various drought projections between models are not convinced of the deepening or mitigation of droughts. As such, SPEI6 is affected by E_o, but it does not certainly deepen future drought like EDDI6, and shows a similar drought trend as SPI6. These results suggest that SPEI6 does not properly reflect the increase in temperature due to climate change in the prospect of future droughts.

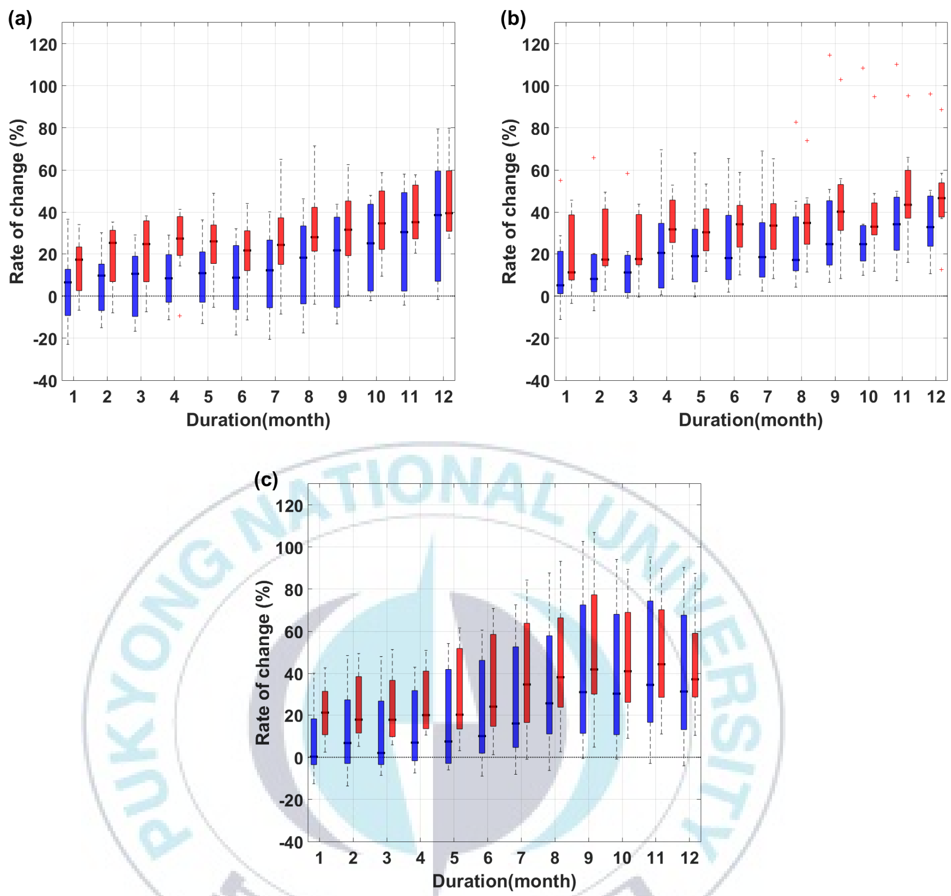

Fig. 3.14 Rate of change in future SDF curves of CJDI6 by RCP4.5(blue box plot) and RCP 8.5(red box plot) scenario at (a) Busan, (b) Chuncheon, (c) Daejeon.

CJDI6, like SPEI6, is a drought index affected by precipitation and E_o. In Fig. 3.14, unlike SPEI6, we can clearly see the characteristics of CJDI6 that properly reflect the effects of precipitation and E_o. The future droughts examined through CJDI6 show that the droughts are intensifying. Each RCP scenario shows an increase in drought at all sites except for some models. However, it does not forecast the drought to be as severe as EDDI6. CJDI6 is a drought index consisting of a combination of SPI6 and EDDI6. It provides a comprehensive assessment of the future behavior of the precipitation and E_o. CJDI6, like SPI6, admits that extreme rainfall events will increase in the future, but nonetheless argue that the drought due to increased temperatures will increase and intensify. This suggests that the rate of change is mostly high in the RCP8.5 scenario where higher temperature rises are expected, suggesting that CJDI6 can adequately reflect the increase in temperature. At the Busan(Fig. 3.14(a)) and Chuncheon(Fig. 3.14(b)), some models show drought mitigation, but most models claim to have drought severity. Indicates deepening. While some models indicate drought mitigation, most of the models claim to increase drought, and in the RCP8.5 scenario, there is a clear increase in drought severity. The Daejeon site is also expected to intensify future droughts and is expected to increase about 40% on average over long-term durations. What can be seen from CJDI6 is that the rate of change at all sites is mostly high over long durations. In other words, CJDI6 suggests that long-term droughts may occur more severely.

3.4 Discussion

The future droughts seen through the four drought indices are diverse. We can expect future precipitation and temperature to increase from the forecast results of drought indices based on different climate variables. In particular, an increase in temperature causes an excessive increase in evapotranspiration, and future drought analysis using only E_o shows unrealistic disasters in Korea. EDDI suggests that future droughts will be very serious because rising temperatures can significantly worsen the severity and impact of droughts(Allen et al., 2010; Mcdowell and Allen, 2015; Allen et al., 2015). On the contrary, the increase in precipitation soon mitigated future droughts. Future droughts identified through the SPI suggest alleviating. These results are also found in several studies that conducted future drought analysis on Korea using SPI(Sohn et al., 2014; Kim et al., 2016a). Under this climate change scenario of predicting the increase of precipitation and temperature, we can see that we need to analyze the future drought by considering both climate variables together.

However, since E_o is estimated from various climate variables, E_o in future is highly uncertain. The behavior of E_o for the RCP scenario can exacerbate uncertainty because it appears in many different forms in different climate models(Ainsworth and Rogers, 2007; Dijkstra et al., 2010; Milly and Dunne, 2016; Swann et al., 2016). The drought index, which is based on E_o, has a high level of uncertainty between models, because drought changes due to rising temperatures vary from region to region and can be very uncertain(Ault et al., 2016; Hessl et al., 2018). Nevertheless, as global warming progresses, E_o must be considered as an important factor that cannot be ignored in drought(Cook et al., 2014; Karnauskas et al., 2016). Therefore, future analysis using SPEI, which is one of the drought indices considering precipitation and E_o, was performed together. The results of SPEI in this study are very similar to those of SPI, and this can be found in various studies(Labudová et al., 2017; Yao et al., 2018). SPEI showed greater drought when SPI showed drought due to the effect of increasing E_o. This is explained by the fact that when E_o demands evaporation demand for water, the impact is felt even more in a moisture shortage condition(Tirivarombo et al. 2018). Although SPEI tends to simulate drought more seriously than SPI, nevertheless, SPEI has also resulted in mitigating future droughts. As the E_o-based EDDI simulated severe drought in future, it can be seen that the SPEI did not properly reflect the effects of E_o. CJDI, on the other hand, presented results that properly consider the effects of precipitation and E_o. CJDI has been evaluated for its applicability as a new drought index because of its excellent reproducibility to observed droughts in Korea. When the SPI or EDDI presents contradictory results on drought events in Korea, CJDI shows drought to reflect the drought expressed by one drought index. In other words, the biggest advantage of CJDI is that it is possible to monitor drought appropriately by comprehensively determining drought caused by changes in two climate variables. Drought does not always occur due to precipitation deficiency, but because E_o may be a major cause of drought(van der Schrier et al., 2013), it is possible to judge CJDI's superiority in the characteristics of drought. CJDI more reasonably suggests future drought projections. SPI and SPEI clearly indicate the mitigation of future droughts, which is inconsistent with a number of studies that suggest the possibility of deepening droughts due to global warming(Solomon et al., 2007; Jentsch et al., 2007; Sterl et al., 2008). In other words, CJDI's future drought seems to provide reliable results when the risk of future drought is sufficiently predicted. However, because CJDI is also a drought index based on E_o, there are also results with high uncertainty between models. It is necessary to select an appropriate estimation methodology or climate model that best simulates E_o to reduce the uncertainty of E_o in future climates.

Ⅳ. Application

4.1 Drought severity map

In this section, Korea drought severity map is written as one of the drought analysis applied with CJDI6. Drought severity map can be used to assess potential drought hazards by region, especially where droughts are vulnerable. The Drought severity map is prepared by deriving the observed SDF curves using observation data of 1973-2018 at 56 locations in Korea and plotting spatially drought severity by return period and duration. Figs. 4.1-4.2 show the drought severity map for different durations of 10 and 30 years return period.

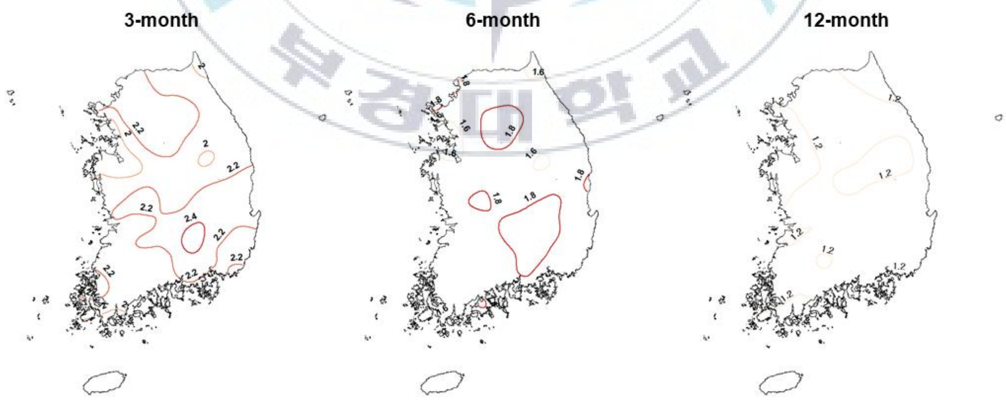

Fig. 4.1 Drought severity map of CJDI6 for 10-year frequency in Korea.

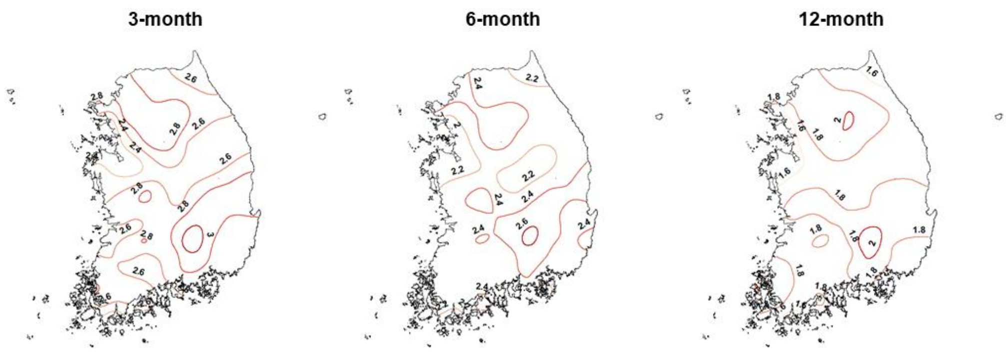

Fig. 4.2 Drought severity map of CJDI6 for 30-year frequency in Korea.

In general, short-term droughts are caused by rapidly changing climate variables, resulting in high drought severity and narrow range of effects. In contrast, long-term droughts occur over a long period of time, resulting in low average drought severity and a wide range of occurrence. The drought map analyzed by CJDI6 expresses the these characteristics of droughts. The 3-month drought, which is a short-term drought, suggests a higher and variety of drought severity in different regions than the 6- and 12-month droughts. The drought condition in Korea, which is examined through the drought map, shows that the drought severity in the southern region is higher than in other regions. In the case of a 3-month drought in Fig. 4.1, which is 10-year, the central region shows a drought severity of about 2-2.2, but in some areas of the southern region there is a high drought depth of 2.4. Similarly, a 6-month duration of drought has a drought severity of about 1.8 in the same area. Drought of 12-month duration shows similar drought severity across the country. In the 30-year return period (Fig. 4.2), the severity and range of droughts are higher than those of the 10-year drought. Also, similar to the result of 10-year of return period, high drought severity is expressed in southern region. There is a high drought severity of about 3 for a 3-month drought, about 2.6 for a 6-month drought, and about 2 for a 12-month drought in southern region. The region has a particularly high drought depth in Korea and can be judged to be a region with high risk of drought.

4.2 Drought condition analysis

It is very important to determine the situation of drought for drought monitoring. In order to analyze how drought occurs, this section analyzes the behavior of CJDI6 for the past drought event. We selected a severe drought that occurred during the 1994-1995 period in Korea and conducted an analysis in Busan of the southern region, where the drought was particularly severe. The time series by duration of the CJDI6 (Fig. 4.3) and the return period corresponding to the drought severity represented by CJDI6 (Fig. 4.4) are shown.

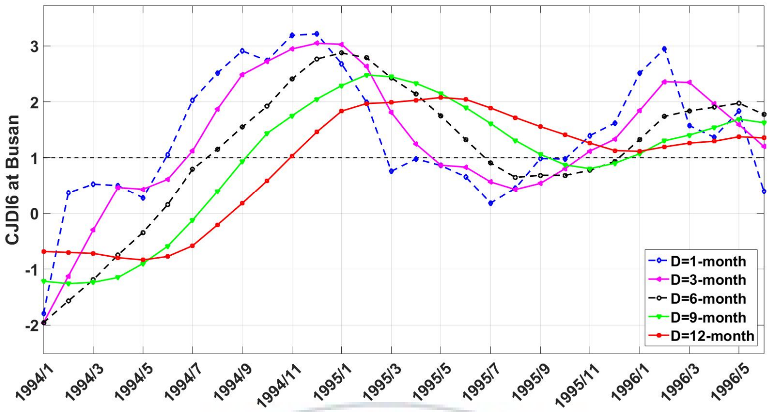

Fig. 4.3 Time series of CJDI6 for 1994-1996 at Busan site.

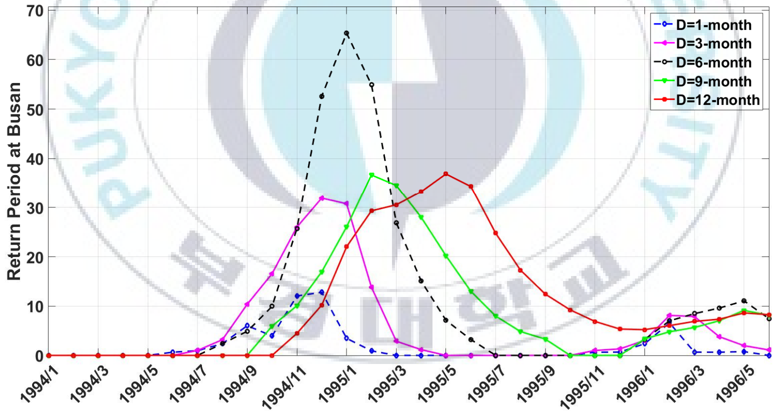

Fig. 4.4 return period of drought severity for 1994-1996 at Busan site.

In Fig. 4.3, short-term CJDI6 immediately expresses drought in mid-1994 when the drought onset, and long-term CJDI6 shows a gradually changing form of drought. The late 1994, when CJDI6 expresses extreme dryness, is a period during which the drought had sustained extremely. Short-term CJDI6 ended the drought in early 1995, while long-term CJDI6 maintained the drought well and lasted weak until 1996.

Fig. 4.4 shows the return period according to CJDI6 by duration. It can be seen that CJDI6, which shows a drought of 6-months duration, has the highest return period of about 60 years. The 3-month duration of CJDI6 represents a return period of about 30 years. In addition, CJDI6 with a long duration(9-months and 12-months) has a frequency of nearly 40 years. On the other hand, 1-month duration of CJDI6 has a frequency of 10 years, despite high drought severity. Even in the same drought event, it can be seen that it is very different to express drought according to duration. It is analyzed that the drought event is severe when analyzed for 6-months duration, but it is difficult to say that it is severe drought in the 1-months duration. Also, it can be regarded as an extreme drought in the 3-, 9- and 12- months duration. The drought event of the 1994-1995 period is drought that maintained for a long time, and it is not reasonable to analyze the drought event for a short-term duration. As the drought analysis is different according to the duration, it can be seen that it is very important to determine drought through various durations in drought monitoring.

4.3 Climate change adaptation

In Section 3.3, we applied the climate change scenarios to derive the SDF curve and quantitatively analyze changes in future droughts. In this section, we tried to examine the most severe drought events in the future using CJDI6. To this end, the most extreme drought events by duration were extracted from the PDS prepared for each future climate change scenarios. The most severe value for each duration is selected from the PDS of each scenarios. The worst drought severity values selected from eight models by RCP scenarios are plotted and shown along with the observed SDF curve(Fig. 4.5). Comparing with the observed SDF curves, we can determine if the most severe drought events in the future by climate change scenarios are drought with the observed years of return period. Some models of the RCP8.5 scenario project that the worst droughts can occur in all duration, over the current 100-year frequency. In particular, this possibility is most likely at the Daejeon site (Fig. 4.5 (c)). At the Daejeon site, most models of RCP4.5 and RCP8.5 express drought events over the current 100-year frequency. Some models suggest drought events of lower return period, but the drought events are also about 50 years current. In the case of the Busan site (Fig. 4.5 (a)), some durations of the RCP4.5 scenario show various results for each model, but for long-term durations, the frequency ranges from about 50 to 100 years. It is predicted that severe long-term droughts will occur in the future. In addition, most models in the RCP 8.5 scenario suggest that droughts corresponding to the current 100-year frequency will be occurred. At the Chuncheon site (Fig. 4.5 (b)), the worst drought events predicted by climate models appear to be in excess of the current 30-year frequency. Some models also have drought events that correspond to 100-year frequency.

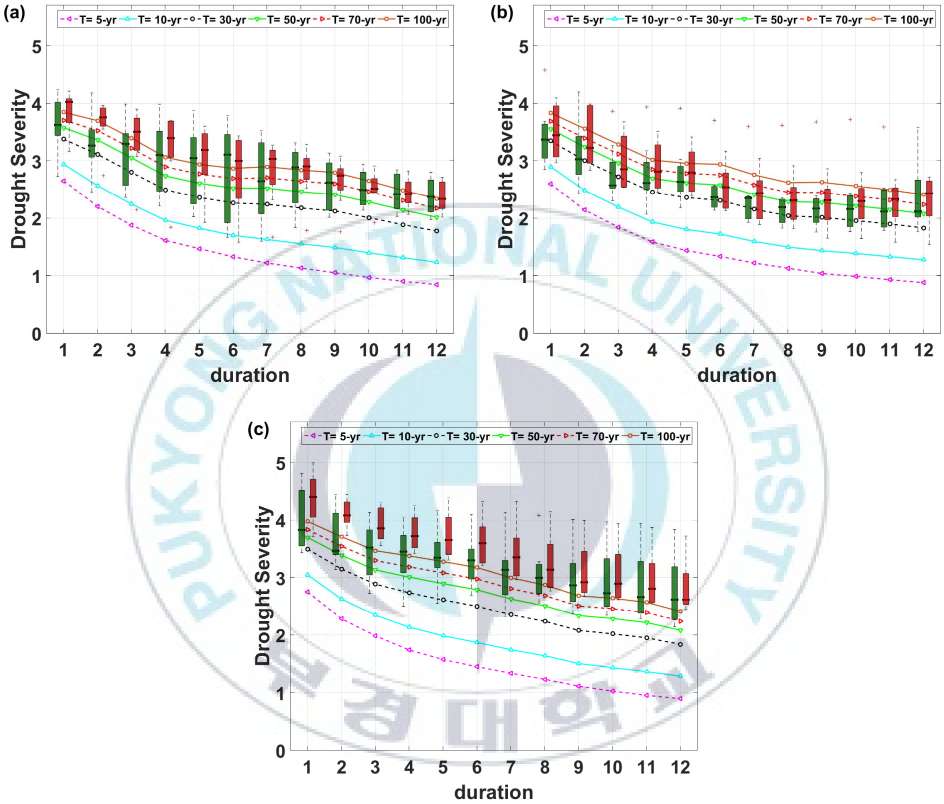

Fig. 4.5 Comparison of observed SDF curve and drought severity of the most extreme drought Event of RCP4.5 scenario(blue box plot) and RCP8.5 scenario(red box plot) at (a) Busan, (b) Chuncheon, (c) Daejeon.

The most severe drought in the future, shown in Fig. 4.5, is more likely to severly occur than the current 100-year frequency of drought. This can be expected to be more severe than the long-term drought event in 1994, which was a drought of 70-year frequency in Figs. 4.3-4.4.

V. Conclusion

The climate change scenario predicts an increase in precipitation, anticipating an increase in extreme rainfall event in the future. However, not only these extreme rainfall events but also the increase in temperature due to climate change are clearly forecasted. The increase in temperature leads to an increase in evapotranspiration, which in turn leads to the occurrence of drought. In these results, a drought index based on one climate variable suggests different future outcomes depending on which drought index is chosen. Therefore, in this study, we developed a drought index that interprets the moisture supply and demand sides of the atmosphere together and compared drought index developed with the existing drought index.

For SPI using only precipitation, future droughts were similar to or rather likely to be mitigated from current droughts. In the RCP8.5 scenario, the SPI proposed mitigation of future droughts. In contrast, EDDI has been shown to deepen future droughts. The prospect for future droughts presented by the SPI are somewhat unsuitable for applying to the pre-response to droughts, and are the result of conflicting opinions that anticipate the deepening drought in future. In this regard, EDDI, which certainly deepens future droughts, can be usefully applied in taking proactive measures to climate change. EDDI, however, had a very severe future droughts, and some models presented unrealistic results. EDDI predicted extreme drought than other drought indices because it only considers E_o and estimates drought with an increase in temperature. In addition, the uncertainty between climate models was very large because EDDI uses a variety of climate variables generated from climate models to calculate E_o. The results of these drought indices(SPI and EDDI) clearly show that when analyzing future droughts, two climate variables should be considered together, rather than taking into account only precipitation or E_o. However, SPEI, which considers precipitation and E_o together, provided similar results to SPI in future drought analysis. Since SPEI is mainly influenced by precipitation rather than E_o, future drought analysis using SPEI did not seem to fully reflect the increase in temperature. On the contrary, the CJDI proposed in this study reflects the effects of rainfall and E_o, and shows that the drought represented by the two climate variables is comprehensively judged. Since CJDI adequately reflects precipitation and E_o, it showed better reproducibility of observed drought events than existing drought indices. The future drought projected using CJDI suggests that it is likely to intensify. Unlike EDDI, CJDI also considers the increase in precipitation, and thus shows more realistic drought prospect without suggesting extreme drought events as EDDI. In the same analysis, CJDI provides more reliable forecasts among the drought indices that provide various future drought outcomes. Therefore, in this study, CJDI was selected as a suitable drought index for drought analysis and applied to various analyzes.

The results of this study suggest that it is more reasonable to analyze and predict droughts by taking together precipitation and E_o, the main variables associated with droughts. Because drought is a complex natural phenomenon caused by various climate variables, it is important to comprehensively express the drought situation by two weather variables, not only one. In this regard, it is deemed that the CJDI proposed in this study can be fully utilized as a drought index to analyze drought.

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