KSCE Journal of Civil Engineering (2021) 25(5):1901-1908
DOI 10.1007/s12205-021-0922-z
pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Development of a PCA-Based Vulnerability and Copula-Based Hazard Analysis for Assessing Regional Drought Risk

Jisoo Yu[a], Ji Eun Kim[b], Joo-Heon Lee[c], and Tae-Woong Kim[d]

[a]Research Institute of Engineering and Technology, Hanyang University, Ansan 15588, Korea
[b]Member, Dept. of Civil and Environmental System Engineering, Hanyang University, Seoul 04763, Korea
[c]Member, Dept. of Civil Engineering, Joongbu University, Goyang 10279, Korea
[d]Member, Dept. of Civil and Environmental Engineering, Hanyang University, Ansan 15588, Korea

ARTICLE HISTORY

Received 22 May 2020
Revised 26 September 2020
Accepted 15 December 2020
Published Online 26 February 2021

KEYWORDS

Drought
Vulnerability
Hazard
Risk
Socioeconomic indicator
Occurrence probability

ABSTRACT

Vulnerability and hazard are terms that are generally applied to drought risk assessment. Vulnerability can be defined as the capacity of a region to cope with and resist the impacts of natural hazards, while hazard can be defined as the likelihood of a natural or human-induced physical event. In this study, principal component analysis (PCA) was used to generate an aggregate drought vulnerability index (DVI) using multiple socio-economic indicators and copula-based drought frequency analysis was performed to calculate a drought hazard index (DHI) considering meteorological drought occurrence patterns. Finally, regional drought risk was evaluated by combining the DVI and DHI among cities within the Chungcheong province, South Korea. Based on the drought risk index (DRI), Jecheon-si (DRI = 0.50) and Gongju-si (DRI = 0.65) were identified as the most hazardous cities in Chungcheongbuk-do and Chungcheongnam-do, respectively. The overall process of drought risk assessment developed in this study is useful for planning drought management and mitigation at the local level.

1. Introduction

Droughts are generally classified into four categories: meteorological, hydrological, agricultural, and socioeconomic (Wilhite and Glantz, 1985). Amongst drought categories, meteorological drought induced by insufficient precipitation is the trigger of all others, which propagates the damage into the local community. However, the process from rainfall deficit to its economic and social consequences is not instantaneous and easily understood. Since the drought risk should be understood in the context of the vulnerability of a region and the hazard of a natural extreme event (Singh et al., 2019), it is necessary to develop a drought risk assessment framework to provide the relationship between the vulnerability and hazard in a region.

Therefore, the drought risk analysis using representative indicators of drought vulnerability and hazard is often used. It should be noted that while the vulnerability and hazard have been used in numerous studies, they do not always imply the same meaning. However, the generally accepted concept of vulnerability is the capacity of a person or group to cope with and resist the impacts of a natural hazard, while hazard is the likelihood of a natural or human-induced physical event (Intergovernmental Panel on Climate Change, 2012). The risk described by vulnerability and hazard can be defined depending on the purpose: 1) a social measure of resilience; 2) exposure that makes people or place dangerous; and 3) interactions between social and environmental systems (Cutter, 1996; Rezaee et al., 2018).

In the social sciences, where risk reduction is major concern, risk is focused on vulnerability and is defined in cultural, political, and economic terms (Adger, 1999; Pelling and Uitto, 2001; Salvati et al., 2009; Abson et al., 2012). In the physical sciences, risk is defined by threatening events or the probability of specific phenomenon occurring within a given time and area (Mirakbari et al., 2010; Li et al., 2015; Yoo et al., 2016). From a socio-physical point of view, risk is derived from interactions between human and natural conditions, and risk becomes a function of both vulnerability and hazard (Shahid and Behrawan, 2008;

CORRESPONDENCE Tae-Woong Kim twkim72@hanyang.ac.kr Dept. of Civil and Environmental Engineering, Hanyang University, Ansan 15588, Korea

Shiau and Hsiao, 2012; Zhang et al., 2013; Kim et al., 2015; Carrão et al., 2016).

Developing a comprehensive drought risk assessment framework is challenging due to the dynamic nature of environmental and socio-economic indicators (Hinkel, 2011). Numerous studies have achieved this goal by composing drought vulnerability index (DVI) and drought hazard index (DHI). In general, DVI and DHI were estimated by aggregating relevant variables through deductive approach such as expert judgment or normative approach such as equal weighting (Shahid and Behrawan, 2008; Lin et al., 2011; Belal et al., 2014; Rajsekhar et al., 2015; Pei et al., 2016; Dabanli, 2018).

The main concern in building vulnerability and hazard index is selecting the major indicators and the weighting schemes to avoid subjectivity (Saisana et al., 2005; Cherchye et al., 2008). This study employed probabilistic approaches to deal with those issues. First, when estimating the DVI, dominant social indicators were chosen based on the regional socioeconomic conditions and the weights were estimated depending on the explained variance in the dataset. Second, when estimating the DHI, the occurrence probabilities of specific drought conditions were estimated by bivariate drought frequency analysis.

2. Study Area and Data

Two provinces in South Korea, Chungcheongnam-do (CCN) and Chungcheongbuk-do (CCB) (Fig. 1), were considered as the study area, which are neighboring provinces with distinct climates. CCB has an average annual temperature and precipitation of 10.9°C and 1350 mm, and the comparable values in CCN are 12.2°C and 1270 mm, respectively. The average temperature and precipitation in overall South Korea, meanwhile, are 12.8°C and 1,360 mm, respectively.

These two provinces are indeed the most drought-prone areas in South Korea. During the extreme drought of 2014-15 summer precipitation of the Chungcheong area was 50 – 60% lesser of normal, and its residents suffered from the limited water supply. In particular, the water level at the Boryeong Dam in CCN reached a record low of 57.98 m (25.5% of reserved water rate) in November 2015. The water level was about 55% of the previous year's, making the drought more severe than any past events.

The drought is provoked by the lack of precipitation, however,

Table 1. The Administrative District Codes of Study Area

CCB		CCN	
Code	Name	Code	Name
CB1	Cheongju-si	CN1	Cheonan-si
CB2	Chungju-si	CN2	Gongju-si
CB3	Jecheon-si	CN3	Boryeong-si
CB4	Boeun-gun	CN4	Asan-si
CB5	Okcheon-gun	CN5	Seosan-si
CB6	Yeongdong-gun	CN6	Nonsan-si
CB7	Jeungpyeong-gun	CN7	Gyeryong-si
CB8	Jincheon-gun	CN8	Dangjin-si
CB9	Goesan-gun	CN9	Geumsan-gun
CB10	Eumseong-gun	CN10	Buyeo-gun
CB11	Danyang-gun	CN11	Seocheon-gun
		CN12	Cheongyang-gun
		CN13	Hongseong-gun
		CN14	Yesan-gun
		CN15	Taean-gun

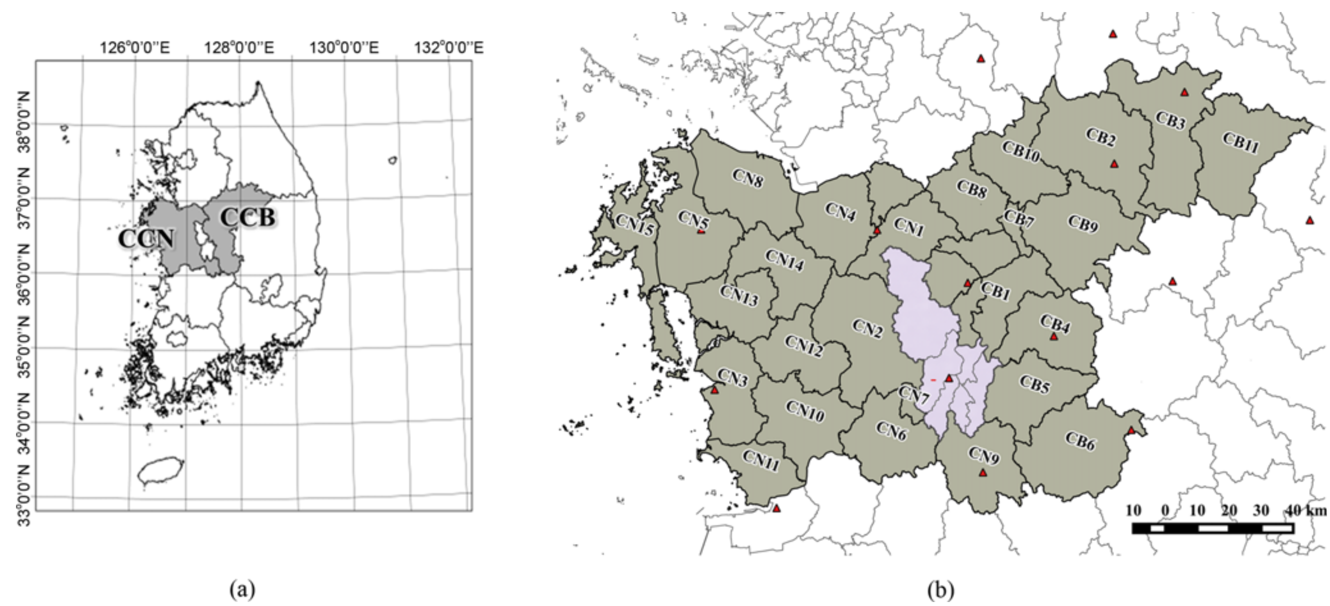

Fig. 1. Study Areas – Chungcheongbuk-do (CCB) and Chungcheongnam-do (CCN) in South Korea: (a) Map of South Korea, (b) Administrative Districts in Chungcheong Province (The triangular points indicate the rainfall stations, the texts in Fig. 1(b) represent the code of administrative districts.)

Table 2. Socioeconomic Drought Vulnerability Indicators and Data Source

Categories	Indicator		Unit	Source
Census	C1	Population	persons	KOSIS (2015)
Land use	L1	Paddy area	ha	KOSIS (2017)
	L2	Cultivated area	ha	
Agricultural water	A1	Water use for paddy area	10^3m^3/year	WAMIS (2014)
	A2	Water use for cultivated area	10^3m^3/year	
	A3	Water use for livestock	10^3m^3/year	
Industrial water	I1	Industrial water use	10^3m^3/year	WAMIS (2014)
Domestic water	D1	Water use of service area	10^3m^3/year	WAMIS (2014)
	D2	Water use of non-service area	10^3m^3/year	
Water supply system	W1	Penetration rate	%	WAMIS (2014)
	W2	Water consumption per capita	m^3/day	

*KOSIS (Korean Statistical Information Service, 2019): www.kosis.kr
**WAMIS (Water Resources Management Information System, 2019): www.wamis.go.kr

the drought damages of the local community are not derived only from the social dimension, but also the local economic conditions. In other words, even though two districts that have the different social-economic conditions have experienced the similar drought magnitude for the same period, the consequences maybe considerably different. Hence, the first step for quantifying the social vulnerability to drought is to identify the relevant indicators that address the attributes of drought damage (Smit et al., 1999).

Numerous indicators have been designed to capture a regional vulnerability to natural disasters, for example, population, number of civic organizations, income, employment, hazard mitigation plan, and infrastructure. Based on the previous studies (Cutter et al., 2008; Sherrieb et al., 2010), eleven indicators that capture a regional vulnerability to drought have been selected, which were reliable and easily accessible using the Korean information services, as summarized in Table 2.

Vulnerability indicators used in the study can be classified into six categories: census, land use, agricultural, industrial, and domestic water use, and water supply system. The social indicators should be re-scaled to dimensionless values because they have different units. The observed datasets with eleven indicators $Q_t = \{o_1, o_2, \cdots, o_k\}, k = 11$ were transformed into $X_t = \{x_1, x_2, \cdots, x_k\}, k = 11$ through Eq. (1).

$$X_t = \frac{O_t - min(O_t)}{max(O_t) - min(O_t)} \tag{1}$$

3. Methodology

3.1 Drought Definition

Before identifying the drought risk, drought events and their characteristics should be clearly identified. Many studies have been undertaken for drought analysis using various indices, however, Standardized Precipitation Index (SPI) is commonly used in South Korea (Kim et al., 2015; Yoo et al., 2016). SPI can be used to identify the start and the end of a drought event and quantify its magnitude. The six-month SPI (SPI-6) was especially estimated to consider drought severity in the study, since Korea Meteorological Administration provides the general drought information based on the SPI-6. The areal average precipitation data (1973 – 2016) that were calculated by the Thiessen polygon method using 15 stations in the study area were used to calculate the SPI-6.

Drought characteristics were calculated based on the SPI-6, which represent different attributes of droughts in terms of duration, severity, intensity, and consequently manifest the hazard. A drought begins when the SPI-6 is less than -1.0, which is the commonly used threshold level. Drought duration indicates the number of consecutive months for that the SPI-6 lies below -1 until it becomes greater than -1, and the sum of the SPI-6 during the period is defined as drought severity. Drought intensity represents the average strength of an event per unit time (month), simply defined as the ratio of the total magnitude to duration.

3.2 Development of the Drought Vulnerability Index Using PCA

PCA is a multivariate statistical technique to choose a sub-set of variables that contain as much information as possible about the original data. In particular, PCA efficiently recognizes data patterns, reducing the high dimensionality of datasets while minimizing information loss (Liu and Schisterman, 2004). The choice of vulnerable indicators is the primary determinant of drought vulnerability indices. Indicators should be easily accessible and reflect the socioeconomic conditions of cities.

Dominant vulnerable indicators and their weights were determined using principal component (PC) loadings, as described in Eq. (2):

$$w_{i,j} = \frac{c_i v_j}{\sum_{i=1}^{n} \sum_{k=1}^{m} c_i v_j}, \tag{2}$$

where $\sum_{i=1}^{n} \sum_{j=1}^{m} w_{i,j} = 1$. m is the number of selected principal components and n is the number of selected indicators in j th principal component. Thus, $w_{i,j}$ indicates the weight of i th indicator of the j th principal component. c_i and v_j are the loading of the i th indicator and the explained variation of the j th principal component, respectively.

The factor score of each principal components (FS_j) can be estimated by Eq. (3), and the DVI was calculated as the sum of factor scores as Eq. (4).

$$FS_j = \sum_{i=1}^{n} x_i W_{i,j} \tag{3}$$

$$\mathrm{DVI} = \sum_{j=1}^{m} FS_j \tag{4}$$

3.3 Development of Drought Hazard Index Using Drought Frequency

DHI is defined based on the drought characteristics of duration, intensity, and frequency in this study. The frequency implies the occurrence probability of the event that has the specific values of duration and intensity. The joint probability distribution of drought duration and intensity is established using copula (Shiau, 2006; Ganguli and Reddy, 2012; Chen et al., 2013), as expressed in Eq. (5). Where $F_X(x) = u$ and $F_Y(y) = v$ are the marginal probability distribution functions of duration and intensity, respectively.

$$F(x,y) = C(u,v) = C(F_X(x), F_Y(y)) \tag{5}$$

Eight candidate probability distribution functions were considered to fit the marginal distributions of durations and intensities: Gaussian, log-normal, exponential, Gumbel, Gamma, Weibull, generalized Pareto, and generalized extreme value. As determined by a Kolmogorov-Smirnov test, the fittest distribution functions were Gamma for the duration and exponential for the intensity. After estimating marginal distributions, three Archimedean copulas, Clayton, Frank and Gumbel were used to derive a joint probability distribution. Based on the maximum likelihood, Frank was determined as the optimal copula function for both CCB and CCN.

In order to generalize the drought occurrence patterns of each district, we distinguished the droughts into nine classes corresponding to the durations of 1-, 3-, and 6-month and the intensities under moderate, severe, and extreme conditions. The nine classes of drought events were ranked and their weights were simply decided by the rank that ranges from zero to unity, as described in Table 3. The average drought duration of the study area was less than 6 months (refer to Table 5), and even the durations of maximum events were rarely maintained one year. It is much appropriate to consider the usual droughts which are not persisted 6 months than extreme events in order to establish drought preparation and mitigation plan.

Table 3. Description of Drought Classes and Their Weights Corresponding to the Rank

Rank	Duration (d_k)	Intensity (m_k)	Weight (r_k)
1	1	1.0 (moderate)	0.1
2	3		0.2
3	6		0.3
4	1	1.5 (severe)	0.4
5	3		0.6
6	6		0.7
7	1	2.0 (extreme)	0.8
8	3		0.9
9	6		1.0

DHI was calculated as the weighted sum of occurrence probabilities of each drought classes as expressed in Eq. (6):

$$\mathrm{DHI} = \sum_{k=1}^{rank} r_k f(d_k, m_k)\,, \tag{6}$$

where r_k is a weight of k th drought class and $f(d_k, m_k)$ represents an occurrence probability of a drought event that has a duration (d_k) and an intensity (m_k).

3.4 Drought Risk Assessment

Various frameworks that have been proposed for risk assessment are in correspondence with the different definitions for risk. Bogardi and Birkmann (2004) developed a holistic framework for disaster risk evaluation. In their framework, vulnerability consists of the environmental, physical, social and economic conditions of the region, while hazard is provoked by natural phenomena. Wisner et al. (1994) presented the risk as the sum of vulnerability and hazard and Intergovernmental Panel on Climate Change (2012) proposed risk as probability of occurrence of events multiplied by the impacts. More recently, the risk has been defined as the product of vulnerability and hazard (Zhang et al., 2014; Kim et al., 2015; Rajsekhar et al., 2015).

Downing et al. (2005) insisted that what is needed is not a dynamic concept of risk, but simple, clearly defined the terms that are easily understandable. The DVI and DHI defined in this study showed how much community is exposed to drought from both hydro-meteorological and socio-economic perspectives. We cannot determine which perspective constitutes the larger portion of the total risk, thus the DVI and DHI should be considered equally when risk assessments are performed. The risk can be evaluated by multiplying DVI and DHI as Eq. (7).

$$\mathrm{Risk} = \mathrm{DVI} \times \mathrm{DHI} \tag{7}$$

4. Results and Discussions

4.1 Socioeconomic Drought Vulnerable Indicators

PCA was conducted with eleven indicators (Table 2), and the dominant indicators were identified. In CCB, three principal components explained 83% of the total variation in the dataset (PC1: 36%, PC2: 28%, PC3: 19%). Indicators with positive PC loadings were chosen as listed in Table 4. Of the three significant PCs in CCN among the total variation of 86%, the first PC

Table 4. Selected Drought Vulnerability Indicators and Their PC Loadings

Indicator	CCB			CCN		
	PC1	PC2	PC3	PC1	PC2	PC3
C1	0.46				0.53	
L1	0.41					0.81
L2		0.29			0.38	
A1		0.51		0.41		
A2		0.52		0.41		
A3		0.52		0.41		
I1	0.45				0.54	
D1	0.47			0.42		
D2			0.57	0.41		
W1	0.33				0.49	
W2	0.23			0.32		

explained most of the variation (46%), and the second and third PCs explained 27% and 13%, respectively. The results of the PCA in CCN are described in Table 4.

Since water usage was closely related to the socio-economic conditions of a province, it can be indicators to describe which are the main activities of regions. The averaged agricultural water use (A1, A2, and A3) in 15 districts in CCB (108.9×10^6 m^3/year) was 33% larger than in 11 districts in CCN (73.4×10^6 m^3/year), while the average industrial water use (I1) in CCN (25.7×10^6 m^3/year) was 63% greater than in CCB (9.5×10^6 m^3/year). Consequently, we can assume that the major economic activities of CCB is agriculture and that of CCN is industrial facilities.

The choice of drought vulnerability factors by PCA effectively explained the socio-economic environments. The selected dominant indicators of each PC were different in CCB and CCN. It was observed in CCB that the six indicators in the first PC were C1, L1, I1, D1, W1 and W2, which are more related to industrial and domestic water use. In contrast, the significant PC1 factors in CCN were A1, A2, A3, D1, D2, and W2, which are related to agricultural and domestic water use.

The DVI indicators can be aggregated as an average sum, generally with each indicator given the same weight in previous researches (Lin et al., 2011; Belal et al., 2014; Rajsekhar et al., 2015; Pei et al., 2016; Dabanli, 2018). However, the proposed method using PCA in the study can identify the dominant indicators responsible for drought damage, also the weights were decided based on how much each indicator had an influence on the districts. The PC loadings in Table 3 described the governing vulnerability indicators and their portion.

4.2 Drought Occurrence Probability

DHI can be defined as the likelihood of specific or overall drought events (Shiau and Hsiao, 2012; Rajsekhar et al., 2015). Establishing a link between drought occurrence and its risk remains a challenge. To solve this problem, the copula function derived from the marginal distributions of drought duration and intensity was used to quantify occurrence probability.

Table 5. Drought Occurrence Characteristics of the Study Area

City	# of occur.	Average		Maximum event		
		Duration	Intensity	Start yr.	Duration	Intensity
CCB						
CB1	21	3.24	1.44	2015	7	1.71
CB2	17	3.76	1.48	2015	6	1.69
CB3	19	3.95	1.52	1994	10	1.96
CB4	17	3.76	1.37	1994	8	2.09
CB5	15	4.67	1.46	1982	10	1.47
CB6	23	3.45	1.55	2015	7	2.05
CB7	19	3.37	1.45	2015	7	1.69
CB8	21	3.48	1.45	2015	8	1.85
CB9	16	4.06	1.52	1994	7	2.31
CB10	19	4.05	1.49	1994	7	2.15
CB11	19	3.63	1.55	2015	7	2.16
CCN						
CN1	15	4.40	1.37	2015	9	1.78
CN2	18	3.72	1.50	2015	8	2.04
CN3	20	3.30	1.55	2015	6	2.23
CN4	15	4.33	1.36	2015	9	1.76
CN5	21	3.76	1.40	1995	6	1.86
CN6	18	4.17	1.54	2015	6	2.15
CN7	19	4.11	1.43	2015	7	1.78
CN8	19	3.74	1.44	1995	6	1.78
CN9	20	4.15	1.48	1973	7	2.01
CN10	21	3.90	1.48	2015	6	2.11
CN11	22	3.41	1.45	2015	6	2.11
CN12	19	4.00	1.52	2015	6	2.16
CN13	20	3.65	1.50	1982	12	1.57
CN14	20	4.05	1.31	2015	9	1.67
CN15	22	3.47	1.42	1982	12	1.51

Table 5 shows the drought occurrence characteristics during 44 years (1973 – 2016) defined using the SPI-6. Among 26 districts of the study area, Yeongdong-gun had been experienced the most frequent droughts, while the average duration and intensity were estimated not so severe, which were 3.45 months and 1.55, respectively. On the other hand, Okcheon-gun, Cheonan-si, and Asan-si were experienced less droughts than other cities. However, there were no significant differences among districts for the mean of durations and intensities.

The maximum events were defined that the one had the least occurrence probability (the longest return period). Their occurrence probabilities were generally less than 1%, so the recurrence intervals were longer than 100 years. We can specify the most extreme dry years as 1982, 1994, and 2015 in CCB, while 1973, 1982, 1995, and 2015 in CCN, respectively. The intensities of maximum events were larger than 1.5 (severe condition) and the sustained periods were over than a half year, however, not exceed one year.

4.3 Drought Risk Analysis Based on Vulnerability and Hazard

DVIs and DHIs were estimated using the social vulnerable factors and drought occurrence probabilities as represented in Figs. 2 and 3, respectively. In CCB, the average DVI was 0.28, with a maximum value in Cheongju-si (0.66) and a minimum in Jeungpyeong-gun (0.11). Similarly, the average DVI in CCN was 0.22, with a maximum in Gongju-si of 0.76 and a minimum in Gyeryong-si of 0.10. Because the PCA was conducted separately in each province, the social dominant indicators reflected the characteristics of the provinces rather than those of each district. This makes the comparison between districts significant, while the comparison between the two provinces was less so.

The drought hazard analysis was carried out using the design droughts for each district, making the regional DHI comparison more useful. The mean of the DHI values for CCB was 0.75, whereas the maximum and minimum values were 0.94 in CB3 (Jecheon-si) and 0.57 in CB1 (Cheongju-si). The mean DHI in CCN was estimated to be bit lower than the CCB estimate of 0.71, the maximum value was 0.98 in CN6 (Nonsan-si), and the minimum value of 0.48 was found in CN14 (Yesan-gun). The DHI was therefore skewed to an upper side than the DVI.

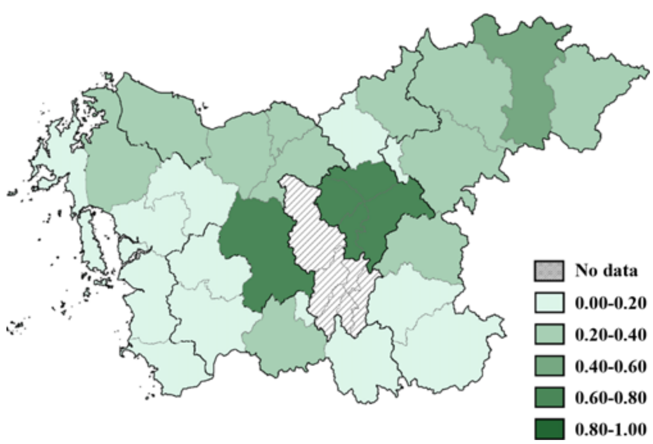

Fig. 2. Drought Vulnerability Index (DVI) in Chungcheong Province

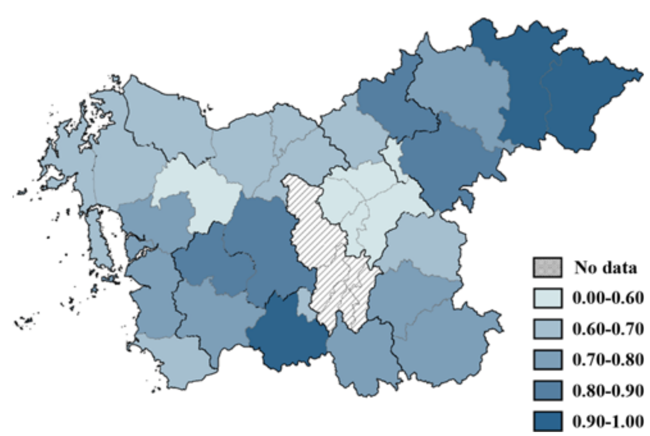

Fig. 3. Drought Hazard Index (DHI) in Chungcheong Province

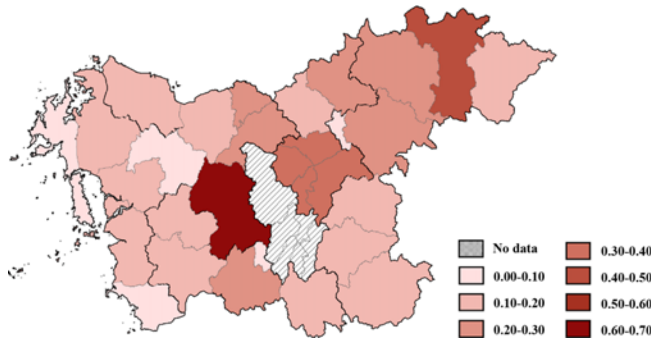

Fig. 4. Drought Risk Index (DRI) in Chungcheong Province

Because the DHI was related to rainfall patterns, its distribution is less controlled.

Considering the need for identifying the drought-prone region, DVI and DHI were overlaid and then generated a drought risk map as shown in Fig. 4. In the drought research, DVI described the infrastructural and socioeconomic ability to anticipate and copes with the droughts, while DHI detected the potential risk of occurrence and the specific characteristics of a drought. Therefore, based on the drought risk map, decision makers can visualize the hazard and appreciate the potential loss of society.

The mean values of DRI in CCB and CCN were 0.25 and 0.17, respectively. Five of eleven districts in CCB (45.5%) were assessed under {DRI $\leq$ 0.20} and nine (81.2%) were under {DRI $\leq$ 0.30}. The most drought-prone area in CCB was CB3 (Jecheon-si), which had the highest values of the DHI (0.94) among districts in the study area and the second-highest value of DVI (0.53) in CCB. On the other hand, nine of fifteen districts (60.0%) in CCN were under {DRI $\leq$ 0.15} and fourteen districts (93.3%) were under {DRI $\leq$ 0.25}. CN2 (Gongju-si) had the highest values for both DHI (0.85) and DVI (0.76) in CN.

5. Conclusions

Evaluation and quantification of drought risk have played important roles in water resources planning and management. In this study, a regional drought risk was assessed as a function of drought vulnerability and hazard. The DVI and DHI independently captured the socioeconomic vulnerability and the drought occurrence pattern, respectively. According to the DVI analysis, the dominant PCs were distinct in CCB and CCN, and the most drought-exposed cities were CB1 (Cheongju-si) in CCB and CN2 (Gongju-si) in CCN. On the other hand, the DHI quantified the drought occurrence probability considering specific durations and intensities that would induce the critical impacts. According to the DHI analysis, the most drought-prone district in the study area was CN6 (Nonsan-si) located in CCN.

Because the mean DRI in CCB was higher than that in CCN, we may conclude that CCB is more vulnerable to drought than CCN. However, the PCA determined different DVI indicators for two provinces (i.e., CCB and CCN) and the estimated weights were relative among selected indicators within the province, it would be beneficial for extending the spatial scale from districts to regions to compare the province drought risks in South Korea. Nevertheless, the overall process of drought risk assessment developed in this study is useful for planning drought management and mitigation at the local level.

Acknowledgments

This work is supported by the Water Management Research Program of Korea Ministry of Environment (MOE) (Grant no. 79616) and Korea National Research Foundation (Grant no. 2020R1A2C1012919).

ORCID

Jisoo Yu https://orcid.org/0000-0001-7482-6268
Ji Eun Kim https://orcid.org/0000-0001-7426-5253
Joo-Heon Lee https://orcid.org/0000-0002-5540-1966
Tae-Woong Kim https://orcid.org/0000-0002-1793-2483

References

Abson DJ, Dougill AJ, Stringer LC (2012) Using principal component analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. *Applied Geography* 35(1-2):515-524, DOI: 10.1016/j.apgeog.2012.08.004

Adger WN (1999) Social vulnerability to climate change and extremes in coastal Vietnam. *World Development* 27(2):249-269, DOI: 10.1016/S0305-750X(98)00136-3

Belal A-A, El-Ramady HR, Mohamed ES, Saleh AM (2014) Drought risk assessment using remote sensing and GIS techniques. *Arabian Journal of Geosciences* 7(1):35-53, DOI: 10.1007/s12517-012-0707-2

Bogardi J, Birkmann J (2004) Vulnerability assessment: The first step towards sustainable risk reduction. In: Malzahn D, Plapp T (eds) Disaster and society - From hazard assessment to risk reduction. Logos Verlag Berlin, Berlin, Germany, 75-82

Carrão H, Naumann G, Barbosa P (2016) Mapping global patterns of drought risk: An empirical framework based on sub-national estimates of hazard, exposure and vulnerability. *Global Environmental Change* 39:108-124, DOI: 10.1016/j.gloenvcha.2016.04.012

Chen L, Singh VP, Guo S, Mishra AK, Guo J (2013) Drought analysis using copulas. *Journal of Hydrologic Engineering* 18(7):797-808, DOI: 10.1061/(ASCE)HE.1943-5584.0000697

Cherchye L, Moesen W, Rogge N, Van Puyenbroeck T, Saisana M, Saltelli A, Liska R, Tarantola S (2008) Creating composite indicators with DEA and robustness analysis: The case of the technology achievement index. *Journal of Operational Research Society* 59(2):239-251, DOI: 10.1057/palgrave.jors.2602445

Cutter SL (1996) Vulnerability to environmental hazards. *Progress in Human Geography* 20(4):529-539, DOI: 10.1177/030913259602000407

Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J (2008) A place-based model for understanding community resilience to natural disasters. *Global Environmental Change* 18(4):598-606, DOI: 10.1016/j.gloenvcha.2008.07.013

Dabanli I (2018) Drought hazard, vulnerability, and risk assessment in Turkey. *Arabian Journal of Geosciences* 11(18):538-549, DOI: 10.1007/s12517-018-3867-x

Downing TE, Patwardhan A, Klein RJ, Mukhala E, Stephen L, Winograd M, Ziervogel G (2005) Assessing vulnerability for climate adaptation. In: Lim B, Spanger-Siegfried E, Burton I, Malone E, Huq S (eds) Adaptation policy frameworks for climate change: Developing strategies, policies and measures. Cambridge University Press, Cambridge, UK, 69-89

Ganguli P, Reddy MJ (2012) Risk assessment of droughts in Gujarat using bivariate copulas. *Water Resources Management* 26(11):3301-3327, DOI: 10.1007/s11269-012-0073-6

Hinkel J (2011) "Indicators of vulnerability and adaptive capacity": Towards a clarification of the science-policy interface. *Global Environmental Change* 21(1):198-208, DOI: 10.1016/j.gloenvcha.2010.08.002

Intergovernmental Panel on Climate Change (2012) Managing the risks of extreme events and disasters to advance climate change adaptation: Summary for policymakers. Cambridge University Press, Cambridge, UK, 1-19

Kim H, Park J, Yoo J, Kim T-W (2015) Assessment of drought hazard, vulnerability, and risk: A case study for administrative districts in South Korea. *Journal of Hydro-Environment Research* 9(1):28-35, DOI: 10.1016/j.jher.2013.07.003

KOSIS (2019) Korea Statistical Information Service, Retrieved December 1, 2019, http://www.kosis.kr

Li Y, Gu W, Cui W, Chang Z, Xu Y (2015) Exploration of copula function use in crop meteorological drought risk analysis: A case study of winter wheat in Beijing, China. *Natural Hazards* 77(2): 1289-1303, DOI: 10.1007/s11069-015-1649-2

Lin ML, Chu CM, Tsai BW (2011) Drought risk assessment in western Inner-Mongolia. *International Journal of Environmental Research* 5(1):139-148, DOI: 10.22059/IJER.2010.299

Liu A, Schisterman EF (2004) Principal component analysis. In: Chow S-C (ed) Encyclopedia of biopharmaceutical statistics. CPC Press, New York, NY, USA, 1796-1801

Mirakbari M, Ganji A, Fallah SR (2010) Regional bivariate frequency analysis of meteorological droughts. *Journal of Hydrologic Engineering* 15(12):985-1000, DOI: 10.1061/(ASCE)HE.1943-5584.0000271

Pei W, Fu Q, Liu D, Li T, Cheng K (2016) Assessing agricultural drought vulnerability in the Sanjiang plain based on an improved projection pursuit model. *Natural Hazards* 82(1):683-701, DOI: 10.1007/s11069-016-2213-4

Pelling M, Uitto J (2001) Small island developing states: Natural disaster vulnerability and global change. *Environmental Hazards* 3(2):49-62, DOI: 10.1016/S1464-2867(01)00018-3

Rajsekhar D, Singh VP, Mishra AK (2015) Integrated drought causality, hazard, and vulnerability assessment for future socioeconomic scenarios: An information theory perspective. *Journal of Geophysical Research: Atmospheres* 120(13):6346-6378, DOI: 10.1002/2014JD022670

Rezaee Z, Fisher PF, Balzter H (2018) Geographical concepts of vulnerability analysis for risk assessments – A review. *Revista Publicando* 5(18):27-59

Saisana M, Saltelli A, Tarantola S (2005) Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A* 168(2):307-323, DOI: 10.1111/j.1467-985X.2005.00350.x

Salvati L, Zitti M, Ceccarelli T, Perini L (2009) Developing a synthetic index of land vulnerability to drought and desertification. *Geographical Research* 47(3):280-291, DOI: 10.1111/j.1745-5871.2009.00590.x

Shahid S, Behrawan H (2008) Drought risk assessment in the western part of Bangladesh. *Natural Hazards* 46(3):391-413, DOI: 10.1007/

s11069-007-9191-5

Sherrieb K, Norris FH, Galea S (2010) Measuring capacities for community resilience. *Social Indicators Research* 99(2):227-247, DOI: 10.1007/s11205-010-9576-9

Shiau J-T (2006) Fitting drought duration and severity with two-dimensional copulas. *Water Resources Management* 20(5):795-815, DOI: 10.1007/s11269-005-9008-9

Shiau J-T, Hsiao Y-Y (2012) Water-deficit-based drought risk assessments in Taiwan. *Natural Hazards* 64(1):237-257, DOI: 10.1007/s11069-012-0239-9

Singh GR, Jain MK, Gupta V (2019) Spatiotemporal assessment of drought hazard, vulnerability and risk in the Krishna River basin, India. *Natural Hazards* 99(2):611-635, DOI: 10.1007/s11069-019-03762-6

Smit B, Burton I, Klein RJT, Street R (1999) The science of adaptation: A framework for assessment. *Mitigation and Adaptation Strategies for Global Change* 4:199-213, DOI: 10.1023/A:1009652531101

WAMIS (2019) Water Resources Management Information System, Retrieved December 1, 2019, http://www.wamis.go.kr

Wilhite DA, Glantz MH (1985) Understanding the drought phenomenon: The role of definitions. *Water International* 10(3):111-120, DOI: 10.1080/02508068508686328

Wisner B, Blaikie P, Cannon T, Davis I (1994) At risk: Natural hazards, people vulnerability, and disasters. Routledge Publisher, London, UK, 1-471

Yoo J, Kwon H-H, Lee J-H, Kim T-W (2016) Influence of evapotranspiration on future drought risk using bivariate drought frequency curves. *KSCE Journal of Civil Engineering* 20(7):2059-2069, DOI: 10.1007/s12205-015-0078-9

Zhang Q, Peng S, Li J, Mingzhong X, Singh VP (2014) Assessment of drought vulnerability of the Tarim River basin, Xinjiang, China. *Theoretical and Applied Climatology* 121(1-2):337-347, DOI: 10.1007/s00704-014-1234-8

Zhang Q, Xiao M, Singh VP, Chen X (2013) Copula-based risk evaluation of droughts across the Pearl River basin, China. *Theoretical and Applied Climatology* 111:119-131, DOI: 10.1007/s00704-012-0656-4