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Identifying the Drought Impact Factors and Developing Drought Scenarios using the DSD Model

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Research Article

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Abstract

Due to climate change, droughts have become increasingly severe and frequent. Droughts do not simply create water scarcity but also various socio-economic issues. Therefore, it is necessary to manage droughts on the government level through water resource management policies that consider drought conditions. The drought characteristics within each administrative division need to be closely analyzed for effective policy. In this study, a drought impact factor analysis using the DSD model was presented as a method. Through the relationship between various hydrometeorological factors and drought index, the drought impact factor was identified for each area. For South Korea, meteorological factors have a greater impact on droughts than hydrological factors. Identified drought impact factors are analyzed depending on spatio-temporal variability to recognize the features in various aspects of droughts. For the temporal variability, water demand change and severe drought period are considered. Also, for the spatial variability, based on the type of water demand, administrative divisions are grouped into four zones and analyzed accordingly. Finally, a drought scenario based on identified drought impact factor was constructed to present the probable drought conditions in the future. Components of drought scenario reflect the organization of water resources within an area and it combine the each level of components. Through the constructed drought scenarios, it is possible to establish an effective policy for managing water resources considering the drought condition.

1 Introduction

Drought is generally defined as a condition of water scarcity, originating from a complex interaction between atmospheric, hydrological, and socio-economic factors. Therefore, sufficient rainfall is not the only requirement for avoiding drought, but effective water resource management and policy for the entire watershed must also be implemented (Booker et al., 2005; Khan et al., 2016; Palazzo et al., 2017). Recent climate change has produced unprecedented drought events with abnormal severity and duration (Trenberth et al., 2014).

Khan et al. (2016) highlighted the importance of a proper water policy to consider water resources that impact economic growth. According to Booker et al. (2005), water use, regions, and drought control strategies have economic trade-offs. It focused on the importance of political and institutional jurisdictions for water resource managmenet. Palazzo et al. (2017) emphasized the necessity of considering biophysical, demographic, ecological, and economic principles for managing water resources efficiently.

To manage water resources efficiently with a policy to reduce drought damage, it is necessary to analyze the drought in administrative divisions. Many studies have been conducted on the drought analysis of several watersheds (Maity et al., 2013; Kallache et al., 2013; Malik et al.,2019), but drought studies focusing on administrative divisions are insufficient.

Most disaster management actions (mitigation, preparedness, response, and recovery) are adopted and applied in administrative systems and divisions. For example, implementing structural/nonstructural measures and checking and quantifying drought damage costs are often completed within administrative boundaries. However, few efforts have been devoted to identifying the critical impact factors of drought with respect to administrative divisions in a country.

The severity of drought changes depending on the duration and regional characteristics. Drought indices, such as the standardized precipitation index (SPI), can be utilized to quantify drought. Many drought indices have been proposed and applied, including the SPI (Mckee et al., 1993) and the Palmer Drought Severity Index (PDSI; Palmer., 1965). SPI is based on precipitation and has been utilized in many studies due to its simplicity (Kallache et al., 2013; Tsakiris & Vangelis., 2004; Livada & Assimakopoulos., 2007; Guttman., 1998). The PDSI describes the moisture conditions and is widely used to measure the cumulative water balance. According to Guttman (1998), PDSI lacks consistency in spatial distribution and is inappropriate for drought analysis that determines spatial variability. However, SPI is determined to be suitable for analysis due to spatial variation, and it has been widely applied to spatial analysis (Tsakiris & Vangelis., 2004; Livada & Assimakopoulos., 2007).

To develop proactive drought risk management, the cause-and-effect relationship between drought occurrence and hydrometeorological factors should be identified. Maity et al. (2013) found that a drought event was triggered by hydrometeorological factors in two watersheds in Indiana, USA. According to Maity et al., soil moisture, precipitation, and runoff can be used as drought triggers with a 1 month lead time. It is possible to access the conditions of water resources in areas with data on hydrometeorological factors. SPI (Mckee et al., 1993) is the drought index, which represents drought severity based on precipitation. Through the relationship between hydrometeorological factors and SPI, drought impact factors (DIF) can be identified, and various statistical methods can be utilized to do that.

Interpreting the results from diverse perspectives, information about the impact on the occurrence and mechanism of drought can be found. An approach with spatio-temporal analysis is required to determine the drought impact due to the characteristics of the area. Haslinger and Blöschl (2017) identified atmospheric drought events based on drought duration, intensity, and severity. Using the proposed method, the analysis focused on determining the trends and characteristics of drought due to space-time patterns. Kallache et al. (2013) analyzed dry spells and spatial patterns using a multivariate extreme value model. The results indicated that the dry spells in subbasin are influenced by the topography and spatial distance from other subbassins. Livada and Assimakopoulos (2007) attributed the drought in Greece to spatiotemporal variability using 51 years of precipitation data. So far, studies have evaluated drought trends in relation to spatio-temporal variability, but analysis of the relationship between specific spatio-temporal characteristics and drought is lacking.

Scenarios can be utilized to determine future development processes in systems with various uncertainties. It is possible to combine several types of system information to establish a plan. Due to the features that reflect changing conditions, a flexible response is possible. To establish the scenario in the

context of uncertainty, we first need to recognize the problem. Next, we identify the factors that affect the problem and rank them to determine the importance and degree of uncertainty. The determined uncertainty axis was utilized to construct the scenario and named accordingly. A previous study has suggested to decide the possible future or direction of the scenario and identify the common aspects of various scenarios (Kang & Lansey., 2014). In this study, the severity of drought and changes in hydrological and meteorological factors are uncertain. Herman et al. (2016) developed a bottom-up method for synthetic streamflow generation by increasing the frequency and severity of droughts. According to the study, this method is a simple way to determine the effects of frequency and magnitude. Conversely, a scenario based on the top -down method using a general circulation model (GCM) to regional climate models (RCM) was developed (Ghosh & Mujumdar., 2007). However, covering all hydrologic status in a district is needed to help decision -makers be ready for an unprecedented drought. In this study, the drought scenario describes the condition of water resources in the each area that can be developed when a future drought occurs. It is possible to explain future water resource conditions specifically through drought scenarios and propose effective precautions and responses.

The novelty of this study is the identification of DIF and the construction of drought scenarios in administrative divisions. First, the DIF for each administrative division was derived using principal component analysis (PCA) with hydrometeorological factors as input and SPI as the output. The results of PCA are analyzed to determine spatiotemporal variability and are utilized in the construction of drought scenarios. Figure 1 illustrates the framework of the study. The results of this study can be used to manage water resource policies for reducing drought damage.

2 Methodologies

2.1 Overview

Figure 1 shows a schematic of the proposed drought scenario development (DSD) model with two primary components: DIF analysis (DIFA) and critical factor combination (CFC). First, hydrologic and meteorological data were collected for each administrative division to be provided as input data to the DSD model. The most critical impact factors for a drought indicator (SPI in this study) were identified in the PCA-based DIFA, where the impact level of each factor is quantified and ranked based on the principal component scores obtained. The highly ranked factors are then combined in the CFC block to construct a set of drought scenarios (output of the DSD model). Note again that the aforementioned processes in the proposed model are performed at individual administrative divisions, and thus, the results can be compared across the areas. The following subsections describe the detailed methodologies used: PCA, ranking method, factor combination, and scenario generation.

2.2 Drought impact factor analysis (DIFA)

PCA is one of the unsupervised machine learning techniques for dimensionality reduction and feature extraction. The linear combination of variables, Eq. (1), that maximizes the variation, Eq. (2), is found, and the principal component, which is the factor with the most impact, is extracted.

$$\boldsymbol{Var(y)} = \sum_i \frac{1}{N}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}^{(i)})^2 = \frac{1}{N}\sum_i \frac{1}{N}\boldsymbol{w}_i^{\mathrm{T}}\boldsymbol{x}^{(i)}\boldsymbol{x}^{(i)\mathrm{T}}\boldsymbol{w} = \boldsymbol{w}^{\mathrm{T}}\sum \boldsymbol{w} \tag{1}$$

$$\boldsymbol{w}^* = \boldsymbol{arg} \max_{||\boldsymbol{w}||=1} \boldsymbol{w}^{\mathrm{T}}\sum \boldsymbol{w} \tag{2}$$

Therefore, it can be utilized to extract input factors that affect output factors and is usually applied in determining explanatory variables, process for factor analysis, and clustering. PCA has been applied to drought analyses in several studies. Maity et al. (2013) identified drought triggers using PCA and copulas model. Tijdeman et al. (2018) determined the correlation between drought indices, stream flow, and human influences. In this study, PCA was applied to determine the causation between SPI and hydrometeorological factors. Additionally, spatial and temporal patterns of drought in Portugal were analyzed by PCA, the relationship between SPI1, SPI6, SPI12, and their principal components (Santos et al., 2010). However, the research into PCA and various hydrometeorological factors and the drought index is insufficient. Most previous studies have focused on identifying the characteristics of drought in a region and there is a lack of studies that contribute to the construction of policies to reduce the damage caused by drought.

PCA is performed using hydrometeorological factors as the input and SPI as the output, and the procedure is as follows. First, the covariance matrix of the existing data is calculated. Second, the eigenvalues and eigenvectors of the covariance matrix are computed. Third, we list eigenvectors in the order of magnitude of eigenvalues. Fourth, we select an eigenvector that can describe most of the total. Finally, the principal component score is calculated using the dot product with the corresponding eigenvector and data. It is possible to determine that the factor with a larger principal component score has a greater impact on drought. Hence, hydrometeorological factors were ranked according to the principal component score. Rank index (RI) is utilized to to interpret the total result in a comprehensive way. RI is calculated by averaging the rank and taking the inverse of each factor of the total area. The value has a range from 0 to 1 depending on the impact on drought, and the larger the value of RI, the bigger the impact of drought. To determine the various characteristics of the IDF for each area, additional analysis is necessary. In this study, an analysis based on spatio-temporal variability was proposed.

2.3 Critical factor combination (CFC) for scenario development

The scenario predicts the probable circumstances under a situation with uncertainty. In the manner of drought, severity is uncertain, and, based on this, hydrological drought status in area changes. Therefore, establishing a drought scenario based on the scarcity of water in the area helps to explain uncertain drought conditions. The hydrologic drought status of an area can be expressed with three components: the inflow volume of water into the area, the water storage stored within the area, and the volume of outflow. Drought scenarios were established by combining different levels of these elements. In Fig. 2,

each arrow represents the level of the component, and each small block consists of three different arrows. For example, block C faces an arrow with a high level of inflow water, a high level of water storage, and a low level of outflow water. The combination of these arrows consists of the scenario for block C. Through these blocks, eight drought scenarios can be expressed.

The process for determining the level of the component for the drought scenario varies by component (Fig. 3). The inflow volume affects the drought significantly, and the water scarcity condition of the area can be represented by a no rainfall period, and severe drought occurs when the no rainfall period increases. Therefore, a no rainfall period was set as an element for water inflow in the drought scenario. To consider the extreme conditions of drought, no rainfall for 6, 9, and 12 months were used for the CFC. Additionally, outflow can be described by the amount of water used within the area and the water demand. High levels and low levels of water demand are critical factors for water outflow. Water demand in the area can be controlled by policies that encourage people to use less water. Finally, water storage is related to stored water in the area and is described by hydrological factors, which are utilized as input for the DSD model. The first DIF among the hydrological factors in the area was identified by the DSD model. The critical factor of the first DIF was determined through frequency analysis, and tercile points under the average were set as the criteria. An example of the frequency analysis is presented in Fig. 3. The first to second tercile criteria and second to third tercile criteria are set as critical factors of water inflow to drought scenarios. Through the CFC of each component, drought scenarios were established.

2.4 Other measures

Drought damage occurs when the supply is lower than the demand, and the input factors for PCA are related to the supply of water. Therefore, analysis of demand is necessary. The demand varies depending on the long-term temporal variation, such as an increase or decrease in population in the area or construction of a plant. Therefore, the temporal variation should be considered for DIF analysis regarding the water demand change. To compare the DIF, the absolute percent error (APE) was calculated using Eq. (3). RI_1 is the RI value from the former period, and RI_2 is from the later period. This index implies a change in the impact of drought due to water demand, and if the value of APE for the factor is large, it is possible to determine that the factor is sensitive to water demand variability.

$$\boldsymbol{APE} = \frac{\boldsymbol{abs(RI_1 - RI_2)}}{\boldsymbol{RI_1}} \times \mathbf{100}\ (\%) \qquad (1)$$

Furthermore, the percentage of rank changing factors (PRCF) can be used as Eq. (4) to determine the influence of water demand on the area. Through the PRCF, it is possible to determine the area that most effects the water demand variability.

$$PRCF = \frac{Number\ of\ rank\ changing\ factors}{Total\ number\ of\ factors} \times 100\ (\%) \qquad (2)$$

The history of drought that is utilized as the water supply date index of the water resources plan or with the lowest precipitation needs to be analyzed. Through the analysis of the period, it is possible to identify the characteristics of severe drought. Following the same process of PCA for applying the DIF, the period of input and output data is distinct depending on the severe drought period. By comparing the results with the total period, it is possible to determine the features of severe drought.

Additionally, drought is related to the spatial characteristics of the area, and it depends on the type of water used. Areas are fed into urban, industrial, and agricultural zones due to the type of water demand to analyze the drought based on spatial variability. The sum of domestic, industrial, and agricultural water demand is set as the total water demand, and the percentages of domestic, industrial, and agricultural water demand are calculated to represent the water demand characteristics of each area. Based on the results of the frequency analysis for each type of water demand percentage of the total area, criteria are set based on the corresponding upper tercile of the total area. Areas are classified into three zones and compared the DIF to identify the characteristics of drought by zone.

3 Study Area: South Korea

3.1 General information and past drought events

The Republic of Korea is located in the middle latitudes of East Asia (Fig. 4) and lies in a temperate region with four seasons: spring, summer, fall, and winter. Depending on the seasonal variability, meteorological factors such as temperature, precipitation, and humidity change with a pattern. Most weather is sunny and dry for spring and fall because of the migratory anticyclone, and drought is likely to occur. In winter, affected by cold arid continental high pressure, temperatures and humidity are low, and summer, influenced by the North Pacific anticyclone, which is hot and humid, has a high temperature. The characteristic that most rainfall is concentrated in summer leads to vulnerability to drought.

Risk related to water has socio-economic implications and causes loss of physical and human resources. Additionally, the Republic of Korea is categorized as a country with water shortage, and the probability of drought occurrence is increasing due to climate change (Nam et al., 2015; Kim et al., 2014). Through policy for conserving water resources, drought analysis on an administrative basis is a necessity. Precipitation in South Korea in 2015 was 80% of the annual average, according to the Korea Meteorological Administration (KMA). A significant amount of support was offered during the drought period, including water vehicle supply support and water supply by the waterway. In 2017, despite a similar amount of precipitation in 2015, there was little damage in the northern region of Ganghwado. This is because of the watercourse connection project in 2016 from the Han River to Ganghwado.

The entire country is composed of 167 administrative divisions, and its geographical characteristics are diverse. In the area population, 19% of the total population lives in Seoul, and 0.017% live in Ulleung. Additionally, Hongcheon has an extent of 1.8% of the whole country, and Guri has 0.033%. In this context, the characteristics of each administrative division vary and affect water resource management.

3.2 Hydrometeorological data and SPI

In this study, six meteorological and five hydrological factors from January 2009 to December 2019, monthly data, are utilized as an input factor of PCA. Meteorological factors are of two types: Automated Synoptic Observing System (ASOS) data with 102 meteorological sites (Fig. 4) and automatic weather station (AWS) data with 510 meteorological sites. AWS data are weather observations to prevent natural disasters due to atmospheric phenomena. Monthly precipitation, average temperature, and average wind speed were used in this study. Hydrological factors provide information about dams from the water resources management information system (WAMIS), including average low water level, average inflow, average discharge, average floodgate discharge, and catchment average rainfall. These factors can be classified into natural and artificial factors. The artificial factor implies the influence of humans, which include average floodgate discharge, average discharge, average inflow, and average low water level.

In contrast, natural factors vary due to inartificial impacts, including average catchment rainfall and all meteorological factors. Through an analysis based on the classification of artificial and natural factors, it is possible to identify whether drought is effected artificially or naturally due to the characteristics of the region. Depending on the cumulative month of precipitation, SPI 3, SPI6, and SPI 9 were applied in this study. The SPI of 167 administrative divisions was utilized from the KMA.

4 Result Applications

4.1 Identify nationwide DIF

Through the results of DIF analysis for nationwide, it is possible to identify the impact of hydrometeorological factors on drought. To determine the comprehensive result of DIF analysis nationwide, RI is utilized based on the rank of DIF by area and integrates the results of 167 administrative divisions (Fig. 5). The average discharge, average inflow, and average floodgate discharge were placed at the top. These are all hydrological factors, indicating that they are related to drought. Additionally, monthly precipitation ranked highest among the meteorological factors. SPI3, 6, and 9 show similar trends.

The value of the principal component score for hydrometeorological factors is presented with a radar chart, and the shape varies depending on the drought impact of the factors (Fig. 6). In the chart, the larger the value, the greater the impact on drought. Seoul, the capital of Korea with the largest population, average discharge, average floodgate discharge, and average inflow, ranked first, second, and third, respectively. In Boryeong, drought has occurred frequently, and based on the result of the IDF analysis, average low level, average discharge, and average floodgate discharged have a high score. Unlike the

Seoul and nationwide results, the average low water level has the most significant impact on drought, which is influenced by the Boryeong dam's waterway operation that induces low water level fluctuations. The results also imply that the Boryeong dam's water reserve rate is under 30%, which is the lowest rate among all dams in Korea, significantly affecting the frequent drought in Boryeong. Busan, Korea's second city, has the top -ranked factor for average inflow, catchment average rainfall, and monthly precipitation. The significant feature of Busan's result is that it has meteorological factors for the third rank, which is the largest DIF among the meteorological factors in the nationwide results. Additionally, the impact of the average floodgate discharge in Busan was lower than that of other areas, which is related to the fact that 93% of the water source is abstracted from downstream of the Nakdong River. Gwangju, a metropolitan city located in southwest Korea, has a DIF of the first rank for average floodgate discharge, second rank for average discharge, and third rank for average inflow. Despite different water resources, population, and size of the area, the shape of the radar chart looks similar to that of Seoul. Based on the results of major areas and areas with frequent droughts, it is possible to determine that major areas have a high impact on hydrological factors, and DIF reflects the characteristics of the area.

4.2 Spatio-temporal analysis

4.2.1 DIF analysis regarding the water demand variability

DIF analysis was performed using data from a period of 132 months, from 2009 to 2019. Fluctuations in water demand due to temporal variability were identified to analyze the DIF regarding water demand. The total water demand (million m^3/year) for each area was calculated by the summation of the domestic, industrial, and agricultural water demand. As a result, it was possible to determine the trend in water demand change over time. The total period is divided into 2009 to 2013 as the high -demand period and 2014 to 2019 as the low -demand period to reflect the demand variability. Through the separated period, it is possible to determine the effect of demand in the DIF analysis.

To identify the change in DIF due to high and low water demand periods, the APE was calculated for each factor (Fig. 7). The overall APE trends for SPI3, 6, and 9 were similar, and SPI9 had the largest value for the sum of all factors' APE (110%). Additionally, the average values of SPI 3, 6, and 9 for each factor are high for average discharge (26%) and average floodgate discharge (20%) and low for average pressure (2%). Therefore, the average discharge and average floodgate discharge significantly affect the temporal variability due to water demand change, and the average pressure affect less. Additionally, the average APE value for hydrological factors is larger than meteorological factors by approximately 3.2 times, and hydrological factors may be more affected by temporal variability due to water demand change than meteorological factors. This implies the changing operation of the dam, depending on the fluctuation of water demand.

The PRCF based on DIF from the high -demand period and low -demand period is calculated to determine the variability of the DIF rank in the area. The total area is classified into four groups based on PRCF values, which are areas with PRCF over 75%, 75–50%, 50–25%, and under 25%. For SPI6, the percentage of area classified into each group is presented (Fig. 8), and the percentages are similar to those of SPI3

and 9. Through the chart, it is possible to identify that in the largest number of areas are changing over 75%, and the smallest number of areas are changing by less than 25% due to temporal variability based on water demand change.

4.2.2 DIF analysis during severe drought period

Two periods of severe drought were chosen to analyze the characteristics of severe drought in Korea. From June 1994 to July 1995, droughts stand out as severe droughts that are utilized as the water supply date index of the water resources plan in Korea. In particular, the Yeongnam and Honam regions, located in the south of Korea, are critically damaged by severe drought. The average precipitation was 76.4% of the normal annual, and the water reserve rate of nine dams was 30%. Thus, farming and fisheries were damaged, restrictive and transport water supply took place.

Additionally, the drought in 2015 was recorded as a severe drought with the lowest precipitation. For central regions of South Korea, such as Gyeonggi and Gangwon, severe drought persisted within a year and expanded nationwide from April. The average precipitation was 62% of the normal annual precipitation, and the lowest precipitation was recorded in the Han River basin. When the water shortage status of the dam is categorized into four levels, most of the dams reach the first and second most severe levels. Due to this, agricultural damage occurred, and there was a restriction in the domestic water supply. The DIF from June 1994 to July 1995 (drought period 1) and 2015 (drought period 2) were carried out to determine the characteristics of severe drought periods..

Using the same method as the total period DIF analysis, the impact on drought was examined using the value of RI during drought periods 1 and 2. Unlike the results of the total period in which hydrological factors have a significant impact, meteorological factors affect severe drought. The average value of RI was calculated to compare the impact of hydrological and meteorological factors on drought. For the total period, meteorological factors have a value of 0.17, and hydrological factors have 0.33, which is about two times larger than meteorological factors. On the other hand, during drought period 1, meteorological factors have a value of 0.33, hydrological factors have a value of 0.31, and drought period 2, meteorological factors have a value of 0.19, and hydrological factors have a value of 0.23. Thus, during the severe drought period, there were no significant differences in the impacts of hydrological and meteorological factors. Additionally, DIF was analyzed through the top three ranked factors depending on temporal variability (Table 1). During the total period, the top three of DIF are all artificial factors; however, during drought period 1, natural factor ranked first, and drought period 2 included two natural factors in the top three of DIF. This implies that during the severe drought period, the impact of artificial factors decreased, and natural factors had a significant influence on drought.

Table 1
Top three of DIF (SPI6) in Total period, drought period 1 and 2

	Total period	Drought period 1	Drought period 2
First rank	Average discharge	Average relative humidity	Average inflow
Second rank	Average inflow	Average inflow	Monthly precipitation
Third rank	Average floodgate discharge	Average discharge	Catchment average rainfall

4.2.3 DIF analysis based on spatial variability

Based on the type of water demand, areas were classified into zones to analyze the DIF depending on spatial variability. The water demand of domestic, industrial, and agricultural areas for 167 areas in Korea is presented in a histogram (Fig. 9). For domestic and industrial water demand, the frequency of the low - demand class section is high, and the frequency exponentially decreases as the water demand increases. In contrast, the frequency of sections at high demand is high in agricultural water demand. By applying the characteristics of the water demand frequency, the criteria are set by the upper third of the water demand for type. If the area's domestic water demand percentage is over 25%, it is classified as an urban zone.

Similarly, the criteria for industrial water demand to be classified as the industrial area is 10%, and the agricultural area is 85%. For example, the percentage of water demand in Seoul is 87.1%, 12.2%, and 0.7% for domestic, industrial, and agricultural purposes, respectively. Based on these criteria, 34% of the area is classified as an urban zone, 19% as an industrial zone, and another 34% as an agricultural zone (Fig. 9). The rest of the area was identified as hard to be grouped and named unclassified. As a result, major cities in Korea such as Seoul, Busan, and Incheon are classified into urban zones and areas where the plants are concentrated; for example, Ansung, Ulsan, and Iksan are grouped as industrial zones. Additionally, the areas where major farm products are produced, such as Gimje, Bonghwa, and Sancheong, are classified as agricultural zones.

Based on the classification of the area, DIF was analyzed to identify the effect due to spatial variability. There were no significant differences and showed similar trends depending on the type of SPI, and the result of DIF analysis using SPI6 was utilized. The percentage of the area where each factor first is the first DIF by zone is presented in a bar chart (Fig. 10). For urban and industrial zones, the percentage of average discharge is largest at 57% and 48%, followed by average inflow at 14% and 19%, respectively. The agricultural zone has the largest percentage of average discharge (36%), followed by monthly precipitation (25%). A large percentage of the area with meteorological factors was the first DIF compared to other zones. Additionally, the percentage of artificial factors is approximately six times and five times larger than natural factors for approximately 6 and 5.2 times for urban and industrial areas, respectively; however, industrial factors are about 1.4 times. Therefore, it is possible to understand that natural factors

have a significant impact on the agricultural zone, and artificial factors affect the urban and industrial zones.

4.3 Drought scenario

Drought scenarios for 167 areas in Korea were established through CFC, utilizing the DSD model results. However, in the results of the analysis based on temporal variability due to water demand, approximately 50% of the area in Korea has a change in DIF rank under 75%. Therefore, water demand provides insufficient explanation for drought conditions and is not utilized in drought scenarios.

An example of a drought scenario in Seoul, Chuncheon, and Busan was presented using the suggested method. The first DIF is the average low level of the Soyanggang and Chungju dams in Seoul, the average low water level of the Soyanggang dam in Chuncheon, and the averag inflow of the Andong dam in Busan. In Fig. 11, the results of the frequency analysis of the corresponding first DIF for each area and the dashed lines are the tercile criteria, which are utilized as critical factors. Through CFC, a drought scenario is constructed (Table 2), which is the key result of this study derived from the DSD model. Through this scenario, it is possible to describe drought conditions with uncertainty.

Table 2
Drought scenario of Seoul, Chuncheon and Busan

Area	Drought scenario
Seoul	6 months of no rainfall, 52% of average discharge compared to normal year
	9 months of no rainfall, 52% of average discharge compared to normal year
	12 months of no rainfall, 52% of average discharge compared to normal year
	6 months of no rainfall, 78% of average discharge compared to normal year
	9 months of no rainfall, 78% of average discharge compared to normal year
	12 months of no rainfall, 78% of average discharge compared to normal year
Chuncheon	6 months of no rainfall, 95% of average low water level compared to normal year
	9 months of no rainfall, 95% of average low water level compared to normal year
	12 months of no rainfall, 95% of average low water level compared to normal year
	6 months of no rainfall, 98% of average low water level compared to normal year
	9 months of no rainfall, 98% of average low water level compared to normal year
	12 months of no rainfall, 98% of average low water level compared to normal year
Busan	6 months of no rainfall, 9% of average inflow compared to normal year
	9 months of no rainfall, 9% of average inflow compared to normal year
	12 months of no rainfall, 9% of average inflow compared to normal year
	6 months of no rainfall, 27% of average inflow compared to normal year
	9 months of no rainfall, 27% of average inflow compared to normal year
	12 months of no rainfall, 27% of average inflow compared to normal year

5 Summary And Conclusions

Drought is a natural disaster that affects human life socioeconomically, and it is necessary to manage droughts through effective water resources management. Drought analysis of administrative divisions should be conducted in order to understand the characteristics of drought in the area. To identify the DIF, data from six meteorological factors and five hydrological factors from January 2009 to December 2019 were used. The relationship between hydrometeorological factors and the drought index (SPI) was analyzed. The results indicated that meteorological factors have a greater impact on droughts than hydrological factors.

Furthermore, an analysis based on spatio-temporal variability was performed to determine the various characteristics of drought by area. The scarcity of water occurs when the inflow is smaller than the

outflow, and all of the factors utilized in the DIF analysis are related to inflow. An analysis based on water demand is necessary, and it is performed considering temporal variability based on water demand. For Korea, it is identified as a high -demand period from 2009 to 2013 and a low demand period from 2014 to 2019, and DIF analysis was performed separately. Hydrological factors are 3.2 times more affected than meteorological factors, and over 75% of the factors are ranked differently in 51% of areas in Korea due to temporal variability based on demand change. Additionally, DIF analysis during the severe drought period was performed, and the results were compared with the total period to determine the characteristics of severe drought periods. From June 1994 to July 1995 and 2015, drought was analyzed; it was found that the influence of artificial factors decreased, and that of natural factors increased. For analysis based on spatial variability, the percentage of the type of water demand is groups the 167 areas into urban, industrial, and agricultural zones and identifies the IDF. For the result of frequency analysis on water demand type percentage, the total area is classified into urban zone (34%), industrial zone (19%), agricultural zone (34%), and unclassified. By comparing the number of areas by the first DIF, the agricultural zone was found to be significantly affected by natural factors.

Through the DSD model, drought characteristics of the area are identified, and a drought scenario can be constructed. Components of water inflow, water outflow, and water storage were considered for the drought scenario. For the drought scenario in Korea, 6, 9, and 12 months of no rainfall are used to describe the water inflow. Additionally, criteria from the frequency analysis of the first DIF among hydrological factors are combined as water storage, while the outflow of water is not combined according to the result of the analysis based on demand variability. Through the constructed drought scenarios, it is possible to predict the drought conditions in each administrative division with uncertainty in drought severity.

There are two limitations to this study that are related to DIF and drought scenarios. First, the DIF presented in this study was identified using the same time period of hydrometeorological factors and SPI. Therefore, it is unclear whether hydrometeorological factors are affected by SPI or SPI fluctuations. It may be possible to perform additional analyses based on the time difference between SPI and hydrometeorological factors. Second, the presented drought scenario was constructed by combining several levels of water resource components. It reflects the characteristics of water resources in an area, so it is possible to describe the probable drought conditions. However, the probability of occurrence depends on the level combination in the scenario. Additional analyses should be performed to identify the probability of occurrence.

Through the results of drought analysis within an area, the characteristics of drought are identified. The following are Seoul’s drought characteristics based on SPI6, as an example: The first DIF for Seoul is that the average discharge and drought are more related to hydrological factors than meteorological factors. Comparing the high -demand period and low -demand period, the value of PRCF is 55% and 125th to be affected by temporal variability based on water demand change among 167 areas in Korea. Furthermore, during drought periods 1 and 2, the first DIF was the percentage of sunshine and average relative humidity. Therefore, it is possible to understand that meteorological factors have a more significant

impact than hydrological factors during severe drought periods in Seoul. It is classified as an urban zone due to the percentage water demand, which is 87% for domestic, 12% for industrial, and 1% for agricultural. The first DIF among hydrological factors is average discharge, and through frequency analysis, the criteria are set as 52% and 78% of the average discharge compared to the normal year. Combining the criteria with 6, 9, and 12 months of no rainfall, a drought scenario was constructed and is presented in Table 2.

This study has a set of limitations that future studies should address. DIF based on administrative division and various related analyses may help establish effective policies for managing water resources in drought conditions. Additionally, through drought scenarios, provisions can predict future drought conditions. This research needs to be carried out in situations with increasingly severe and frequent droughts due to climate change, and policies should be constructed to reflect the predicted conditions.

Declarations

Authors Contributions

Data collection and analysis were performed and the first draft of the manuscript was written by Soyeon Lim. Donghwi Jung designed the study and reviewed, edited, and approved the manuscript. All authors read and approved the final manuscript.

Acknowlegement

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Competing interests

None.

Data availability

The hydrometeorological data and SPI used during this study are available from the Korea Meteorological Administration (KMA) website (https://data.kma.go.kr). The following models or code used during this study are available from the corresponding author upon reasonable request.

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Figures

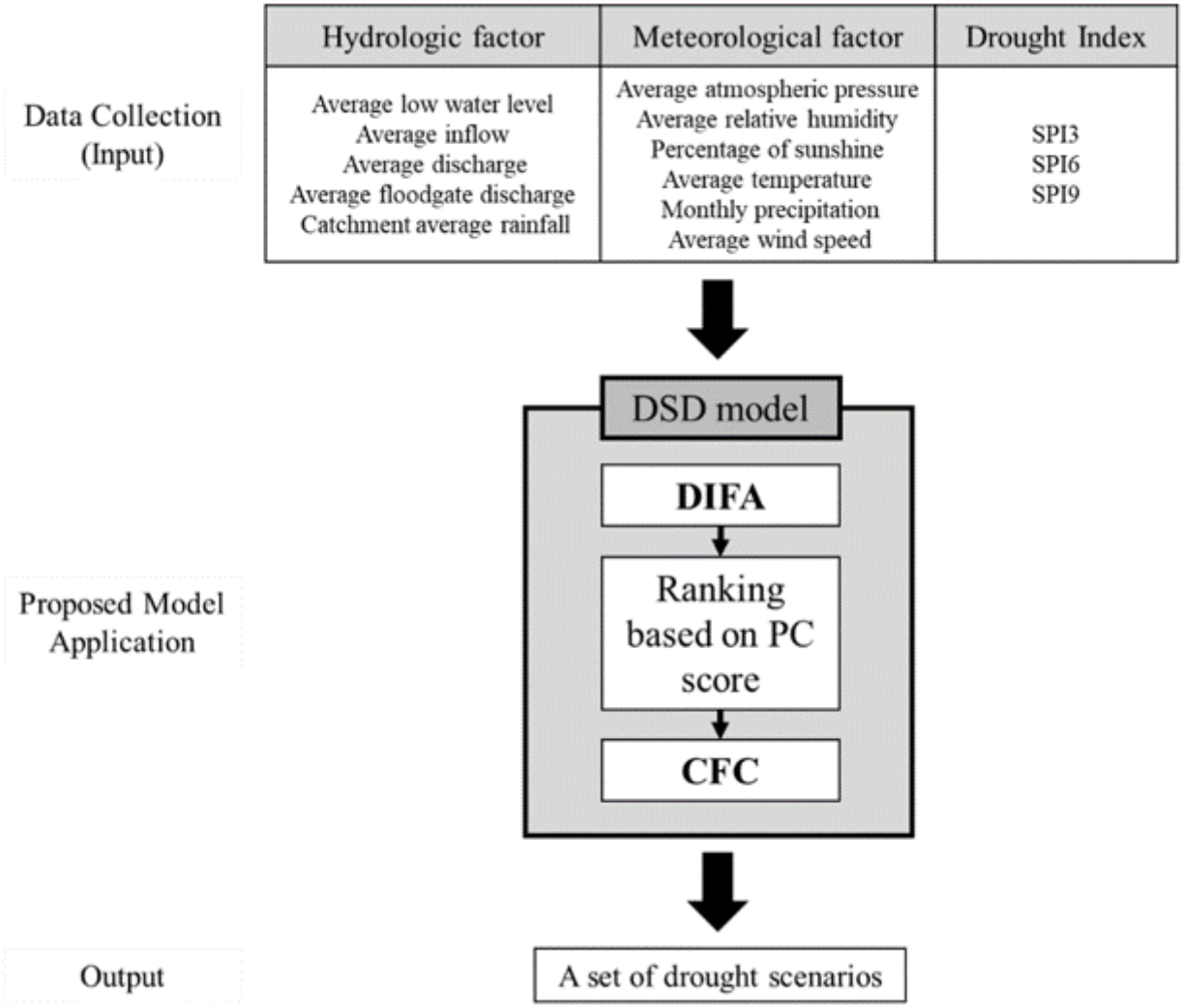

Figure 1

A schematic of the proposed DSD model with its input/output

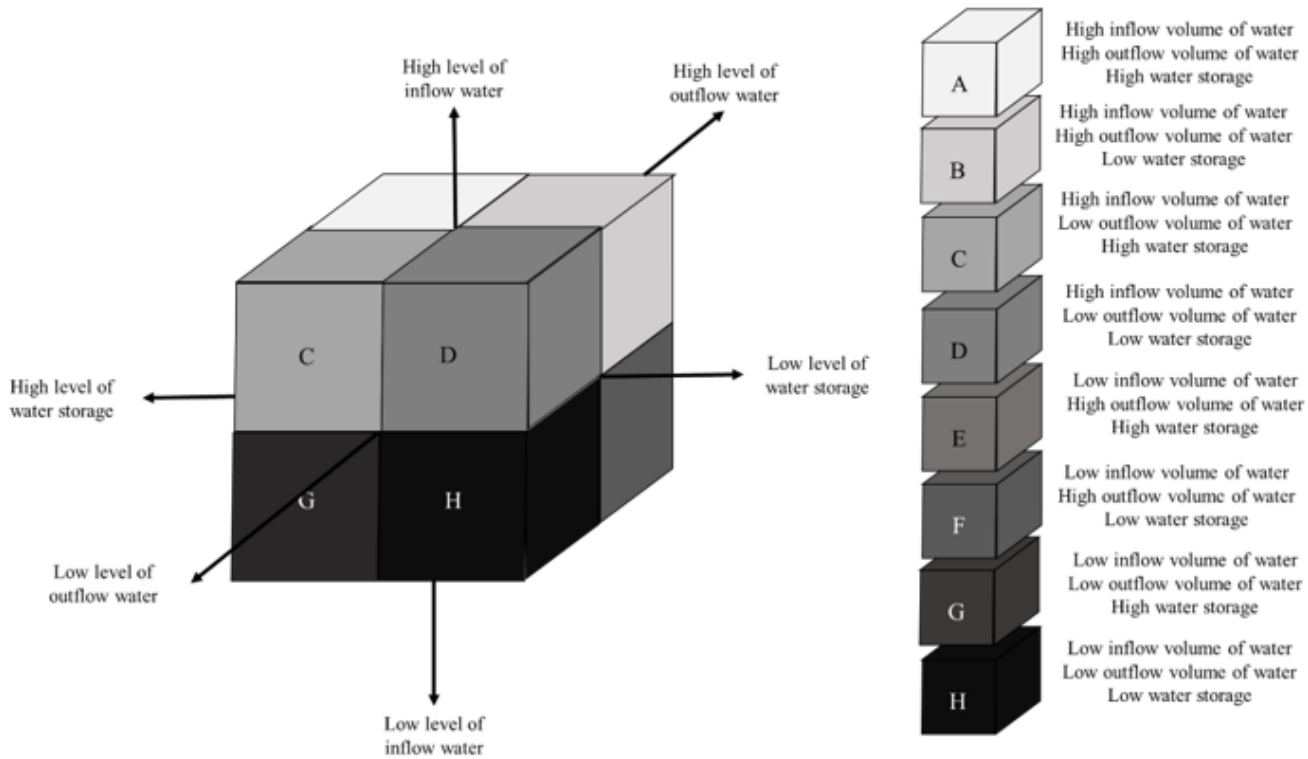

Figure 2

Components and application method to drought scenario (Second Figure 1 in manuscript.)

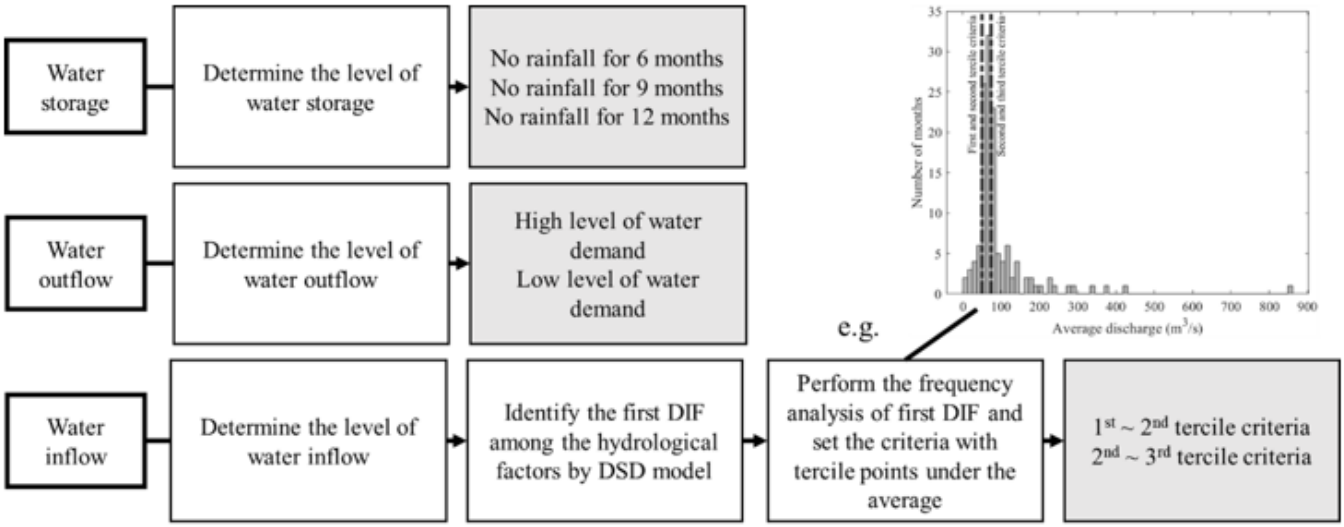

Figure 3

Diagram of CFC for drought scenario

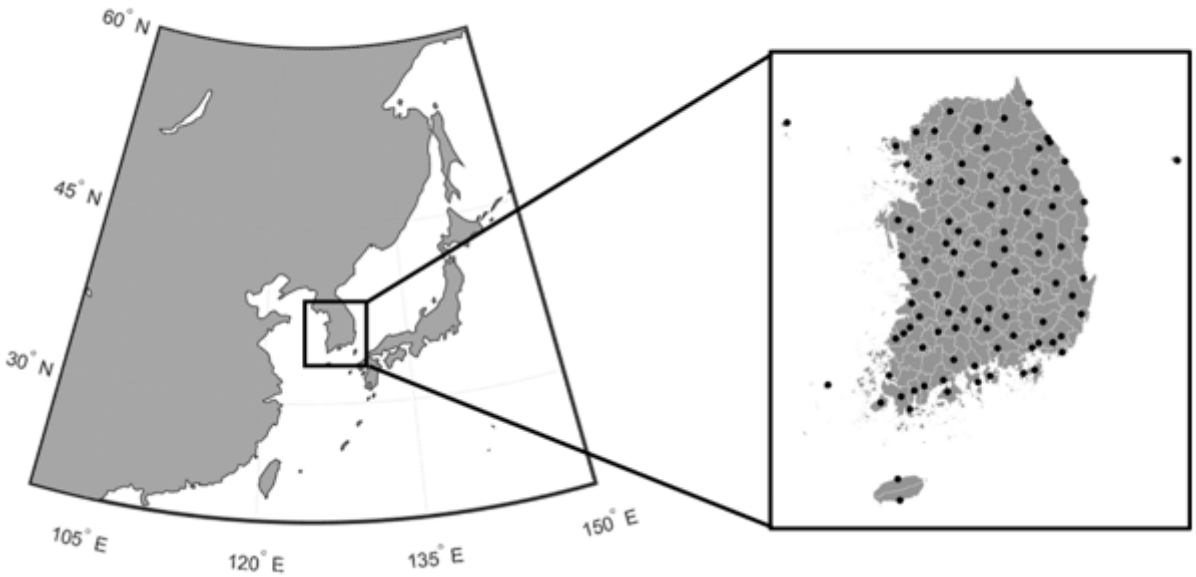

Figure 4

Location of Korea, China and Japan (left) and meteorological site of ASOS (right). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

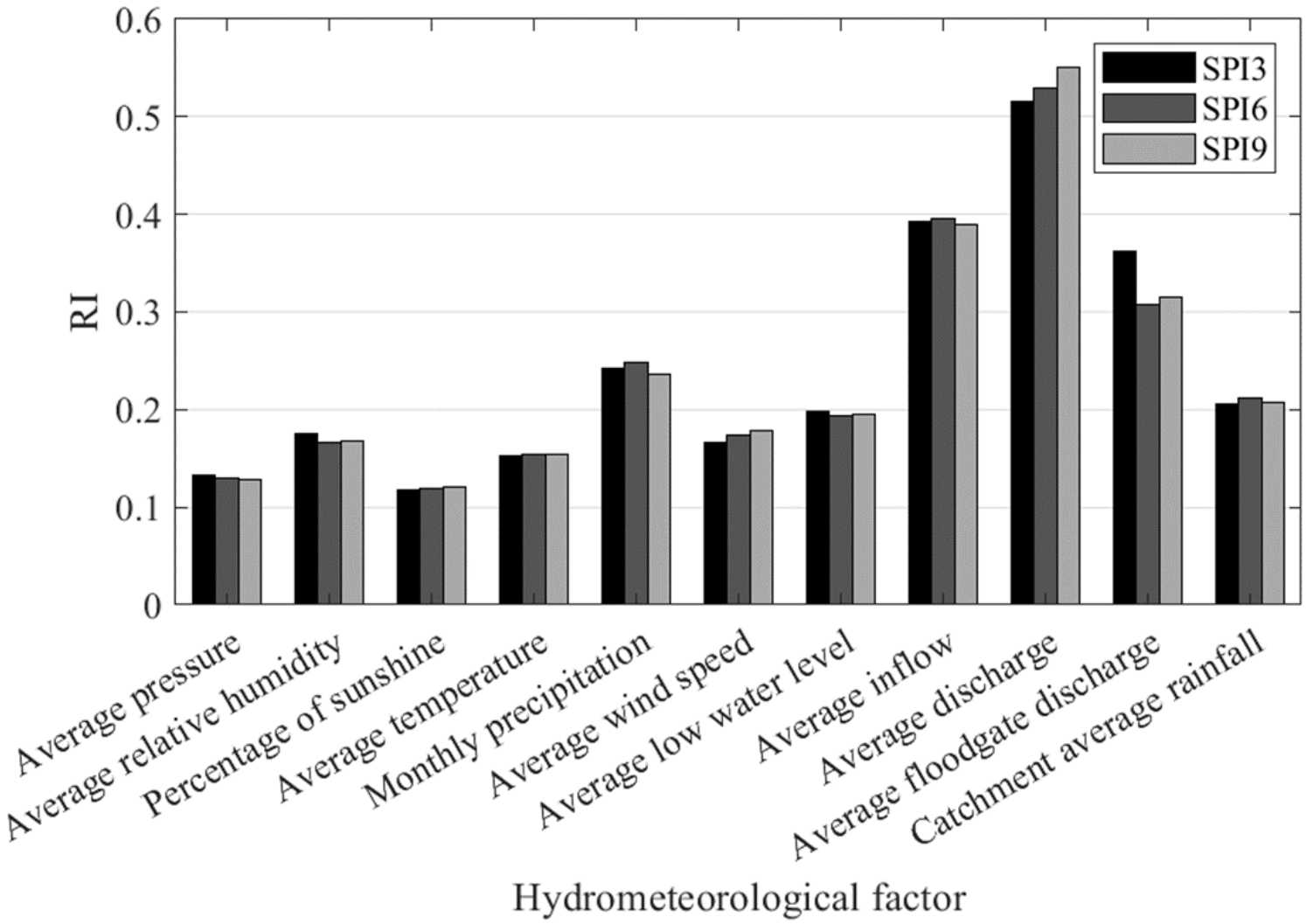

Figure 5

Integration of nationwide DIF analysis results

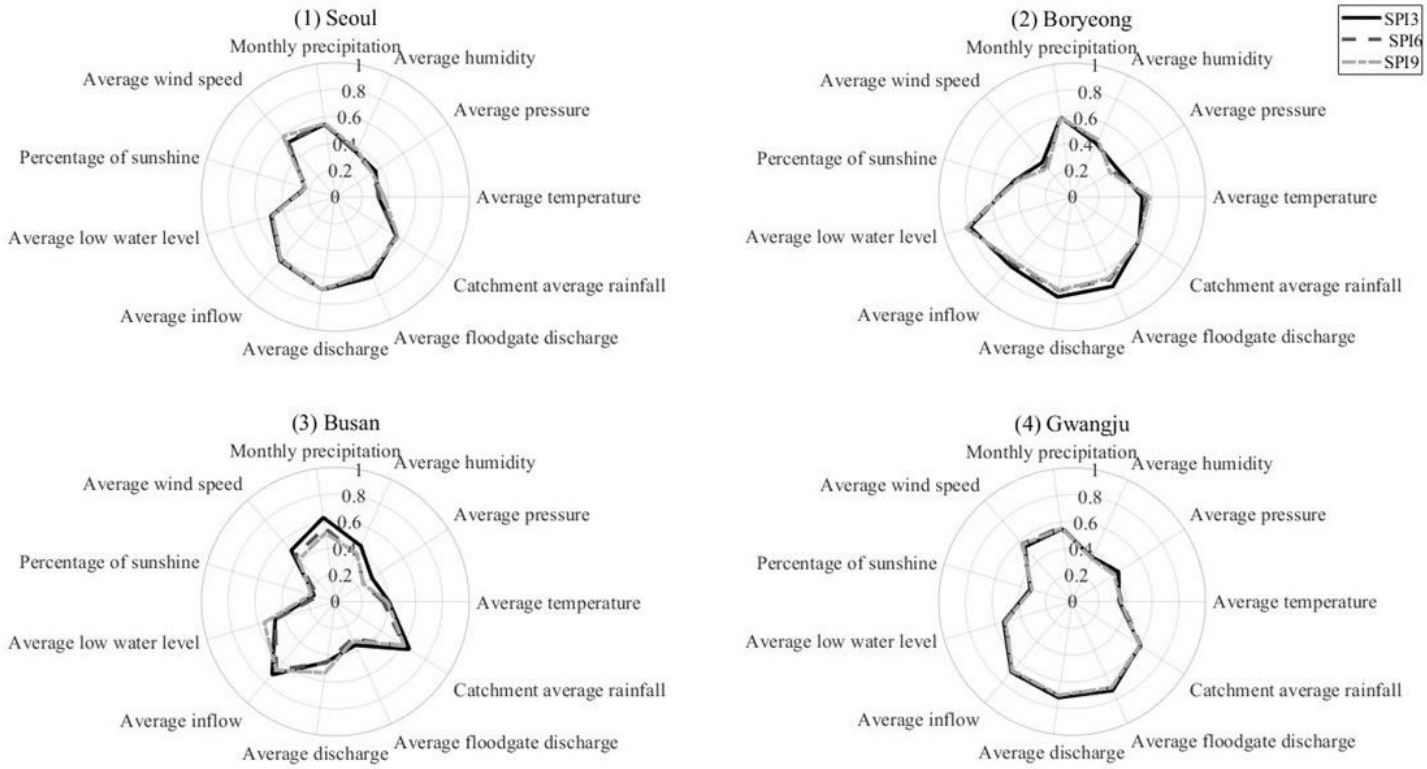

Figure 6

Result of DIF analysis for (1) Seoul, (2) Boryeong, (3) Busan, and (4) Gwangju. The black solid line is of SPI3 while SPI6 and SPI9 are represented with the black and gray-dashed lines, respectively.

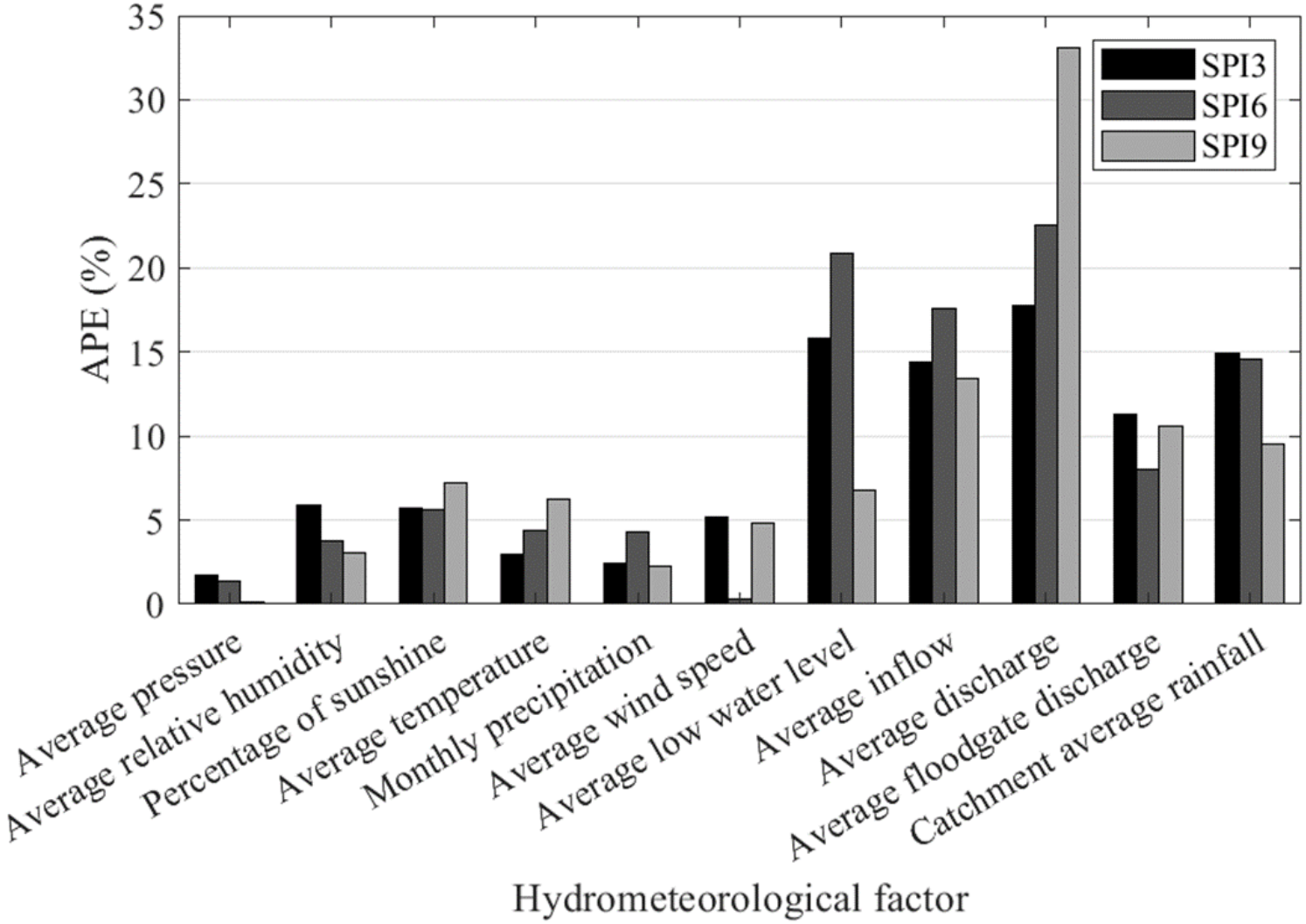

Figure 7

APE for DIF in 167 administrative divisions in Korea

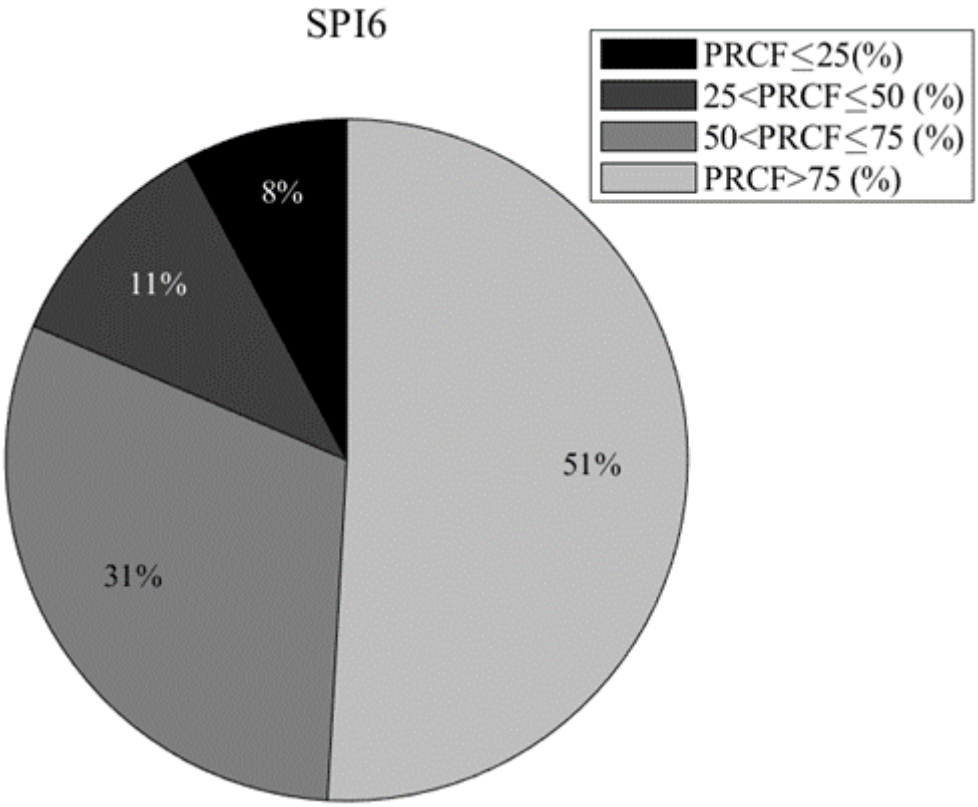

Figure 8

Classification of 167 area into 4 groups based on PRCF (SPI6)

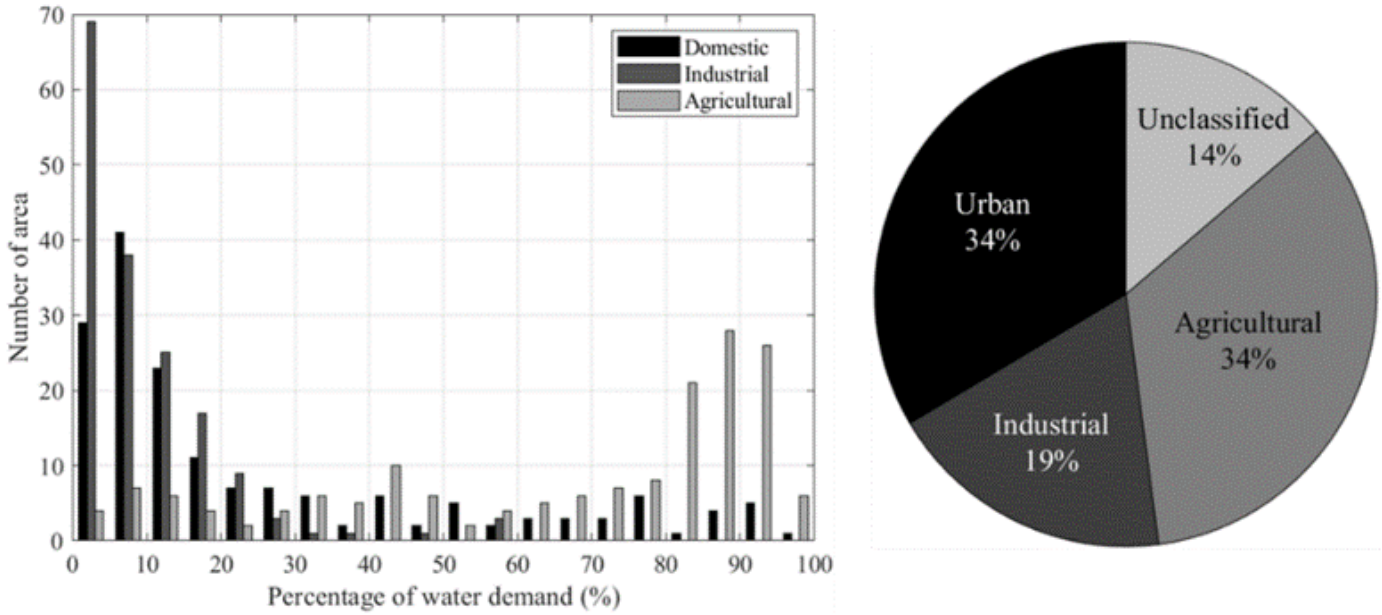

Figure 9

Histogram of domestic, industrial and agricultural water demand percentage(left) and classification of 167 area into urban, industrial and agricultural zone

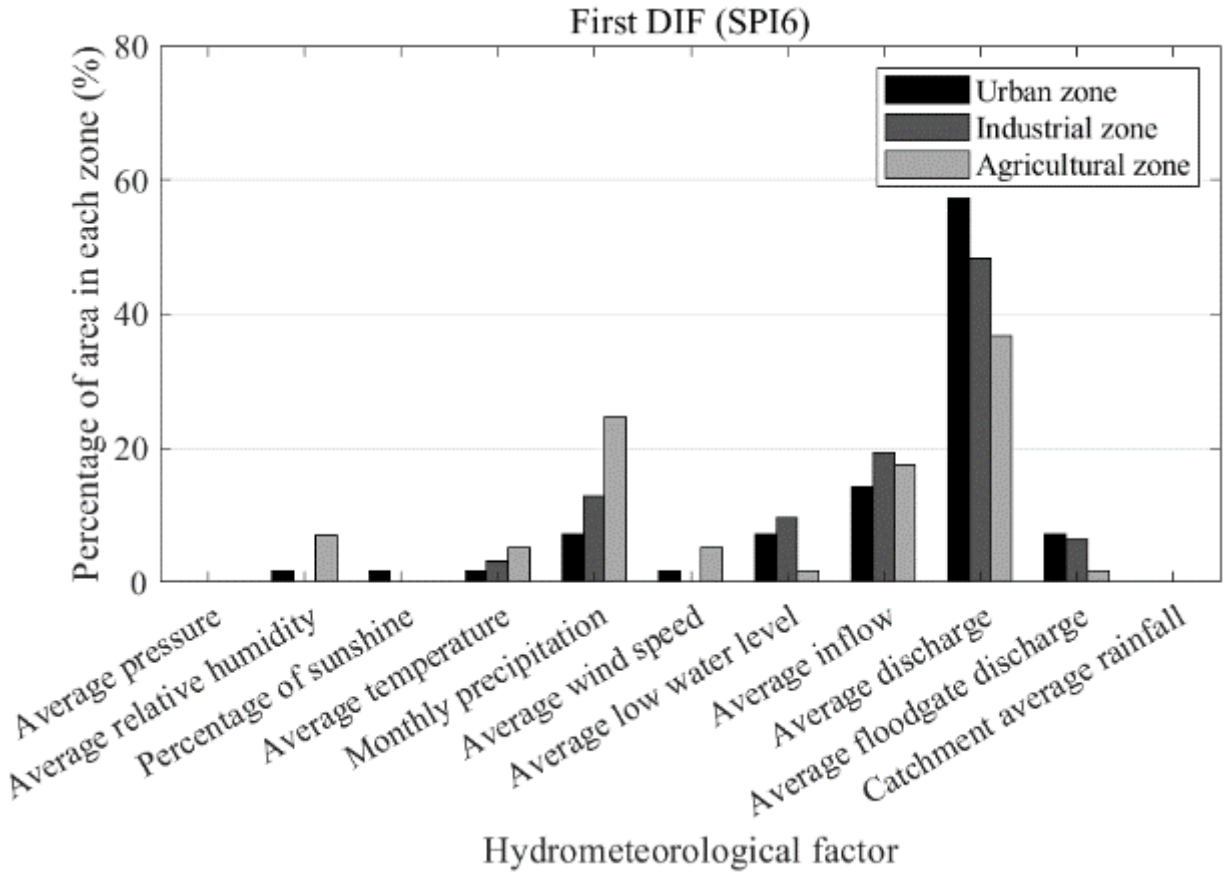

Figure 10

Percentage of area corresponding to first DIF (SPI6) in urban, industrial, and agricultural zone

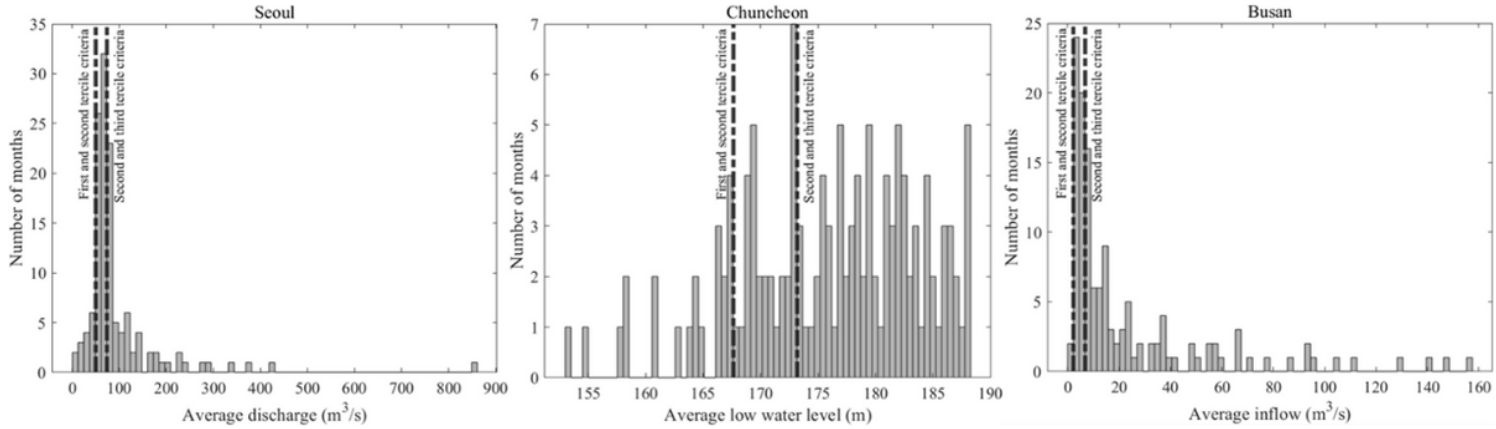

Figure 11

Histogram of average discharge in Seoul (left), average low water level in Chuncheon (center), and average inflow in Busan (right)