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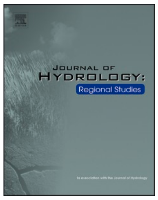

Comprehensive drought risk assessment using structural equation modeling and objective weighting methods

Ji Eun Kim [a], Jiyoung Yoo [b], Hyun-Han Kwon [c], Tae-Woong Kim [d,*]

[a] *Research Institute of Engineering Technology, Hanyang University, Ansan 15588, Republic of Korea*
[b] *Research & Development Center, Sooil Engineering Co., Ltd., Anyang 14057, Republic of Korea*
[c] *Department of Civil and Environmental Engineering, Sejong University, Seoul 05006, Republic of Korea*
[d] *Department of Civil and Environmental Engineering, Hanyang University, Ansan 15588, Republic of Korea*

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ABSTRACT

Study region: Gyeongsang province in Korea
Study focus: Drought is a complex phenomenon influencing the natural, physical, and social sectors depending on the occurrence probability, regional characteristics, and the water supply and demand. To reduce the damage resulting from drought, it is necessary to assess the drought risk that can identify the impacts, causes, and vulnerability of drought. Previous drought risk assessment has usually been conducted by combining drought hazard and vulnerability, but such assessment is of limited value because the regional response capacity for drought is not considered. Moreover, it contains high uncertainty because indicators and weighting factors are determined by subjective methods. In this study, the comprehensive drought risk was assessed including the drought response capacity and with consideration of the regional water supply system. To remove the uncertainty in the drought risk assessment, this study employed partial least squares – structural equation modeling (PLS-SEM) to select effective indicators including the regional drought response capacity, and also applied objective weighting methods such as entropy, principal component analysis (PCA), Gaussian mixture model (GMM), and Bayesian networks to determine optimal weighting factors.
New hydrological insights into the region under study: As a result of application to Gyeongsang province in Korea, PLS-SEM selected 10 indicators for drought risk assessment. Using the selected indicators and the objective weighting methods, this study determined that the drought hazard, vulnerability, response capacity, and risk were highest in GS26 (Ulleung), GS27 (Changwon), GS16 (Cheongsong), and GS28 (Jinju), respectively. The districts with large actual drought damage had high drought risk, indicating that the results of this study were reasonable and useful in the identification of the major impacts and risk of regional drought and may facilitate the decision-making process for selecting drought countermeasures to reduce drought risk.

1. Introduction

Drought may gradually progress over a long period and its impacts can continue for months or years even after the drought is relieved. Therefore, it is difficult to determine the start and end dates of a drought event. Drought can be considered to occur in various

* Corresponding author.
E-mail address: twkim72@hanyang.ac.kr (T.-W. Kim).

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fields depending on its impacts, and is generally categorized as meteorological, hydrological, agricultural, and socioeconomic (Wilhite and Glantz, 1985). In this sense, drought refers to a complex phenomenon composed of natural ecosystems, physical and social components. With a long-term lack of precipitation, the impact of drought reverberates throughout society and the economy.

Even when regions have similar meteorological characteristics, their drought impact and damage will vary depending on regional characteristics or ability to cope with the drought. In other words, when different regions suffer from similar precipitation deficits, water resources or supplemental water sources sufficient to support population water use can reduce the impact of drought. In 2017, the drought forecasting and warning of meteorological drought in the southern part of Korea was 'Red' (certain), but some districts in the region had different drought impacts. For example, while Ulju issued the 'Yellow' (probable) because the reservoir storage rate for agricultural water fell to less than 10%, and Miryang had serious problems with domestic, agricultural, and industrial water because the water supply rate Miryang Dam was 18.2%, Gijang did not experience drought damage because Gijang continued to receive plenty of water from the Nakdong River. The 2017 drought taught us that drought impacts and damage depend on meteorological factors, characteristics of the affected area, and water resource capacity. Therefore, to identify regional drought risk, the overall situation of waters in the region needs to be considered.

To quantitatively identify drought impacts, the concept of drought risk is introduced and evaluated. Prior to drought risk assessment, a definition of drought risk should be established. In this study, concepts related to drought risk were based on Intergovernmental Panel on Climate Change (IPCC) (2014) and various references (Ahmadalipour, 2017; Fan et al., 2017; Sam et al., 2017; Vargas and Paneque, 2017): drought hazard is a meteorological aspect indicating the probability of drought occurrence, drought vulnerability is a socioeconomic aspect of regional systems negatively related to drought, drought response capacity is the water supply capacity of regional water systems to mitigate drought damage, and drought risk is related to the potential damage caused by drought.

Drought risk consists of three components: hazard, vulnerability, and response capacity. However, drought risk is generally assessed only based on hazard and vulnerability due to difficulties determining drought response capacity. A few studies considered drought response capacity; however, most applied the socioeconomic factors of the region, not the water supply capacity. For example, Blauhut et al. (2016) estimated the adaptive capacity consisting of corruption, drought awareness, drought recovery capacity, inability to finance losses, public participation, and river basin management plans. Vargas and Paneque (2017) calculated an adaptive capacity index of drought by assigning the same weight to public participation, drought management plan, reservoir capacity, and drought risk perception. It is very important to understand the water supply capacities of a region; however, it is difficult to assess the drought response capacity of the region using only simple water resource information or socioeconomic indicators. The drought response capacity should be correlated with information related to the water supply and demand of a particular region.

Most water-related studies regularly analyze only water supply capacity from dams or reservoirs, rather than within a region. Kuria and Vogel (2014) estimated the reliability and uncertainty associated with water supply yields derived from surface water reservoirs. They identified the water supply capacity of the reservoir to document the uncertainty inherent in water supply yield estimates for a wide range of reservoir systems subject to the hydrologic variations and conditions. Choi et al. (2022) calculated the number of days available at upstream water intake sources for drought response using the Soil and Water Assessment Tool (SWAT). However, it is difficult to accurately evaluate drought risk in the region because most studies have individually estimated drought response capacity to link water supply and demand without considering the probability of drought occurrence within the drought risk assessment. Drought response capacity related to water supply and demand is a very important element that can reduce drought risk, so it should be considered within the drought risk assessment framework. Namely, comprehensive drought risk considering the occurrence probability of drought, socio-economic vulnerability, and water supply capacity of the region should be quantified by combining drought hazard, vulnerability, and response capacity. As such, drought risk consists of various factors, so it is necessary to apply a method to determine drought response capacity that is intuitive and easy to calculate.

Before assessing the drought risk, it is very important to extract drought influencing indicators that are usually selected under the subjective judgment of the researcher. Structural equation modeling (SEM) was recently introduced to explore influencing indicators and ensure objectivity in selecting indicators. SEM is regarded as one of the most robust statistical techniques capable of analyzing complex interrelationships among variables in terms of quantifying complex relationship models in many different fields (Zhou et al., 2022). Fatemi et al. (2021) tested nine hypothetical relationships between the multi-layered and inter-connected dimensions of flood vulnerability, damage and risk reduction in Dhaka, Bangladesh, using structural equation modeling. Zhou et al. (2022) confirmed the relationship between multi-dimensional factors for the earthquake resilience of water supply systems by a method of triangulation through quantitative analysis of partial least squares-structural equation modeling (PLS-SEM) combined with qualitative literature analysis. Despite the advantages of SEM, there are few studies applying SEM to drought risk assessment. Using SEM to understand the relationship and influence of indicators on drought risk, we attempt to validate the selection of appropriate indicators by region.

Drought risk has high uncertainty because various hydro-meteorological and socioeconomic factors are involved, especially in the determination of vulnerability. Weights are allocated to integrate these multiple factors in the assessment of drought vulnerability. Weighting is critical as it represents relative importance among indicators (Handayani et al., 2017). The equal-weighting method is commonly used due to the lack of information on the importance of indicators, in part because it is difficult to assign the relative contribution of each indicator. Survey methods are widely used by experts to allocate relative contributions, and the uncertainty of vulnerability assessment arises primarily from the human judgment "subjective nature" of weights and ratings assigned (Agossou and Yang, 2021). Thus, if probability and statistical methods are applied in the vulnerability assessment to give an objective weight to indicators, it is possible to calculate more reliable results by reducing the uncertainty associated with subjectivity. Balaganesh et al. (2020) developed a composite drought vulnerability index comprising both crop and dairy indicators for 30 districts of Tamil Nadu, India, and weights were assigned to each indicator based on principal component analysis (PCA). Mihunov and Lam (2020) examined the dynamics of resilience to drought hazard for 503 counties in the South-Central USA using a Bayesian network approach, which modeled the interaction effects of the resilience variables from both the natural and human systems. Kim et al. (2021) applied the PCA, a Gaussian mixture model (GMM), and the equal-weighting method to objectively determine the weights for drought vulnerability assessment in Chungcheong Province, South Korea. Using these methods, it is possible to reduce the subjectivity introduce by researchers through calculating the objective weights in consideration of the characteristics of the indicators. Thus, we used objective weighting methods to reflect the characteristics of the indicators.

Recently, there has been a growing emphasis on drought risk assessment. The main purpose of this study is to assess comprehensive drought risk that integrates response capacity while considering the regional water supply system as well as drought hazard and vulnerability. The comprehensive drought risk assessment procedure is described in Fig. 1. The novelty of this study is to quantify drought risk by drawing on a formula for drought response capacity that reflects the regional water supply network, which has close ties with human society and has a great impact on drought. In addition, to exclude the subjective influence of investigators, SEM is used for selecting drought influencing indicators and various objective weights are integrated for drought vulnerability assessment.

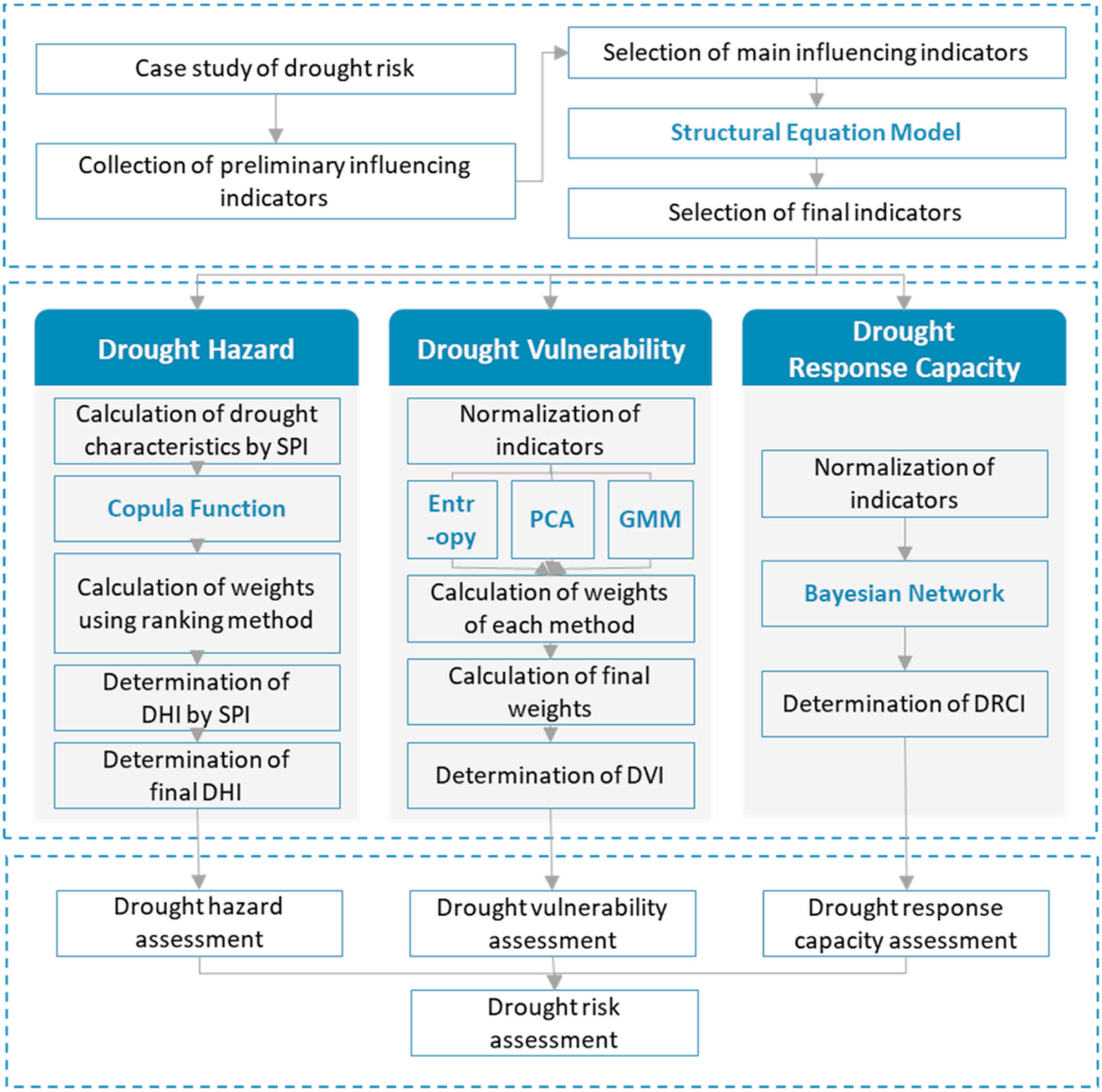


Fig. 1. The drought risk assessment procedure proposed in this study.

2. Study area and data

In this study, comprehensive drought risk based on the regional water supply system was assessed for the Gyeongsang (GS) province located in the southeastern part of Korea. As shown in Fig. 2, the GS province consists of 23 districts in the north, 18 districts in the south, and three metropolitan cities including Busan, Daegu, and Ulsan. The GS province is a mountainous region with an east high and west low topography, covers an area of 32,289 km^2, and has a population of 12.78 million. The annual average temperature in the GS is around 11 – 15 °C and the annual average precipitation is about 1032 – 1930 mm. The GS suffered great and small droughts occur every few years, especially severe water shortage in 2017. Considering drought damage the drought impacts are evident from meteorological to hydrological perspectives. In addition, the area is very large, and the cities are developed along the coast, so there is a significant difference in characteristics between regions. In addition, the regional water resource characteristics of GS are spatially heterogeneous because there are 29 dams and the Nakdong River that passes through the GS from the north to south. Therefore, it would be advantageous to identify the pattern of drought risk according to regional characteristics.

To build SEM and assess drought risk in this study, we determined influencing indicators related to hazard, vulnerability, response capacity, and risk of droughts. Influencing indicators are usually determined by the definition of drought risk. The preliminary influencing indicators consistent with the definition and concept of drought risk mentioned in Section 1 were collected (Appendix A: Table A1). Observed precipitation data collected from the Korea Meteorological Administration (KMA) were used to calculate the drought hazard, and socioeconomic data relevant to affecting drought damage were collected to analyze the drought vulnerability. The drought response capacity was investigated using water resource retention, water intake, and water usage. Finally, the drought risk-related data were collected for water damage and drought forecasting and warning. This risk-related data was also used as drought damage data compared to the drought risk index. All the data for influencing indicators must have the same spatial and temporal resolution, so the resolution for the drought risk index was set to that of from 2001 to 2019 for each district. However, precipitation data for drought hazard were analyzed for the observed period from 1976 to 2019 to calculate the probability of drought occurrence.

Since the factors that affect drought risk in practice among the preliminary influencing indicators vary slightly depending on regional characteristics, we need to derive the main influencing indicators for drought risk. Because the preliminary influencing indicators were limited in indicating drought hazard, risk, and response capacity, the main influencing indicators were reassigned according to the definition based on the data presented in Table A1 (Appendix A). The main influencing indicators used as input data for structural equation modeling is presented in Table 1. The final indicators selected from SEM are consolidated to express drought

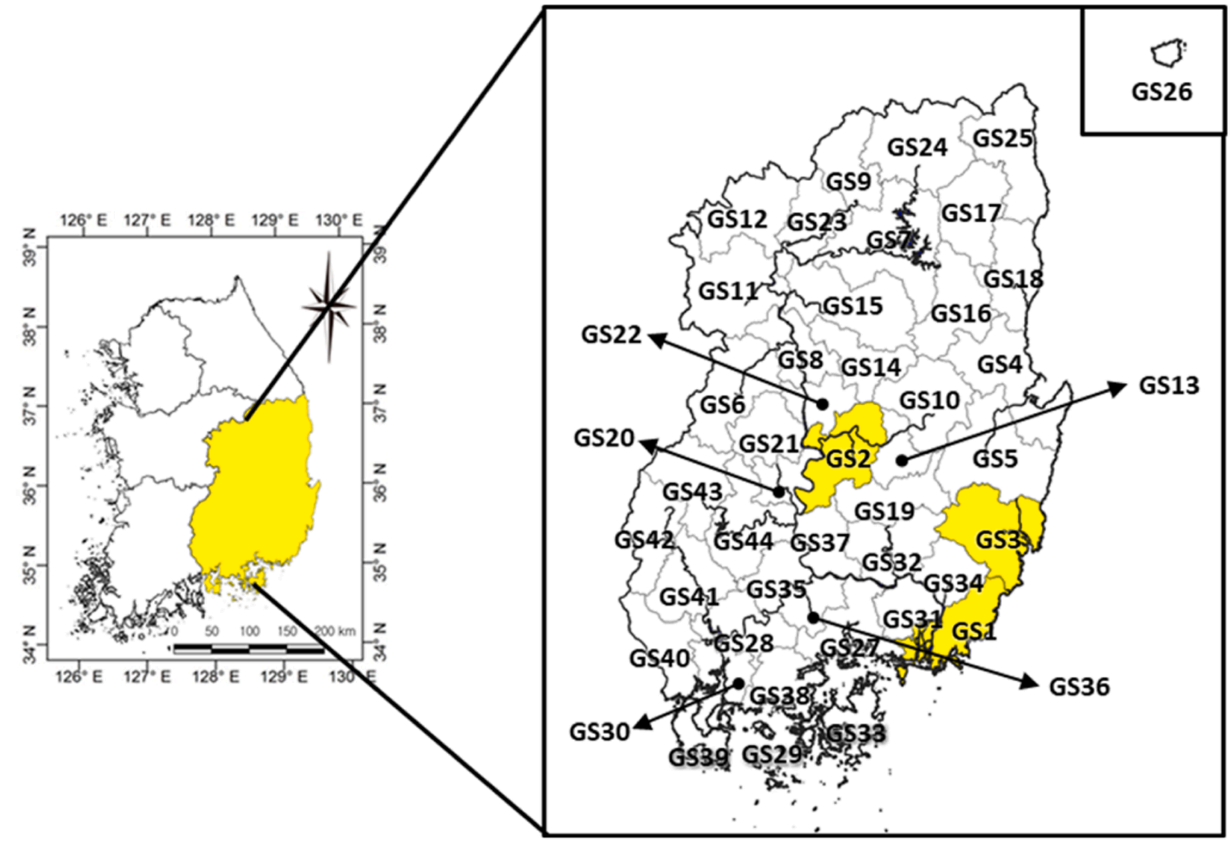


Fig. 2. The map of this study areas.

hazard, vulnerability, and response capacity. The process of determining the indicators in Table 1 from Table A1 (Appendix A) is described in Section 3. For convenience of analysis and expression, the drought hazard is expressed as H, drought vulnerability is V, drought response capacity is expressed as C, and drought risk is expressed as R.

3. Methodology

3.1. PLS-SEM for selecting indicators

SEM is a combination of PCA, regression analysis, and factor analysis to infer the influential relationship between various indicators and to stand for the structural relationship between variables in the form of a linear equation. SEM can provide objectivity and validity by inferring relationships between the indicators of drought risk and using them to adopt appropriate indicators for each region. SEM is a method of estimating the causal relationship between variables by simultaneously considering the relationship between measurement variables and latent variables. Measurement variables refer to directly observed variables, and latent variables are indirectly measured variables that depend on measurement variables but are not measured or observed directly. If explanatory variables are not measurable or observed, SEM can solve the problem by introducing latent variables. It can analyze the relationship between the latent and observed variables, as well as the cause–effect relationship in the latent variables path coefficient of the path analysis diagram to measure the influence degree between variables or the effect of variables (Wang et al., 2021).

SEM can be classified into covariance based-SEM (CB-SEM) and partial least squares-SEM (PLS-SEM). Compared with CB-SEM, PLS-SEM has the advantage of not making assumptions about the population or scale of measurement and sample size and is therefore suitable for the construction of theoretical models and exploratory research (Huang, 2021). The general conceptual diagram of PLS-SEM is shown in Fig. 3, which comprises a measurement model and a structural model. The measurement model represents the relationship with the measurement variable explaining the latent variable, and the structural model represents the relationship between the latent variables. The causal relationship between variables is indicated by a unidirectional arrow, and the direction and value of the causal relationship can be determined through the path coefficient. PLS-SEM is expressed in Eqs. (1) - (3) as:

$$X = \lambda_X \xi + \delta \tag{1}$$

$$Y = \lambda_Y \eta + \varepsilon \tag{2}$$

$$\eta = \gamma \xi + \zeta \tag{3}$$

where X and Y are the observed variables, and λ_X and λ_Y are the path/regression coefficient for X and Y, respectively. δ and ε represent the error of exogenous and endogenous latent variables, respectively. In the measurement model (Eqs. (1) and (2)), ξ is the exogenous latent variable, and η is the endogenous latent variable. In the structural model (Eq. (3)), the regression coefficients between exogenous

Table 1
The main influencing indicators for structural equation modeling.

Code	Indicators
H1	SPI-30 (30-day SPI)
H2	SPI-60 (60-day SPI)
H3	SPI-90 (90-day SPI)
H4	SPI-120 (120-day SPI)
H5	SPI-270 (270-day SPI)
H6	SPI-360 (360-day SPI)
V1	Population
V2	Farm population
V3	Recipients of basic living
V4	Solitary senior citizen
V5	Total area of district
V6	Agricultural area
V7	Area of industrial complex
V8	Ratio of water leakage
V9	Daily water supply per capita
V10	Water supply ratio
C1	Water supply capacity
C2	The amount of available precipitation per capita
C3	The amount of potential groundwater development per capita
C4	The ratio of effluents of sewage treatment
C5	The ratio of sewage reuse
C6	The ratio of rainwater reuse
R1	The number of occurrences of restrictive/carrying water rationing
R2	Population of restrictive/carrying water rationing
R3	Drought damage articles
R4	The number of days of restrictive/carrying water rationing
R5	Drought forecasting and warning

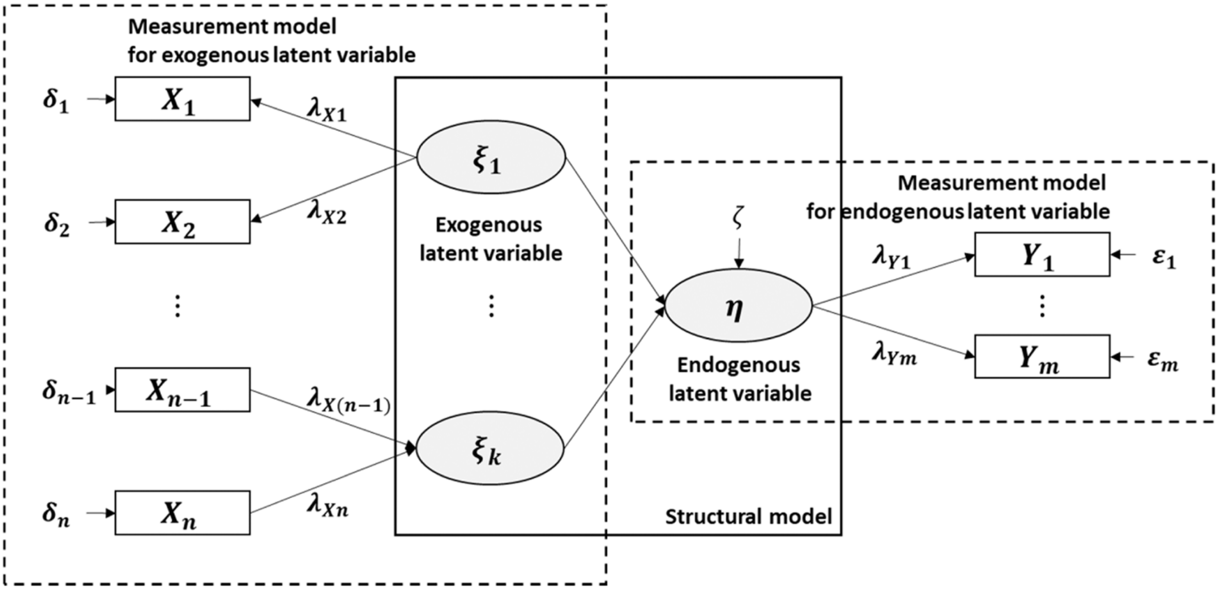


Fig. 3. The general structure of PLS-SEM.

and endogenous latent variables are represented by γ, and the residual terms are represented by ζ (Chai et al., 2020).

PLS-SEM can be used to evaluate the causal relationship between the model and variables divided into a measurement model and a structural model. We evaluated how well measurement variables represent latent variables through the internal consistency reliability, convergent validity, and discriminant validity, and evaluated the validity of the relationship between latent variables through the multicollinearity, coefficient of determination, and model's goodness-of-fit. Table 2 shows the criteria of evaluation for PLS-SEM. In this study, PLS-SEM was employed to select the final indicators for drought risk assessment, and the appropriateness of PLS-SEM was verified by using evaluation criteria. Based on PLS-SEM theory, the SmartPLS was used for data analysis such as inferring the path coefficient and evaluating relationship between the model and variables.

3.2. Drought hazard index using copula functions

Drought hazard represents the potential occurrence of meteorological drought, which can be quantified using the drought index. The standardized precipitation index (SPI) is a commonly used drought index because it can consistently quantify drought in certain regions and periods. The calculation of SPI can be found in McKee et al. (1993). In addition, it can identify the beginning and end of a drought event and monitor long- and short-term droughts depending on the time scale. Using daily SPIs with different time scales of 30, 60, 90, 180, 270, and 360 days, a drought event was identified when the values of SPI are consecutively lower than − 1.0. Each drought event has a duration defined by its beginning and end, a magnitude defined the cumulative sum of SPI values, and an intensity defined as the average SPI value during the drought event which is given by the ratio of magnitude and duration. Drought duration and intensity were calculated for drought events, and the optimal marginal distributions of duration and intensity were determined based on the Kolmogorov-Smirnov (K-S) test for nine probability distributions including exponential, normal, Gamma, lognormal, Poison, Weibull, generalized extreme value, and Gumbel distribution. The joint probability distribution was calculated by applying the marginal distribution to the three Archimedean copula functions such as Clayton, Frank, and Gumbel, as given in Eq. (4).

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

Table 2
Evaluation criteria for PLS-SEM.

Model	Criteria		Note		
Measurement model	Internal consistency reliability	Cronbach's alpha	Cronbach's alpha ≥ 0.6		
	Convergent validity	AVE	AVE > 0.5		
	Discriminant validity	Fornell-Larcker	$\sqrt{AVE} > \text{Max(Correlation coefficient)}$		
		Cross loading	Outer loading > Cross loading		
Structural model	Multi-collinearity	Inner VIF	Inner VIF < 5.0		
	Model's goodness-of-fit	R^2	High: $R^2 > 0.26$	$0.13 \leq R^2 < 0.26$	Low: $R^2 < 0.13$
		f^2	High: $f^2 > 0.26$	$0.13 \leq f^2 < 0.26$	Low: $f^2 < 0.13$
		Predictive relevance	Predictive relevance ≥ 0.6		
		Goodness-of-fit	High: > 0.36	0.25–0.36	Low: 0.10–0.25

where, $F_X(x) = u$ and $F_Y(y) = v$ are the marginal distributions of duration and intensity, respectively.

When drought characteristics was identified and the joint probability distribution was estimated using the copula function, the drought hazard index (DHI) was determined by applying the ranking method considering the drought frequency and severity developed by Yu et al. (2021). The nine classes of drought severity were ranked, and their weights were simply decided by the rank that ranges from zero to unity, as described in Table 3 (Yu et al., 2021). The DHI was calculated by weighting the probability of occurrence of each drought class as expressed in Eq. (5). For example, the occurrence probability of drought with duration of less than 30 days and intensity of less than − 1.0 is multiplied by a weight of 0.1, and the occurrence probability of drought with duration between 90 and 120 days and intensity less than − 1.0 is multiplied by a weight of 0.2. The DHI is calculated as Eq. (5).

$$DHI = \sum_{k=1}^{rank} r_k f(d_k, m_k) \tag{5}$$

where, r_k is the weight of the kth drought stage, $f(d_k, m_k)$ is the occurrence probability of drought with duration (d_k) and intensity (m_k).

3.3. Objective weighting method for drought vulnerability index

To avoid the subjectivity of the researcher for determining weights of influencing factors to drought vulnerability index (DVI), this study used three objective weighting methods. The entropy method developed by Shannon (1948) has been applied in various studies (Ge et al., 2013; Xu et al., 2018; Yi et al., 2018), and PCA has also been applied in many references (Mainali and Pricope, 2017; Balaganesh et al., 2020; Yu et al., 2021). GMM was commonly used in computer and industrial engineering and was first applied to drought risk assessment in Kim et al. (2021).

The entropy method is an information weight model that has been extensively studied and practiced. If the information entropy value is small, it means that the data are provided by numerous useful attributes. Then, the weight assigned to the evaluation object should be larger and vice versa (Bai et al., 2020). Therefore, entropy is an objective means of defining the weights of indicators based on the useful information in the available data (Taheriyoun et al., 2010).

The PCA is a dimension reduction technique to transform a high-dimensional dataset into a low-dimensional one while preserving the information content (Conlon et al., 2020). It can be handy for identifying the most critical variables or the main contributing factors to the phenomenon based on the common factors under investigation and to conclude the linear relationship between variables by extracting the most relevant information in the dataset (Wu et al., 2022). The PCA can be used for creating a composite index, which can be used to derive statistically the weights of individual variables and components (Mainali and Pricope, 2017). The process of weighting using the PCA is as follows: the first step is to create correlation matrices of the indicators. From this, the principal component (PC) loadings are calculated, and the variance explanation is calculated by estimating the eigenvalues and eigenvectors (Kim et al., 2021). The PC scores that are the weights of the indicators are determined by combining PC loadings and variance explanation.

The GMM the probabilistic model that assumes all the data are generated from a mixture model of a finite number of Gaussian distributions with unknown parameters (Kim et al., 2021). In the GMM, it is important to estimate the model parameters such as the weight α_i of the ith element to distinguish the categories to which the data belong (Moraru et al., 2019). The weight is calculated by performing an expectation-maximization (EM) algorithm on the probability distribution of indicators. To estimate the parameters, the EM algorithm is performed that alternately applies the expectation step (E-step) of calculating the expectation of log-likelihood and the maximization step (M-step) of obtaining the variable value that maximizes this expectation. It is possible to draw confidence ellipsoids for multivariate models and compute the Bayesian Information Criterion (BIC) to evaluate the characteristics of GMM in the indicators (Kim et al., 2021).

Detailed processed of determining weights using Entropy, PCA, and GMM methods are described in Eqs. (B.1) - (B.8) in Appendix B. Because each method reflects specific information in weighting, it is more appropriate to consider all methods than to adopt one method. The integrated weight was finally calculated by arithmetically averaging the weights of each of the three methods.

Table 3
Description of drought classes and weights corresponding to rank.

Rank	Duration (d_k) (days)	Intensity (m_k)	Weight (r_k)
1	30	− 1.0 (moderate)	0.1
2	90		0.2
3	120		0.3
4	30	− 1.5 (severe)	0.4
5	90		0.6
6	120		0.7
7	30	− 2.0 (extreme)	0.8
8	90		0.9
9	120		1.0

3.4. Drought response capacity index using a Bayesian network

Since drought response capacity refers to a factor related to water resources and water supply capabilities of regional systems, it can be quantified through regional water resource information. However, there is a limit to judging the regional water supply capacity simply from the raw data of the water resource information. Qin and Zhang (2018) developed a formula for a supply matching index to measure the regions' ability to provide water resources using water supply, water demand, water utilization rate, and groundwater. Kang and Lee (2012) developed a formula to estimate the water supply capacity of a dam using factor analysis and multiple regression model of the basin area, the inflow, reservoir, and water usage that affect water. Thus, we employed the Bayesian network to calculate the water supply capacity in consideration of the regional water supply system and integrate the water supply capacity and various water resource information. The indicators of the drought response capacity are mainly composed of water supply capacity, the amount of available water resources, and ratio of reuse. The amount of available water resources is a measure of regional water resource conditions, which is calculated by precipitation per capita (C2 =c22/c23) and potential groundwater development per capita (C3 =c15/c23). The ratio of reuse is calculated considering the ratio of effluents of sewage treatment (C4 =c19/c20), sewage reuse (C5 =c16), and rainwater reuse (C6 =c18/(c21 ×c22)).

Water supply capacity is determined by the amount of water supply against the amount of water usage in the region (Kang and Lee, 2012; Qin and Zhang, 2018), as given in Eqs. (6) - (10).

$$\mathrm{WS}_{dam} = \frac{WR_{dam}}{WU_{domestic} + WU_{industrial}} \times \frac{WI_{dam}}{\int_{district} WI} \tag{6}$$

$$\mathrm{WS}_{river} = \frac{WR_{river}}{WU_{domestic} + WU_{industrial}} \times \frac{WI_{river}}{\int_{district} WI} \tag{7}$$

$$\mathrm{WS}_{reservoir} = \frac{WR_{reservoir}}{WU_{agricultural}} \times \frac{WI_{reservoir}}{\int_{district} WI} \tag{8}$$

$$\mathrm{WS}_{ground} = \frac{Groundwater}{WU_{ground}} \times \frac{WI_{dam}}{\int_{district} WI} \tag{9}$$

$$WSC = \left\{ \left(WS_{dam} + WS_{river} + WS_{reservoir} \right) \times WSR + WS_{ground} \right\} \times \frac{\int_{district} WI}{\int_{region} WI} \tag{10}$$

where *WS* is the water stress that represents the ratio of *Retention* to *Water Usage*. *WR* is the water retention of dams, rivers, and reservoirs, and *WU* is the amount of usage of domestic water, industrial water, agricultural water, and groundwater. *Groundwater* is the amount of groundwater. *WI* represents the amount of water intake by each type of water retention, $\int_{district} WI$ is the total amount of water intake of the district, $\int_{region} WI$ is the total amount of water intake of the region. *WSC* is the water supply capacity and *WSR* is the water supply ratio. The reason for applying the water intake ratio and the water supply rate is to consider the dependence of the region on the source of water intake or water supply.

The final indicators selected through PLS-SEM are integrated into the Drought Response Capacity Index (DRCI) using the Bayesian network, which is widely used to combine various factors. This study referred to Shin et al. (2020). The Bayesian network consists of nodes representing various variables and arcs representing dependencies between variables. Causal relationships between nodes are represented by probability information of variables. That is, the relationship between prior probability $\mathrm{P(Y)}$ and posterior probability $\mathrm{P}(Y|X)$ with variables X and Y as given in Eq. (11).

$$P(Y|X) = \frac{P(Y)P(X|Y)}{P(X)} = \frac{P(Y = y, X = x)}{P(X = x)} \tag{11}$$

where, $P(X)$ is known as a normalization constant using empirical values or observations.

Among inference algorithms such as likelihood weighting, rejection sampling, and Gibbs sampling, the likelihood weighting method is usually applied because it is simple to utilize and can estimate the posterior probability even in continuous probability distribution. The process of inference of the likelihood weighting method is described in Eqs. (B.9) - (B.13) (Appendix B).

3.5. Drought risk index combining hazard, vulnerability, and response capacity

Since risk refers to the potential for consequences where something of value is at stake and where the outcome is uncertain, and recognizing the diversity of circumstances (IPCC, 2014), in this study, drought risk is defined as the potential damage that may result from drought in a specific region. Drought risk is characterized as a function of drought hazard, vulnerability, and response capacity. In practice, the three components are geometrically averaged, because they have multiplicative effects on the drought risk. The reason is that with greater regional exposure to drought hazard and vulnerability, the greater effect they have on drought risk (Guillaumont, 2009). Thus, in this study, drought risk index (DRI) was calculated by multiplying a cubic root of the DHI, DVI, and DRCI, where the DRCI was modified as shown in Eq. (12) due to the opposite nature of risk unlike hazard and vulnerability.

$$DRI = \{DHI \times DVI \times (1 - DRCI)\}^{1/3} \tag{12}$$

When other factors remain constant, drought risk increases as drought hazard increases, which means that despite a magnifying hazard, drought risk can be mitigated by reducing vulnerability or increasing response capacity (Ahmadalipour, 2017). In addition, even if the local water supply system is vulnerable to drought, there is no risk of actual drought without a meteorological drought. If one factor appears to be zero in the drought risk assessment, the DRI is also calculated to be zero.

The DHI, DVI, DRCI, and DRI have values between 0 and 1. The DHI, DVI, and DRI are more dangerous when they approach to 1, and less dangerous when they approach to 0. Conversely, the closer the DRCI is to 0, the more dangerous it is, and the closer the DRCI is to 1, the less dangerous it is.

4. Results and discussion

4.1. Selection of drought risk influencing indicators

In this study, SEM was preliminarily constructed and evaluated by setting relationships among elements and indicators based on previous studies of drought hazard, vulnerability, response capacity, and risk. Drought hazard and vulnerability are common elements that increase risk, and drought response capacity is an element that reduces risk. In addition, it was assumed that the water resources and water usage of the region are affected by precipitation or population. As a result of evaluating the measurement and structural model of PLS-SEM in several combinations using SmartPLS, the final drought risk assessment model was constructed as shown in Fig. 4. The solid lines represent the relationship between elements and indicators that passed the evaluation criteria, and the red dotted lines indicate the relationship between elements and indicators that were excluded from the final model because they failed to meet the evaluation criteria.

The suitability of PLS-SEM was mainly evaluated by dividing it into measurement and structural models. First, to evaluate the reliability and validity of the measurement model, internal consistency reliability, convergent validity, and discriminant validity were evaluated. The internal consistency reliability that determines the consistency of the measurement variables constituting the latent variable was evaluated as composite reliability. The composite reliability of hazard, vulnerability, response capacity, and risk were 0.78, 0.92, 0.67, and 0.70, respectively, indicating that the factors were consistent. The convergent validity of determining the relationship between the measurement variable and the latent variable was evaluated through average variance extracted (AVE). The AVEs of the four latent variables were calculated as 0.65, 0.67, 0.57, and 0.55, respectively, indicating that all satisfied the criteria. The discriminant validity of determining that the measurement variable is not related to other latent variables was evaluated with Fornell-Larker criteria and cross-loading. As shown in Tables 4 and 5, the Fornell-Larker criterion showed that the square root of the AVE of each latent variable exceeded all the largest correlations between the latent variables, and the outer loading of all indicators exceeded the cross-loading. The results confirmed that most of the measurement variables explain the latent variables well.

Multicollinearity, coefficient of determination, and model's goodness-of-fit were evaluated for the suitability of structural model. Internal variance inflation factor (VIF) was used for the multicollinearity to determine whether there is a strong correlation between

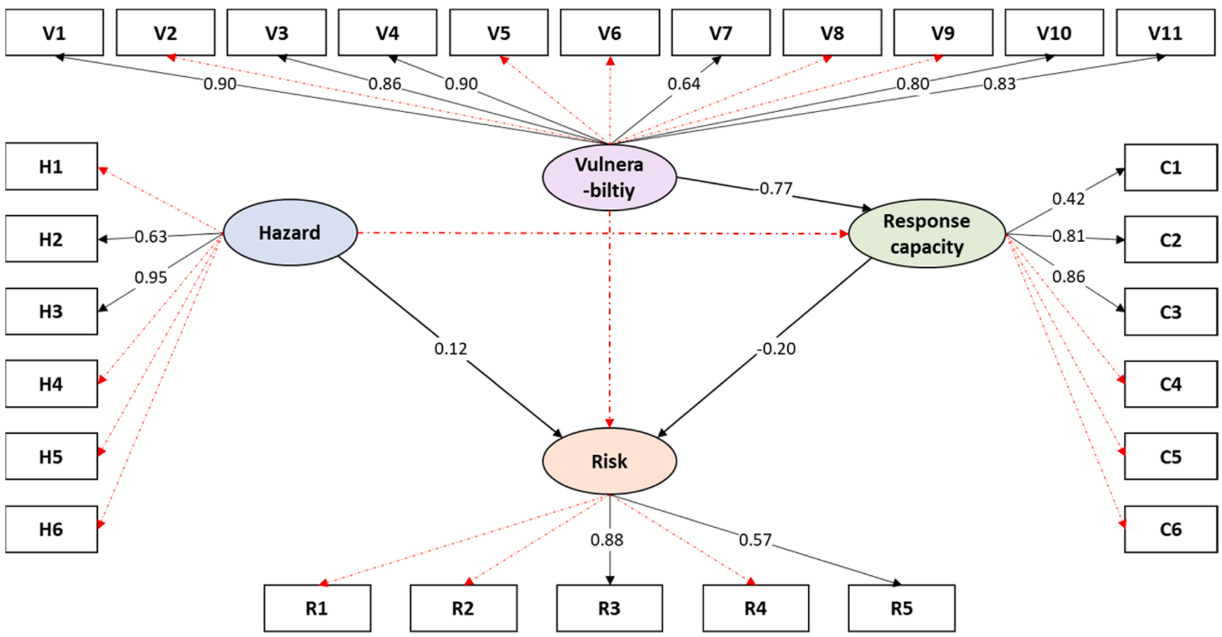


Fig. 4. Model structure for drought risk assessment using PLS-SEM.

Table 4
Fornell-Larcker criteria for assessment components.

	Hazard	Vulnerability	Response capacity	Risk
Hazard	0.81			
Vulnerability	0.03	0.82		
Response capacity	-0.04	-0.77	0.79	
Risk	0.13	0.23	-0.20	0.74

Table 5
Cross loading criteria for indicators.

Indicator	Hazard	Vulnerability	Response capacity	Risk
H2	0.63	-0.02	-0.03	0.05
H3	0.95	0.04	-0.04	0.14
V1	-0.02	0.90	-0.64	0.16
V3	-0.05	0.86	-0.70	0.19
V4	0.03	0.90	-0.66	0.24
V7	0.03	0.64	-0.48	0.12
V10	0.09	0.77	-0.57	0.20
V11	0.06	0.83	-0.68	0.21
C1	-0.01	-0.09	0.42	-0.07
C2	-0.09	-0.58	0.81	-0.19
C3	0.01	-0.69	0.86	-0.15
R3	0.11	0.19	-0.19	0.88
R5	0.08	0.16	-0.10	0.57

endogenous latent variables. The hazard and response capacity to risk, and vulnerability to response capacity were all 1.0, which is less than 5.0. The coefficient of determination, which is the predictability of structural model, defined as the square correlation between the actual value and the predicted value was calculated very high at an average of 0.32. The effect size, which means the contribution of exogenous latent variables to the coefficient of determination of the endogenous latent variable, had a vulnerability to response capacity of 1.42, and the hazard and response capacity of risk were 0.02 and 0.04, respectively. However, all evaluation criteria can be found to be satisfied. Finally, the structural model had the predictive relevance of 0.15 for endogenous latent variables. Considering all results of evaluation, the overall goodness-of-fit of PLS-SEM was low at 0.22. However, this model met the most evaluation criteria through combinations of several factors.

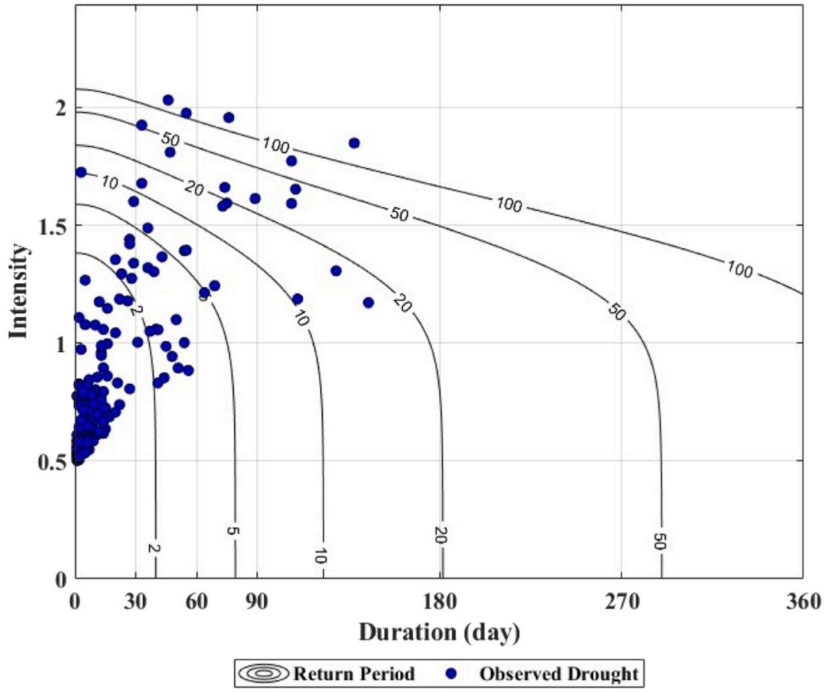
Consequently, SPI-60 and SPI-90 (H2 and H3) were selected for the drought hazard, which are related to the short and medium-term drought. The population, recipients of basic living, solitary senior citizens, areas of industrial complex, water supply ratio, and sewage supply ratio (V1, V3, V4, V7, V10 and V11) were selected for drought vulnerability. Water supply capacity, available water resources per capita, and groundwater development per capita (C1, C2, and C3) were selected for the drought response capacity, indicating that water supply capacity and available water resources were highly related to the drought response capacity.

4.2. Drought hazard assessment

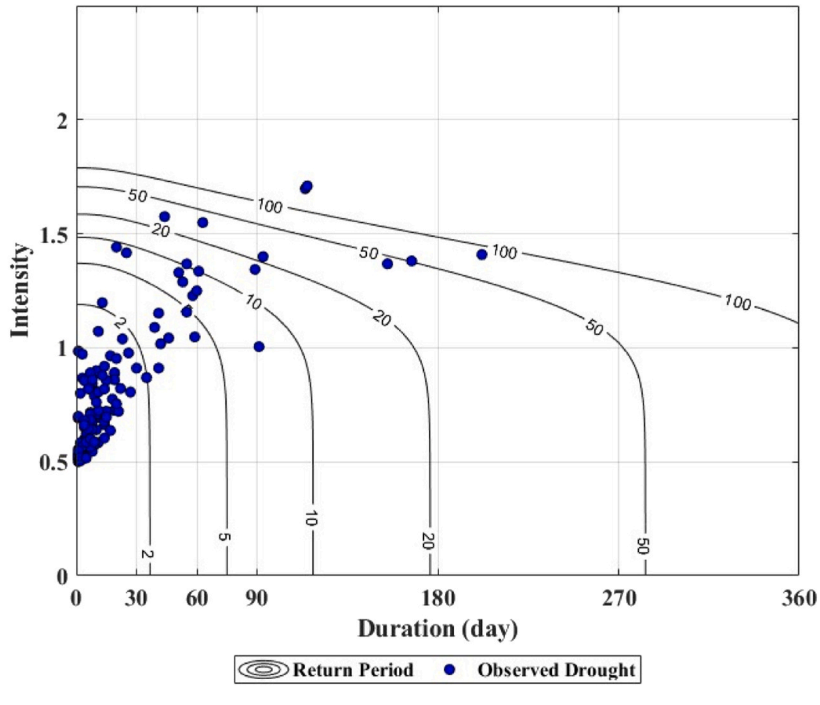
Drought hazard is a meteorological factor that means the occurrence probability of drought. In this study, using daily precipitation data, the SPIs were calculated for six timescales to assess the meteorological drought hazard. Drought characteristics according to the SPI selected from PLS-SEM were confirmed, and the probability of drought occurrence was quantified using the copula function. As shown in Fig. 4, the SPI-60 and SPI-90 were selected to calculate the DHI of GS from PLS-SEM. Using the SPI-60, GS17 (Yeongyang) had the longest average duration of about 23.63 days, and GS12 (Moonkyung) had the highest average intensity of about 0.85. Using the SPI-90, GS26 had the longest average duration of about 28.38 days and GS18 (Yeongdeok) had the highest average intensity of about 0.82. The drought duration was large in the inland region of GS, and the drought intensity was high in the coastal region of GS.

The optimal distribution for each district was determined based on the p-value of the KS-test for nine probability distributions, and the optimal marginal distribution for the duration and intensity were dominated by the lognormal and normal distribution, respectively. Based on the likelihood of the maximum likelihood method, the optimal copula function was adopted to combine the marginal probability distributions for each region, and the Frank function dominated as the optimal distribution function. For example, Fig. 5 provides the probability of drought occurrence for SPI-60 and SPI-90 in GS1 (Busan). Using the SPI-60 and SPI-90, GS26 and GS9 had four and nine extreme droughts with probabilities of occurrence of less than 5%, respectively.

The DHIs were calculated in consideration of drought duration, intensity, occurrence probability, and the weights in Table 3. For example, in GS1 (Busan), Eq. (5) was applied to calculate the DHI, resulting in 0.27 for the SPI-60 and 0.24 for the SPI-90. The final DHI in GS1 (Busan) determined by averaging the two values is 0.30. The DHIs of GS are shown in Fig. 6. GS26 (Ulleng) had the highest DHI within the GS, which has very high average duration and intensity of drought as well as a very high probability of drought occurrence. GS24 (Bonghwa) had the lowest DHI, which is less likely to cause drought damage. DHI was overall high in the northeast coast. Moazzam et al. (2022) evaluated drought characteristics with SPI and SPEI, and similar to our results, both the frequency of occurrence and duration were calculated as high in the northeast coastal area in a short-term SPI. The reason is that Taebaek Mountain, located



(a) SPI-60



(b) SPI-90

Fig. 5. Probability of drought occurrence in GS1(Busan).

from the northwest to the southeast, divides the region and allows little precipitation in the northeast. GS24 (Bonghwa), located in Taebaek Mountain, which has the least amount of precipitation, has the lowest probability of occurrence, resulting in low DHIs. It is worth noting that using an effective drought index, which is a hydrological drought index, resulted in high DHIs in eastern coastal areas (Kim et al., 2015).

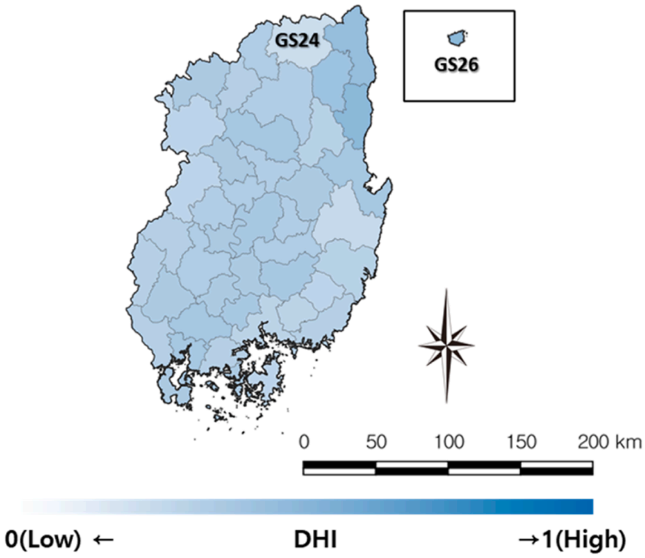


Fig. 6. Drought hazard map for Gyeongsang province.

4.3. Drought vulnerability assessment

Prior to performing drought vulnerability assessment, standardization or normalization is necessary to integrate various indicators with different characteristics and units into one index. The ranking, Z-scoring, and re-scaling methods are generally used in practice. The re-scaling method was used in this study considering that it is the most appropriate when knowing the range of indicators and it has the advantage of not generating negative values.

To estimate the drought vulnerability index, which represents the socio-economic sensitivity of the regional system to drought, weights representing the effects of vulnerability indicators were calculated. Entropy, PCA, and GMM methods were applied to indicators selected from PLS-SEM in this study, which are objective weighting methods. Final weights were calculated by averaging the weights obtained from the three methods, and the results are shown in Table 6.

In the entropy, PCA, and GMM methods, the largest weights were calculated to be the solitary senior citizen, the solitary senior citizen, and the population (V4, V4, and V1), respectively. Since each method differs in the way in which importance is assigned, the weights were slightly different. To comprehensively consider this importance, we estimated the integrated final weight by averaging weights from the three methods. As a result, GS is a fast-aging region, which is why the weight of V4 was the highest. The DVI calculated with the final weight is shown in Fig. 7. GS2 (Daegu) had the highest DVI, meaning that it can be greatly damaged by drought within the GS. GS17 (Yeongyang) had the lowest DVI, indicating that it is expected to suffer less damage by drought than other districts with higher DVIs. Drought vulnerability was high around big cities. This is because the weight of drought vulnerability in GS is related to the number of people, and big cities have large populations and the elderly. In Kim et al. (2015), big cities had high drought vulnerability, but the pattern is slightly different. The reason is that the indicators and weights are different.

4.4. Drought response capacity assessment

It is very important to identify the regional water supply network and determine the drought response capacity in assessing the drought risk. The regional water supply network can be prepared by considering the water sources including rivers, dams, and reservoirs, the path of water supply, and the water balance within the watershed. The water supply capacity was calculated by applying the water intake source, water intake ratio, and water supply ratio to Eqs. (6) - (10) based on the regional water supply network. Indicators for the DRCI were selected from PLS-SEM among water supply capacity, precipitation per capita, potential groundwater

Table 6
Weights of indicators using entropy, PCA and GMM methods.

Indicators		Entropy	PCA	GMM	Final weights
V1	Population	0.15	0.13	0.23	0.17
V3	Recipients of basic living	0.21	0.17	0.22	0.20
V4	Solitary senior citizen	0.27	0.24	0.21	0.24
V7	Area of industrial complex	0.12	0.11	0.01	0.08
V10	Water supply ratio	0.13	0.15	0.22	0.17
V11	Sewage supply ratio	0.12	0.20	0.11	0.14

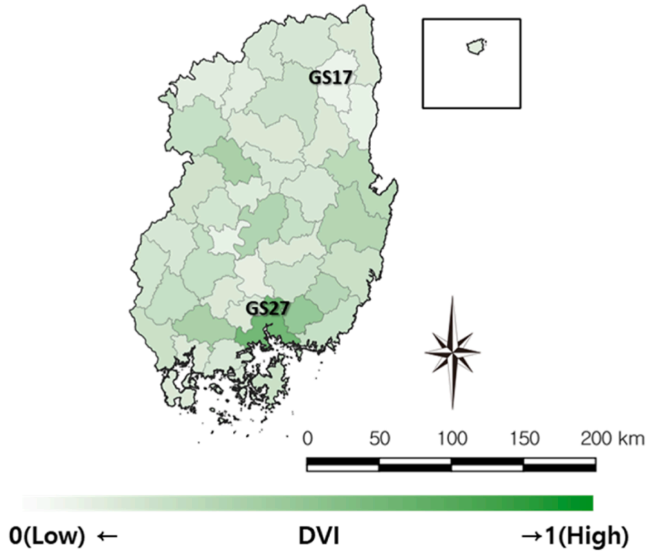


Fig. 7. Drought vulnerability map for Gyeongsang province.

development per capita, sewage treatment, sewage reuse, and rainwater reuse. Water supply capacity, precipitation per capita, and potential groundwater development per capita were selected as suitable for the GS and used as Bayesian network nodes. In this study, different methods of determining hazard, vulnerability, and response capacity were applied, because the characteristics are distinct from each factor as follows: For the DHI, frequency analysis using copula was appropriate, because the DHI has time-varying attributes. For the DVI, the weighting methods were applied because the DVI brought together various time-invariant factors. For the DRCI, the Bayesian network was applied because the DRCI combined diverse time-varying has characteristics that change with water conditions and time. Therefore, Bayesian network factors.

Since the Bayesian network is based on the normal distribution, a standard normalization was applied to unify the range of the indicators with different units. To compute the parameters for accurate normalization, outliers were removed; the parameters of the normal distribution were calculated after excluding outlier data exceeding 99% of the confidence interval. The estimated probability distribution was applied to the Bayesian network model to determine the DRCI. The DRCI had a negative value because of using the standard normalization. Therefore, when determining drought risk, unlike DHI and DVI, it was standardized to display that the closer it is to zero, the worse the response capacity.

The results of the drought response capacity assessment are shown in Figs. 8 and 9. Fig. 8 is the boxplot representing the variation of indicators of DRCI (C1, C2, C3, and C4) in GS. The red dots in the figure indicate the data of GS26 (Ulleng). GS26 (Ulleng) had the least amount of potential groundwater development per capita(C3), however the DRCI was high due to the greater amount of available

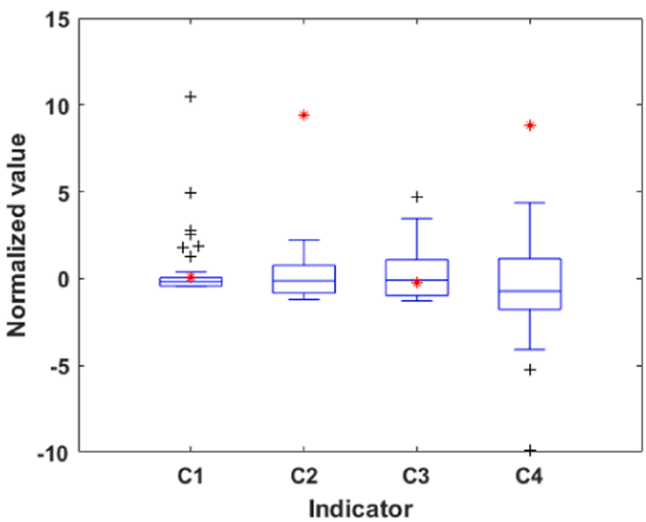


Fig. 8. Boxplots of indicators of DRCI (C1, C2, C3, and C4) in GS.

precipitation per capita (C2). Although the water resources retention is small, the response capacity is sufficient. This is because the precipitation is high compared to the number of people and overall water usage is very low. Since it is comparatively rich in available water resources, it is judged to have the capacity to recover quickly during drought. On the other hand, GS16 (Cheongsong) had a low DRCI due to the low water supply capacity (C1). This is an area that relies on rivers, and the streamflow is not sufficient. In addition, as an agricultural area, the water usage is relatively high. This area is confirmed to have poor water supply capacity or low available water resources, and there is a high possibility of damage or long-lasting damage during drought. As shown in Fig. 9, the response capacity to drought was high in inland regions. Because the inland area is in mountains of Taebaek and Sobaek, the groundwater is very abundant, and the population is small, leading to low demand for waters. Whereas coastal areas with low drought response capacity have a large population compared to streamflow and reservoirs, leading to very high demand for waters.

4.5. Drought risk assessment

In this study, drought risk was defined as the potential damage that may result from drought in a specific region. Drought risk was quantified by integrating drought hazard, vulnerability, and response capacity. The validity of the drought risk index was verified by comparing the drought risk-related data mentioned in Section 2, that is, drought damage factors.

The results of the drought risk assessment are shown in Fig. 10. Since drought risk assessment is usually conducted for regional comparisons, drought risk map is schematized according to rankings for clear comparison. The drought risks of GS28 (Jinju), GS27 (Changwon), and GS4 (Pohang) were high, whereas the drought risks of GS26 (Ulleng), GS20 (Goryeong), and GS24 (Bonghwa) were low in a row. In fact, the drought risk in GS25 and GS7, where a lot of damage was incurred, were high at 0.38 and 0.34, respectively. On the other hand, the GS26 (Ulleng) had frequent occurrence of drought leading to high DHI, thus many drought warnings have been issued. However, drought damage did not occur due to low DVI and high DRCI. The risk of drought in GS was high in most big cities. Since ancient times, as cities have developed in the coastal areas of GS, the population has increased. However, since two mountains distinguish inland and coastal areas, precipitation is low and water resources are insufficient in coastal areas. Consequently, there is a lot of significant damage. Kim et al. (2015) showed the most serious drought risk in the eastern coastal regions because of the high DHI and DVI. However, the southern coastal area was low in risk, and inland cities were also low in risk. The reason is that water resources and water demand of the DRCI were not reflected.

5. Conclusion

Drought risk interacts with regional water supply capacity and socio-economic vulnerabilities, as well as meteorological hazard. Thus, drought risk can be determined by a function that includes drought hazard meaning meteorological hazard, drought vulnerability meaning socio-economic sensitivity of the regional systems to drought, and drought response capacity meaning regional water supply capacity. We assessed comprehensive drought risk by integrating drought hazard, vulnerability, and response capability considering the regional water supply system. Our main findings can be concluded as follows:

1) Previous studies of drought risk have been conducted without considering the response capacity to drought based on the water supply system. It is important to measure the water supply capacity of the region to identify its capacity to cope with drought. However, due to difficulties in the calculation, it has often been conducted as independent research. To accurately quantify drought risk, response capacity should be accompanied by the probability of occurrence of drought in the region and the degree of vulnerability to drought risk. We assessed the drought risk by integrating response capacity with drought hazard and vulnerability. In particular, the drought response capacity was considered in a simple and intuitive way. This framework identifies the capacity to respond to drought, including the water supply system and capacity of the region. The findings from this study underscore the relevance of analyzing drought risk from a holistic and spatially explicit perspective. In addition, probability statistical methods were applied to select and weight indicators and to present regional drought risk assessment from an objective perspective. So far, many studies have selected indicators at the discretion of involved researcher and then weighted them by survey methods or arithmetic average (equal weight) methods. In this study, indicators suitable for GS were selected by SEM and weighted by averaging entropy, PCA, GMM, and Bayesian networks. It goes beyond previous studies by including a separate analysis of the elements of drought risk and subjective factors as well as assigned objectivity and validity.
2) PLS-SEM selected the SPI-60 and SPI-90, population, recipients of basic living, solitary senior citizens, areas of industrial complex, water supply ratio, water supply capacity, available precipitation per capita, and potential groundwater development per capita for drought risk assessment. The regions with the highest DHI and DVI were GS26 (Ulleng) and GS27 (Changwon), respectively. Located on the right coast of Taebaek Mountain, this area had low precipitation and a large elderly population. Assessing the drought response capacity in consideration of regional water supply systems and networks, the GS16 (Cheongsong) was the lowest capacity. In GS16, the water supply capacity is very low due to low streamflow and large amount of water usage. Assessing drought risk by integrating drought hazard, vulnerability, and response capacity, the GS28 (Jinju) appeared to be dangerous within the GS due to highest risk. This is because this area has high DHI and DVI and low DRCI. In most regions with high risk, the number of occurrences, population of occurrences, and number of days were all high, confirming that the region was significantly damaged in the past. In addition, regions where the actual damage was very large showed a high risk of drought, suggesting that the accuracy of the results of this study was high.
3) Due to various characteristics of drought, the damage caused by drought can be considerable. Risk management to facilitate action before drought occurs is needed. Drought reduction, which enable risk management from a long-term perspective based on risk

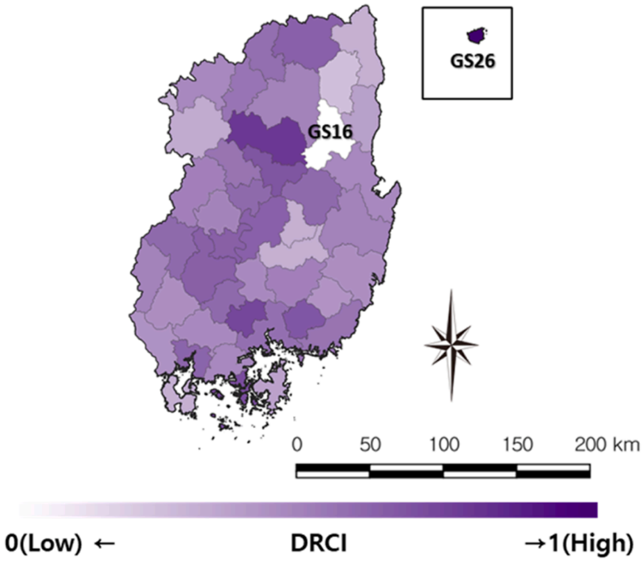


Fig. 9. Drought response capacity map for Gyeongsang province.

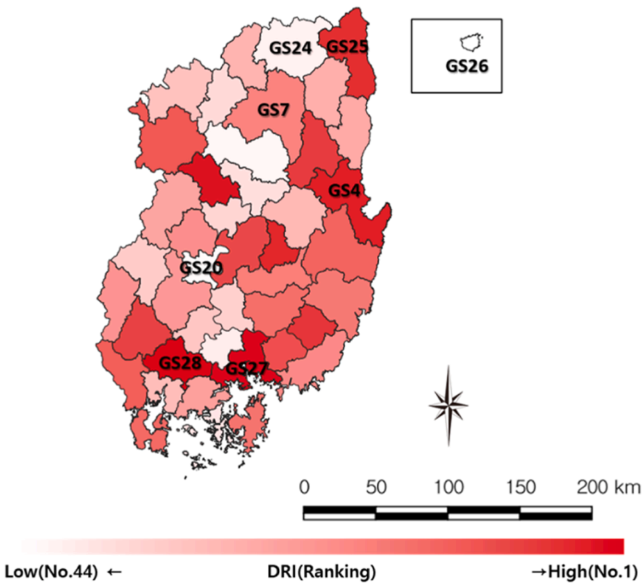


Fig. 10. Drought risk map for Gyeongsang province.

information, is very important. Through drought risk assessment, it is possible to analyze the interaction of drought impact factors and to identify drought risk and causes in advance. In other words, the results of this study can be used to identify the main causes of drought risk and to establish suitable countermeasures. Hazard is generally not an adjustable factor, and direct response capacity adjustment or indirect vulnerability management is required to reduce the risk. Areas with low response capacity can control supply by identifying water demand, improving dam and reservoir storage, or by collaborating with areas with good water supply capacity. There is also a way to increase the amount of available water resources or the ratio of reuse. Vulnerability can generally be complemented by policies. In GS, since the elderly population had a significant impact on vulnerability, policies related to the elderly or other vulnerable social groups can be established to adapt to drought. In the case of hazards, direct resolution is not possible, but it can be prevented through constant monitoring. GS26, which is in drought-prone areas or high-risk areas, should be intensively managed.

The results and analysis process of this study will be useful in the decision-making process for enacting drought countermeasures by identifying major impact factors and risk areas for drought by region. In addition, drought mitigation from a long-term perspective is possible based on risk information. Nevertheless, the study is currently limited to one province in Korea. An analysis of the whole country is needed to utilize it for national drought policies. The results of drought risk depend on the type and accuracy of data, which have a significant impact on the uncertainty of drought risk. In the future, it is important to improve the reliability of the model based on diverse and accurate data gathered in conjunction with national and local governments. In addition, drought is expected to become generally more serious due to climate change. Various future climate change scenarios can be used to consider drought risk outlooks and changes due to future climate change. The uncertainty of drought risk can be quantified if the range of changes of drought risk considering the data is identified.

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CRediT authorship contribution statement

Ji Eun Kim: Methodology, Software, Data curation, Writing – original draft preparation. **Jiyoung Yoo:** Conceptualization, Visualization. **Hyun-Han Kwon:** Validation, Investigation. **Tae-Woong Kim:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request. The Datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2023.101538.

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