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Thesis for the Degree of Master of Engineering

Identification of River Water Temperature Vulnerable Sections to Meteorological Drought at Major Rivers in Korea

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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Identification of River Water Temperature Vulnerable Sections to Meteorological Drought at Major Rivers in Korea
(전국 주요하천에서 기상학적 가뭄에 대한 하천 수온 취약 구간 식별)

Advisor: Prof. Sangdan Kim

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전국 주요 하천에서 기상학적 가뭄에 대한 하천 수온 취약 구간 식별

서지유

부 경 대 학 교　대 학 원　지 구 환 경 시 스 템 과 학 부
환 경 공 학 전 공

요　　약

가뭄은 인간의 직접적인 물이용뿐만 아니라 수생태계에도 큰 영향을 미치는 자연현상이다. 본 연구에서는 수생태계의 전반적인 건강성에 중요한 역할을 하는 하천 수온에 기상학적 가뭄이 미치는 영향을 확률론적인 관점에서 분석하였다. 기상학적 가뭄은 대기로부터 수분이 부족하게 공급되는 상황과 대기가 지표면으로부터 과도하게 수분을 요구하는 상황으로 구분된다. 코퓰러 이론을 이용하여 하천 수온과 두 가지 원인으로 발생하는 각각의 기상학적 가뭄 사이의 결합 확률 모델이 제안된다. 한국의 주요 하천 구간들에 제안된 모델을 적용한 결과, 대기로부터 수분이 부족하게 공급되는 기상학적 가뭄이 발생할 때는 대부분의 하천 구간들에서 수생태계는 봄, 여름, 가을에 고수온 스트레스를 받을 가능성이 컸으며, 겨울에 저수온 스트레스를 받을 가능성이 컸다. 반면에, "대기가 지표면으로부터 과도하게 수분을 요구하는 기상학적 가뭄"이 발생할 때는, 계절에 상관없이 고수온 스트레스가 수생태계에 부과되는 것으로 나타났다. 제안된 모델을 이용하여 사용자에 의해 정의된 기상학적 가뭄 심각도 조건하에서 수생태계가 받게 되는 수온 스트레스에 대한 위험도 지도가 그려질 수 있음이 보여진다. 위험도 지도를 이용하여 수온의 측면에서 기상학적 가뭄에 상대적으로 더 민감하게 반응하는 하천 구간들이 식별될 수 있음이 드러난다. 식별된 하천 구간들은 기상학적 가뭄의 발생 원인에 따라, 지역에 따라, 그리고 계절마다 다르게 나타남이 드러난다.

Ⅰ. Introduction

Drought is a natural phenomenon that can occur in all climatic zones, and is temporally persistent and spatially widespread (Tallaksen and van Lanen, 2004; Bond et al., 2008; Yeh et al., 2015; Apurv et al., 2017; Kim et al., 2017; Lee et al., 2018; Park et al., 2018; Gao et al., 2019). Extreme drought is a complex natural disaster with severe impacts on agriculture, socio-economic systems, and ecological environments (Mishra and Singh, 2010; Van Loon and Van Lanen, 2013; Fang et al., 2019; Guo et al., 2019; Han et al., 2019; Huang et al., 2019). Due to the increasing trend of rainfall variability and surface air temperature, the frequency, duration, severity, and affected area of droughts are increasing in many regions of the world (Dai, 2013; Won and Kim, 2020). Future climate change will not be temporally and spatially uniform, and regional changes in precipitation and surface air temperature may lead to more severe droughts and consequent changes in hydrological patterns (Mishra and Singh, 2010; Trenberth et al., 2014; Mosley, 2015; Ahmadalipour et al., 2017). Meteorological drought caused by insufficient precipitation or excessive evaporative demand extends to agricultural, hydrological, and socioeconomic droughts (Van Loon and Laaha, 2015; Hobbins et al., 2016; Heudorfer and Stahl, 2017). In addition, extreme meteorological drought can be transferred to environmental drought that seriously affects the aquatic ecosystem (Mulholland et al., 1997), which can again cause significant social and economic damage to us (Mosley, 2015).

Many studies have been conducted on the relationship between meteorological drought and river water quality. Peña-Guerrero et al. (2020) found a negative correlation between drought and electrical conductivity and major ions in the Maipor river in central Chile. Kim et al. (2019) analyzed the change in water quality corresponding to the severity of drought in the Nakdong river in Korea, and reported that there was a significant correlation between drought and BOD, COD, Chloropyll-a, and TP. In some studies, the proportion of groundwater runoff in stream flow during drought increased relatively, and most rivers found a tendency to increase in salinity (Mayer et al., 2010; Hrdinka et al., 2012; Mosley et al., 2012). Conversely, suspended solids have been observed to decrease during drought in many streams (van Vliet and Zwolsman, 2008; Mosley et al., 2012). Different water quality factors showed complex responses during drought. Several studies have found that there is little change in dissolved oxygen during drought or an increase in dissolved oxygen concentration other than at night during drought (van Vliet and Zwolsman, 2008; Hrdinka et al., 2012). Some other studies have reported a decrease in dissolved oxygen in streams where the water temperature rises or in streams where pollutants are present (Chessman and Robinson, 1987; Sprague, 2005; van Vliet and Zwolsman; 2008, Ylla et al., 2010). Osterholm and Astrom (2008) observed that river pH continued to decrease for several years after drought, Sprague (2005) and Zielnski et al. (2009) found an increase in river pH with an increase in alkalinity. Nitrogen and phosphorus concentrations decreased in many streams through a decrease in the load input to the stream and absorption of nutrients by aquatic algae and macrophytes during drought (Mosley et al., 2012; Baures et al., 2013). In contrast, there have been studies showing elevated nitrogen and phosphorus concentrations in some streams (van Vliet and Zwolsman, 2008; Macintosh et al., 2011; Hrdinka et al., 2012).

In this study focused on the relationship between meteorological drought and water temperature among various water quality items in rivers. Since water temperature is one of the key parameters of river ecology that determines the overall health of aquatic ecosystems, water temperature is an environmentally and ecologically important water quality parameter (Coutant, 1999; Caissie, 2006). Water temperature controls many physical, chemical, and biological processes in streams, such as dissolved oxygen concentrations and metabolism of aquatic plants and animals (Matthews and Berg, 1997; Lessard and Hayes, 2013; Marzadria et al, 2013). In addition, since water temperature can change significantly under anthropogenic perturbations such as dam construction and climate change, water temperature is also an important indicator of hydrological change and climate variability (Olden and Naiman, 2009; Isaak et al., 2012; Soto, 2018). A decrease in stream flow and an increase in surface air temperature due to drought can cause changes in the water temperature of streams (Morse, 1972; Sinokrot and Gulliver, 2000).

In recent years, climate change has been identified as an important cause of disturbances on a large or global scale (Sinokrot et al., 1995; Schindler, 2001). Murdoch et al. (2000) and Whitehead et al. (2009) reviewed a wide range of potential impacts of climate change on surface water quality and aquatic ecosystems. Although these studies include some of the effects of drought on water quality and aquatic ecosystems, more detailed investigations are needed given the possibility of an ever-increasing risk of drought. In particular, an increase in water temperature during drought has been reported, and since many aquatic organisms can only survive in a specific water temperature range, changes in water temperature during drought will have a significant impact on river ecosystems (Coutant, 1977; Ahmadi et al. al., 2019). Water temperature influences the growth rate and distribution of aquatic organisms (Markarian, 1980; Jensen, 1990; Elliott and Hurley, 1997; Ebersole et al., 2001). Therefore, it is essential to consider water temperature in order to maintain the ecological and biological integrity of water systems (Vannote et al., 1980; Matthews and Marsh-Matthews, 2003; Lake, 2011). Climate change can significantly modify the distribution of aquatic organisms because the water temperature in some systems has already reached critical limits for aquatic ecosystems (Eaton et al., 1995). For example, from cases such as California (Brumbaugh et al., 1994; Israel and Lund, 1995), Australia (Leigh at al., 2015), and the southern United States (Buskey et al., 2001), it can be found all over the world that plants and animals are being damaged by drought. According to these studies, the causes of damage to aquatic ecosystems due to drought were increased water temperature and oxygen demand, loss of natural habitats, loss of river connectivity, and disruption of food chains (Lake, 2003). Therefore, when drought occurs, accurate and reliable water temperature information and risk management in various climatic and hydrological conditions can help protect and manage river ecosystems (Qiu et al., 2020).

Changes in river water temperature during drought have been reported in many studies (Davies, 1978; Boulton and Lake, 1992; Caruso, 2002). van Vliet and Zwolsman (2008) found a median water temperature increase of 2°C during the drought period in the Meuse river, with an average increase of 1.7°C in some streams in the Czech Republic and 1.3°C in some streams in Poland during the same drought period (Zielnski et al, 2009). Ha et al. (1999) reported a very large increase (approximately 7°C) in water temperature in artificially controlled lower Nakdong River in Korea during drought. In general, it is known that an increase in water temperature during a drought is meteorologically related to an increase in surface air temperature during a drought event (Hrdinka et al., 2012). In contrast, Wilbers et al. (2009) did not find a significant increase in water temperature in the Dommel river in the Netherlands due to the large amount of groundwater flowing from deep aquifers during drought. Mosley et al. (2012) noted that the water temperature downstream of the Murray river in Australia did not increase as expected even during extremely low flow rates, stating that this was because the surface air temperature did not increase during the drought period. In addition, in the South Platte river basin of the United States, the water temperature of the rivers in the forest area increased, but the rivers in the urban and agricultural areas showed little change (Sprague, 2005). This was analyzed to be attributable to the more efficient heat transfer of relatively smaller streams and the normally cooler influent in forested areas, and dilution from point sources or downstream groundwater in urban and agricultural areas.

When trying to quantify the effect of meteorological drought on river water temperature, there is a limit to using only river water temperature information. Therefore, systematic investigation using the relationship between meteorological variables or meteorological drought indices and river water temperature is important. When a meteorological drought event is realized, the process from climate to river water temperature is very complex, so it is not easy to capture important correlations between climate and river water temperature only by monitoring river water temperature using simple trend analysis. Constructing an appropriate joint probability that can describe the relationship between climate variables - stream water temperature can be an appropriate approach to understand the climate - stream water temperature process (Jha et al., 2019). The dependence structure of multivariate distributions can be constructed using classical distributions such as multivariate normal distributions (Laux et al., 2011), but the dependence between climate variables and river temperature is usually very complex and varies in both time and space. Therefore, it may not be appropriate to describe the subordinate structure between data in a classical way (Bardossy and Pegram, 2009; Kim et al., 2012). Since the copula function has the advantage of handling all types of marginal distributions, it is a powerful approach to combining various random variables (Ryu et al., 2012; Li et al., 2018; Guo et al., 2020). In fact, the stochastic framework using copula can investigate the response of the dependent variable to the external force resulting from the independent variable, so the copula theory has been applied in various fields including drought (Fang et al., 2019; Wang. et al., 2021). It is also applied to model the structure of dependence between various drought indices (Won et al., 2018).

In this study, the risk of water temperature stress to aquatic ecosystems due to meteorological drought is evaluated through probabilistic modeling between climate and river water temperature in river sections in Korea. Meteorological drought that affects river water temperature is divided into two causes. The first is a meteorological drought caused by a lack of precipitation, a source of moisture from the atmosphere. This is explained by the Standardized Precipitation Index (SPI; Mckee et al., 1993), which is a representative drought index based on precipitation. The second is meteorological drought caused by excessive evapotrative demand, which is an aspect of atmospheric moisture demand. This is expressed as the Evaporative Demand Drought Index (EDDI; Hobbins et al., 2016), which is a representative drought index based on reference evapotranspiration (Eo). Based on the copula theory, the joint probability distribution between the river water temperature and the meteorological drought index representing the drought resulting from two causes is modeled. The effect of meteorological drought classified by the cause on the river water temperature is analyzed for each season in major river sections in Korea.

Ⅱ. Materials and Methods

2.1 Data

To calculate the meteorological drought index, the daily maximum surface air temperature (°C), daily minimum surface air temperature (°C), daily dew point temperature (°C), daily average wind speed (m/s), and daily precipitation (mm/d) was used. These are all data from January 1980 to December 2020 of 56 ASOS (Automated Surface Observation System) sites operated by the Korea Meteorological Administration (https://data.kma.go.kr/). Eo for estimating EDDI, a meteorological drought index in terms of atmospheric moisture demand, was calculated on a monthly basis using the Penman-Monteith method (Allen et al., 1998). Monthly precipitation was also aggregated to estimate SPI, a meteorological drought index in terms of moisture supply from the atmosphere. Monthly precipitation and monthly Eo were spatially averaged using the Thiessen area – weighted averaging method based on the observation sites for river water temperature. Fig. 2.1 shows the watershed map divided by the water temperature observation sites and the locations of 56 meteorological observation sites. The unit basin of the Han River is indicated in green, the unit basin of the Nakdong River in yellow, the unit basin of the Geum River in pink, and the unit basin of the Yeongsan River in blue, and the meteorological observation point is indicated by a red dot. In addition, the unit basin marked in dark black represents the HG-F of the Han River.

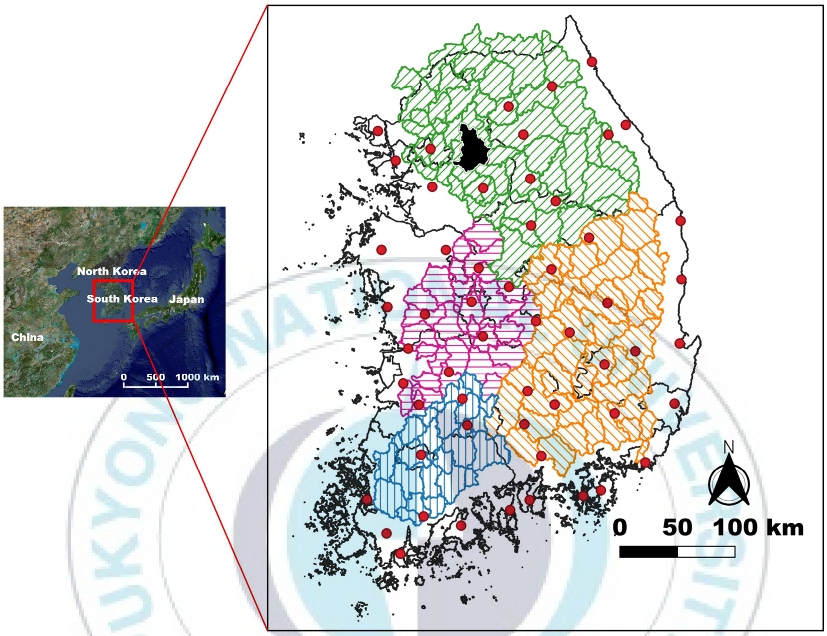


Fig. 2.1 Location of study sub-basins and meteorological observation sites.

The spatial extent of a sub-basin includes not only that sub-basin, but all sub-basins upstream of that sub-basin. This is because the spatial range that affects the river water temperature of the sub-basin includes not only the sub-basin but also all sub-basins upstream. For example, the spatial extent of NB-M, the sub-basin of the lowest downstream of the Nakdong River Basin in the southeast, is the entire Nakdong River Basin.

The river water temperature data were prepared from 140 observation sites (48 sites in the Han River Basin, 40 sites in the Nakdong River Basin, 30 sites in the Geum River Basin, and 22 sites in the Yeongsan River Basin). The data period is from January 2004 to December 2020, and was obtained from the Water Environment Information System operated by the Korean Ministry of Environment (http://water.nier.go.kr/). Since the river water temperature is measured with a rather irregular observation period of about 40 times per year, the data observed in a specific month are arithmetic averaged to form monthly data.

2.2 Conversion of river water temperature data

Fig 2.2 shows the monthly river water temperature time series of sub-basin HG-F. The river water temperature data clearly has a 12-month periodic component, and water temperature data from other sites have a similar periodic component. These periodic components act as noise in the correlation analysis with the meteorological drought index. Therefore, after removing the periodic component of the data using Equation (1) or (2), the subsequent procedure was performed.

$$x_{i,j} = \frac{y_{i,j} - y_j^m}{y_j^M - y_j^m} \tag{1}$$

$$x_{i,j} = \frac{y_j^M - y_{i,j}}{y_j^M - y_j^m} \tag{2}$$

where, $y_{i,j}$ is the river water temperature for year i and month j, y_j^m is the minimum value of the month j data, y_j^M is the maximum value of the month j data, and $x_{i,j}$ is the converted value of the river water temperature.

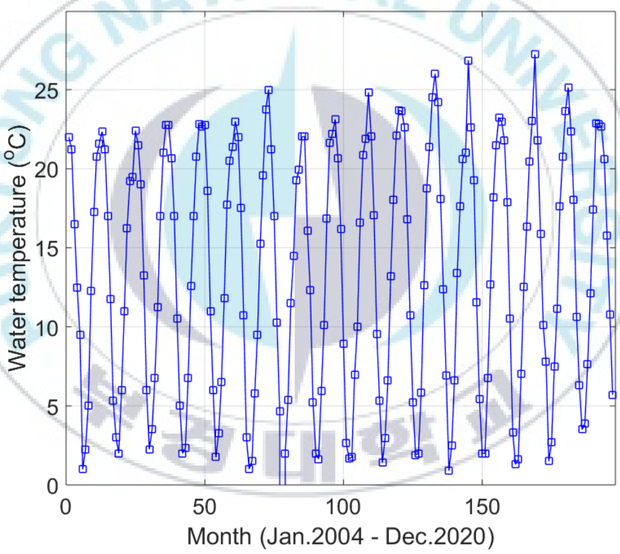


Fig. 2.2 Monthly water temperature time series at HG-F of Han river.

In this study, the correlation between river water temperature and meteorological drought index was analyzed for each season. For convenience, spring was classified into March, April, May, summer in June, July, August, autumn in September, October, November, and winter in December, January, and February, respectively. For the convenience of analysis, the river water temperature data were converted by applying Equation (1) or (2) so that the transformation variable $x_{i,j}$ for each season has a positive correlation with the meteorological drought index. That is, after converting the river water temperature data using Equation (1), if the correlation with the meteorological drought index has a positive value, the subsequent procedure was performed using the converted variable as it is. However, if the correlation had a negative value, the transformed variable using Equation (2) was applied to the subsequent procedure.

2.3 Meteorological drought index

In this study divided meteorological drought into drought caused by insufficient moisture supply from the atmosphere and drought in which the atmosphere requires excessive moisture from the surface. SPI is a drought index designed from the perspective that drought occurs when there is insufficient moisture supply from the atmosphere. That is, drought is identified using only precipitation (Chang et al., 2006; Kim et al., 2011). The EDDI is a drought index designed with the view that drought occurs when the atmosphere requires excessive moisture from the earth's surface. EDDI is attracting attention as a reasonable drought monitoring method in the coming global warming era (Ciais et al. 2005; Sharafati et al., 2020). The applicability of EDDI has been evaluated in various regions

(McEvoy et al., 2016; Yao et al., 2018; Won and Kim, 2020).

The EDDI in this study is estimated from Eo calculated by the Penman-Monteith method. Both SPI and EDDI were reported by Mckee et al. (1993) was calculated based on the SPI calculation formula. SPI and EDDI are calculated using the moving average daily precipitation or Eo for each duration. After estimating a probability distribution suitable for 365 time series configured for each day, it is converted into a cumulative probability value according to the probability distribution of each time series. A value of the standard normal distribution is calculated for the converted cumulative probability value, and in this case, the value means SPI or EDDI. The probability distribution type used is a two-variable Gamma distribution, and the probability density function equation is as follows.

$$f(x) = \frac{1}{\alpha^{\beta}\Gamma(\beta)} x^{\beta-1} e^{-(x/\alpha)} \quad \cdots (3)$$

where x is the moving average daily precipitation for each duration (mm), α is a scale parameter, and β is a shape parameter. The parameters and are estimated by the probability weighted moment method.

The two meteorological drought indices conceptually represent oppositely the moisture state. A negative value of SPI means insufficient precipitation, and a positive value of EDDI means an excessive increase in Eo. Therefore, as the drought deepens, SPI has a large negative value and EDDI has a large positive value. For an intuitive comparison of the two meteorological drought indices, nEDDI (negative EDDI) with a (-) sign attached to EDDI was used in the actual analysis.

In this study, 12 time-scales (1-month to 12-month) SPI and nEDDI were used. After analyzing the correlation between the river water temperature and the meteorological drought index calculated by each time-scale for each season, the copula function combined with the river water temperature was constructed using the most correlated time-scale meteorological drought index.

2.4 Copula function of meteorological drought index and river water temperature

According to Sklar's theorem (Sklar, 1959), the joint cumulative probability distribution $F(x,z)$ of water temperature X and drought index Z can be expressed as follows:

$$F(x,z) = C(F_X(x), F_Z(z)) = C(u,v) \tag{4}$$

where $F_X(x)$ and $F_Z(z)$ are the marginal cumulative probability distribution functions (CDFs) of water temperature and drought index, respectively, indicating u and v, respectively, and C is the copula function.

Before modeling the joint probability distribution, it is necessary to determine the appropriate marginal probability distribution for each variable, namely water temperature and drought index. To select the optimal probability distribution of water temperature for each season, six commonly used theoretical probability distributions were compared, including Normal distribution, Log-Normal distribution, Gamma distribution, Weibull distribution, Log-Logistic distribution, and GEV distribution. The parameters of each distribution were estimated by the maximum likelihood method. The optimal marginal distribution was selected using the chi-square goodness-of-fit test. Since the drought index has no choice but to follow the standard normal distribution due to the nature of the induction process, the standard normal distribution was selected as the optimal marginal distribution for the drought index. Once the optimal marginal distribution is determined, an appropriate copula function is needed to model the joint probability distribution. In this study, several copula functions widely used in various literatures, namely Clayton, Frank, Gumbel, Gaussian, and Student-t copula functions, were used (Salvadori and De Michele, 2004). The parameters of the copula function were estimated using the maximum likelihood method. To obtain the bivariate empirical CDF for constructing the likelihood, the bivariate plotting position formula proposed by Zhang and Singh (2006) was applied. The copula function that best captures the dependency structure between water temperature and drought index was determined using the Akaike Information Criterion (AIC, Akaike,

1973) (Sadegh et al., 2017). The optimal copula function was selected using 17*3 (i.e., 17 years*3 months) water temperature-drought index pairs per season.

Given the joint probability distribution of water temperature and drought index, it is possible to derive a conditional probability distribution of water temperature in the drought severity condition set by the user. If the water temperature is transformed using Equation (1), given $Z \leqq z$ (i.e., the condition that SPI≤-1), one may be interested in a certain conditional exceedance probability of $X \geqq x$ (that is, the probability of being above a certain water temperature, or the probability of being subjected to high water temperature stress), and it can be expressed as follows (Zhang and Singh, 2007):

$$F_{X \geqq x | Z \leqq z}(x, z) = \frac{1 - C(F_X(x), F_Z(z))}{F_Z(z)} = \frac{1 - C(u, v)}{v}. \tag{5}$$

Equation (5) can be applied to calculate the conditional exceedance probability of water temperature under various drought severity conditions. In fact, event u can be defined as risk when u exceeds a certain threshold level (Salvadori and De Michele, 2004). In this study, when $u \geqq 0.85$, the aquatic ecosystem was considered to be in a stressful state (i.e., at risk) by high water temperature.

Also, given $Z \leqq z$, one may be interested in the specific conditional non-exceedance probability of $X \leqq x$ (i.e., the probability of being below a specific water temperature or the probability of being subjected to low water temperature stress), which can be expressed as follows:

$$F_{X \leq x | Z \leq z}(x,z) = \frac{C(F_X(x), F_Z(z))}{F_Z(z)} = \frac{C(u,v)}{v} \tag{6}$$

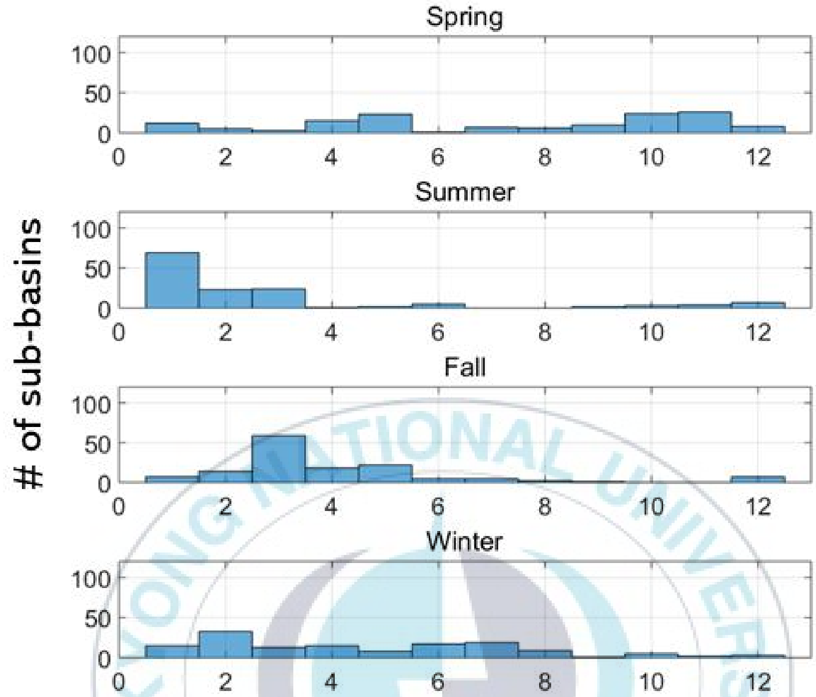
Equation (6) can be applied to calculate the conditional non-exceedance probability of water temperature under various drought severity conditions. In this case event u can be defined as risk when u does not exceed a certain threshold level. In this study, the case where $u \leqq 0.15$ was considered to be in a state where the aquatic ecosystem was stressed by the low water temperature.

When the water temperature is converted using Equation (2), the high water temperature stress probability and the low water temperature stress probability can be defined in a similar manner to the above. In this study, the risk of water temperature stress has been investigated using a scenario in which the moisture supply from the atmosphere is moderately severe, that is, a scenario with an SPI of -1 or less, and a scenario where the atmospheric moisture demand is moderately severe, that is, a scenario with an EDDI of 1 or more. This means that $v \leqq 0.1587$ is given as the meteorological drought severity condition. It would be possible to apply other drought severity conditions (e.g., SPI≤-1.5 or EDDI≥1.5). In addition, it would be possible to investigate the conditional probability of water temperature using different water temperature stress threshold levels (e.g., $u > 0.95$ or $u \leqq 0.05$). Based on the joint probability distribution established for water temperature and drought index, various combinations of water temperature threshold level and meteorological drought severity condition can be applied in a similar way by Equation (5) or (6).

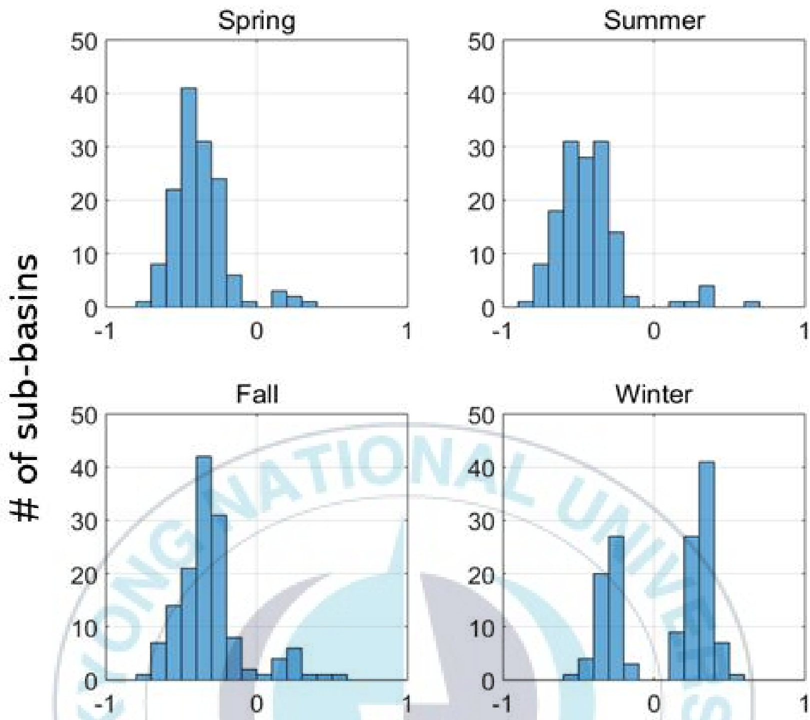
Ⅲ. Results and Discussion

3.1 Time-scale for drought index

The drought index was calculated using the 1-month to 12-month time-scale for the period from 1980 to 2020. In order to construct a bivariate copula model of drought index and water temperature, the correlation between water temperature and drought index of various time-scales was analyzed. Correlation analysis was performed separately for each season. The time-scale of the drought index with the highest absolute value of the cross-correlation coefficient with water temperature was selected as the optimal time-scale. Fig. 3.1 shows the optimal time-scale adopted for the correlation analysis between SPI and water temperature and the corresponding cross-correlation coefficient in 140 river sections. Fig. 3.2 shows the results using nEDDI.

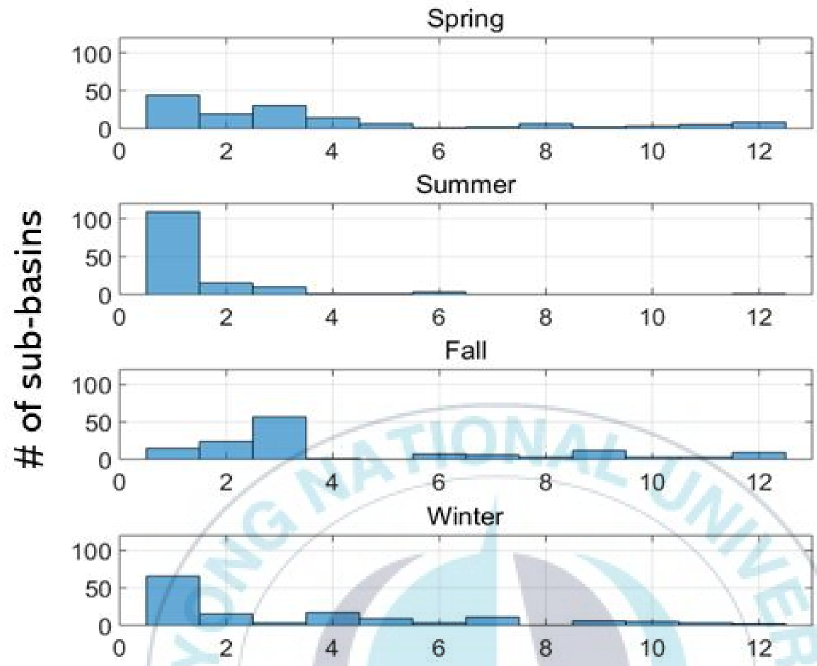


(a) Time-scale (month) at SPI

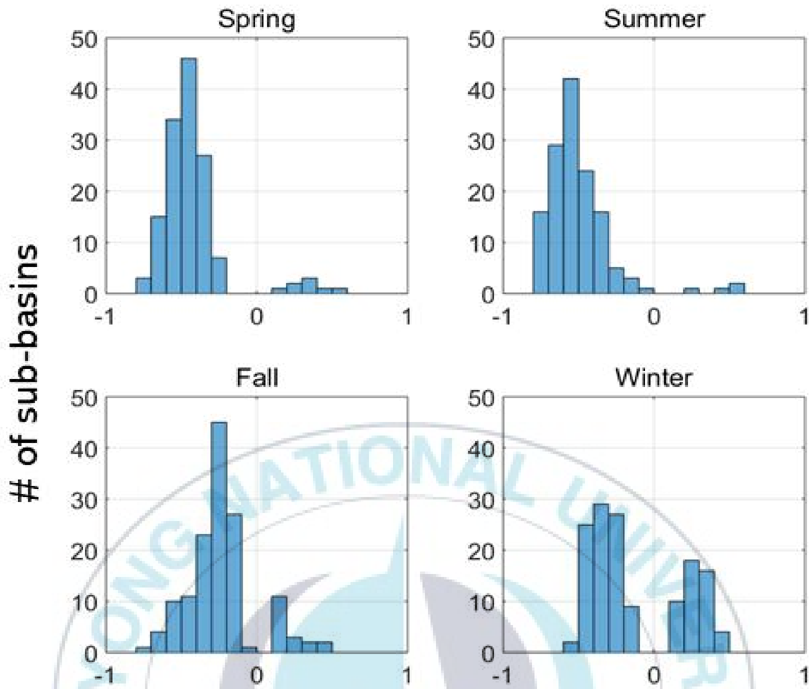


(b) Cross-correlation coefficient

Figure 3.1 Histogram of optimal time-scale for SPI and cross-correlation between water temperature and SPI.



(a) Time-scale (month) at nEDDI



(b) Cross-correlation coefficient

Figure 3.2. Histogram of optimal time-scale for nEDDI and cross-correlation between water temperature and nEDDI.

In summer, the short time-scale SPI has a high correlation with water temperature, and in spring, it can be found that the relatively long time-scale SPI has a high correlation with the water temperature. The water temperature and the SPI of the selected optimal time-scale show a negative correlation in most river sections in spring, summer and autumn. It can be seen that in winter, the number of river sections showing a positive correlation increases. From these results, the following facts can be inferred. 1) In summer, river water temperature reacts sensitively to short-term lack of moisture supply. 2) In spring, summer, and autumn, when the moisture supply from the atmosphere is insufficient, the temperature of the river is likely to be higher than usual. 3) In winter, when moisture supply from the atmosphere is insufficient, it is divided into a river section in which the temperature of the river tends to be lower and a river section in which the water temperature is higher.

The optimal time-scale and cross-correlation coefficients of nEDDI are somewhat different from their SPI counterparts. In general, the short time-scale nEDDI shows a higher correlation with water temperature. For most sites, the optimal time-scale of nEDDI is shorter than the optimal time-scale of SPI. This means that river water temperature responds more sensitively to sudden atmospheric moisture demand than to gradual atmospheric moisture demand. Signs of correlation were similar for SPI and nEDDI. In other words, it can be recognized that the river water temperature tends to be higher than usual when excessive moisture demand from the atmosphere occurs in spring, summer, and autumn. It is also found that some river sections occur in winter where the water temperature is drawn in a lower direction by the excessive demand for moisture in the atmosphere. However, the number of river sections where the river water temperature decreased in winter was not as large as when the moisture supply was insufficient.

Another important fact that can be recognized from Fig. 3.1 and

3.2 is that the correlation between the meteorological drought index and water temperature varies from season to season. This indicates the fact that it is reasonable to perform the analysis by dividing the seasons. In addition, depending on the time-scale applied to the drought index, the correlation between the drought index and water temperature is variously shown. This fact means that it is reasonable to apply the drought index calculated from the appropriate time-scale by identifying the time-scale most correlated with water temperature.

3.2 Bivariate copula model of drought index and water temperature

In this section, based on the data of the HG-F (the location of the HG-F can be confirmed through Fig. 2.1) among the unit watersheds of the Han River, the copula theory based joint probability distribution is used to quantify the possibility of water temperature-related environmental drought under the given drought index condition. An example of the application of the distribution is described. In this study, data were divided into spring (March-May), summer (June-August), autumn (September-November), and winter (December-February), and analysis was performed by season. When the drought index of the optimal time scale is adopted through the correlation analysis between the drought index and water temperature, bivariate copular coupling modeling of the drought index of the adopted optimal time scale and the water temperature conversion variable is performed. First, an appropriate marginal distribution for seasonal water temperature conversion variables is determined. Table 3.1 shows the optimal time scales of SPI and nEDDI adopted by season in Han River F, and Table 3.2 shows the appropriate distribution of limits for water temperature conversion variables.

Table 3.1 Optimal time-scales at HG-F of Han river

Optimal time-scale (month)	Spring	Summer	Fall	Winter
SPI	11	3	3	1
nEDDI	3	3	3	1

Table 3.2 Goodness-of-fit statistics (Chi-square p-value) of different theoretical distribution for water temperature in different seasons at HG-F of Han river

Distribution	Spring	Summer	Fall	Winter
Normal	0.5601	0.2602	0.0315	0.5332
Log-Normal	0.0000	0.0000	0.0000	0.0000
Gamma	0.0000	0.0000	0.0000	0.0000
Weibull	0.2426	0.0000	0.0060	0.0136
Log-Logistic	0.0000	0.0000	0.0000	0.0000
GEV	0.5831	0.0653	0.0072	0.0812

Table 3.2 shows the limit distribution applied for the water temperature conversion variable and the p-value statistics of the Chi-square test by time period. The p-value of the optimal marginal

distribution is indicated in bold. The most appropriate marginal distribution varies by season. This is because the interaction between the water temperature conversion variable and the drought index is different for each season, so it is important to select the optimal marginal distribution for each season. Then, a combined probability distribution of the drought index and water temperature transformation variable is constructed using a copular-based method. When the combined probability distribution is determined, the conditional distribution of the water temperature transformation variable under the given drought index is obtained.

Fig. 3.3 and 3.4 show the bivariate copula modeling results in HG-F, one of the sub-basins of the Han River Basin. The AIC of the copula functions calculated for each season, the Q-Q plot of the selected optimal copula function, and the conditional distribution of water temperature under a user-set drought severity condition are shown sequentially from left to right.

For the relationship between SPI and water temperature in sub-basin HG-F, Frank in spring and summer, Clayton in summer, and Gumbel in winter were found to be the most appropriate copula function. For the copula function of nEDDI and water temperature, Frank in spring, Clayton in summer, Student-t in autumn, and Gumbel in winter were most appropriate. The most appropriate copula function varied from season to season. This is because the interaction between water temperature and drought index was different for each season, and this fact suggests that it is important to individually select the optimal copula function for each season. Looking at Q-Q plots drawn from various sites, some sites exhibited large deviations, mainly due to the fact that the number of observations to fit the copula function was insufficient. Therefore, it should be taken into account that the uncertainty caused by this is included in the results of this study.

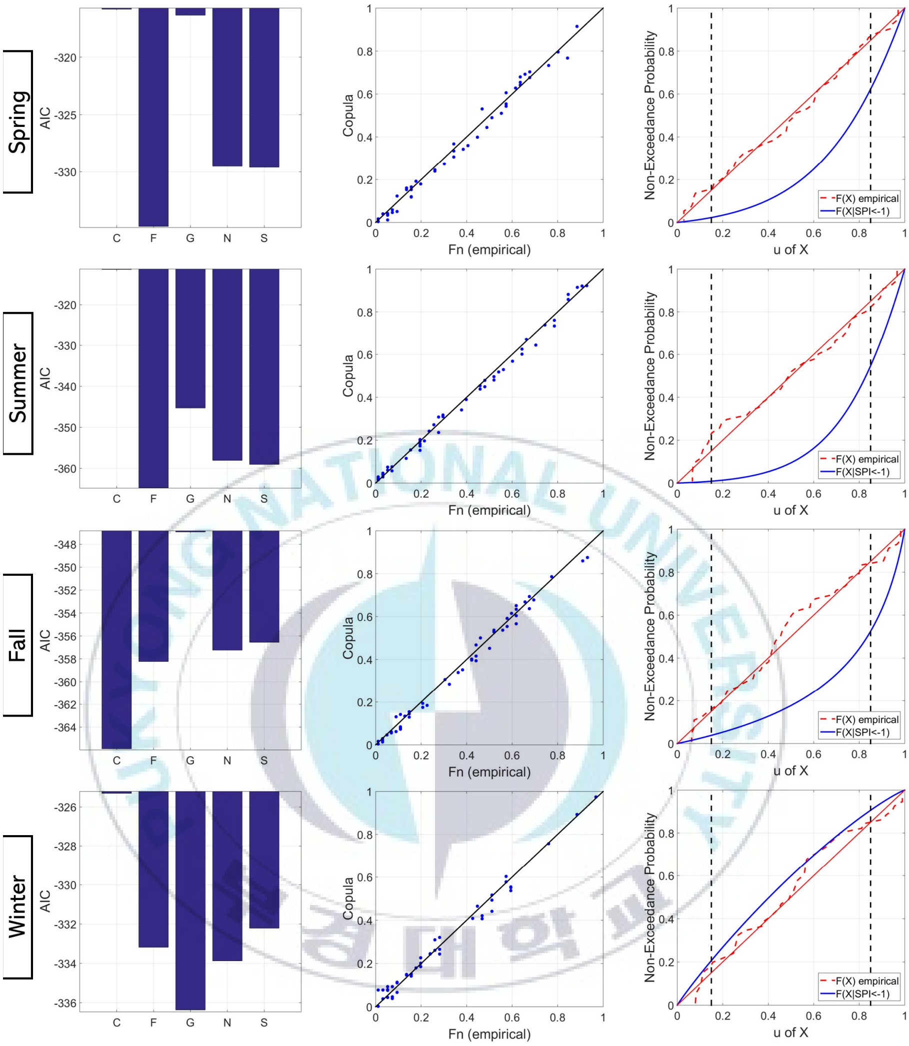


Fig 3.3 AIC values of five copulas for water temperature anomaly and SPI (Left) (C, F, G, N, and S indicates Clayton, Frank, Gumbel, Gaussian(or Normal), and Student-t copula, respectively), Q-Q plot using best-fitted copula (Center), and conditional CDF of water temperature anomaly under a meteorological drought scenario: SPI ≤ -1 (Right) at HG-F of Han river.

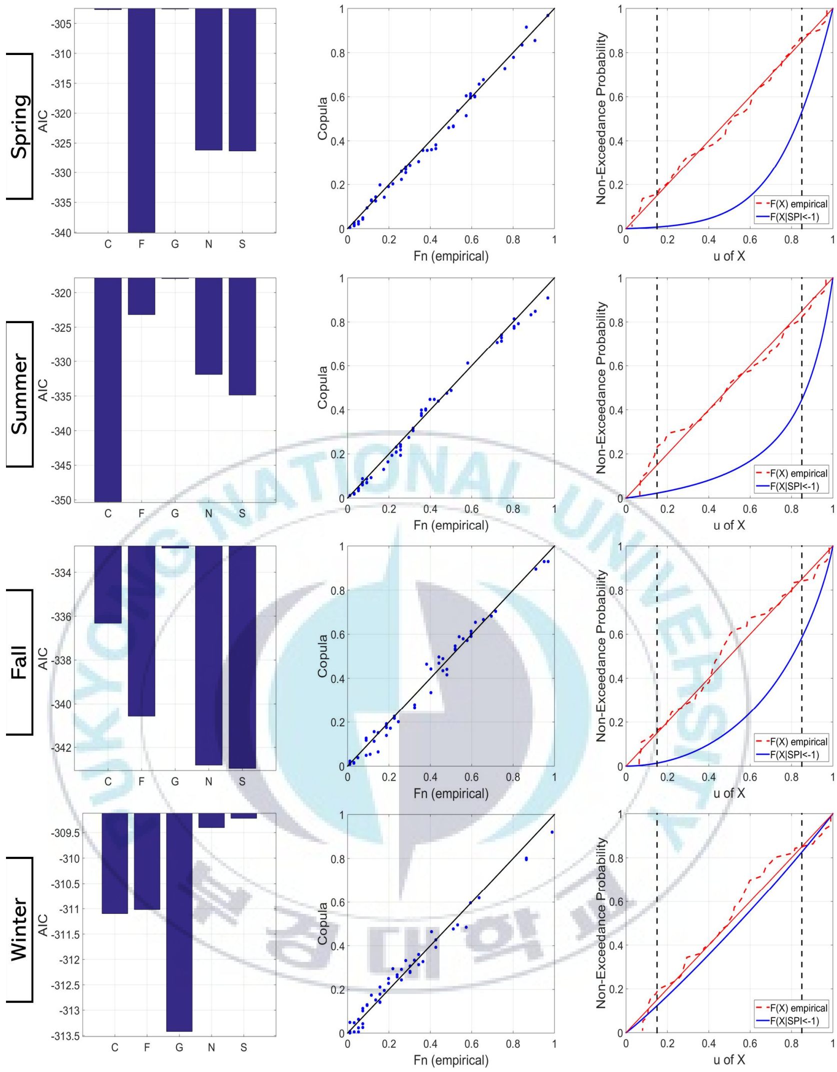


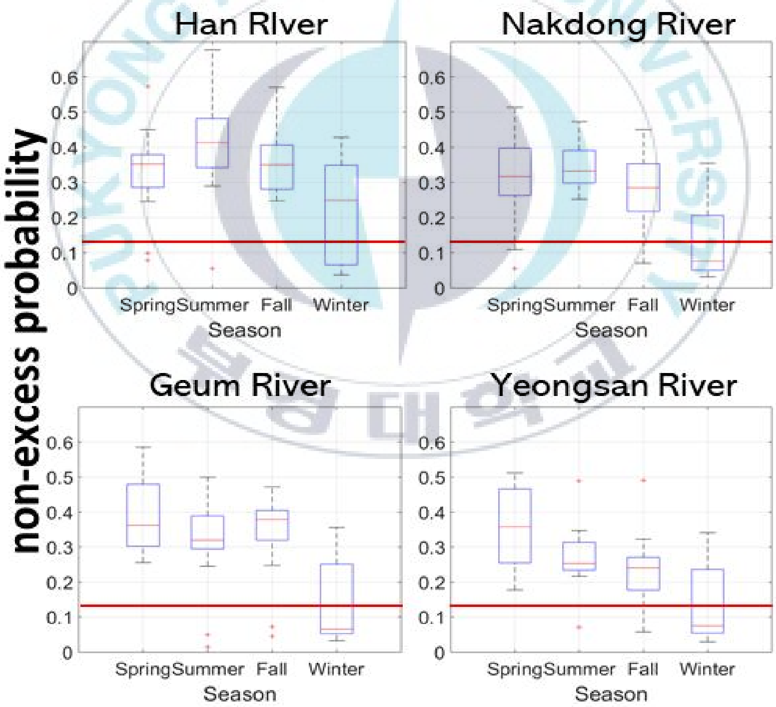
Fig. 3.4 AIC values of five copulas for water temperature anomaly and nEDDI (Left) (C, F, G, N, and S indicates Clayton, Frank, Gumbel, Gaussian(or Normal), and Student-t copula, respectively), Q-Q plot using best-fitted copula (Center), and conditional CDF of water temperature anomaly under a meteorological drought scenario: nEDDI ≤ -1 (Right) at HG-F of Han river.

If the condition of SPI≤-1 in sub-basin HG-F is given, the probability of high water temperature in spring, summer, and autumn increases than usual. This is already inferred from the fact that water temperature and drought index have a negative correlation in spring, summer, and autumn in HG-F. This fact can also be confirmed once again from the conditional CDF shown in the rightmost panel of Fig. 3.3 It can be recognized that the conditional non-exceedance probability distribution of u (blue curve) under the condition of SPI≤-1 in spring, summer, and autumn is lower than the non-exceedance probability distribution of u (red straight line or red dotted line) under normal moisture supply conditions. If the threshold level of high water temperature stress is set to $u \geqq 0.85$, it can be found that the probability of being subjected to high water temperature stress is usually 0.15, whereas in the SPI≤-1 condition, the probability of being subjected to high water temperature stress is greater than 0.15. This means that if a meteorological drought with an SPI of -1 or less occurs in the sub-basin HG-F in spring, summer and autumn, the aquatic ecosystem is more likely to experience high water temperature stress. Conversely, since the possibility of low water temperature stress is lower than usual, it seems unlikely that the aquatic ecosystem will experience low water temperature stress in the river section of HG-F when a meteorological drought occurs due to insufficient moisture supply from the atmosphere. However, as water temperature and SPI have a positive correlation in winter, when a meteorological drought due to lack of moisture supply occurs in winter, the probability of low water temperature is higher than usual. In other words, when a drought occurs due to lack of moisture supply in winter, the probability of non-exceedance of low water temperature is higher than usual ($u = 0.15$). This means that low water temperature stress is more likely to be caused by meteorological drought. Conversely, the possibility of high water temperature stress is reduced. However, in the sub-basin HG-F, it can be found that the change in water temperature stress in the aquatic ecosystem due to lack of moisture supply in winter is not large compared to other seasons.

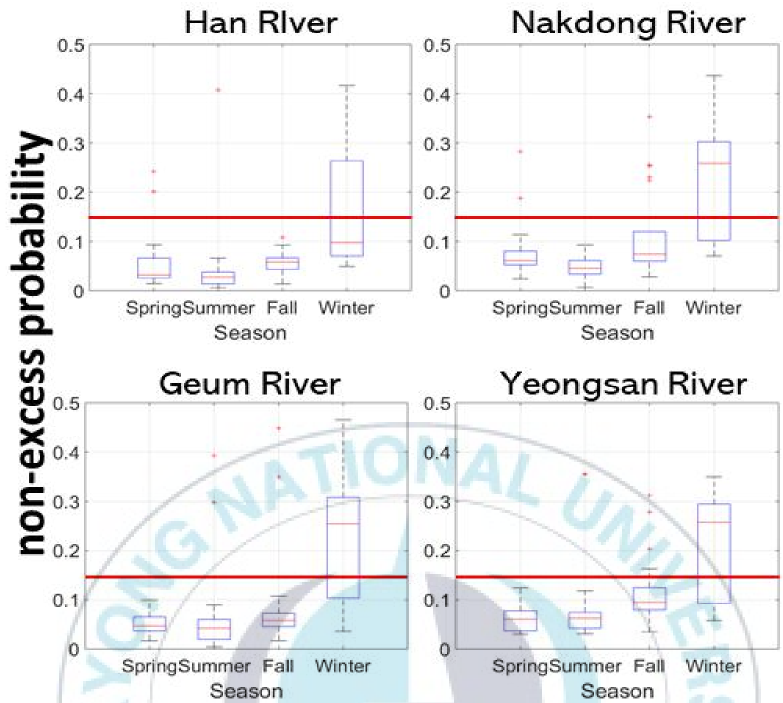
Given a condition of nEDDI≤-1, i.e. a moderate severity meteorological drought caused by excessive moisture demand in the atmosphere, in sub-basin HG-F, it can be found that the possibility of stress caused by high water temperature increases regardless of the season (see Fig. 3.4). However, in winter, the degree of increase in stress due to high water temperature imposed on the aquatic ecosystem is very small.

3.3 Water temperature stress due to meteorological drought

At 140 water temperature observation sites, water temperature-related stresses in aquatic ecosystems were analyzed under drought conditions with an optimal time-scale drought index of moderate severity (SPI≤-1 or EDDI≥1). The threshold level at which the aquatic ecosystem is stressed by the water temperature was set as the upper 15% (high water temperature) and the lower 15% (low water temperature) based on the probability distribution of the normal state. Fig. 3.5 shows the probability that the aquatic ecosystem will be subjected to high (or low) water temperature stress in 140 river sections in a meteorological drought of SPI≤-1 or less in a box-plot format. Fig. 3.6 was plotted from the results for meteorological drought below nEDDI≤-1.

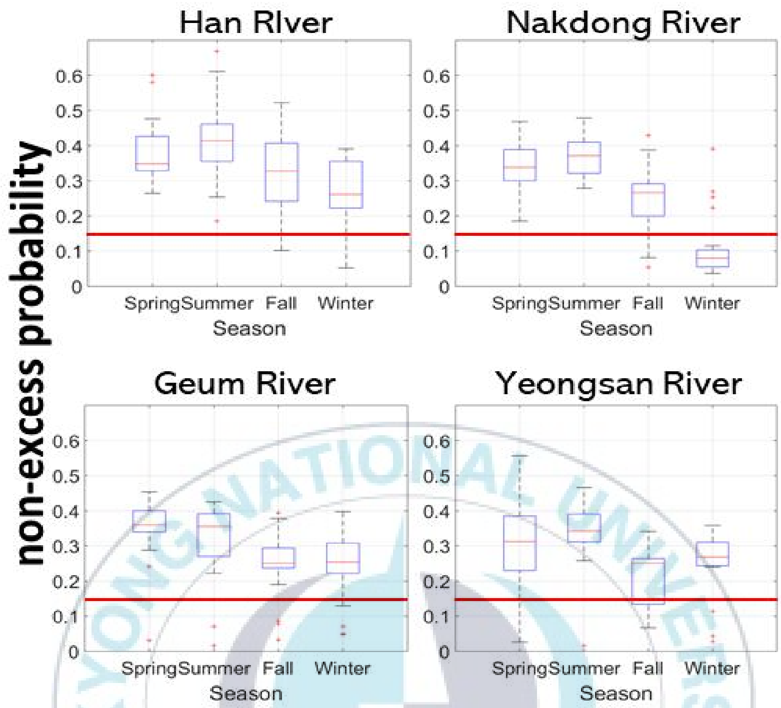


(a) High water temperature

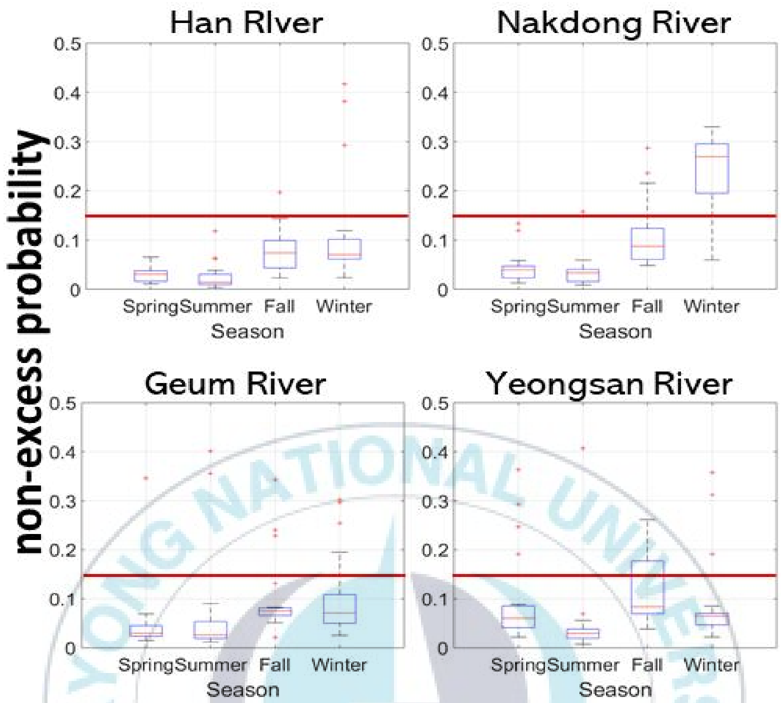


(b) Low water temperature

Fig. 3.5 Probability of water temperature stress in aquatic ecosystems under meteorological drought due to moderate moisture supply deficit.



(a) High water temperature



(b) Low water temperature

Fig. 3.6 Probability of aquatic ecosystems subjected to water temperature stress under meteorological drought due to moderate excessive moisture demand.

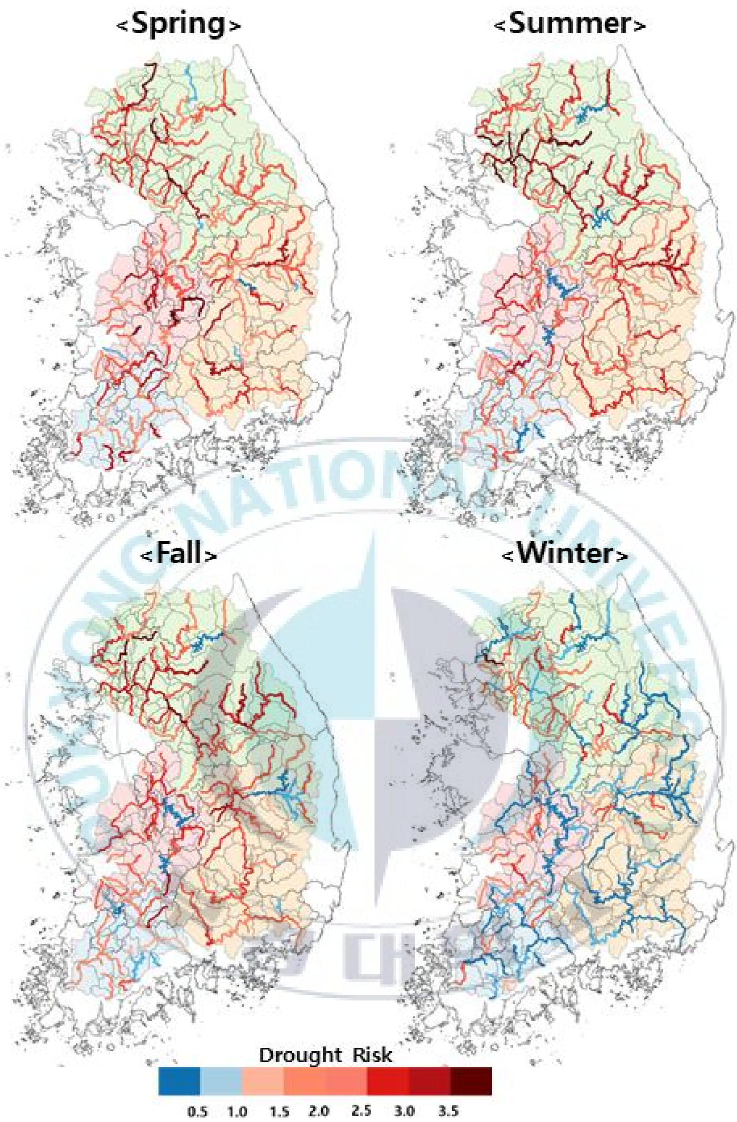
In the event of a meteorological drought with insufficient moisture supply from the atmosphere, in spring, summer, and autumn, the aquatic ecosystems in most river sections in Korea are more likely to be stressed by high water temperatures than usual. Conversely, when a meteorological drought with insufficient moisture supply from the atmosphere occurs in winter, there are many river sections that are more likely to be stressed than usual due to low water temperature. However, the river sections of the Han River Basin in winter were different from those of other watersheds. Even in winter, the number of stream sections with increased likelihood of high water temperature stress was greater than the number of stream sections associated with low water temperature stress. The response of river water temperature to meteorological drought caused by insufficient moisture supply from the atmosphere was similar in the Nakdong River Basin, Geum River Basin, and Yeongsan River Basin (low water temperature stress in winter and high water temperature stress in the rest of the season). It can be found that there are many river sections in the Han River Basin that show different behavior from other basins, especially in winter (High water temperature stress and low water temperature stress are compatible in winter, but high water temperature stress in the rest of the season).

Fig. 3.6 shows the distribution of 140 stream sections for the response of water temperature to a moderate severity meteorological drought that requires excessive moisture in the atmosphere. Stream sections of the Han River Basin, Geum River Basin, and Yeongsan River Basin were more likely to be subjected to high water temperature stress regardless of the season. On the other hand, most river sections of the Nakdong River Basin were more likely to be subjected to low water temperature stress in winter, and were more likely to be subjected to high water temperature stress in the rest of the season.

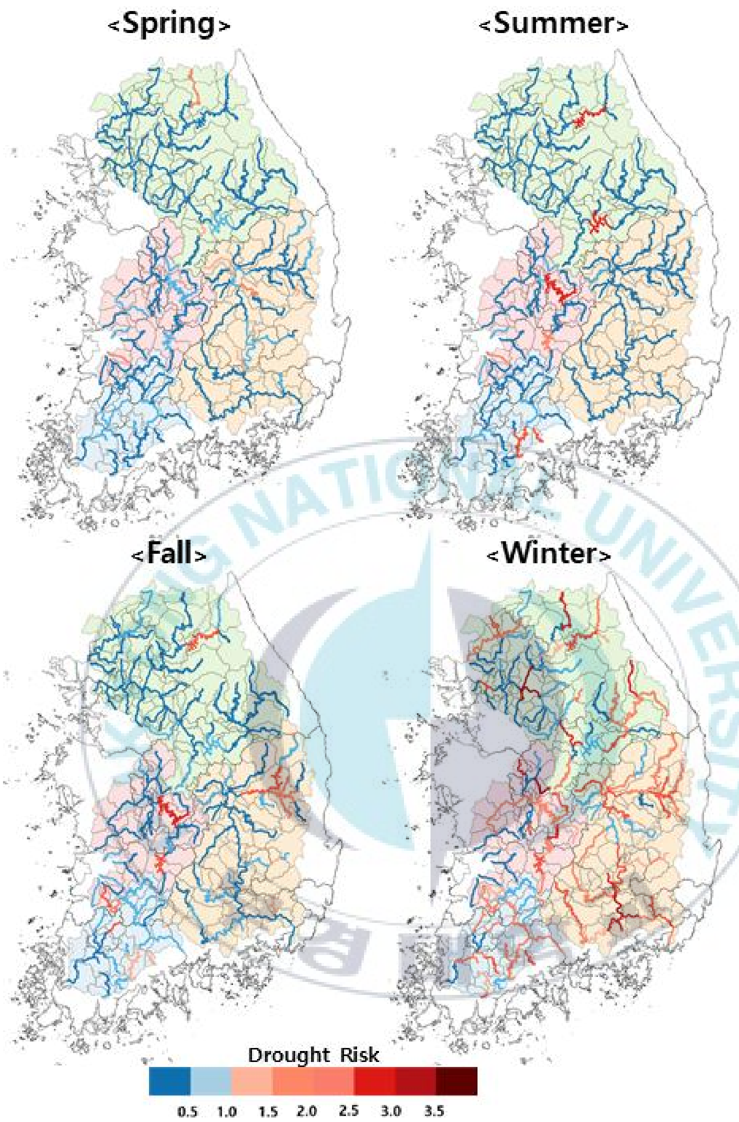
The above results show that water temperature stress for meteorological drought depends on 1) what causes the meteorological drought, 2) when the meteorological drought occurs, and 3) where the meteorological drought occurs. It can also be said that both the direction (high water temperature or low water temperature) and probability of water temperature-related stress imposed on aquatic ecosystems are affected by how these three conditions are given.

3.4 Risk map for water temperature Stress

Water temperature stress risk R can be defined using the probability that the aquatic ecosystem will be subjected to water temperature stress during normal state and meteorological drought. In this study, the water temperature stress risk R was defined as the conditional probability that the aquatic ecosystem would be subjected to water temperature stress when a meteorological drought occurred compared to the probability that the aquatic ecosystem would be subjected to water temperature stress under normal conditions (i.e., 0.15). That is, a risk $R > 1$ means that the probability of being subjected to water temperature stress becomes greater than usual. The greater the risk R, the higher the probability that the aquatic ecosystem will be subjected to water temperature stress. Fig. 3.7 and 3.8 show water temperature stress risk maps of major river sections in Korea when a moderate-severity meteorological drought occurs (i.e., SPI≤-1 or EDDI≥1). Fig. 3.7 is a risk map when a meteorological drought caused by lack of moisture from the atmosphere occurs with moderate severity, and Fig. 3.8 is a risk map when a meteorological drought with moderate severity due to excessive moisture demand in the atmosphere occurs.

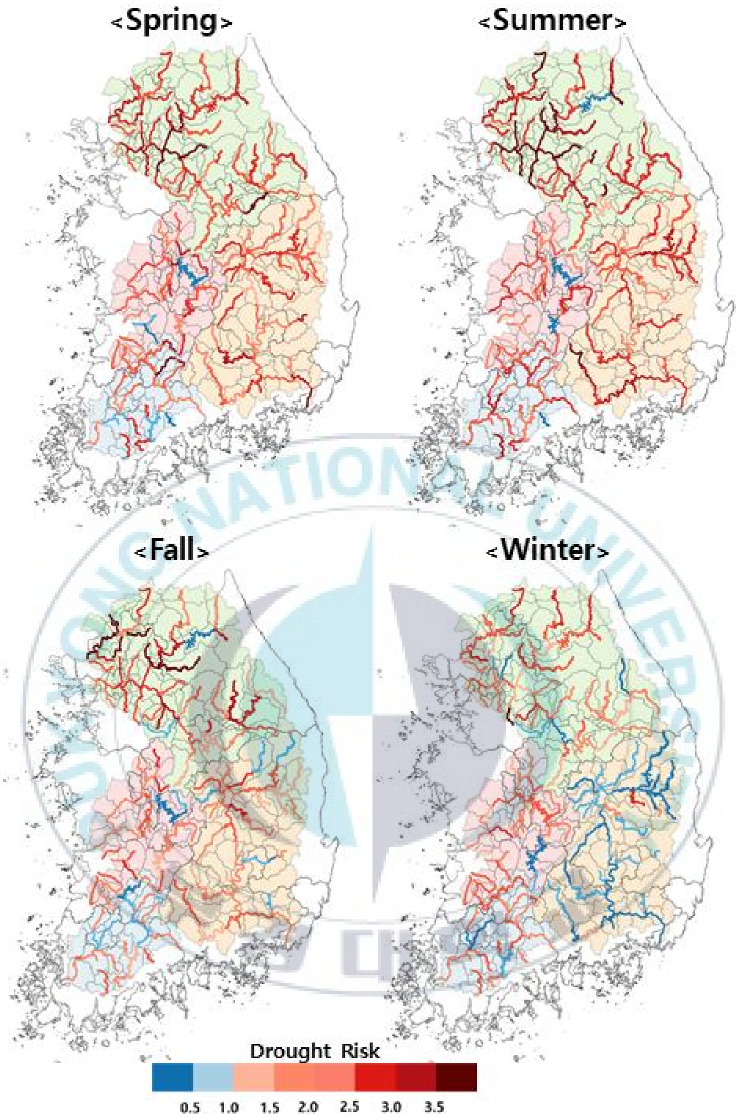


(a) High water temperature

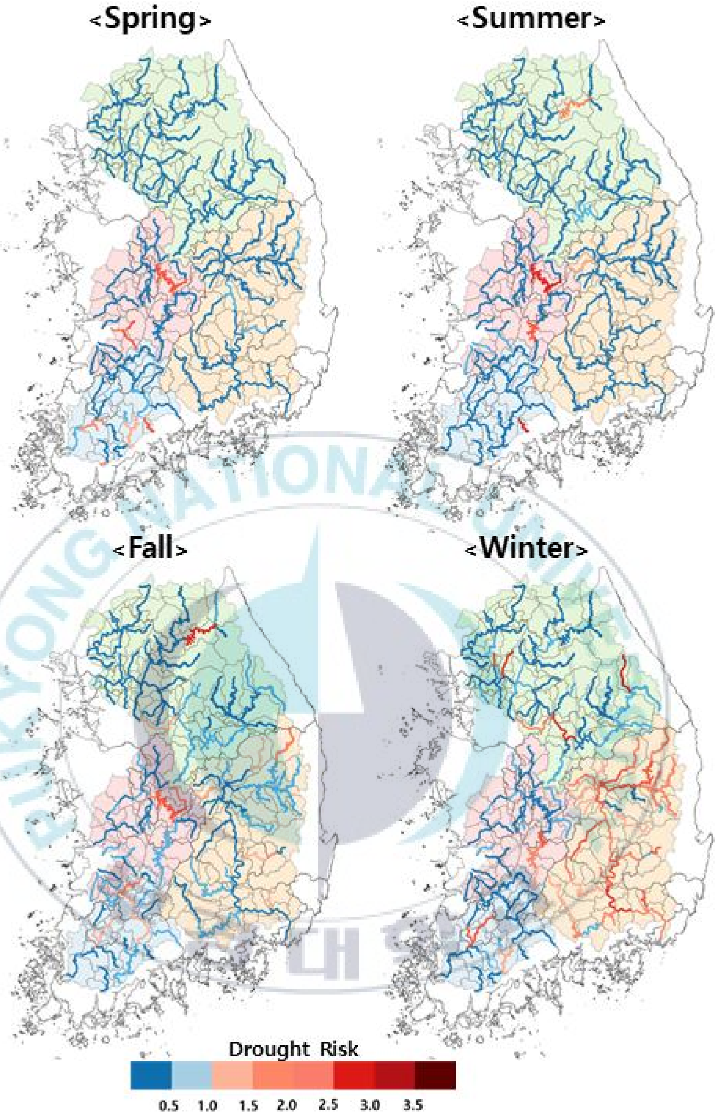


(b) Low water temperature

Fig. 3.7 Water temperature drought risk map in Korea at SPI.



(a) High water temperature



(b) Low water temperature

Fig. 3.8 Water temperature drought risk map in Korea at nEDDI.

When a meteorological drought occurs due to insufficient moisture supply from the atmosphere, most river sections have a high risk of high water temperature stress in spring, summer, and autumn, and in winter, river sections with a high risk of high water temperature stress and river sections with a high risk of low water temperature stress are compatible (see Fig. 3.7). When a meteorological drought occurs due to excessive moisture demand in the atmosphere, it can be found that the risk of high water temperature stress increases regardless of the season in most river sections except for the Nakdong River Basin in southeastern Korea. In most river sections of the Nakdong River Basin, the risk of low water temperature stress increases in winter.

Risk maps can provide us with information about which stream sections will be more sensitive to water temperature stress when a meteorological drought of a specific cause occurs with a specific severity, in a specific season, or in a specific region. For example, if a meteorological drought caused by a lack of moisture supply from the atmosphere occurs in the spring with moderate severity in the Han River Basin, the risk map in the upper left-most panel of Fig. 3.7 reveals that the river sections marked in dark brown are more likely to be subjected to high water temperature stress. Similarly, if a meteorological drought caused by excessive atmospheric moisture demand occurs in the Nakdong River Basin in winter with moderate severity, the risk map in the lower right-most panel of Fig 3.8 shows that the probability of experiencing low water temperature stress increases in most river sections of the Nakdong River Basin. However, it also turns out that the risk in winter is not that high compared to other seasons.

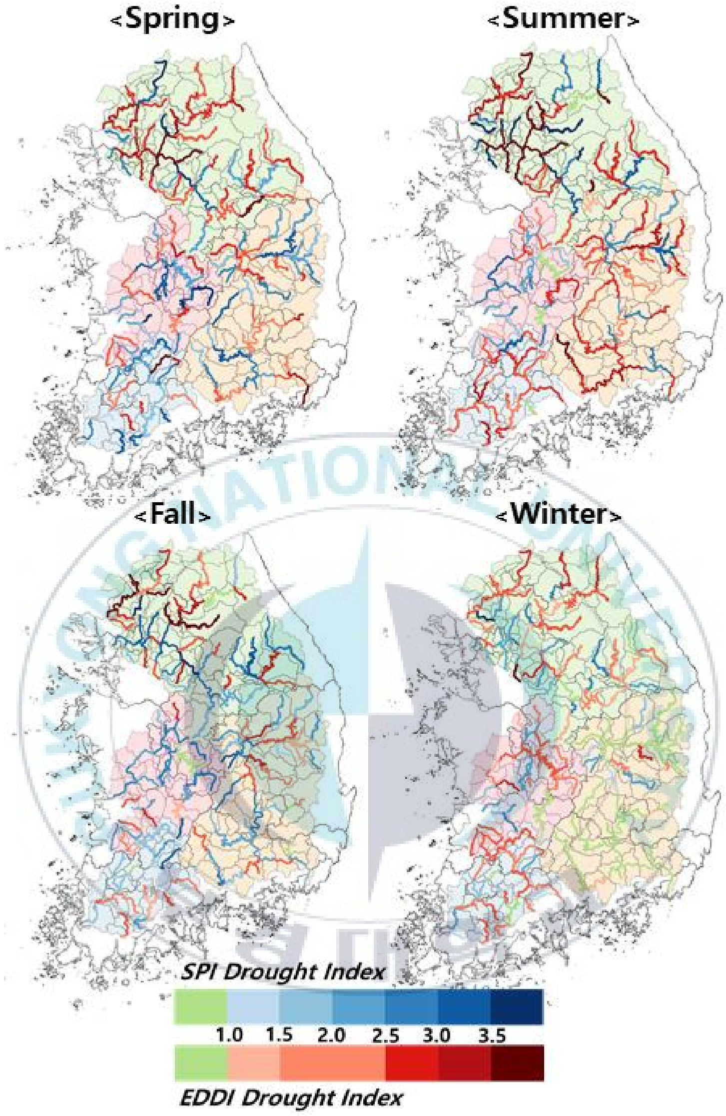
In addition to the combination used in this study, namely the combination of the severity level of meteorological drought (moderate drought) and the threshold level at which the aquatic ecosystem will be subjected to water temperature stress (the upper and lower 15% levels of the water temperature distribution under normal conditions), different risk maps can be drawn using different combinations of meteorological drought severity levels and water temperature stress threshold levels.

3.5 Discussion

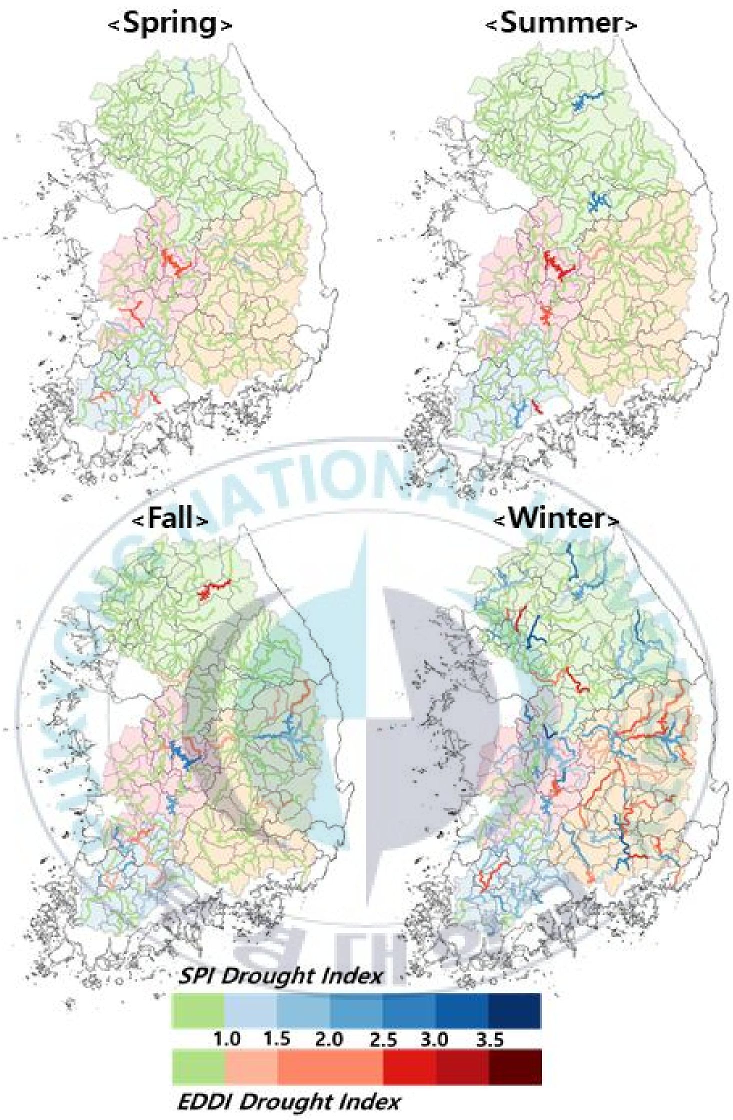
Changes in climatic conditions due to drought have various effects on water quality and aquatic ecosystems (Poff et al., 2002; Park et al., 2010; Sjerps et al., 2017). Although the scope of drought-related impacts is diverse, the impact on water quality in particular requires a more in-depth analysis. Attrill and Power (2000) analyzed the effects of drought on freshwater by using multiple linear regression with modeling, Peña et al. (2020) and Giri et al. (2021) evaluated the potential impact of drought on water quality in terms of meteorological and hydrological droughts based on SPI and Standardized Streamflow Index (SSI). Kim et al. (2019) proposed a probabilistic water quality monitoring method when SPI conditions are given using non-parametric kernel density estimation, and then evaluated the risk of water quality degradation due to climate change. Like the above studies, many studies have been conducted using meteorological drought caused by insufficient moisture supply from the atmosphere, which is mainly represented by SPI. However, the meteorological drought index using only precipitation has a limitation in that it does not properly reflect the meteorological drought resulting from changes in various climatic variables, including the rise in surface air temperature due to global warming (Teuling et al., 2013; Zhang and He, 2016). In addition, in the field of drought monitoring, interest in evapotranspiration, which is an aspect of atmospheric moisture demand, is growing (Otkin et al., 2016; Christian et al., 2019; Sharafati et al., 2020), reflecting the trend of increasing fresh drought events caused by an abnormal and sudden rise in surface air temperature (Otkin et al., 2015).

In this study, meteorological drought was modeled as SPI in terms of atmospheric moisture supply and EDDI in terms of atmospheric moisture demand. The probabilistic approach based on the bivariate copula model of meteorological drought Index and stream water temperature enabled the identification of river sections that are likely to be subjected to water temperature stress in the aquatic ecosystem when a meteorological drought occurs. By classifying the causes of meteorological drought into insufficient moisture supply from the atmosphere and excessive moisture demand in the atmosphere, could find that river sections that were likely to be subjected to water temperature stress might appear differently depending on the cause of the meteorological drought. This finding implies that the water temperature stress imposed on aquatic ecosystems depends on the causes of meteorological drought. Also, even when a meteorological drought of the same severity and the same cause occurs, river sections in which high-temperature stress and low-temperature stress occur differently depending on when the drought occurred. From this fact, it can be said that the water temperature stress imposed on the aquatic ecosystem also depends on the timing of the occurrence of meteorological drought.

Fig. 3.9 is a map showing which causes of meteorological drought lead to a relatively higher risk of water temperature stress. Water temperature stress risk was plotted for each season. Fig. 3.9 reveals that the risk of high water temperature stress in summer is greater when a drought caused by excessive atmospheric moisture demand occurs rather than a drought caused by a lack of moisture supply from the atmosphere. On the other hand, in autumn, it can be found that there are more river sections with a higher risk of high water temperature stress when a meteorological drought occurs due to insufficient moisture supply from the atmosphere rather than excessive atmospheric moisture demand. In spring, in the Han River Basin, there were many river sections with a higher risk of high water temperature stress when a drought caused by excessive atmospheric moisture demand occurred. However, in the high water temperature stress risk in other watersheds in spring, it can be found that the drought caused by the excessive demand for moisture in the atmosphere and the drought caused by the lack of moisture supply from the atmosphere are compatible with each other. Regardless of the cause of meteorological drought, the risk of low water temperature stress is mainly shown in winter, but the risk value itself is small compared to the risk of high water temperature stress in other seasons. From the results in Fig. 3.9, i can identify the sensitivity of water temperature stress risk to meteorological drought caused by precipitation or Eo in any river section for each season. It can be recognized that the sensitivity of water temperature stress risk to the cause of meteorological drought is also different for each season and region where drought occurs.



(a) High water temperature



(b) Low water temperature

Fig. 3.9. Sensitivity of stream water temperature stress risk to causes of meteorological drought. If the risk of water temperature stress when a meteorological drought of SPI <= -1 occurs is greater than the risk of water temperature stress when a meteorological drought of EDDI >= 1 condition occurs, the river

sections were colored in blue. If the risk of water temperature stress for meteorological drought under the condition of EDDI >= 1 was greater, the river sections were colored in red. The greater the risk of water temperature stress, the darker the color. Stream sections with a risk of water temperature stress of 1 or less for both causes of meteorological drought were indicated in green.

V. Conclusion

In this study, a copula model between meteorological drought and river water temperature was proposed, and the probability of water temperature stress imposed on the aquatic ecosystem when a meteorological drought occurred was investigated using the proposed model. Meteorological drought was modeled with SPI, which expresses a drought caused by insufficient moisture supply from the atmosphere, and EDDI, which expresses drought that occurs when the atmosphere demands excessive moisture from the surface. Water temperature stress experienced by aquatic ecosystems was divided into high water temperature stress and low water temperature stress. From the results applied to 140 river sections in Korea, the probability of experiencing high temperature stress in spring, summer, and autumn is greater than usual when drought occurs regardless of the cause of meteorological drought. In winter, when a meteorological drought due to lack of moisture supply from the atmosphere occurs, there are some river sections where the probability of low water temperature stress is higher than usual. When a meteorological drought caused by excessive atmospheric moisture demand occurred in winter, the probability of high water temperature stress was still higher than usual in most river sections except for the Nakdong River Basin.

From the results of this study, it can be recognized that the water temperature stress for meteorological drought in a certain river section can appear in various ways depending on the cause of the meteorological drought and the season in which the meteorological drought occurred. Also, it was found that the sensitivity of water temperature stress to the cause of meteorological drought was different for each season and river section. The relationship between climate variables and river water temperature is intertwined with several processes, and exhibits a wide range of variations in time and space. The risk map drawn using the proposed model can provide us with information about which stream sections are more sensitive to water temperature stress when a specific cause meteorological drought occurs with a specific severity, in a specific season, and in a specific watershed. The proposed model can be extended to cover more items of interest in aquatic ecosystems including water temperature in the future, and it is expected that it will ultimately contribute to monitoring the environmental drought of the river for meteorological drought.

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