creative commons

C O M M O N S D E E D

저작자표시-비영리-변경금지 2.0 대한민국

이용자는 아래의 조건을 따르는 경우에 한하여 자유롭게

- 이 저작물을 복제, 배포, 전송, 전시, 공연 및 방송할 수 있습니다.

다음과 같은 조건을 따라야 합니다:

저작자표시. 귀하는 원저작자를 표시하여야 합니다.

비영리. 귀하는 이 저작물을 영리 목적으로 이용할 수 없습니다.

변경금지. 귀하는 이 저작물을 개작, 변형 또는 가공할 수 없습니다.

- 귀하는, 이 저작물의 재이용이나 배포의 경우, 이 저작물에 적용된 이용허락조건을 명확하게 나타내어야 합니다.
- 저작권자로부터 별도의 허가를 받으면 이러한 조건들은 적용되지 않습니다.

저작권법에 따른 이용자의 권리는 위의 내용에 의하여 영향을 받지 않습니다.

이것은 이용허락규약(Legal Code)을 이해하기 쉽게 요약한 것입니다.

Disclaimer

dCollection

공학석사 학위논문

Index Development of Drought Risk Assessment on Regional Scale

지역 단위 가뭄리스크평가를 위한 지수 개발

2021 년 2 월

서울대학교 대학원

건설환경공학부

지 희 원

Index Development of Drought Risk Assessment on Regional Scale

지역 단위 가뭄리스크평가를 위한 지수 개발

지도 교수 김 영 오

이 논문을 공학석사 학위논문으로 제출함

2021년 2월

서울대학교 대학원

공과대학 건설환경공학부

지 희 원

지희원의 공학석사 학위논문을 인준함

2021년 2월

위 원 장 서 일 원 (인)

부위원장 김 영 오 (인)

위 원 Van Thinh Nguyen (인)

Abstract

Index Development of Drought Risk Assessment on Regional Scale

Hee Won Jee

Department of Civil & Environmental Engineering

The Graduate School

Seoul National University

Due to the growing awareness regarding the seriousness of droughts, every year since 2017, a South Korean national drought policy has been established jointly by related ministries. Although the risk of droughts is an important concept widely considered in drought policies around the world, it is not included at the domestic policy of South Korea. In addition, the framework of drought risk assessment has developed into a conceptual model, the verification part of which remains insufficient. Therefore, research must be conducted to explain and verify the risk.

In this proposed framework, risk is composed of hazard, exposure, and capacity indicators, and the drought risk index (DRI) is calculated using these three indicators. The hazard indicator refers to the cause of droughts, such as a lack of precipitation. The exposure indicator includes factors that are most significantly influenced by droughts, such as water demand. The capacity indicator, used as socio-economic data, is divided into the coping capacity for reducing and the adaptive capacity for addressing the damage. The DRI is calculated via data preprocessing processes and weighted with random values of 0.1 units. For verification, the Pearson correlation coefficient between the DRI and drought damage estimation is utilized to select weighting coefficient sets. Finally, the future DRI in the 21st century is projected and analyzed under RCP 4.5 and RCP 8.5. The national average DRI is highest in the early 21st century. The highest DRI was calculated to be in the Seomjin River region, and the increase in the number of sub-basins was the largest in the Han River region.

Keywords: Drought, Risk, Drought risk assessment, Risk assessment framework

Student Number: 2018-27401

Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background of Research

Drought is a natural disaster that causes severe human damage in developing countries, starting with problems of drinking water and food shortage, famine, and starvation. It also causes economic damage and social problems resulting from water shortages in the commercial sector in developed countries.

In South Korea, there was a severe drought in 2015, which led to a 127-day limited water supply in Chungcheongnam-do. Moreover, in 2017, the lowest water storage rate ever was recorded after the completion of the Boryeong Dam. In addition, the frequency of droughts was 0.36 times/year between 1904 and 2000, but it increased to 0.72 times/year from 2001 through 2018 (MOIS, 2019). Because of climate change, the increase of rainfall in seasonal and regional imbalances makes it more challenging to manage and plan existing water resources, and the damage from future droughts is expected to become more serious (Smith and Katz, 2013; IPCC, 2014).

Most drought-related studies have focused on developing a drought index that quantifies the drought hazard. However, the research on determining the damage cause by natural disasters to society remains insufficient. Moreover, droughts occur periodically, and after a drought ends, the research interest decreases significantly compared with the time when the drought is active (Sung, 2018). After a drought ends, drought management plans are perceived as unimportant in terms of disaster prevention, and they remain focused on short-term postdrought measures, such as compensation and recovery. However, because droughts is natural disasters that can cause human casualties as well as social problems, it is imperative to develop a preemptive and comprehensive plan to manage droughts, starting with mitigation of economic damage. The paradigm of the international drought management has traditionally been postcrisis management. Recently, however, the prerisk management approach has been recognized as essential (Wilhite, 2019).

Risk management is classified into three policy strategies: risk identification, risk reduction, and disaster management. Risk identification refers to the risk perception, social expression, and estimation before a policy is presented, and risk reduction and disaster management include prevention–mitigation and response–recovery policies, respectively (Cardona et al., 2003). Through this classification, risk management should be based on understanding how society perceives and expresses risks and how to estimate and quantify them. Risk is a complicated concept in which disaster-related and socio-economic characteristics have a relationship that is complex. Accordingly, many international organizations, such as the United Nations Office for Disaster Risk Reduction (UNISDR), Organization for Economic Cooperation and Development (OECD), and Intergovernmental Panel on Climate Change (IPCC), are evaluating risks by developing conceptual frameworks for their own purposes. The first step in the conceptual framework is to define the concept of risk; however, in reality, a wide variety of definitions exist and are mixed. Therefore, the first step in the risk assessment procedure is to define the concept of risk uniquely by setting its purpose correctly, and that is the first focus of this thesis.

Another feature of the risk assessment framework presented by the above international organizations is that most of them are intercountry comparisons. In other words, most international organizations have focused on factors for different levels of development between countries by defining and evaluating risks for the purpose of comparison by country. If the conceptual framework is applied without considering the spatial scale, regional characteristics and differences will not clearly appear. Furthermore, drought damage can cause regional social conflicts in allocating limited water resources in a country, occurring in various ways, including water shortages, the environment, and the economy (Wilhite et al., 2014); hence, socio-economic factors between regions should be reflected to measure risk. For example, drought risk studies on a regional scale have been conducted that do not consider socio-economic factors related to local water supply facilities or focus on covering specific fields, such as agriculture and hydroelectric power (Shahid and Behrawan, 2008; Park et al., 2012; Nam et al., 2014; Kim et al., 2015; Choi, 2018). Because the purpose of this thesis is to evaluate drought risk between regions in South Korea, the focus is on developing a suitable conceptual framework and selecting components.

Finally, it must be pointed out that prior studies on risk assessment have neglected to verify the results. The first reason is that the combination of various components required too many weighted coefficients, and most of the studies used equivalent coefficients because estimation was very difficult. Second, as mentioned above, the appropriate way to compare the results of the risk evaluated by indexing from a conceptual framework is unclear. In this study, drought risk assessment was improved by considering the verification issues included in these two reasons.

1.2 Objectives

The purpose of this research was ultimately to develop a drought risk conceptual framework that can be compared by region and to calculate the future drought risk index (DRI). For this purpose, first, the conceptual framework of risk is suitable for comparing regions complying with the standard concepts of the international community. Because risk has various definitions by users, this thesis focuses on the field of climate change adaptation and disaster reduction and conforms to the international agreements on all definitions. Second, the accuracy of drought risk is improved by verifying and weighting through damage estimation. Finally, the future drought risk is forecast as an index by applying climate change scenarios, and the results can be used as basic data for drought management on the Korean Peninsula.

1.3 Thesis Organization

The theoretical background in Chapter 2 is concentrated on the definition and conceptual framework of risk among the international community. In Chapter 3, a conceptual framework of risk on a regional scale is proposed, and the subconcepts are discussed in detail. In addition, the method to calculate the index is described. As discussed in Chapter 4, in the proposed framework of risk, the DRI results were calculated for 113 basins in the Korean Peninsula, and the future DRI under the climate change scenario is projected. Finally, conclusions and future studies are summarized in Chapter 5.

Chapter 2. Theoretical Background

2.1 Definition of Risk

Risk is a concept applied in various areas. Mathematically, it is defined as the probability of a negative outcome (Hann, 2002). With comprehensive access to the social domain, risk refers to "(exposure to) the possibility of loss, injury, or other adverse or unwelcome circumstance; a chance or situation involving such a possibility" ("Risk," 2020). Because the definitions of risk vary depending on the issues applied by the field, risk is defined for the purpose of this study by referring to international communities in the fields of climate change adaptation and disaster reduction.

The definitions of international organizations are summarized in Table 1, and the meanings contained in risk terms were divided into three categories of meanings. First, the words "adverse," "harmful," "threat," and "loss" explain the negative meaning. Second, the words "consequence" and "effect" include the results of the situation. Finally, the words "potential," "possibility," "probability," and "uncertainty" contain the meaning of the possibility of the results. Combining these meanings, in this study, the risks of climate change adaptation and disaster areas were defined as the possibility of the damage consequences of disasters caused by climate change.

Table 1 Definitions of the risk by international organizations

Name	Year	Definition
IPCC[1]	2012	The possibility of adverse effects in the future. It derives from the interaction of social and environmental processes, from the combination of physical hazards and the vulnerabilities of exposed elements.
WMO[2]	2013	A threat or uncertainty associated with an event that may have a negative effect on the achievement of the results defined in the Strategic Plans of the Organization.
IPCC	2014	The potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values. Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk reults from the interation of vulnerability, exposure, and hazard.
UNFCCC[3]	2015	The effect of uncertainty on objectives or an uncertain, generally adverse consequence of an event or activity with respect to something that humans value.
IRGC[4]	2017	The uncertainty about and the severity of the consequences of an activity or event with respect to something that humans value.
UNISDR[5]	2017	The potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society, or community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability and capacity.
ISO[6]	2018	The effect of uncertainty on objectives.

[1] Intergovernmental Panel on Climate Change (IPCC)
[2] World Meteorological Organization (WMO)
[3] United Nations Framework Convention on Climate Change (UNFCCC)
[4] International Risk Governance Center (IRGC)
[5] United Nations Office for Disaster Risk Reduction (UNISDR)
[6] International Organization for Standardization (ISO)

2.2 Conceptual Framework of Risk

Before reviewing the previous research on risk, vulnerability is explained because of its similarity to risk. In the field of climate change adaptation, “vulnerability” has traditionally been used as a framework for understanding and assessing the phenomenon, and “risk” has been considered in the health, disaster, and infrastructure fields (Wolf, 2012). However, the study of climate change has gradually expanded to fields such as health and disasters, and the need for integrated terms has emerged. Among these two terminologies, “vulnerability” is a negatively interpreted word that can lead to a passive attitude and result in the importance of social resilience being overlooked when used in the policy application. In contrast, a risk-based framework promotes the participation of various stakeholders in transdisciplinary subjects (Meadow et al., 2015) and is more appropriate for prioritization and communication on comprehensive concepts (Weaver et al., 2017).

For the measurement and management of drought damage, in this study, a conceptual framework based on risk, not on passive vulnerability, which could be caused by confusion and reduce the authority of the result, was used. Thus, the conceptual framework of risk presented by international organizations in climate change adaptation and disaster reduction is discussed and organized in the following sections.

2.2.1 United Nations Office for Disaster Risk Reduction

The United Nations Office for Disaster Risk Reduction (UNISDR, formerly UNISDR) explains that the understanding of disaster risk should be the basis for policies implemented for disaster risk management and assessment. The UNISDR defines risk as the probability of harmful consequences, or expected loss (deaths, injuries, property, livelihoods, disruption of economic activity, or environmental damage) resulting from interactions between natural or human-induced hazards and vulnerable conditions. The UNISDR formulates risk with two elements: hazard and vulnerability (UNISDR, 2004).

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability}$$

From here, hazard is a potential damaging physical event, phenomenon or human activity, and vulnerability is the conditions determined by physical, social, economic, and environmental factor or processes, which increases the susceptibility of an individual, a community, assets, or systems to the impact of hazards.

In the risk framework of the UNISDR, which focuses on various natural disasters, the hazard is categorized by natural disaster characteristics, and various phenomena are grouped as shown in Table 2. Vulnerability is demonstrated in aspects of the physical, economic, social, and environmental spheres, as in Table 3.

Table 2 Hazard classification in terms of risk by the UNISDR (UNIDSR, 2004)

Classification	Examples
Hydro-meteorological hazards	Floods, drought, tropical cyclones, etc.
Geological hazards	Earthquakes, surface collapse
Biological hazards	Outbreaks of epidemic diseases
Technological hazards	Industrial pollution, nuclear release
Environmental hazards	Loss of biodiversity, air pollution

Table 3 Aspects of vulnerability in terms of risk according to the UNISDR (UNIDSR, 2004)

Aspects	Examples
Physical	Population density levels, remoteness of a settlement, the site, design and materials used for critical infrastructure and for housing
Social	Levels of literacy and education, systems of good governance, basic infrastructure, institutional organizations and governance structures
Economic	Levels of individual, community, and national economic reserves, levels of debt and the degree of access to credit, loans, and insurance
Environmental	Extent of natural resource depletion and the state of resource degradation

2.2.2 United Nations University Institute for Environment and Human Security

The World Risk Report (WRR), published in 2011 by United Nations University Institute for Environment and Human Security (UNU-EHS), described disaster risks in terms of the World Risk Index (WRI). In the WRI, risk is defined as the product of the interaction between a natural hazard event (earthquake, flood, storm, drought, sea level risk) and the vulnerability of exposed elements or society (UNU-EHS, 2011). The WRI is measured for two sphere and four indicators: the natural hazard sphere (exposure) and vulnerability in the societal sphere (susceptibility, coping capacities, and adaptive capacities).

$$\mathrm{WRI} = \mathrm{f}(\mathrm{Exposure}, \mathrm{Susceptibility}, \mathrm{Coping\ \ capacity}, \mathrm{Adaptive\ \ capacity})$$

Although the WRI has adopted risk as a comprehensive definition used by the international community, this conceptual framework divides vulnerabilities into three categories, underscoring social, economic, and governance factors, compared with other frameworks. These three main indicators are explained by Birkmann and Welle (2015) as follows.

1. Susceptibility, which means that societies or communities have deficiencies and limited capacities to deal with adverse events

2. Coping capacity, which is the capacity to deal with the direct impact and consequences of an extreme event

3. Adaptive capacities, which encompass elements that help to build the capacity to deal with extreme events and slower changes in the medium

and longer terms

In particular, the WRI classifies short-term responses and long-term strategies of national and other social groups, respectively, by the coping and adaptive capacity described in index calculations.

The four indicators in the WRI are summarized in Figure 1 with detailed subcategories. Initially, exposure is defined as "entities exposed and prone to be affected by a hazard event" and is included in the natural hazard sphere because it is described as a hazard-related subconcept. The data at the exposure indicator are the historical average number of entities (persons, resources, infrastructure, etc.) to natural disasters with a base in the past period (Birkmann et al., 2011). Susceptibility refers to "the structural characteristics of a society and the conditions in the social actors" and is described to the likelihood to suffer harm and damage. This indicator is categorized as five sectors: 1) nutrition, 2) housing conditions, 3) public infrastructure, 4) poverty and dependencies, and 5) economic capacity and income. Coping capacity, the third indicator of WRI, explains "the capacities of societies to minimize damages of natural hazards through direct and short term actions." The five categories are 1) government and authorities, 2) disaster preparedness and early warning, 3) medical services, 4) social networks (neighborhood, family, and self-help), and 5) material coverage. Here, "susceptibility" and "coping capacity" are closely connected; therefore, it is difficult to distinguish between the two concepts in practice (Birkmann et al., 2011). Finally, adaptive capacity mentions "capacities, measures, and strategies that can change the communities to deal with the negative impact of natural hazards in the long term." The subcategories of this indicator are 1) education and research, 2) gender equity, 3) environmental status and ecosystem protection, 4) adaptation strategies, and 5) investment.

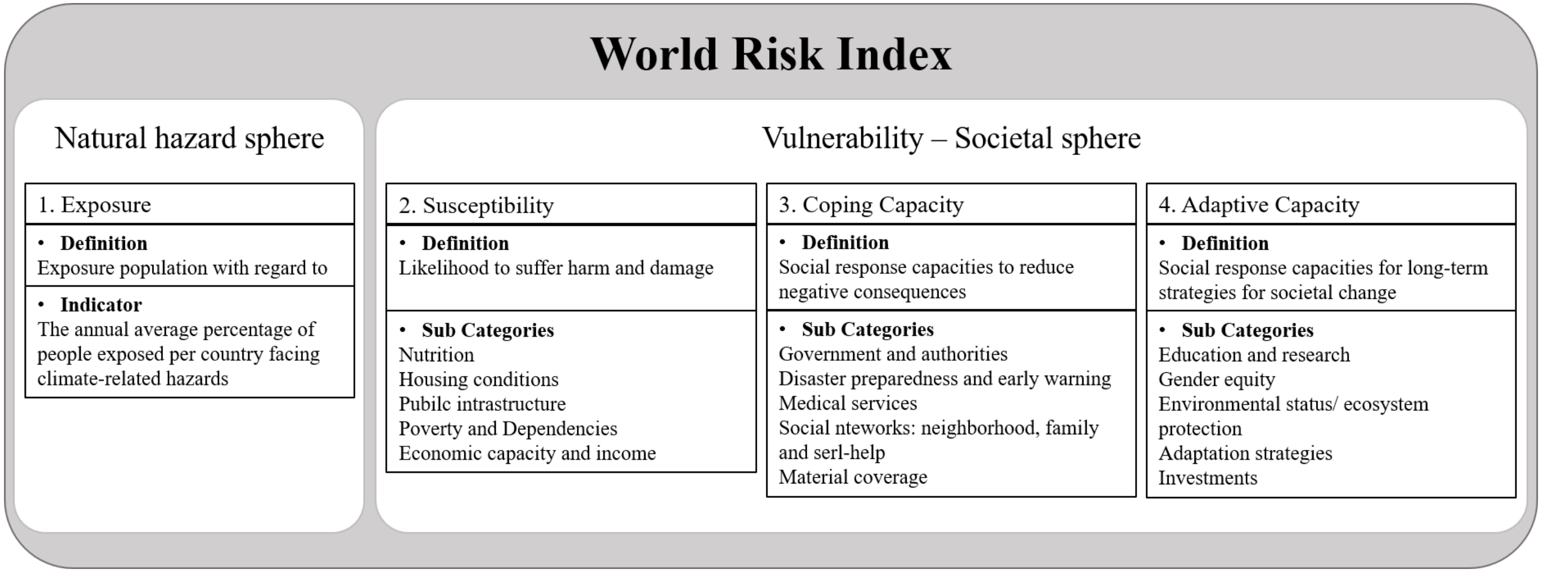


Figure 1 Structure of the concept for the WRI (Birkmann and Welle, 2015)

Johnson et al. (2016) and Wannewitz et al. (2016) applied the framework of the WRI to calculate a complex disaster risk index that considers heat waves, typhoons, and landslides in Hong Kong and the Philippines. The WRR, which developed the WRI, noted that there is an ambiguity between the susceptibility and the coding capacity. Thus, it is necessary to beware in selecting the suitable categories for division and purpose, such as spatial scale.

2.2.3 Intergovernmental Panel on Climate Change

The Intergovernmental Panel on Climate Change (IPCC), an organization that publishes regular climate change impact assessment reports, adopted the risk assessment in climate change assessment paradigm in 2012 when it published the Special Report Management of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX). To integrate with other fields, such as disaster reduction and health, the IPCC assessed the negative impacts of human or social systems by risk. Although a conceptual framework focused on risk is examined in this research, the major differences between the vulnerability assessment of Annual Report 4 (AR4) in 2007 and the risk assessment of Annual Report 5 (AR5) in 2014 are summarized in Table 4 and explained in the comparison.

Table 4 Comparison of the assessments in AR4 and AR5

Classification	AR4	AR5
Consequence (adverse effects and harm to the system)	Vulnerability (V)	Risk (R)
External factor (stressors or the degree of physical event)	Exposure (E)	Hazard (H)
Internal factor (state and ability of the system)	Sensitivity (S) Adaptive Capacity (AC)	Exposure (E) Vulnerability (V)
Function of assessment	V = f(E, S, AC)	R = f(H, E, V)

The main transformations in the new paradigm of AR5 lie in the concepts of exposure, hazard, and vulnerability (Sharma and Ravindranath, 2019; Das et al., 2020). First, the IPCC defined that exposure is "nature and degree to which a system is exposed to significant climate variations" in the third assessment report (TAR) and explained the external factor of the climate-related stress in AR4. However, AR5 defined exposure as "the presence (location) of people, livelihoods, environmental services and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected by physical events and which, thereby, are subject to potential future harm, loss, or damage." Hence, exposure implied "driver perspective" in the AR4, and it was shifted to a "spatial concept" in the AR5.

Second, SREX contained a new main concept, hazard, defined as "the potential occurrence of a natural or human-induced physical event that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, and environmental resources." Thus, hazard in AR5 plays the role of exposure in AR4 to explain external stress.

Last, vulnerability, according to AR4, is the consequence of the interaction between exposure, sensitivity, and adaptive capacity and defined as "the degree to which geophysical, biological and socio-economic systems are susceptible to, and unable to cope with, adverse impacts of climate change, including climate variability and extremes" (IPCC, 2007). Moving to a new paradigm of AR5, vulnerability becomes one of the subconcepts of risk and refers to "the propensity or predisposition to be adversely affected" (IPCC, 2014). In addition, it is considered independent of physical events, such as exposure in AR4 and hazard in AR5. In brief, the concept of vulnerability included cause, condition, and effect in the previous IPCC, yet, after the SREX report in 2012, the meaning of the term was reduced to a term describing the lack of socio-economic capacity, excluding physical causes.

The risks of AR5 addressed in this study are caused by the impact of climate and socio-economic processes and are organized in Figure 2 as an interaction of hazard, exposure, and vulnerability by climate change. Hazard in this framework is “the potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources.” Exposure is defined as “the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected.” Vulnerability is interpreted as “the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt.”

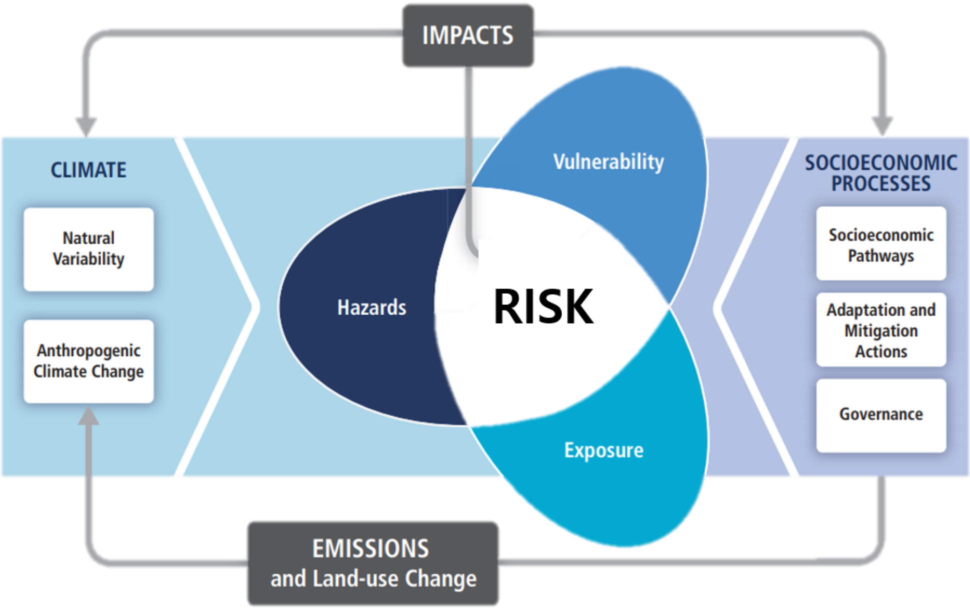


Figure 2 Conceptual framework of risk by IPCC (IPCC, 2014)

Although the components that constitute the subconcepts vary among scholars, these conceptual frameworks with three dimensions are suitable for dividing the state of a system or society and the ability of governments to respond to disaster damage for preparing countermeasures. World Bank (2019) and Carrao et al. (2016), who employed the risk framework of the IPCC, mapped drought risk by country, and Vogt et al. (2018) conducted a drought risk assessment for major areas of agriculture and hydropower.

2.3 Composite Indicator

A composite indicator (or index) is used to quantify a multidimensional concept, such as well-being, development, and social equity, on the basis of an underlying model. It is formed when individual indicators are combined into a single index (OECD, 2008; Mazziotta and Pareto, 2017). It is mainly utilized for relative evaluation based on complex concepts in rank or quantity and is useful for prioritizing policies and attracting the interest of the public (Saltelli et al., 2006). There is some debate about using an index because it can cause analytical problems in simplifying various indicators. However, composite indexes have been developed in many fields because they support understanding of and communication with ordinary citizens, summarize complex problems into a single one, and facilitate the selection of priority regions for drought management. An analysis performed in December 2020 on composite indicators (or composite indices) in SCOPUS shows that more than 600 research reports had been published until 2020, as shown in Figure 3.

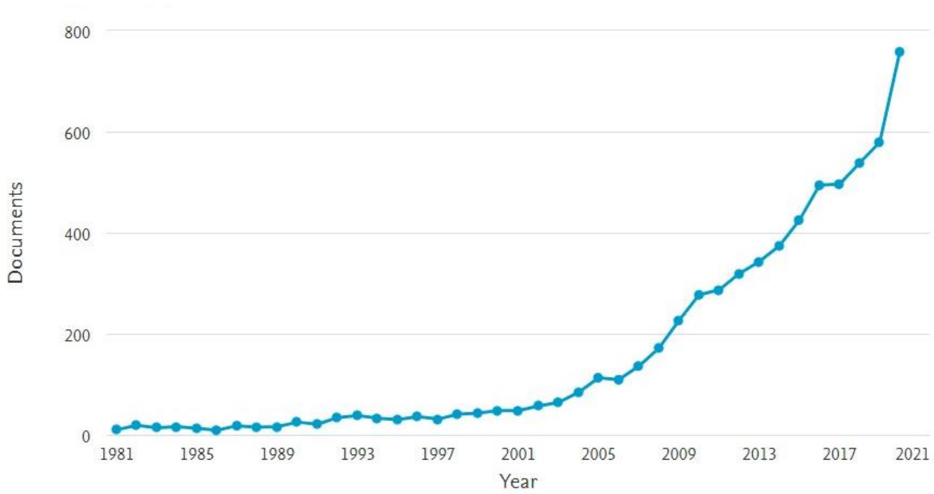


Figure 3 Results of searching with the terms "composite indicators" or "composite index" on SCOPUS from 1981 to 2020

In the field of drought research, the drought index has been developed for the purpose of determining whether the drought phenomenon has started and will continue. The representative indices are the Palmer drought severity index, which uses precipitation and evapotranspiration, and the standardized precipitation index (SPI), which defines drought only with precipitation. Depending on the factors for consideration, dozens of other drought indices have been suggested. The drought index for physical phenomena plays an important role in measuring the severity of the drought compared with the past. The drought index is different from the risk that explains the degree of damage to society and considers socioeconomic aspects. The DRI includes social factors that can be reflected in drought management plans or policies and used as information to compare different plans or policies (Hall and Leng, 2019).

In general, the index calculation process involves four steps: 1) theoretical framework development, 2) data collection for each indicator, 3) normalization, and 4) weighting and aggregation (Anand and Sen, 2000; Jeong et al., 2004; OECD, 2008). It was conducted based on the preceding studies discussed in Section 2.2 about the first step of defining a phenomenon and selecting a subgroup and the second step of selecting an appropriate proxy variable. Therefore, in this section, the processes of Steps 3 and 4 are described.

2.3.1 Normalization

Among the various normalization methods, the ranking, standardization (or z-scores), and min-max (or rescaling) methods are mainly used. The ranking method is the simplest normalization method using the ranking of the data, although the ratio scale is transferred to the equidistant of the hierarchy scale, resulting in a distortion of values. The standardization method is the most commonly used method to normalize the mean with zero and the standard deviation with one. The min-max method can be calculated between 0 and 1 based on the range using the difference between the maximum and minimum values. It can be applied inversely on the opposite scale. The equations of the three methods are shown in Table 5.

Table 5 Methods of normalization

Method	Equation
Ranking	$x_{nor} = \mathrm{Rank(x)}$
Standardization (or z-scores)	$x_{nor} = \frac{\mathrm{x} - \bar{\mathrm{x}}}{\sigma_x}$
Min-max (or rescaling)	$x_{nor} = \frac{x - \min(x)}{\max(x) - \min(x)}$ or $x_{nor} = 1 - \left(\frac{x - \min(x)}{\max(x) - \min(x)}\right)$

2.3.2 Aggregation

Among the procedures of calculating the index, aggregation is the step in which information is reduced and simplified. It is important to choose the appropriate method at this stage, but the criteria for choice do not exist (Kang, 2002; Korea Environment Institute (KEI), 2008; Blancas et al., 2013). Therefore, the formula is chosen according to the purpose of the researcher.

The simple additive weighted (SAW) formula and the weighted product (WP) formula are mainly used, and there are other methods of selecting maximum and minimum values. The SAW formula computes the index with the weighted sum of individual indicators, as in Equation (2.1).

$$\text{Index (or composite indicator)} = \sum_{i=1}^{m} w_i \cdot x_i \tag{2.1}$$

where x_i is the individual indicator, w_i is the weighting factor of x_i, and m is the number of individual indicators. Next, the WP formula determines the index by computing through geometric aggregation using Equation (2.2):

$$\text{Index (or composite indicator)} = \prod_{i=1}^{m} {x_i}^{w_i} \tag{2.2}$$

The subscript is the same as in Equation (2.1). The predominant difference between the methods is that, if any of the individual indicators has zero, the index always becomes zero in the WP formula.

2.4 Drought Damage Estimation

Drought damage can occur throughout society, including homes, environments, and industries. Spatially, compared with other natural disasters, drought has more indirect effects than the direct effects (Logan and van den Bergh, 2013). In addition, the drought damage determined by institutions tends to be underestimated or limited to specific fields, such as agriculture (So et al., 2015). Therefore, it is challenging but essential to identify and evaluate drought damage.

Studies on estimating drought damage are mainly conducted in the economic field, and the cost classification according to droughts is classified into four categories: 1) direct cost, 2) indirect cost and associated economy-wide impacts, 3) intangible (or nonmarket) costs, and 4) risk mitigation costs (Freire-Gonzales et al., 2017). As explained the damage area in Figure 4, the first category is the water scarcity for industry and households. According the first category, the market economy may change in second category, and social problems (such as unemployment) and environmental problems (such as health and pollution) may occur with costs in third category. Finally, the fourth category is associated with the government efforts implemented to control society.

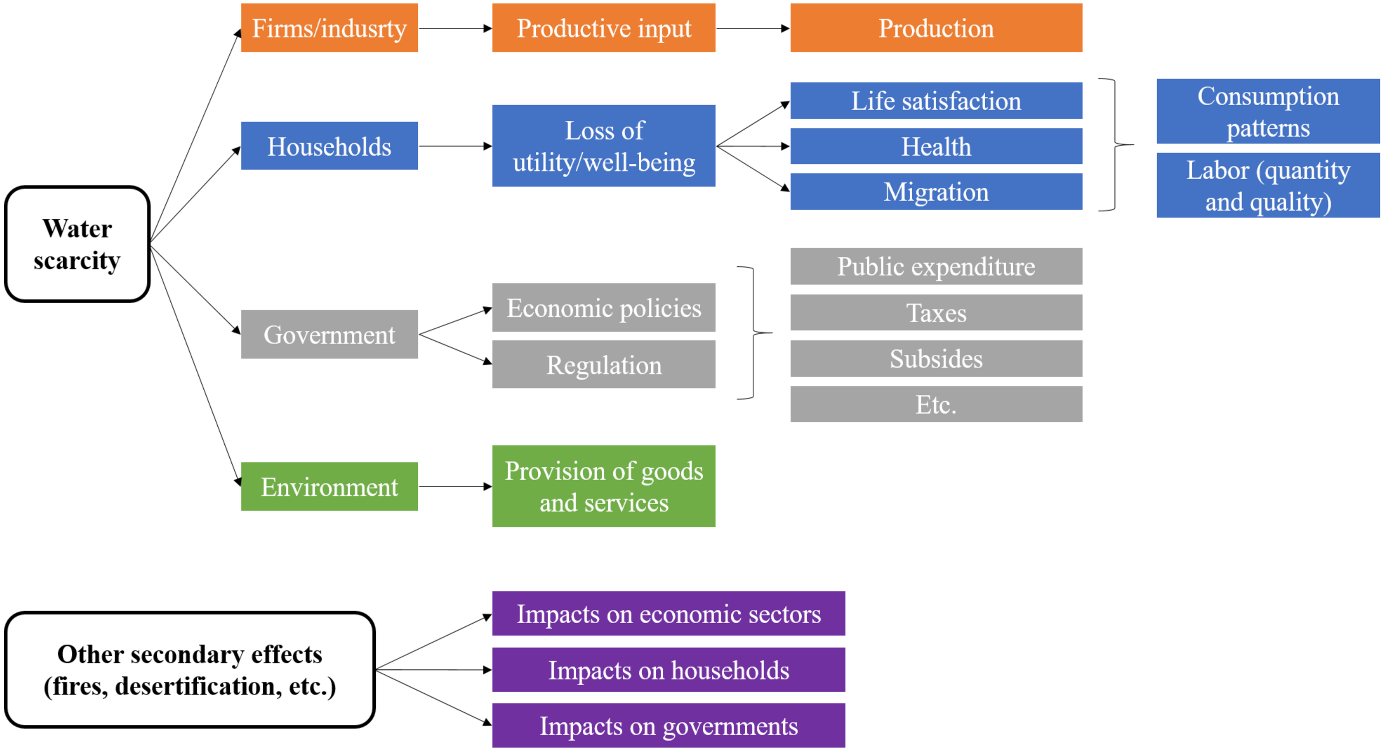


Figure 4 Economic impact of drought (Freire-Gonzales et al., 2017)

The major methods for cost estimation include market valuation techniques, computable general equilibrium analysis (CGE), input/output (I/O) analysis, and coupled hydrological–economic modeling. Market valuation techniques are commonly used to evaluate the direct cost of droughts, such as traded products or services, in a manner that incorporates a market price method, production function, avoided-cost approach, and replacement- or repair-cost approach (Logan and van den Bergh, 2012). In case studies, this technique is generally used to estimate the profit or loss associated with the drought adaptation rather than quantify the damage caused by the drought. The CGE model is a highly sophisticated economic models used to investigate the impact of a drought on the overall economy, such as policies, technologies, and exports. It requires a large amount of data and is used to estimate indirect costs (Freire-Gonzales et al., 2017). I/O analysis considers the interdependence of changes of one economic sector (price, demand, labor costs, etc.) on another (Miller and Blair, 2009). Furthermore, it is a method for explaining the relationship between economic sectors and is generally used to investigate the effects of water prices and consumption on water policies between economic sectors. Like the CGE model, it is useful for indirect costs. Finally, coupled hydrological–economic modeling is used to analyze the effects of water allocation and water use by sector and includes hydrological, economic, and institutional factors. This model assists stakeholders as a decision-support tool in the government and industrial sectors. Furthermore, among the aforementioned models, it is the only one applicable to all direct, indirect, and nonmarket costs (Logan and van den Bergh, 2012).

To estimate drought damages, Naumann et al. (2015) used the damage function according to power-law dependence to correlate the SPI and the reduction of cereal crop production and hydropower generation. In addition, So et al. (2015) defined the duration and depth of drought using the bivariate joint drought index and established a linear regression equation among different types of damage data for agricultural land. These studies used the drought index only to express drought damage, regardless of socio-economic characteristics. There is also a limitation that it can be applied only to a specific field of creating economic profit, such as agricultural and industrial fields.

Chapter 3. Methodology

In this chapter, the conceptual framework of risk is modified appropriately from a global scale by international organizations to a regional scale, and calculation of the DRI is proposed for cross-regional comparisons.

The research method is explained in the following: 1) the conceptual framework of risk for a regional scale, 2–4) definition of drought hazard, exposure, and capacity, 5) method for calculating the DRI, and 6) drought damage estimation for DRI verification.

3.1 Overview of Conceptual Framework of Risk for Regional Scale

The purpose of the conceptual framework of drought risk is to assess the degree of risk arising from future droughts. The proposed framework, which is suitable for a regional scale, is composed of indicators that categorize risk into three subconcepts: hazard, exposure, and capacity.

$$\mathrm{Risk} = \mathrm{f}(\mathrm{Hazard}, \mathrm{Exposure}, \mathrm{Capcity})$$

First, the conceptual framework of this study is mainly based on the risk framework of AR5 by the IPCC. Risk is a function of hazard, exposure, and vulnerability. As mentioned in Section 2.2.3, vulnerability is one of the subconcepts of risk and encompasses elements including sensitivity or susceptibility to harm and the lack of capacity to cope and adapt (IPCC, 2014), i.e., vulnerability is not a concept of consequences unlike in AR4. This definition can eventually be seen as the same concept as vulnerability in the WRI, which is divided into susceptibility, coping capacity (CC), and adaptive capacity (AC). From the WRI, CC is closely related to the susceptibility in the WRI, whereas it is clearly distinguished from AC. To clarify the separation between terms, this research selected coping capacity and adaptive capacity and organized them in terms of capacity.

Moreover, vulnerability has connotations with a wide range and complex meaning and can cause confusion in communication (Birkmann, 2013). However, capacity is easy to understand compared with vulnerability. In addition, it has a positive meaning, so it is appropriate to explain the active ability of the social system, such as local governments, in regional comparisons. Thus, it is considered suitable to be used as a subconcept of the risk framework.

Therefore, in this study, drought risk is defined as potential damage from drought caused by future climate change, and it is classified into three subconcepts (hazard, exposure, and capacity), as shown in Figure 4. Each concept is described in detail in Sections 3.2 through 3.4.

Figure 5 Conceptual framework of risk for regional scale

3.2 Drought Hazard

Drought hazard is a concept to indicate the cause of drought. In the risk framework, the hazard indicator reflects the disaster characteristics of drought. “Drought as a hazard” and “drought as a disaster” are often mingled in research. Drought as a hazard is a natural phenomenon of drought, and drought as a disaster means an event in which adverse effects on society and the environment have occurred. The DRI, the ultimate result of this study, is used to assess the damage of drought as a disaster; otherwise, the drought hazard indicator involves the physical characteristics of drought as a hazard, applied by a variety of drought indices.

Drought as a disaster occurs because of an imbalance between the supply and demand of water resources required by nature or human society, and the cause is a lack of precipitation that has deviated extremely from the normal climate.

In general, the types of drought are classified into meteorological drought, hydrological drought, agricultural drought, and socioeconomic drought. When the meteorological drought is prolonged, different droughts gradually occur in combination. Hence, the meteorological drought is the starting point of the drought (Wilhite et al., 2014). This study is based on the fact that the fundamental cause of drought begins with insufficient precipitation. The SPI is calculated using only precipitation data and easily reflects regional characteristics among the various drought indices. In addition, WMO and Globar Water Partnership (2016) recommends the SPI as a drought index representing meteorological drought. Therefore, the drought hazard indicator is determined from SPI.

The SPI was developed by McKee et al. (1993) based on the fact that droughts occur because of a lack of precipitation. The SPI is used to calculate the cumulative probability by taking the cumulative precipitation on a monthly time scale and calculating the probability distribution, traditionally using the gamma probability distribution proposed by Edwards (1997). Because, in this study, drought risk is calculated for the purpose of preparing drought management, it is calculated as drought hazard indicators by selecting lower SPI values within the same period using 3-month and 12-month time scales to represent short- and long-term drought.

The cumulative gamma probability distribution $G(x)$ used for SPI calculations is Equation (3.2).

$$G(x) = \frac{\int_0^x x^{\alpha-1}\exp(-x/\beta)\,dx}{\beta^{\alpha}\Gamma(\alpha)} \tag{3.2}$$

Here, x is precipitation, α is scale parameter, β is shape parameter, and $\Gamma(\cdot)$ is the gamma function. The maximum-likelihood solutions are used to estimate α and β using Equation (3.3) and (3.4) (Thom, 1966). In Equation (3.5), A is a statistic for the gamma distribution, and n is the number of observed precipitation data.

$$\alpha = \frac{\bar{X}}{\beta} \tag{3.3}$$

$$\beta = \frac{1 + \sqrt{1 + \frac{4A}{3}}}{4A} \tag{3.4}$$

$$\mathrm{A} = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{3.5}$$

In cumulative gamma probability distribution $G(x)$, the gamma function is not defined when x has a value of 0, so the cumulative probability H(x) is expressed in Equation (3.6).

$$H(x) = q + (1 - q)G(x) \tag{3.6}$$

Here, q is the probability that x is zero. Finally, switching the calculated $H(x)$ to the standard normal distribution yields the SPI. The calculated SPIs are classified as shown in Table 6.

Table 6 Drought category by SPI (Mekee et al., 1993)

Drought Category	SPI Values (unitless)
Mild Drought	0 to −0.99
Moderate Drought	−1.00 to −1.49
Severe Drought	−1.50 to −1.99
Extreme Drought	≤ −2.00

To apply the SPI as a drought hazard indicator, the process of reprocessing in the range from 0 to 1 is required. With consideration of the SPI category shown in Table 3, the hazard indicator is calculated to be dimensionless using Equation (3.7). If the SPI is 0, which is the standard of mild drought, the hazard indicator becomes the mean of the range from 0 to 1, and the SPI is smaller than −2; in extreme drought, it is 1, the highest value in the indicator.

$$h_0 = \frac{SPI - 2}{-4} \tag{3.7}$$

Additionally, the hazard indicator should have a range from 0 to 1. Values less than 0 and more than 1 are reprocessed using Equation (3.8). Finally, the higher the SPI value, the lower the drought risk indicator; the lower the SPI value, the higher the drought risk indicator.

$$Drought\ hazard\ indicator = \begin{cases} 0 & (h_0 < 0) \\ h_0 & (0 \le h_0 \le 1) \\ 1 & (h_0 > 1) \end{cases} \tag{3.8}$$

3.3 Drought Exposure

Drought exposure refers to objects that can be damaged by drought. In assessing the risk, rather than the risk divided into two indicators: the external stimulus and the internal condition, an approach that includes the object being lost is more appropriate to explain the damage suffered by region, reflecting the size or state of the object. When the cause and the target are separated, such characteristics as the frequency and intensity of the harm can be demonstrated individually from the exposed object on the damage. Furthermore, when the quantity and quality of the object are distinguished, the indicators that constitute the risk are reflected in more detail and the risk can be evaluated closely.

The targets of drought damage include the population, crops, and products requiring water resources. Because the water resource demand based on use is estimated in Ministry of Land, Transport and Maritime Affairs (MLTMA, 2011), the drought exposure index developed in this study is based on the water demand.

3.4 Drought Capacity

Drought capacity refers to the internal ability of society to cope with and adapt to drought. In this study, the term "capacity" not "vulnerability," was used as a subconcept of risk. Only the coping and adaptive capacity was used, excluding sensitivity (or susceptibility) among the related vulnerability elements addressed by the IPCC and UNU-EHS.

First, the reason for excluding sensitivity is that, in the IPCC and UNU-EHS, drought, unlike other natural disasters, does not exacerbate the damage depending on the condition of the objects. For example, sea-level rise is an especially catastrophic disaster in coastal regions, and flooding is devastating to the number of underground households and rivers. However, drought is related to water and causes the same degree of damage to all objects. Thus, the classification of housing conditions used for WRI sensitivity is not related to drought. Next, because this study focused on the risk on a regional scale, there is no need for an index to compare the degree of national development. Among the subcategories of susceptibility in the WRI, public infrastructure is computed by a share of the population without assessing to improved sanitation and clean water. Moreover, nutrition, poverty, and dependencies show the development gap between countries on a global scale on the premise that developing countries suffer more than developed countries. However, this is not required for regional comparisons within countries where development has progressed to some extent. Moreover, considering that coping capacity is a concept that is closely related to sensitivity (Birkmann et al., 2011), coping capacity can sufficiently account for the capability related to drought risk, even if the sensitivity indicator is excluded. Therefore, in this study, the concept of capacity was used to reflect the ability of a social system or local governments to reduce and address drought damage. Drought capacity is divided into coping capacity and adaptive capacity. In this research, coping capacity refers to direct actions and resources to minimize negative effects, and adaptive capacity refers to long-term measures or strategies against negative effects (Birkmann et al., 2011).

3.5 Drought Risk Index

In this section, the process of calculating the DRI for a regional scale applied to the conceptual framework is described. To determine the terms before arranging the index calculation process, the index is the most complex (comprehensive) level. An indicator is the level of subconcepts of the index, and the smallest level is the component calculated using data. In this section, the index calculation process is explained by dividing it into data preprocessing, aggregation, and the weighting coefficient.

3.5.1 Data Preprocessing

The data used in the DRI calculation were preprocessed through outlier detection, normalization, and reprocessing steps using beta CDF. The first step, outlier detection, is to identify and remove outliers among the data collected for each sub-basins. There are various outlier detection methods depending on time series data or the number of variables. Because the drought risk in this study is used for spatial comparison, outlier detection with univariate data was applied to individual components. For univariate data, using standardized scores, statistical hypothesis tests (chi-square test, Grubbs T-test, etc.) and quartile ranges are popular to search for outliers; however, these methods assume that the data follow a normal distribution. This study handles multiple types of socio-economic data that are skewed according to regional characteristics. To detect outliers in skewed data, there are a semi-interquartile range method and an adjusted boxplot outlier detection method. The latter method, developed by Hubert and Vandervieren (2008), can be applied regardless of whether the data distribution is symmetric. This adjusted boxplot outlier detection utilizes skewness and modifies the interquartile range with medcouple (MC), a robust statistic for skewness suggested by Brys et al. (2003).

The detection of outliers using the modified interquartile range is a method using MC to modify the existing interquartile range. Equation (3.9) for MC is as follows:

$$\mathrm{MC} = \text{median}\ \{h(x_{(i)}, x_{(j)})\}, x_{(i)} \le med(x) \le x_{(j)} \tag{3.9}$$

Here, $x_{(i)}$ is less than the median of x, and $x_{(j)}$ is greater than the median of x. Moreover, $h(x_{(i)}, x_{(j)})$ is computed by Equation (3.10), and every combination of $(x_{(i)}, x_{(j)})$ is applied.

$$h(x_{(i)}, x_{(j)}) = \frac{[x_{(j)} - med(x)] - [med(x) - x_{(i)}]}{x_{(j)} - x_{(i)}} \tag{3.10}$$

Equation (3.11) is the definition of outliers using the existing interquartile range. If the coefficient, c, in front of the interquartile range (IQR) is calculated using MC from Equation (3.9), Equation (3.11) is modified to Equation (3.12), the adjusted boxplot outlier.

$$[Q_1 - c \times IQR, Q_3 + c \times IQR] \tag{3.11}$$

$$\begin{cases} [Q_1 - 1.5e^{-4MC} \times IQR, Q_3 + 1.5e^{3MC} \times IQR], where\ \ MC \geq 0 \\ [Q_1 - 1.5e^{-3MC} \times IQR, Q_3 + 1.5e^{4MC} \times IQR], where\ \ MC < 0 \end{cases} \tag{3.12}$$

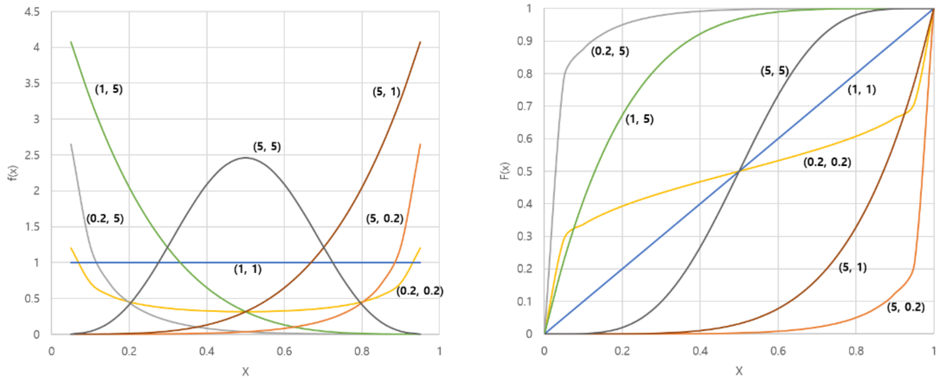
Here, Q_1, Q_3 are the first and third quartiles, respectively, and IQR is calculated as $Q_3 - Q_1$. The detected outliers with the adjusted boxplot outlier detection were treated by replacing a value close to the maximum value among the remaining values excluding outliers.

After the outlier detection, the normalization was applied to handle the data unit dimensionless to facilitate the computation of the index. Among various normalization methods, the min-max method, which can be easily used even when the relationship between the data and the index is inverse, was used to calculate the range from 0 to 1 as well as to describe the distance between data. In this study, Equation (3.13) was used because all data of the minimum value are zero.

$$x_i = \frac{x^r{}_i}{max(x^r{}_i)} \tag{3.13}$$

Here, x_i is the *i*th arbitrary component, and superscript r represents the raw data.

Finally, although the outlier detection process was finished, some of the variables for reflecting the socio-economic impact in this study, such as research and development and gross regional product, have absolutely larger values in urban areas compared with rural areas. Compared with municipal administrative districts, the average of the upper two regions is more than 10 times the average of the other lower regions. If these variables are normalized and expressed in a range from 0 to 1, most of the values are less than 0.1. This tends to underestimate the indicators and indices, and spatial comparison between subregions becomes difficult. Accordingly, in this study, the scale of data located at small values was adjusted using the cumulative probability distribution. The beta distribution was chosen as the scale adjustment function of this study because it can flexibly explain various types of data, as shown in Figure 6 using two shape parameters, α and β.



(a) PDF (b) CDF

Figure 6 Beta distribution

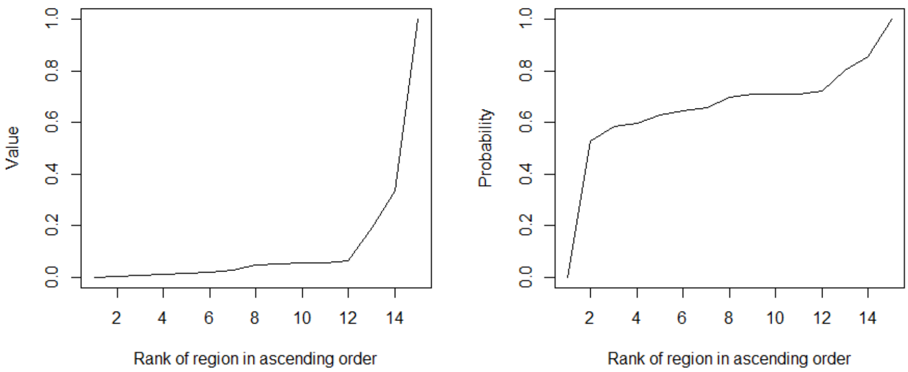
The beta distribution probability density function is shown in Equation (3.14).

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \tag{3.14}$$

Here, α and β are shape parameters and both are greater than 0, and x has a value between 0 and 1. In addition, $B(\alpha,\beta)$ refers to the beta function for t, which is an arbitrary variable given by Equation (3.15).

$$B(\alpha,\beta) = \int_0^1 u^{\alpha-1}(1-u)^{\beta-1}\,du \tag{3.15}$$

The scale adjustment method uses standardized data to obtain the CDF of the beta distribution and uses the corresponding cumulative probability value. For example, Figure 7(a) is a graph that plots the ranking of the regions sorted in ascending order, and the values of the corresponding regions and values of the first to thirteenth ranking are distributed below 0.2. However, Figure 7(b) shows the CDF of the beta distribution obtained from same data, and the probability values from second to thirteenth ranking are evenly distributed from 0.5 to 0.8 except for the minimum value. Thus, the corresponding method enables rescaling data to remain in a similar range to that of the raw data.



(a) Raw data (b) Beta distribution CDF

Figure 7 Rescaling with beta CDF

3.5.2 Aggregation of Components and Indicators

There are three aggregation steps in the DRI calculation process. First, the first aggregation step is needed in the process of calculating the capacity indicator using components. In this process, each component has the effect of reinforcing the indicator. Equation (3.16) was used employing the SAW formula in Section 2.3.2.

$$Capacity\,indicator\,(C) = \sum_{j=1}^{10} w_{s,j} \cdot c_{s,j} \tag{3.16}$$

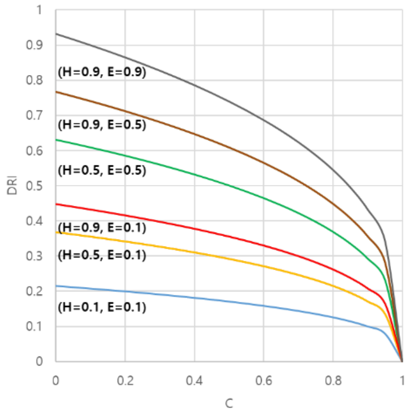
The subscript s represents the three water sectors—municipal, agricultural, and industrial water—and j denotes the number of the components in each sector. In addition, $w_{s,j}$ is the weighting coefficient.

Second, the WP formula was used to integrate three indicators — the hazard (H), exposure (E), and capacity (C) indicators — into the DRI. Risk arises when all three subconcepts exist. According to the definition in this study, there is no damage from drought in areas where there is no water demand. When a single indicator becomes 0, the value of the integrated index must be 0, so the WP formula reflecting this relational expression was applied. Equation (3.17) is shown with three indicators of the DRI. The weighting coefficient can be assigned differently depending on the relationship between each individual indicator with risk; however, in this study, the same weight was applied and calculated as a geometric mean.

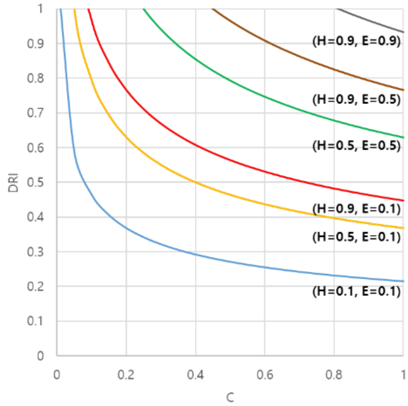
$$\mathrm{DRI} = \prod_{i=1}^{3} indicator_i^{\,w_i} \tag{3.17}$$

Here, w_i is the weighting coefficient assigned to each indicator, and $indicator_i$ refers to the hazard, exposure, and capacity indicator of the DRI. Because H and E have a positive relationship with the DRI, each indicator can be multiplied by the values of these parameters. However, C has a negative relationship, so the higher the value of C, the lower the DRI. The smaller the DRI, the higher the DRI that should be reflected in Equation (3.17).

There are two methods for a negative relationship between index and indicator. The first is a method of subtracting the value from 1, the maximum value of the indicator, and second is taking the reciprocal of values. Regarding the DRI, Figure 8 compares the DRIs obtained using the two aforementioned methods. Figure 8(a) shows the former method using $(1 - \mathrm{C})$, and Figure 8(b) is the latter one with $(1/\mathrm{C})$.



(a) $\mathrm{DRI} = [\mathrm{H} \times \mathrm{E} \times (1 - \mathrm{C})]^{1/3}$



(b) $\mathrm{DRI} = [\mathrm{H} \times \mathrm{E} \times (1/\mathrm{C})]^{1/3}$

Figure 8 DRI depending on the formula of capacity indicator

In Figure 8(a), as the C indicator increases, the rate of change of the DRI increases. In Figure 8(b), the rate of change of the DRI decreases as the value of the C indicator increases. Because the impact of the C indicator on the risk varies according to the nature of the disaster, an appropriate formula should be selected. To explain the detailed process of selecting the formula for the DRI, the black line in Figure 8 shows that the H and E indicators are 0.9. In Figure 8(a), the DRI gradually decreases as the C indicator changes from 0 to 1. However, in Figure 8(b), when the C indicator has a value from 0 to 0.8, the DRI exceeds the upper limit of the DRI, 1. Thus, the C indicator can affect the narrow range of the DRI from 0.8 to 1. Because this study should reflect the change in the DRI according to the capacity as much as possible to emphasize the role of local governments, the DRI formula is suggested using Equation (3.18).

$$DRI = f(H,E,\mathrm{C}) = \mathrm{H}^{1/3} \times E^{1/3} \div C^{1/3} \tag{3.18}$$

Finally, the integrated DRI for every sub-basin of three sectors is calculated using Equation (3.19).

$$DRI = \frac{DRI_M + DRI_A + DRI_I}{3} \tag{3.19}$$

3.5.3 Weighting Coefficient of Capacity Components

To calculate individual indicators as an index, the three indicators were assigned the same weighting coefficients, as described in Section 3.5.2. However, in the process of integrating capacity components into indicators, different weighting coefficients were set because a certain component can be relatively effective in drought mitigation. It is assumed that the weighting coefficients of each component are different for every sub-basin, whereas they are the same in one sub-basin regardless of the temporal change. Every weighting coefficient is generated by decreasing in 0.1 increments from 1 to 0. Among the weighting coefficient combinations, the combination with the highest correlation coefficient between the DRI and drought damage estimation is selected — that is, if a capacity indicator needs m components, combinations with a sum of 1 among $(11)^m$ combinations are used for sets of weighting coefficients. After calculating the DRI with each set of weighting coefficients, the set with the highest correlation coefficient is selected for the weighting coefficients of each sub-basin.

3.6 Drought Damage Estimation for Weighting Coefficient

The perspective of the hydrologic–economic modeling method was adopted to verify the DRI. Using a hydrological model based on the hydrologic–economic modeling method, Booker et al. (2005) and Ward et al. (2006) calculated the water supply in accordance with the water resource policy for management and allocation using. The output was used as input data for economic models in the water-resource-based sector to calculate the cost of damage caused by droughts. The aforementioned studies determined whether the economic damage caused by drought can be reduced by changing existing water policies. Thus, they aimed at changing water resource allocation but focused on selecting areas where drought management is a priority.

Research focused on spatial priorities was conducted by KEI (2012) in the economic damage analysis of drought considering future climate change effects. Based on the RESCON model developed by the World Bank, the economic impact was analyzed by calculating the demand and runoff of the four major rivers in the Korean Peninsula. The study by KEI (2012) presented and compared the damage cost of water systems by future period. Because the target of the drought in the DRI is the amount of water demand, it can be estimated that the areas with less use compared with past demand have suffered from drought significantly. Therefore, the water deficit ratio (WDR) calculated using Equation (3.20) can be used as the verification data for the DRI. The WDR is the ratio of the water consumption to the water demand by region.

$$\mathrm{WDR} = \frac{Water\ \ Demand\ \ Estimation - Water\ \ Use}{Water\ \ Demand\ \ Estimation} \tag{3.20}$$

Chapter 4. Application

4.1 Study Area

In this chapter, the conceptual framework of risk proposed in Chapter 3 was applied to calculate drought risk by sub-basin in the Korean Peninsula. Because drought is a natural disaster managed under the National Water Resources Plan, it is necessary to analyze spatially at the basin level. The watershed unit for water resource planning has undergone three changes, and the most recent revisions are summarized in Table 7. This water resources unit map, including the five largest basins, coastal areas, and Jeju Island, is classified into 21 basins, 117 sub-basins, and 850 standard basins for the development, planning, and management of water resources at the national level (Han River Flood Control Office (HRFCO), 2013). First, the five largest basins (Han River, Nakdong River, Geum River, Seomjin River, and Yeongsan River) are divided into 21 basins based on independent rivers originating from mountain ranges, environmental and climatic characteristics, and coastal topographic characteristics. These basins are classified into 117 sub-basins to utilize domestic water-related data, and the sub-basins are separated to 850 standard basins in consideration of the confluence of national and local rivers, major dams, and water stage stations (HRFCO, 2013).

Table 7 Basin information of Korean Peninsula

Basin name	Basin code	Number of Sub-basins	Number of standard basins
Hangang	10	24	237
Anseongcheon	11	1	18
Han River West Sea	12	2	14
Han River East Sea	13	3	21
Nakdonggang	20	22	195
Hyeongsangang	21	1	9
Taehwagang	22	1	6
Nighttime, swimming	23	2	9
Nakdonggangdonghae	24	3	25
Nakdonggangnamhae	25	4	28
Geumgang	30	14	78
Sapgyocheon	31	1	16
Geumgang West Sea	32	3	19
Mangyeong, Dongjin	33	3	24
Seomjingang	40	9	46
Seomjin Gangnam Sea	41	6	27
Youngsangang	50	8	34
Tamjingang	51	1	4
Yeongsan Gangnam Sea	52	2	10
Yeongsan River West Sea	53	3	14
Jeju	60	4	16
Total	21	117	850

In this study, to evaluate the drought risk by region, the sub-basin, which is the most widely used division criterion, was set as a spatial unit. In the relative comparison of space units, Jeju Island, which has strong regional characteristics, was excluded from the study area. Therefore, in this study, the DRI was calculated for 113 sub-basins in 20 basins, excluding Jeju Island. Figure 6 shows the sub-basins covered in this study as a map, provided by the National Water Resources Management Comprehensive Information System (WAMIS). In addition, when calculating the DRI, data that existed in administrative units were converted into sub-basins using the area ratio of administrative districts for each sub-basin.

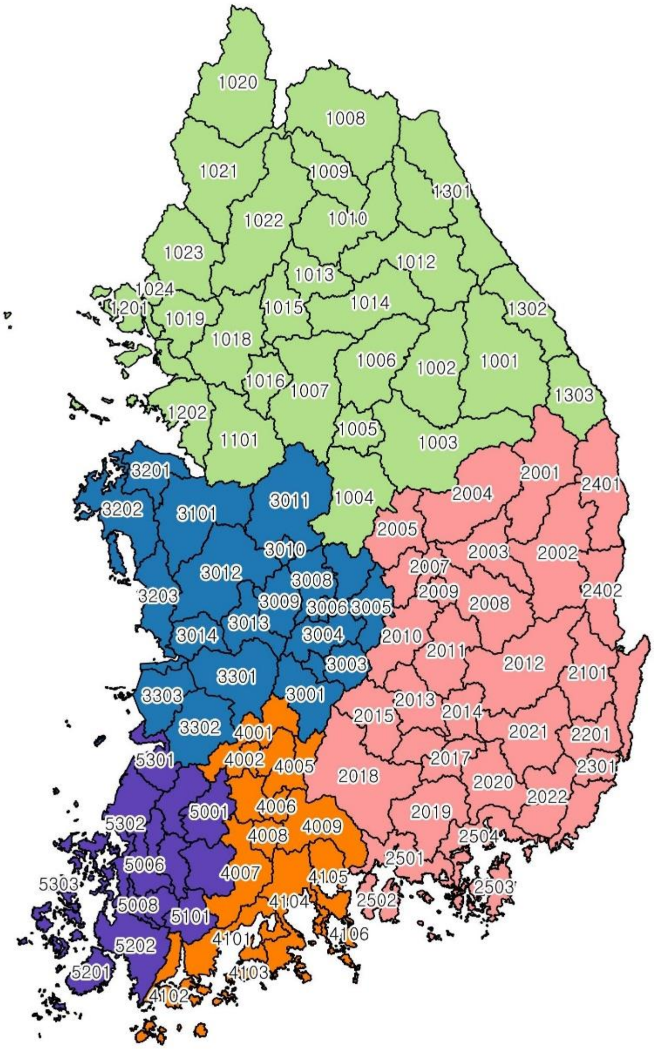


Figure 9 Water resources unit map of Korean Peninsula

4.2 DRI Components Selection

For DRI calculation, components that can represent each indicator were selected based on previous studies (Birkmann et al., 2011; Kim and Chung, 2013; Carrao et al., 2016; Freire-Gonazalez et al., 2017; Choi, 2018; Vogt et al., 2018).

Subjective opinions depending on the researcher are involved in the selection of components. To minimize this, components used in previous studies were referenced, and whether the components were consistent with the definition of each indicator and whether it was suitable for the regional scale were reviewed. Next, because the quality of the data is important to the index research, the components in which data with accurate sources provided by public institutions exist were selected. The 23 data used in the DRI calculation are classified by sector, and the names and sources of the data are summarized in Table 8. Except the hazard indicator component, all the data were preprocessed as described in Section 3.5.

In the hazard indicator component, the cause of the drought was explained by selecting the SPI index on a 3- and 12-month time scale. In the process of calculating the SPI index, one step is estimating the parameters of the gamma distribution, as shown in Equations (3.3) and (3.4), and historical observation data from 1973 to 2017 and precipitation data from future climate scenarios until 2100 are used.

In the components for exposure indicator, the drought objects by sector were described using the amount of water demand. MLTMA (2011) estimated demand for municipal, agricultural, and industrial water in 2011, 2016, and 2020. Furthermore, because of uncertainties in the future projection, such as population and economic growth rate, water demand estimation was divided into high-demand, standard-demand, and low-demand scenarios

To estimate municipal water demand, data such as the future population, planned water supply rate, target water flow rate, daily water supply per person, amount of demand for water supply areas (excluding industrial use), demand for water supply areas, and other groundwater use were used, and the integrated demand was obtained by adding the demand and usage data. Next, agricultural water demand was estimated using data such as cultivated area, number of livestock heads, and demand management savings, as well as demand for agricultural water, field water, and livestock water. Finally, after estimating the demand for the existing industrial complex and individual location companies and the demand for the planned industrial complex and individual location companies using data such as the status of the industrial park and industrial water reuse rate, the demand for industrial water was obtained by adding the two aforementioned types of demand. The aforementioned report also estimated the demand for river maintenance water. However, in the present study, only three types of water demand were considered. In addition, the demand for the standard scenario was used, and the year was selectively considered according to the required result.

Next, capacity indicators were classified into municipal, agricultural, industrial, and common sectors that are subject to drought risk and were classified into coping capacities (CCs) and adaptive capacities (ACs) for each sub-basin.

CCs aim to maintain the system and its functions in the face of adverse conditions and mainly focus on short-term action (IPCC, 2012). In the event of a drought, the ability to prepare water resources for water shortages was considered as a short-term ability of society to reduce adverse effects. For instance, CCs explained how many facilities were secured to supply water using a multiregional water supply system, a local water supply system, and dam storage in common for municipal and industrial water. In the field of municipal water, energy water supply facilities were added to CC as an immediate capacity to use in case of drought, and groundwater use was added to the field of industrial water as an individual CC. CCs for agricultural water were selected as facilities that explain the functions of agricultural water with river improvement rate, agricultural reservoir, pumping station, weir, infiltration gallery, and well.

In contrast, ACs involve changes and require reorganization processes for long-term strategies. In the case of ACs, this means the ability to take measures or strategies for social change in the long term in preparation for the occurrence of drought, and it expresses potential capacities, such as education, research, environmental statue, adaptation strategies, and investment. Components that explain directly or indirectly were selected. First, for common ACs, the research and development cost was used to represent the amount of research and development investment for each region. Next, using the financial self-reliance ratio and gross regional domestic product, when there is economic margin, investment is made in long-term countermeasures, and it was selected as a component to explain ACs indirectly. In addition, an attempt is made to explain the degree of government capability through the number of public employees. Per capita personal income is added as component of municipal water, and number of companies and wages are added as components of industrial water to represent the degree of interest in long-term change as an economic factor. The basic life recipient is used to explain the state of the government through negative correlation in municipal water. Finally, the insurance coverage rate explains the attitude toward long-term action rather than immediate change in agricultural water.

Table 8 Components of DRI

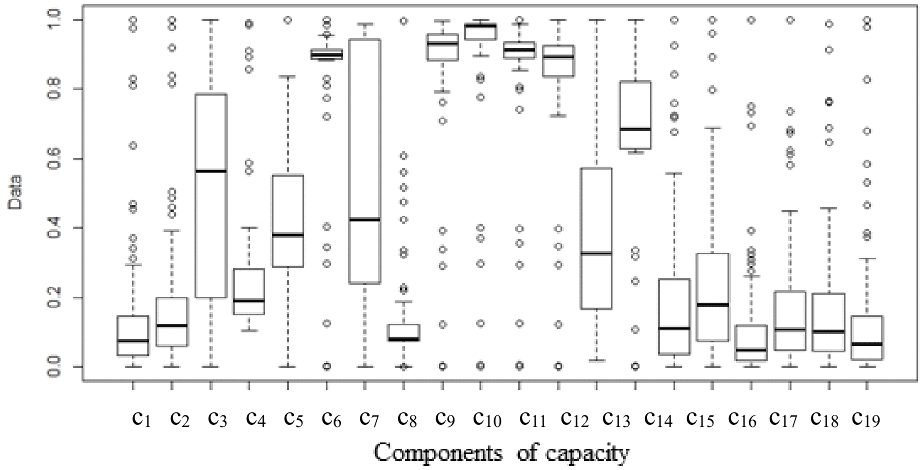
Indicator	Component				Source
Hazard	Metrology		Standard Precipitation Index	h	KMA[7]
Exposure	Municipal		Municipal water demand	e_1	MOLIT[8]
	Agricultural		Agricultural water demand	e_2	MOLIT
	Industrial		Industrial water demand	e_3	MOLIT
Capacity	Municipal	Adaptive capacity	Basic life recipient	c_5	KOSTAT[9]
			Per capita personal income	c_6	KOSTAT
		Coping capacity	Emergency water supply facilities	c_{10}	KOSTAT
			Multiregional water supply system	c_{11}	KOSTAT
			Local water supply system	c_{12}	KOSTAT
			Dam storage	c_{13}	ME[10]
	Agricultural	Adaptive capacity	Agricultural insurance ratio	c_7	data.go.kr
		Coping capacity	River improvement rate	c_{14}	WAMIS[11]
			Agriculture reservoir	c_{15}	WAMIS
			Pumping station	c_{16}	WAMIS
			Agriculture weir	c_{17}	WAMIS
			Agriculture well	c_{18}	WAMIS
	Industrial	Adaptive capacity	Number of companies	c_8	KOSTAT
			Wage	c_9	KOSTAT
		Coping capacity	Multiregional water supply system	c_{11}	KOSTAT
			Local water supply system	c_{12}	KOSTAT
			Dam storage	c_{13}	ME
			Groundwater	c_{19}	WAMIS
	Common	Adaptive capacity	Financial self-reliance ratio	c_1	KOSTAT
			Number of government officials	c_2	KOSTAT
			Research and development costs	c_3	KOSTAT
			Gross regional domestic product	c_4	KOSTAT

7 Korea Meteorological Administration
8 Ministry of Land, Infrastructure and Transport
9 Statistics Korea
10 Ministry of Environment
11 Water Resources Management Information System

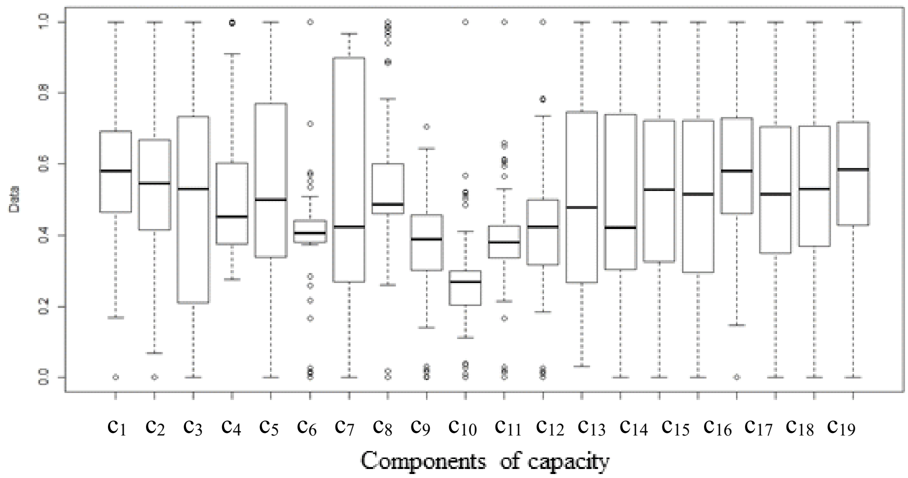
The socioeconomic data used in the calculation of the capacity indicator were processed through outlier detection, normalization, and rescaling with the beta CDF. Table 9 summarizes the number of outliers and the beta distribution parameter corresponding to the results of preprocessing data from c_1 to c_{19}. All values corresponding to outliers in the data were adjusted to the maximum value among the values that were not detected as outliers. For example, c_1 has two outliers, so two outlier values were adjusted by setting the upper third value as the upper limit. Next, Figure 7 shows the data distribution after rescaling with the beta CDF. Certain components, such as c_6, c_8, and c_{11}, are evenly spread after applying beta distribution rescaling, as shown in Figure 7(b).

Table 9 Data preprocessing of components

Component		Number of outliers	Beta distribution parameter	
			shape1	shape2
Financial self-reliance ratio	c_1	2	0.28	1.74
Number of government officials	c_2	2	0.43	1.98
Research and development costs	c_3	14	0.83	0.76
Gross regional domestic product	c_4	6	0.94	2.63
Basic life recipient	c_5	8	1.95	3.01
Per capita personal income	c_6	3	2.75	0.42
Agricultural insurance ratio	c_7	0	0.75	0.72
Number of companies	c_8	0	0.62	3.91
Wage	c_9	0	2.10	0.27
Emergency water supply facilities	c_{10}	14	1.02	0.08
Multiregional water supply system	c_{11}	0	2.34	0.32
Local water supply system	c_{12}	0	2.83	0.47
Dam storage	c_{13}	0	0.96	1.57
River improvement rate	c_{14}	0	5.10	2.17
Agriculture reservoir	c_{15}	0	0.44	1.95
Pumping station	c_{16}	0	0.70	2.33
Agriculture weir	c_{17}	0	0.27	2.40
Agriculture well	c_{18}	0	0.54	2.69
Groundwater	c_{19}	1	0.28	1.99



(a) Removing outliers without the beta CDF



(b) Rescaling with the beta CDF

Figure 10 Boxplots of capacity components

4.3 Estimation of Weighting Coefficient

The following procedure was employed to estimate the weighting coefficient used for each component of the capacity indicator in the DRI. After calculating the DRI values for all possible combinations of weighting coefficient in increments of 0.1 from 0 to 1, the combination that computed the highest correlation coefficients between the DRI and WDR was finally selected. These estimations of the weighting coefficient were consistently used to calculate the DRI of the reference and future periods. As an exception, when there was a sub-basin where the WDR value was 0 because the amount of use and demand of water did not exist, the same value of the weighting coefficient was applied for every component.

Among the data for the DRI, there were many cases in which the period for which the data were constructed was relatively short or existed as a constant value for a specific year rather than in the form of time series. Taking this into account, the data period for the weighting coefficient was based on the period from 2010 to 2017. Table 10 shows the data period used for the weighting coefficient. As explained in the remarks column, between 2010 and 2017, the weighting coefficient was selected differently depending on the situation of the data.

The DRI and WDR correlation coefficient values are summarized in Table 11 for each of the 21 basins, and the national average was 0.489. As data accumulate in the future, the weighting factor should be updated continuously.

Table 10 Data period for the weighting estimation

Category	Available data year	Data year used for weighting coefficient	Remark
Hazard	1973–2017	2010–2017	Estimation of the gamma distribution parameter of the SPI calculation uses precipitation data from 1973 to 2017, and calculation for weighting coefficient uses data from 2010 to 2017.
Exposure	2011, 2016, 2020	2011, 2016	(Constant) The input data for 2010–2015 are the values for 2011, and the input data for 2016–2017 are the values for 2016.
Capacity	By data	2010–2017, 2016	Different by, for example, the data of financial independence and the number of public officials use the type of time series, and the data of water resource facilities use the type of constants.
WDR	Water usage: by data Water demand: 2011, 2016, 2020	2010–2017, 2011, 2016	Use the type of time series for water usage and the type of constants for water demand (the same way as exposure).

Table 11 Correlation coefficients by basin on average

Basin name	Basin code	Correlation coefficient
Hangang	10	0.320
Anseongcheon	11	0.523
Han River West Sea	12	0.423
Han River East Sea	13	0.453
Nakdonggang	20	0.645
Hyeongsangang	21	0.307
Taehwagang	22	0.313
Nighttime, swimming	23	0.626
Nakdonggangdonghae	24	0.637
Nakdonggangnamhae	25	0.479
Geumgang	30	0.499
Sapgyocheon	31	0.477
Geumgang West Sea	32	0.535
Mangyeong, Dongjin	33	0.449
Seomjingang	40	0.490
Seomjin Gangnam Sea	41	0.573
Youngsangang	50	0.543
Tamjingang	51	0.470
Yeongsan Gangnam Sea	52	0.489
Yeongsan River West Sea	53	0.537
Total		0.489

4.4 Results

In this study, the DRI was calculated for reference and future periods. Here, the reference DRI refers to the DRI period obtained by inputting data for the past 30 years (1988–2017) into the hazard indicator while maintaining the weighting coefficient selected in Section 4.3. By comparing this with the DRI of the future period, the relative change by sub-basin is projected.

The reference DRI was set to an average of 30 years, and the future DRI was set to 30 years, including the 10 years before and after the 2030s, 2060s, and 2090s. For the exposure and capacity indicators, data from the year shown in Table 12 were used to predict how much drought risk due to future climate change will change if the socio-economic status remains the same as at that time.

Table 12 Data period for the reference DRI and future DRI

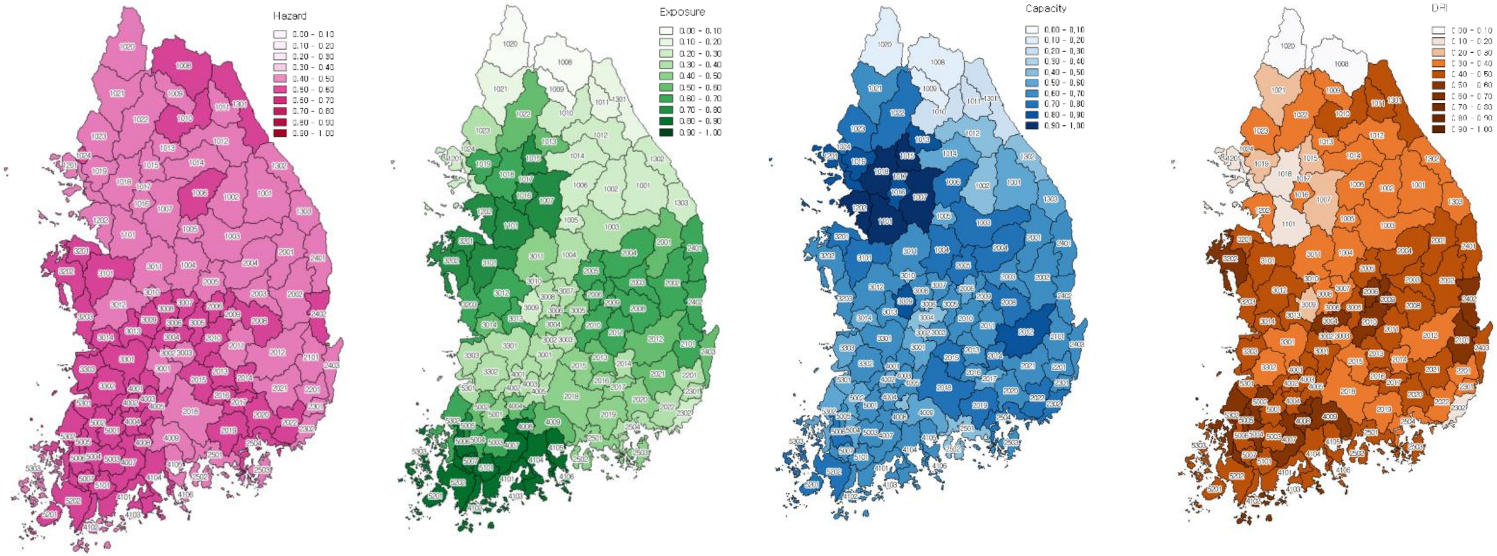
Category	Reference	Future	Remark
Hazard	1988–2017 (Observation data)	2019–2099 (Climate Change Scenario)	SPI parameters are estimated using precipitation data for the entire period from the past to the future.
Exposure	2016	2020	-
Capacity	2016	2016	-

4.4.1 Reference DRI

With the reference data in Table 12, the hazard, exposure, and capacity indicators are calculated, as shown in Figures 11(a)–(c). The deviation hazard indicator of the three indicators was the lowest, and the exposure indicator was the largest.

The drought hazard indicator was high in the Nakdong River and low in the Seomjin River basins. In terms of drought exposure indicators, Gyeongancheon, Paldang Dam, and Sihwa Lake recorded the highest values in the Han River basin near the Seoul metropolitan area. The lowest values were also recorded in the Han River basin, specifically, in the Geumgangsan Dam and Peace Dam. Finally, the drought capability index was high in the Han River area, where infrastructure is located in the vicinity of the Seoul metropolitan area and the Nakdong River area in Gyeongsangbuk-Do.

The DRI, given in Figure 7(d), was calculated for three indicators. As a result, the highest DRIs were in Yeongdeokosib-cheon and Sinan-gun, where the hazard indicator is relatively high, while the capacity indicator is low. The metropolitan area had a particularly large exposure indicator, and a high DRI value was calculated in the region where the capacity indicator was low. Nevertheless, Hangangseoul had a low DRI value because of a high capacity indicator.



(a) Drought hazard (b) Drought exposure (c) Drought capacity (d) DRI

Figure 11 Spatial distribution in drought hazard, exposure, capacity, and DRI for the reference period

Table 13 Sub-basin with highest and lowest DRIs for the reference period

Category	Rank (out of 113)	DRI	Sub-basin [sub-basin code]
Highest	1	0.666	Seomjingokseong [4006]
	2	0.634	Watancheon [5302]
	3	0.619	Gumibo [2009]
Lowest	113	0.000	Gomitancheon [1020]
	112	0.070	Geumgangsan Dam [1008]
	111	0.117	Suyeong-gang [2302]

4.4.2 Future DRI

Among the future data in Table 12, rainfall data from future climate scenarios were used to calculate the hazard indicator. To determine the future drought risk, the HadGEM3-RA model, a regional climate model produced at the national level by the National Institute of Meteorology, was employed in this study. As for the emission scenarios used, the RC4.5 and RCP8.5 emission scenarios, which are the most widely used among Representative Concentration Pathways (RCP) suggested in AR5, were selected. RCP4.5 is a future scenario in which greenhouse reduction policies are effectively reflected, and RCP8.5 is a future scenario in which greenhouse gases are emitted without reduction, as per the current trend.

The results of the future DRI using the HadGEM3-RA model are shown in Figure 12 as spatial distributions under RCP4.5 and RCP8.5. Future DRI averages had the highest values in the 2030s of 0.427 and 0.418, respectively, from RCP4.5 and RCP8.5. After the 2030s, RCP4.5 had the lowest DRI, 0.402, in the 2060s, and RCP8.5 showed the lowest DRI, 0.396, in the 2090s (Figure 13). In Table 8, the maximum values are projected to be higher than the present in the 2030s and 2090s under RCP 4.5, and the minimum values are higher except in the 2090s under RCP8.5. In contrast to the IPCC's expectation that the drought risk by future era will gradually increase over the 21st century, this study predicts that the future DRI in 2030s will be the highest in the average, maximum, and minimum values.

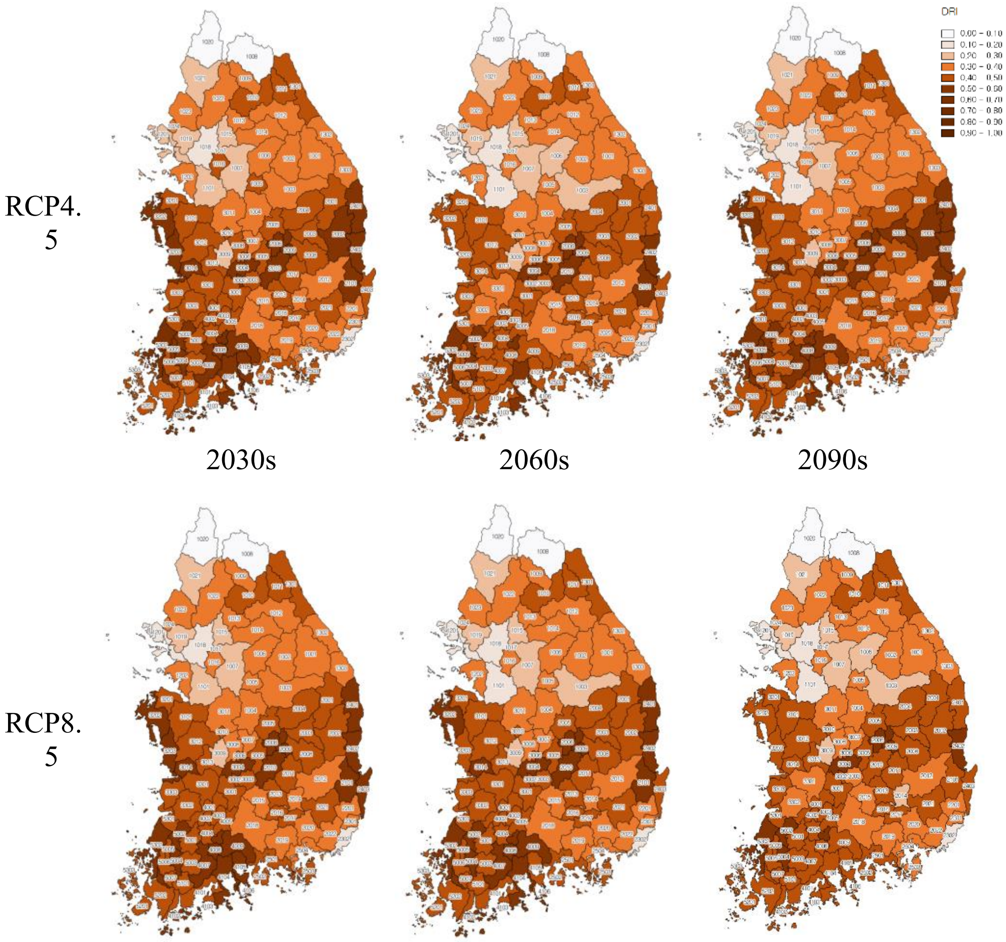


Figure 12 Future DRI with HadGEM3-RA

Figure 13 DRI over the future 30-year periods with HadGEM3-RA

Table 14 Statistics of the future DRI with HadGEM3-RA

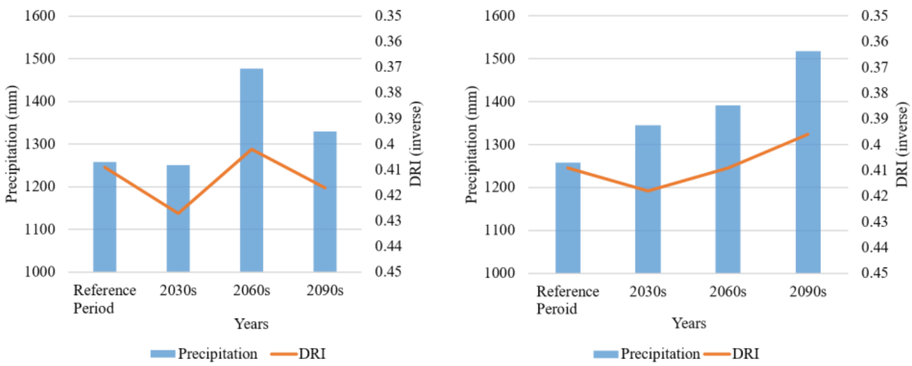
Scenario	Statistics	Reference period	2030s	2060s	2090s
RCP4.5	Mean	0.409	0.427	0.402	0.417
	Max	0.467	0.484	0.445	0.474
	Min	0.330	0.361	0.338	0.346
RCP8.5	Mean	0.409	0.418	0.409	0.396
	Max	0.467	0.465	0.463	0.453
	Min	0.330	0.376	0.357	0.294

For the entire future period, the Han river has the largest number of the sub-basins, where the future DRI increased compared with the reference DRI during the future period, 94 and 67, respectively, under RCP4.5 and RCP8.5 in the 2030s (Table 15). The rate of change of the future DRI compared with the reference period is analyzed to identify the sub-basin where the risk increases the most compared with the present. Geumgangsan Dam showed the highest rate at +11.83% and +7.54%, respectively, under RCP4.5 and RCP8.5. Next, the sub-basin with the largest increase in the DRI ranking under RCP4.5 was Nonsancheon; this region was 45th in the reference period but rose 12 places to 33rd in the 2030s. In RCP8.5, Nonsancheon and Yeosu rose from 20th to 13th and 23rd to 12th, respectively. The sub-basin that exhibited the greatest descrease in ranking was Bunambangjojae, which was ranked 14th in the reference period but fell to 27th in the 2060s for RCP4.5.

Table 15 Number of sub-basins where the future DRI increased over the reference DRI with HadGEM3-RA

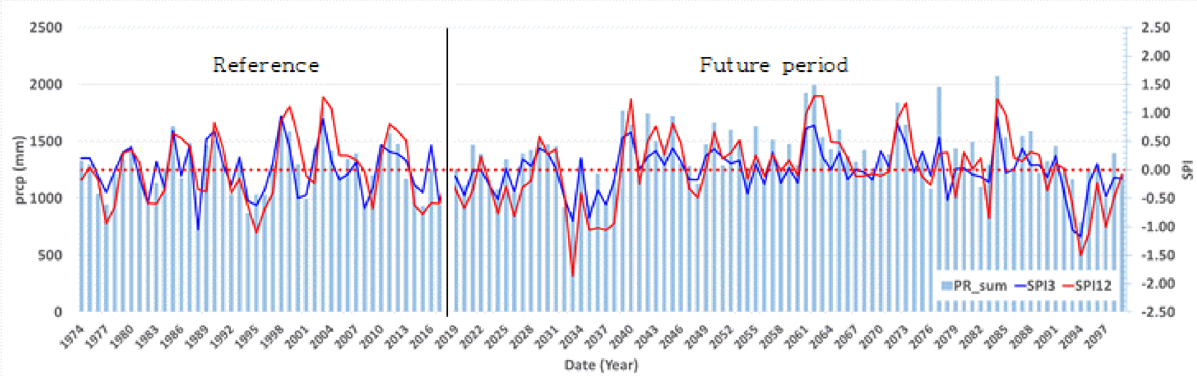
Basin (number of sub-basins)	Scenarios & Periods					
	RCP4.5			RCP8.5		
	2030s	2060s	2090s	2030s	2060s	2090s
Han River (30)	26	0	15	24	4	1
Nakdong River (33)	21	2	19	14	3	0
Geum River (21)	20	2	13	16	4	1
Seomjin River (15)	15	0	10	10	7	0
Yeongsan River (14)	12	1	7	3	2	0
All (113)	94	5	64	67	20	2

As shown in Figure 14, the precipitation and DRI in the future period showed the same trend. The time series of annual precipitation and SPI (3 and 12 months) is shown in Figure 15. Years below zero classified as drought based on SPI3 and SPI12 were the most common in the 2030s, with 12 and 15 occurrences in RCP4.5 and 13 and 12 occurrences in RCP8.5, respectively. In particular, in RCP4.5, it was confirmed that moderate drought, with SPI12 of less than −1, occurring three years consecutively.

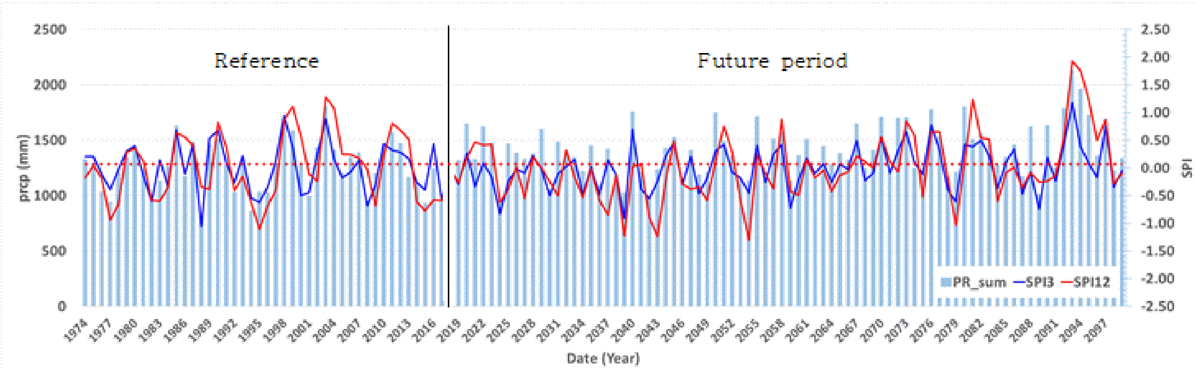


(a) RCP4.5 **(b)RCP8.5**

Figure 14 Annual precipitation and DRI with HadGEM3-RA: national average



(a) RCP4.5

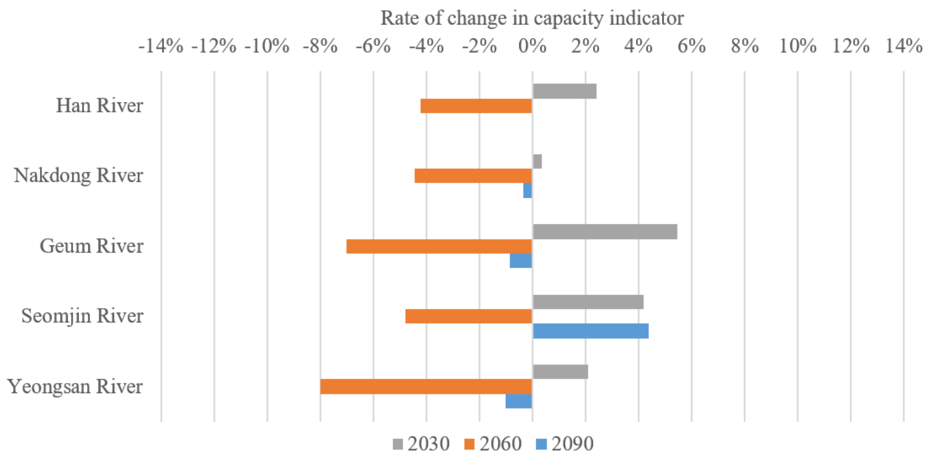


(b) RCP8.5

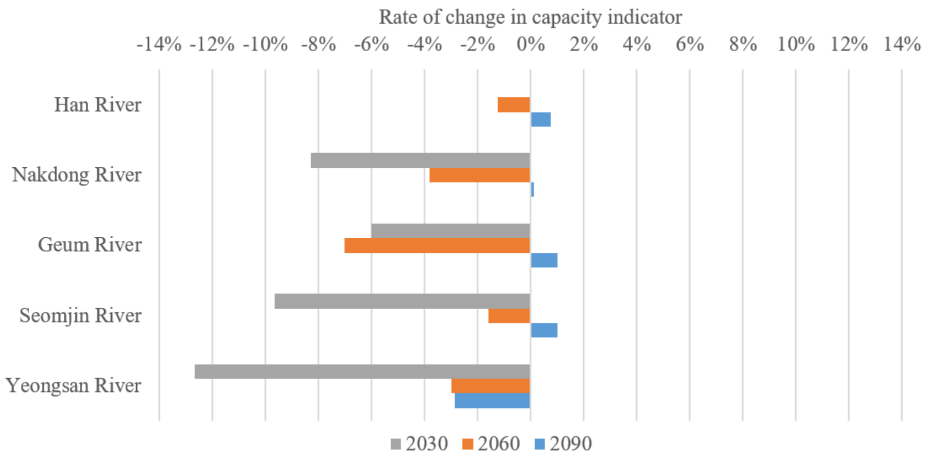
Figure 15 Time series of annual precipitation, SPI3, and SPI12 with HadGEM3-RA

4.4.3 Sensitivity Analysis of Capacity Indicator

Finally, to maintain the future drought risk at the same level as that in the reference period, the extent to which the capacity indicator should increase or decrease was examined. Figure 16 illustrates the rate of change in the capacity indicator in the five largest basins. Figure 13(a) is a graph corresponding to RCP 4.5. In the 2030s, all five largest basins must increase their capacity indicators to maintain the same drought risk as the reference period in the future. In particular, the capacity of the Geum River basin must be strengthened most strongly. However, in the 2060s, drought risk decreased even if all basins had a lower response capacity than that at present, and drought risk was also confirmed to decrease in the 2090s except for the Seomjin River. As shown in Figure 13(b), in RCP 8.5, the drought risk would remain the same as the present risk because of an increase in capacity in the four largest basins excluding Youngsan River in 2030s. However, in the 2060s and 2090s, the current level of drought risk can be maintained even if the capacity is not strengthened.



(a) RCP4.5



(b) RCP8.5

Figure 16 Rate of change in capacity indicator to maintain the reference DRI

4.4.4 Uncertainty Analysis with Additional GCMs

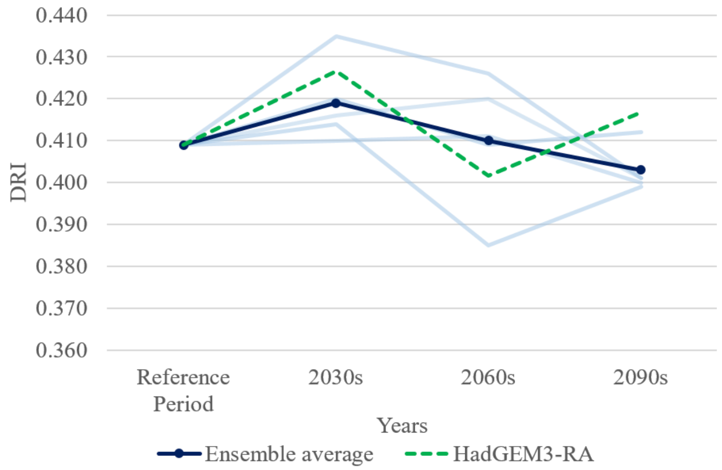
To account for future drought hazard on the Korean Peninsula, the precipitation data from global circulation models (GCMs) are used to describe the climate change. Seo and Kim (2018) and Seo et al. (2019) selected five representative models that best reproduce the uncertainty of all 27 models for low flow among the Coupled Model Intercomparison Project Phase 5 (CMIP5), as shown in Table 16. Therefore, because the variability of future climate change was efficiently reflected, uncertainty was expressed using the corresponding GCMs in this study.

Table 16 GCMs used for uncertainty analysis (Seo and Kim, 2018; Seo at el., 2019)

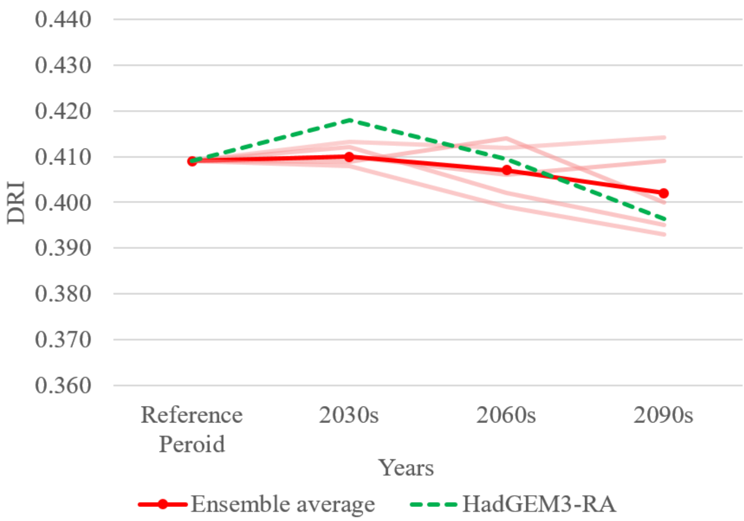
GCMs	Institution
BCC-CMS1-1	Beijing Climate Center, China Meteorological Administration
CMCC-CMS	Centro Euro-Mediterraneo per I Cambiamenti Climatici
HadGEM2-ES	Met Office Hadley Centre
IPSL-CM5A-MR	Institut Pierre-Simon Laplace
MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M)

The future DRI results calculated with five representative GCMs are shown in Figure 13. The ensemble average of future DRI using representative GCMs was higher than the present in the 2030s under RCP4.5 and in the 2030s and 2060s under RCP8.5. The lowest value was calculated for the 2090s. The uncertainty expressed as a range was the largest, at 0.041, in the 2060s for RCP4.5, and it was the smallest, at 0.005, in the 2030s for RCP8.5. The difference in the future DRI between the ensemble average and HadGEM3-RA was 0.0138 in the 2090s and 0.0079 the 2030s for RCP4.5 and RCP8.5, respectively, resulting in a higher drought risk predicted by the HadGEM3-RA model than the ensemble average. The ensemble average calculated, including the HadGEM3-RA, increased 36.6% (0.013 to 0.018) in the 2090s for RCP4.5 and 92.8% (0.005 to 0.01) in the 2030s for RCP8.5 compared with the existing uncertainty range.

Table 17 summarizes the rankings of representative GCMs and future DRIs of HadGEM3-RA in descending order. HadGEM3-RA was the model with the most variability among the six models, and MPI-ESM-LR was the model with the least variability. This shows that when a single GCM model is used, the characteristics of the corresponding GCM can influence the future projection results excessively.



(a) RCP4.5



(b) RCP8.5

Figure 17 DRI over the future 30-year periods with HadGEM3-RA and representative GCM ensemble average: national average

Table 17 GCM rank of future DRI

GCMs	Scenarios & Periods					
	RCP4.5			RCP8.5		
	2030s	2060s	2090s	2030s	2060s	2090s
HadGEM3-RA	2	5	1	1	3	4
BCC-CMS1-1	6	3	5	2	2	1
CMCC-CMS	1	1	4	5	1	3
HadGEM2-ES	4	2	3	3	5	5
IPSL-CM5A-MR	3	4	2	4	4	2
MPI-ESM-LR	5	6	6	6	6	6

Chapter 5. Conclusions

5.1 Summary and Conclusions

The purpose of this study was to evaluate the degree of risk arising from future droughts through a newly proposed drought risk conceptual framework to raise public awareness of drought and to provide information that is easily prepared and to make decisions about preparedness policies of state and local governments.

The existing drought risk conceptual framework is mainly based on studies by international organizations, but the study focus was on a global scale, which was reduced to a regional scale and needed to be modified. Moreover, during this process, components that reflect regional characteristics had to be arranged properly. In addition, in many cases, the verification step was omitted, so there was regret. Accordingly, the existing risk conceptual framework was improved to fit the regional scale, and a DRI that was easy to compare by region was developed to predict the future drought risk on the Korean Peninsula.

In this study, the conceptual framework was developed to be easy for users to understand the concept, improved the sub-concepts to be suitable for regional comparison, and selected components for each indicator to explain nationwide differences in the Korean Peninsula. Drought risk refers to the possibility of potential damage resulting from a disaster caused by drought. The drought risk conceptual framework is composed of hazard, exposure, and capacity. For the proxy explaining the drought hazard indicator, SPI3 and SPI12 were used for the drought index. For the drought exposure indicator, the amount of demand by water was selected. For the drought capacity indicator, among proxy variables (i.e., economic status of society, water infrastructure, etc.), short-term capacity was selected as a coping capacity, and long-term capacity was classified as adaptive capacity.

The data used in the components were detected for outliers, standardized to a range from 0 to 1, and rescaled using beta CDF to distribute the data evenly. In this study, a combination of the weighting coefficient for the capacity indicator from 0 to 1 in 0.1 units was generated. The drought risk was calculated for each combination, and the combination with the highest correlation coefficient with the drought damage was selected. After the DRI was calculated for all combinations, the weighting coefficient for each sub-basin was selected as the combination with the highest correlation coefficient between the DRI and the drought damage estimate. In the verification period from 2010 to 2017, the correlation coefficient was 0.489, confirming that the two variables had an appropriate positive relationship; therefore, the DRI properly explains drought damage.

The DRI was calculated over the past 30 years (1988–2017) to be used as the reference DRI and for future periods (2020–2100) to be used as the future DRIs. As a result, the Seomjin River and Yeongsan River have the highest reference DRI with high values of hazard and exposure indicators, while the Han River has the lowest reference DRI because of the high value of its capacity indicator. In the Yeongsan

River and Seomjin River, precipitation is insufficient, while the amount of water demand is high due to agriculture and tourism industries. However, compared with other basins, water infrastructure and socio-economic factors are insufficient. As a result, the DRI was measured higher. Since the Youngsan River and Seomjin River basins continue to maintain high DRI in the future, it is necessary to suggest solutions through structural measures. As drought management, water resource facilities expansion is essential to reduce drought risk in the two basins. In particular, these basins are difficult to intake and supply water sources due to their characteristics as islands. Therefore, a plan to supply water by establishing separate water intake stations, such as the desalination, rather than multi-reservoir operation or dam conduit construction project, can be proposed.

Next, the future DRI was applied with HadGEM3-RA under RCP4.5 and RCP8.5, and precipitation data were used to calculate the hazard indicator. The 2030s was the period with the highest future DRI and with the largest number of sub-basins where the DRI had increased compared with that in the reference period. Contrary to the report of the IPCC (2014) finding that drought risks on the Korean Peninsula and in the East Asian region will gradually increase during the 21st century, the highest drought risks occurred in the 2030s and the lowest in the 2090s according to the future projection of the DRI. It was confirmed that the trend of the HadGEM3-RA projecting low precipitation in the early 21st century was due to the DRI results. Based on the DRI results, the rate of change in the capacity indicator was calculated to determine the extent to which the predicted future DRI is maintained at the same level as the reference DRI. In particular, the Geum River basin should be prepared the most for droughts in the 2030s for RCP 4.5 and RCP8.5, and the response capacity of the Seomjin River basin should be strengthened in the 2030s and 2090s for RCP 4.5.

In addition, the uncertainty in the future DRI was analyzed using five representative GCMs. HadGEM3-RA is a representative climate change scenario provided by the Korean government; however, the range of the uncertainty is greatly increased in the future DRI. Therefore, various scenarios should be considered in the future projection of climate change because the single scenario is not sufficient to explain uncertainty and can yield biased results.

5.2 Future Study

In this study, the weighting coefficient for each subbasin was calculated in the eight-year period from 2010 to 2017, in which the data used were sufficient. However, it is expected that the research results will be superior to the present ones if reliable data continue to accumulate and the weighting coefficients are updated. Furthermore, the results will be elaborately calculated if the weighting coefficient is generated at a smaller decimal point than 0.1.

The most important part of this research is the relationship between the DRI and indicator. In previous studies, if the relationship between risk and indicator is positive, the calculated index value is used as it is; if negative, the value is subtracted from the maximum value of the indicator, or the reciprocal is used. In this study, as mentioned in Section 3.5.2, the capacity indicator is applied as (1 − C) in the DRI equation owing to the negative relation to drought risk, and the final result, DRI, is computed as geometric average of three indicators. However, the impact of the indicator on the risk may vary depending on the disaster. For example, an earthquake or tsunami is a disaster in which the initial response capacity is extremely significant, and, when the risk is small, the impact of capacity is large; however, when the risk is large, the impact of capacity may be small. If the relationship between drought risk and capacity is analyzed in depth and applied to the risk equation, it is thought that the credibility of the DRI can be further improved.

Finally, the purpose of this study was to project the future drought risk resulting from climate change when the current socio-economic status is maintained. Thus, the capacity indicator of the future DRI was calculated with the same data as the reference DRI. However, if the capacity indicator is calculated considering future social changes or various policies, the results can be used as one of the evaluation methods for policy-specific decision making.

Bibliography

Anand, S., and Sen, A. (2000). "Human development and economic sustainability." *World development*, Vol. 28, No. 12, pp. 2029-2049.

Birkmann, J. (2011). "First-and second-order adaptation to natural hazards and extreme events in the context of climate change." *Natural Hazards*, Vol. 58, No. 2, pp. 811-840.

Birkmann, J., and Welle, T. (2015). "Assessing the risk of loss and damage: exposure, vulnerability and risk to climate-related hazards for different country classifications." *International Journal of Global Warming*, Vol. 8, No. 2, pp. 191-212.

Blancas, F. J., Contreras, I., and Ramírez-Hurtado, J. M. (2013). "Constructing a composite indicator with multiplicative aggregation under the objective of ranking alternatives." *Journal of the Operational Research Society,* Vol. 64, No. 5, pp. 668-678.

Booker, J.F., Michelsen, A.M., Ward, F.A. (2005). "Economic impact of alternative policy responses to prolonged and severe drought in the Rio Grande Basin." Water Resources Research, Vol. 41, No. 2, p. W02026.

Brys, G., Hubert, M., and Struyf, A. (2004). "A robust measure of skewness." *Journal of Computational and Graphical Statistics*, Vol. 13, No. 4, pp. 996-1017.

Cardona, O. D., Hurtado, J. E., Duque, G., Moreno, A., Chardon, A. C., Velásquez, L. S., and Prieto, S. D. (2003). The Notion of Disaster Risk: Conceptual Framework for Integrated Management. National University of Colombia/Inter-American Development Bank, DC, United States of America.

Carrão, H., Naumann, G., and 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*, Vol. 39, pp. 108-124.

Choi, S. Y. (2018). *Drought risk index development for drought risk assessment*. Master dissertation, Seoul National University, Seoul, Republic of Korea.

Das, S., Ghosh, A., Hazra, S., Ghosh, T., de Campos, R. S., and Samanta, S. (2020). "Linking IPCC AR4 & AR5 frameworks for assessing vulnerability and risk to climate change in the Indian Bengal Delta." *Progress in Disaster Science*, Vol. 7, 100110.

Edwards, D. C. (1997). *Characteristics of 20th century drought in the United States at multiple time scales*. Master dissertation, Colorado State University, CO, United States of America.

Freire-González, J., Decker, C., and Hall, J. W. (2017). "The economic impacts of droughts: A framework for analysis." *Ecological economics*, Vol. 132, pp. 196-204.

Haan, C. T. (1977). "Statistical methods in hydrology." The Iowa State University Press, Iowa, IO, United States of America.

Hall, J. W., and Leng, G. (2019). "Can we calculate drought risk… and do we need to?" *Wiley Interdisciplinary Reviews: Water*, Vol. 6, No. 4, p. e1349.

HRFCO (2013). Standard of water resources unit map, accessed 5 February 2021, <http://www.wamis.go.kr:8081/watermap2013/WMS.aspx?paramTab=2>

Hubert, M., and Vandervieren, E. (2008). "An adjusted boxplot for skewed distributions." *Computational statistics &data analysis*, Vol. 52, No. 12, pp. 5186-5201.

IPCC (2007). *Climate Change 2007: Synthesis Report*. IPCC, Geneva, Switzerland.

IPCC (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation*. IPCC, Geneva, Switzerland.

IPCC (2014). *Climate change 2014: Synthesis report.* IPCC, Geneva, Switzerland.

IRGC (2012). *An Introduction to the IRGC Risk Governance Framework, revised version.* EPFL International Risk Governance Center, Lausanne, Switzerland.

ISO (2018). *Risk management – guidelines.* ISO, Geneva, Switzerland.

Johnson, K., Depietri, Y., and Breil, M. (2016). "Multi-hazard risk assessment of two Hong Kong districts." *International journal of disaster risk reduction*, Vol. 19, pp. 311-323.

Jeong, Y. G., Gang, S. M., Yeo, J. H., (2004) "Indexation of Sustainable Development Indicators.", *Environmental and resource economics review*, Vol. 13, No. 3, pp. 549-572.

Kang, S. M. (2002). "A sensitivity analysis of the Korean composite environmental index." *Ecological Economics,* Vol. 43, No. 2-3, pp. 159-174.

KEI (2008). Development and application of a climate change vulnerability index. KEI, Sejong, Republic of Korea.

KEI (2012). Prioritization of Climate Change Adaptation Measures by Sector, KEI, Sejong, Republic of Korea.

Kim, Y., and Chung, E. S. (2013). "Assessing climate change vulnerability with group multi-criteria decision making approaches." *Climatic change*, Vol. 121, No. 2, pp. 301-315.

Kim, N. S., Kim, J. S., Jang, H. W., Lee, and J. H. (2015). "Hydrologic risk analysis based on extreme drought over the Korean peninsula under climate change." *Journal of the Korean Society of Hazard Mitigation,* Vol. 15, No. 4, pp. 45-52.

Logar, I., and Van den Bergh, J. C. (2013). "Methods to assess costs of drought damages and policies for drought mitigation and adaptation: review and recommendations." *Water resources management*, Vol. 27, No. 6, pp. 1707-

1720.

Mazziotta, M., and Pareto, A. (2017). *Synthesis of indicators: The composite indicators approach. In Complexity in society: From indicators construction to their synthesis.* Springer, Cham, pp. 159-191.

McKee, T. B., Doesken, N. J., and Kleist, J. (1993). "The relationship of drought frequency and duration to time scales." *In Proceedings of the 8th Conference on Applied Climatology*, Vol. 17, No. 22, pp. 179-183.

Meadow, A. M., Ferguson, D. B., Guido, Z., Horangic, A., Owen, G., and Wall, T (2015). "Moving toward the deliberate coproduction of climate science knowledge." *Weather, Climate, and Society,* Vol. 7, No. 2, pp. 179-191.

Miller, R. E. and P. D. Blair. (2009). "Input-output analysis: Foundations and extensions, 2nd ed." Cambridge University Press, New York, NY, United States of America.

Ministry of Land, Transport and Maritime Affairs (MLTMA) (2011). The long-term comprehensive plan for water resources (2011- 2020). Seoul, Republic of Korea.

Ministry of the Interior and Safety (2019). "Government, systematic drought management system operation." January 9, <https://www.mois.go.kr/frt/bbs/type010/commonSelectBoardArticle.do?bbsId=BBSMSTR_000000000008&nttId=68217>

Nam, W. H., Hayes, M. J., Svoboda, M. D., Tadesse, T., and Wilhite, D. A. (2015). "Drought hazard assessment in the context of climate change for South Korea." *Agricultural Water Management*. Vol. 160, pp. 106–117.

Naumann, G., Spinoni, J., Vogt, J. V., and Barbosa, P. (2015). "Assessment of drought damages and their uncertainties in Europe." *Environmental Research Letters*, Vol. 10, No. 12, p. 124013.

OECD (2008). *Handbook on constructing composite indicators. Methodology and user guide.* OECD, Paris. France.

Park, J. Y., Yoo, J. Y., Lee, M. W. and Kim. T. W. (2011). “Assessment of drought risk in Korea: Focused on data-based drought risk map”, *KSCE Journal of Civil Engineering*, Vol. 32, No. 4B, pp. 203-211.

Risk (2020). *Oxford English dictionary*. accessed 5 February 2021, <https://www.oed.com/view/Entry/166306?rskey=OcyRiq&result=1&isAdvanced=false#eid>

Saltelli, A., Ratto, M., Tarantola, S., Campolongo, F., and Commission, E. (2006). “Sensitivity analysis practices: Strategies for model-based inference." *Reliability Engineering &System Safety,* Vol. 91, No. 10-11, pp. 1109-1125.

Seo, S. B., and Kim, Y. O. (2018). “Impact of spatial aggregation level of climate indicators on a national-level selection for representative climate change scenarios.” *Sustainability*, Vol. 10, No. 7, p. 2409.

Seo, S. B., Kim, Y. O., Kim, Y., and Eum, H. I. (2019). “Selecting climate change scenarios for regional hydrologic impact studies based on climate extremes indices.” *Climate Dynamics,* Vol. 52, No. 3, pp. 1595-1611.

Shahid, S., and Behrawan, H. (2008). “Drought risk assessment in the western part of Bangladesh.” *Natural Hazards*, Vol. 46, No. 3, pp. 391-413.

Sharma, J., and Ravindranath, N. H. (2019). “Applying IPCC 2014 framework for hazard-specific vulnerability assessment under climate change.” *Environmental Research Communications*, Vol. 1, No. 5, p. 051004.

Smith, A. B., and Katz, R. W. (2013). “US billion-dollar weather and climate disasters: Data sources, trends, accuracy and biases.” *Natural hazards,* Vol. 67, No. 2, pp. 387-410.

So, J. M., Shon, K. H., and Bae, D. H. (2015). “Development and assessment of drought damage estimation technique using drought characteristic factors.” *Journal of the Korean Society of Hazard Mitigation*, Vol. 15, No. 2, pp. 93-101.

Sung, J. H. (2018). *Development and Assessment of Non-stationary SPEI for Risk-based Low Flow Management.* Ph.D. dissertation, Seoul National University, Seoul, Republic of Korea.

Thom, H. C. S. (1966). “Some methods of climatological analysis.” Secretariant of the WMO, Geneva, Switzerland.

UNFCCC (2015). *Climate Change: A Risk Assessment.* UNFCCC, Geneva, Switzerland.

UNISDR (2004). *Living with risk: a global review of disaster reduction initiatives.* UNISDR, Geneva, Switzerland.

UNISDR (2017). *Words into Action Guidelines: National Disaster Risk Assessment, special topic: Public Communication for Disaster Risk Reduction.* UNISDR, Geneva, Switzerland.

UNU-EHS (2011). *World Risk Report 2011.* Bündnis Entwicklung Hilft, Berlin, Germany.

Vogt, J.V., Naumann, G., Masante, D., Spinoni, J., Cammalleri, C., Erian, W., Pischke, F., Pulwarty, R., and Barbosa, P. (2018). *Drought risk assessment. A conceptual framework.* Publications Office of the European Union, Luxembourg.

Wannewitz, S., Hagenlocher, M., and Garschagen, M. (2016). “Development and validation of a sub-national multi-hazard risk index for the Philippines.” *GI_Forum*, Vol. 1, pp. 133-140.

Ward, F. A., Booker, J. F., and Michelsen, A. M. (2006). “Integrated economic, hydrologic, and institutional analysis of policy responses to mitigate drought impacts in Rio Grande Basin." *Journal of Water Resources Planning and Management*, Vol. 132, No. 6, pp.488-502.

Weaver, C. P., Moss, R. H., Ebi, K. L., Gleick, P. H., Stern, P. C., Tebaldi, C., ... and Arvai, J. L. (2017). "Reframing climate change assessments around risk: recommendations for the US National Climate Assessment." *Environmental Research Letters*, Vol. 12, No. 8, p. 080201.

Wilhite, D. A. (2019). "Integrated drought management: moving from managing disasters to managing risk in the Mediterranean region." *Euro-Mediterranean Journal for Environmental Integration*, Vol. 4, No. 1, pp. 1–5.

Wilhite, D. A., Sivakumar, M. V. K., and Pulwarty, R. (2014). "Managing drought risk in a changing climate: The role of national drought policy." *Weather and Climate Extremes*, Vol. 3, pp. 4–13.

Wolf, S. (2012). "Vulnerability and risk: Comparing assessment approaches." *Natural Hazards*, Vol. 61, No. 3, pp. 1099-1113.

WMO and Global Water Partnership (GWP) (2016). *Handbook of Drought Indicators and Indice*. WMO, Geneva, Switzerland.

World Bank (2019). *Assessing Drought Hazard and Risk: Principles and Implementation Guidance*. World Bank, Washington, DC, United States of America.