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Master's Thesis of Economics

An Analysis of Regional Climate Change Vulnerability in Korean Agriculture

한국 농업의 지역별 기후변화 취약성 분석

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Graduate School of Seoul National University

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An Analysis of Regional Climate Change Vulnerability in Korean Agriculture

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Abstract

An Analysis of Regional Climate Change Vulnerability in Korean Agriculture

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Human-activity induced climate change is a global phenomenon that causes more frequent and intense extreme weather events. While extreme weather events may have various degrees of impact, they certainly create many negative aspects to nations around the world. Korea, not being an exception to the phenomenon, is predicted to experience changes that are more intense than most, which calls for appropriate adaptations.

Assessment of regional climate change vulnerability

has been studied and proven to be an appropriate measure of climate change adaptations and to be helpful in terms of providing an outlook for top-down adaptation policy making. It has also increased the efficiency of policy making by allowing detection of relatively more vulnerable areas and determining the factors that make them vulnerable.

In preceding research, many efforts with different approaches were made to construct accurate vulnerability assessment models. To summarize the results of preceding research, climate change related studies should: reflect spatial and temporal relationships in regards to their dynamic nature, be region and industry-specific, and the analysis should be quantitative. While each of these characteristics is proven to increase the accuracy of the analysis, most preceding research has focused on one approach at a time, rather than simultaneously applying more than one approach.

This study attempts to evaluate the vulnerability of climate change in Korea more accurately by utilizing various existing approaches to climate change vulnerability assessment. Thus, in this study, the

relationship between vulnerability factors and regional damage costs is identified through regression analysis of panel data and use of the resulting coefficients as the weights. Regression analysis takes damage cost from natural disasters as its dependent variable and takes exposure, sensitivity, and adaptive capability variables as independent variables. Proxy variables for exposure include heatwave, flood, drought, typhoon, and heavy snow. Sensitivity variables include farmer population and crop area, and adaptive capability variables such as government support. Correlation analysis between vulnerability results with productivity variables is conducted after the regression analysis to confirm whether the modified model more accurately reflects the reality than the existing climate change vulnerability model.

The results of the analysis indicate that not all of the proxy variables used in the previous studies show statistical significance with damage cost. However the variables that did turn out to be significant do, in fact, support theoretical relationships. Also, the correlation test results indicate that a modified version of the

Vulnerability Model shows higher correlation values compared to the original model.

Overall, this study shows that the original climate change vulnerability model can be made more realistic by assigning weights through regression analysis rather than selecting proxy variables and conducting vulnerability analysis by a qualitative approach. Also, it is more accurate to consider not only multi-year data for analysis but also the multi-year average value of the results. Therefore, the results of this study support the argument that the accuracy of climate change vulnerability assessment can be improved by reflecting multi-year data analysis and weighting models with statistically significant variables. The results will provide foundational data for climate change adaptation related policymaking.

Keyword : climate change adaptation, vulnerability resilience index, panel data regression analysis

Student Number : 2015-21526

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Chapter 1. Introduction

1.1. Research Background

As the impacts of climate change become more and more apparent around the globe, the United Nations set eight different Sustainable Development Goals (SDGs) in 2015. These goals include climate change mitigation and adaptation actions, shedding light on the importance of adaptations to climate changes to acquire sustainable development. The rate of global climate change has accelerated as GHG(Greenhouse Gas) emissions have escalated. According to reports by IPCC(International Panel for Climate Change), climate change is an apparent global phenomenon, which is caused by human activities. The phenomenon makes it safe to assume that the trend will persist as long as the damaging human activities continue. No individuals or countries are capable of avoiding the impacts of climate change entirely, and all are in need of an appropriate adaptation process, making it necessary to increase adaptation efforts (Wiggler, 1996).

In many preceding studies, assessing regional climate change vulnerability is considered a sound starting point for climate change adaptation. This research aims to improve the regional climate change vulnerability model by IPCC in an effort to understand climate change adaptation and establish a more accurate means to assess climate change vulnerability.

1.2. Current Climate Change Trends and Future Projections

The World Meteorology Organization(WMO) defines climate as “weather that has been consistent over 30 years in a region.” This implies that climate change refers to a statistical and measurable shift from average weather in the past 30 years to that of recent times.

Climate change is not a new phenomenon. Historically, the climate has changed over centuries, if not millennia. What differentiates the recent trends in climate change are the characteristics: its rapid pace and severe impacts. Climates across nations have been through more changes in the past ten years than they have in many centuries, leading many of these nations to suffer unprecedented extreme weather events.

Although Korea has yet to suffer any devastatingly extreme events, climate change in Korea is more apparent than that of the global average. Temperature rise is most apparent in winter and spring, with relatively little difference for summer, and a decreasing average year-round temperature difference, but an increase in the overall average temperature. The Korean peninsula's average temperature has increased by 1.7℃ in the past 50 years, which is higher than the global temperature increase (0.73℃) by a large margin. Such a trend in temperature change became even more apparent after the 1980s, recording 0.23 degree celsius/decade (Jung et al., 2002).

Increased temperatures led to high-heat related extreme events such as more frequent heatwaves, extended and more intense summer heat, and a shortened winter. Korea's overall precipitation change shows an incremental trend in the last century between the years 1910 and 2000. Precipitation levels rose almost 19%, going from 1,155.6 mm to 1,375.4 mm (NIMR, 2004). Precipitation changes in Korea are characterized by their variability more than temperature change.

Precipitation pattern change seems to trend toward being more intense in a short period rather than being extensive; as the overall precipitation level increases, the number of rainy days decreases, and flood frequency increases, particularly in the summer season. Lastly, future precipitation is also characterized by smaller precipitation areas rather than precipitation over a large area. Such trends make matters even more problematic because this implies a trend of heavier rainfall occurring over a short period in a smaller area. This makes it more difficult to prevent damage and utilize rain resources. Damage from precipitation occurs when it rains past the capacity of the area within a certain amount of time. The concentrated rainfall, even if the amount of precipitation is similar, has a higher probability of causing damage. Also, it is more difficult to utilize rainwater for different purposes.

Climate change prediction is climate information prediction based on a climate model which analyzes climate factors such as temperature, precipitation, wind, and moisture level projections. At the most basic level, the prediction is conducted using the GCM(Global

Climate Model). The GCM predicts the future global climate change from analyzing radiative forcing changes caused by human activities. This model uses long-term, low definition spatial data, which only use 400 blocks total to cover the entire globe. While the GCM provides useful insight for monitoring climate change at a global level, the model is not appropriate for predicting regional climate change on a microscopic scale. The model is employed at the local/regional level through dynamic downfalling, implemented by countries around the world including South Korea, and was conducted by the NIMR(National Institute of Meteorological Science) .

According to the Korean Climate Change Report (NIMR,2009), under climate change scenario A1B, the climate of Korea is predicted to rise 4℃ for the entire peninsula, including North Korea, with a speculated change of 3.8℃ specifically in the south. Temperature rise becomes more apparent as the altitude increases. Seasonal temperature change was most apparent in winter and summer. In the case of the A2 scenario, a greater rise in temperature is forecasted relative to the A1B scenario (NIMR, 2008; Ko et al. 2006). Annual

temperature difference will decrease down to 1.7℃, as well as a daily temperature difference due to the minimum temperature rising. Extreme cold event frequency will decrease by 99%, while extreme heat events will increase by a large margin.

Precipitation levels are expected to increase up to 21% in all areas of the Korean Peninsula from an average of 1,206.51 mm to 1,465 mm, according to scenario A1. In scenario A1B, a 17% increase is predicted for the Korean peninsula, although only 13% for South Korea. Precipitation change is most apparent in August and September. Seasonal variance is expected to increase as well (refer to table 1-1).

<Table 1-1> Future Projection of Precipitation of Korea

Years	10yr ave	JFM	AMJ	JAS	OND
2010's	1219.26	217.98	663.87	247.79	100.24
2020's	1256.91	242.12	641.16	273.34	87.94
2030's	1172.45	225.28	594.24	245.74	95.47
2040's	1331.19	231.59	743.36	299.74	89.04
2050's	1399.87	246.19	783.94	314.80	90.51
2060's	1371.89	236.20	744.66	304.32	108.14
2070's	1393.77	263.64	678.39	321.31	107.50
2080's	1361.21	237.50	709.66	313.47	112.45

Note. Economic Analysis of Climate Change in Korea, 2011, Ministry of Environment

According to the Climate Projection Report of the National Institute of Environmental Research under the Ministry of Environment(NIMR, 2008), there is a large probability that the Korean peninsula's climate will transition to a subtropical climate. The subtropical climate line has gradually risen in altitude, and it is very likely that Korea will enter a subtropical zone under the A1B Scenario. Additionally, the rainy season that happens from summer to autumn occurs in the form of heavy rainfall, which is concentrated in the summer season, and the damage caused by heavy rain and typhoons has increased. The Korean Peninsula is observed to be more sensitive to climate change than most countries around the globe in regards to greenhouse gas concentration. This means the country has experienced temperature rises larger than the global average, and rapid land cover and vegetation changes are already apparent.

The Korean Peninsula's temperature is predicted to rise gradually for at least the next 100 years. Additionally, with some uncertainties in the precipitation, it is expected that Korea will be categorized as a subtropical climate with frequent rains in the future.

Concerning the impacts of climate change on each sector, floods and droughts are frequent in the water sector due to the seasonal bias of the Korean peninsula, and the possibility of extreme events will increase in the future. In the ecosystem and agriculture sector, the increase in flowering time, crop growing season, and subtropical species (damage from weeds and pests) will continue in the future, and the risk of forest fires due to forest development and heatwaves is expected to increase. Extreme events that are forecast to happen due to these changes are shown in the table below (NIMR, 2004; Kwon, 2012).

<Table 1-2> Extreme Event Trend Forecast in Korea (Summary)

Increased warming days	Warming days are estimated to increase by 23.8 days and 57.4 days for CPR scenario 4.5 and 8.5 respectively by the end of the 21st century (2070-2099).
Increased tropical nights	Tropical nights are expected to increase from 30.9 days to 34.6 days in the CPR 4.5 scenario by the end of the 21st century and 62.8 days in the CPR 8.5 scenario by the end of the 21st century.
Intensified torrential rainfall	The intensity of the torrential rainfall is currently estimated to be 2.20 days at the end of the 21st century, 6.54 days for the CPR 4.5 scenario, and 4.24 days for the CPR 8.5 scenario, and 6.59 days for the CPR 8.5 scenario.
Increased heavy rain and high temperature	Overall distribution of daily precipitation and maximum temperature is increased but the phenomenon is more apparent in the upper tail of temperature and precipitation, indicating that the probability of heavy rain and high temperature event occurrence will increase in the future.

Note, Climate Change Report, 2011, National Institute of Meteorological Science

1.3. Climate Change Impacts on Agriculture

The agricultural sector is one of the most, if not the most, sensitive industry in regards to climate change. Climate change can readily cause disturbances in the core production and the market where seemingly insignificant changes in weather factors - both in magnitude and time - can make significant differences. For example, heavy snowfall in Seoul prevented 64.5% of the red lettuce harvest from being produced in comparison to its usual crop yield in January 2010. Moreover, there are many other cases where weather change is inflicting notable damage to the industry as a whole. Due to climate change, much of the crop production system itself is changing: germination time of flowers and leaves, the growth period of main crops are shifting altogether, and microclimate changes in regions even cause major production areas for weather-sensitive crops to migrate.

Additionally, unexpected or even unprecedented breakouts of pests and diseases are increasing, the damage from which is predicted to increase more in the future. Moreover, as the water temperature increases, it is expected that fish species or fishery resources will

change depending on climate change. Due to these characteristics, with the addition of the idea that a nation's sustainability is dependent on agricultural production, some scholars even argue that climate change vulnerability for the nation as a whole is best represented by the vulnerability of the agricultural sector alone (Whebe et al., 2005).

The temperature is predicted to rise throughout the country, a result of which will change the nation's seasonal characteristics. Winter, along with a low-temperature phenomenon, will be shortened, and it could possibly even disappear in some warmer, southern areas. Plant growth periods will be extended since there will be more warming days. In the case of facility cultivation, winter heating costs will decrease, while summer cooling costs will increase. Summer and other high-temperature related events will be more extensive and intensive. Such changes will significantly increase the breakout of certain weeds, pests, and diseases, as well as intensified heatwaves.

Studies state that current climate change scenarios show that temperature and precipitation are increasing in East Asia, along with evaporation of both land and sea

surface. This can cause drought in some areas and heavy rainfall in others, both of which are erratic. While the precipitation levels increase as a whole, the characteristics are expected to change to more local and short-term rainfall. Also, due to the increase in evaporation, it is estimated that surface water and soil moisture levels are likely to decrease.

A prolonged dry season can increase the occurrence of drought, damage crop fibers, and create a cholorosis issue due to dry air. Heavy rainfall in a short period is more likely to lead to flooding, which can cause damage to the crop area. Damage also occurs from increased river pollution caused by muddy and eutrophic components, leading to a destruction of agricultural infrastructure (Kwon, 2012).

Climate change is a dual-faceted phenomenon where both opportunities and risks exist simultaneously. Climate change adaptation is required for evolution and change, but since the uncertainty of damage outweighs possible opportunities, it is more critical to address the risks of climate change before considering the opportunistic adaptation of climate change.

1.4. Research Objectives

It is clear that adaptation for climate change is essential for the future of South Korea. For successful adaptation, a quantitative analysis of climate change becomes a necessity. As mentioned above, vulnerability analysis can provide an excellent outlook for top-down policy-making and resource allocation.

The nature of climate change is time dynamic and locale specific, calling for quantitative analysis . Also, the model itself requires improvement, as each variable is not weighted, and all of the variables cannot be considered equally crucial for vulnerability analysis. While there are many different attempts in Korea to assess climate change vulnerability, it is difficult to find a case where all of the characteristics of climate change are reflected at once.

This research attempts to combine various approaches to climate change vulnerability assessment. This research implements quantitative statistical analysis that reflects time dynamics to statistically test relationships between selected proxy variables and damage cost to derive appropriate weights for each variable. Then, different

time specifications are applied to test whether or not multi-year results are better than single year results. The results will then be compared with three rice productivity[1] variables to determine which model and time configuration shows the strongest relationship with productivity.

1) Rice production data (90% grain)

Chapter 2. Literature Review

2.1. Climate Change Vulnerability Concept

Moss et al. (2001) first implemented the concept of vulnerability in climate change and analyzed climate change vulnerability on a global scale. Vulnerability is calculated from bio-physical sensitivity and socio-economic adaptation variables. The sensitivity index included human life, food security, healthcare, ecology, and water resource variables while the adaptation index included economics, human resources, and environmental resources.

Brooks et al. (2005) attempted to extract key variables for each country by generalizing climate change variables. Key components of vulnerability are suggested as adaptation capability at the national level.

Whebe et al. (2005) suggested a method that assesses vulnerability based solely on agricultural sector analysis. The study states that adaptation capability in the agricultural sector is also related to the sustainability of the system, and takes individual variables from the

agricultural sector only. This method works under the assumption that the agricultural industry is the most sensitive industry and the most foundational one as well, without which sustainable development is implausible.

Yoo et al. (2008) attempted to calculate the climate change vulnerability index in Korea using 33 proxy variables from 3 vulnerability categories. The sensitivity and adaptive capacity used by UNTAP (2005), UNEP (2006), and the IPCC (2001) concept framework were compared to assess the vulnerability of 16 regions (si-do) and provinces in Korea. Additionally, they conducted a principal component analysis to determine common indicators and regional factors. The concept includes climate change exposure, the sensitivity of the system, and the ability of the system to adapt to the concept of climate change vulnerability. A total of 33 proxy variables were collected and standardized for the Vulnerability-Resilience Index (VRI) calculation. Additionally, he tried to check the validity of the index by conducting the Pearson correlation test with fatalities from natural disasters of each region. The research seemed to have limitations with testing for the model

and variables' validities since fatalities from extreme weather events rarely occur in Korea.

Hwang et al. (2016) attempted to apply the IPCC climate change vulnerability test in Gangwon-do, South Korea using 22 proxy variables consisting of three categories: exposure, sensitivity, and adaptive capability. Additionally, he attempted to predict future vulnerabilities based on climate change scenarios. The number of variables has significantly reduced due to limitations in data acquisition.

2.2. Spatial Analysis Approach

George(2006) attempted a hotspot analysis for the Regional Climate Change Index(RCCI) using mean surface air temperature change and precipitation along with inter-annual temperature variables. RCCI is a comparative index that identifies the most susceptible regions to climate changes. He analyzed 26 land regions by 20 global climate models for A1b, A2, and B1 IPCC emission scenarios. The analysis results show that different factors over different regions contribute to the magnitude of the RCCI, which includes the change in

precipitation in specific seasons or temperature changes.

Choi et al. (2009) attempted to assess climate change vulnerability based on Spatio-Temporal information of Korea. Variables from ecology, natural disasters, water resources, and healthcare fields were collected and categorized into exposure, sensitivity, and adaptive capabilities. Then the variables were analyzed using the GIS spatiotemporal analysis. The results were projected by analyzing individual variables, rather than a single score of regional vulnerability.

Ko (2009) reviewed existing climate change vulnerability assessment models and derived vulnerability assessment indices that could apply to local municipalities and compared the relative vulnerability of 31 si-do in Gyeonggi province. A literature review, AHP survey, and GIS analysis were conducted to review extreme weather-related events and derive a vulnerability index and relative vulnerability mapping. The index was found to be useful for analyzing the climate change and effectiveness of the adaptation policies and local level monitoring for future adaptation.

Park et al. (2006) used four indicators of agricultural

drought vulnerability for each region in Korea to determine the start time and intensity of drought by using parameters including agricultural water reservoir storage rate, standard precipitation index, and normal rainfall rate.

Kim C H. (2012) developed a CCGIS(Climate Change Geographical Information System) tool to use as a climate change assessment tool. The main objective of the tool is to facilitate relevant information for climate change vulnerability assessment to draw key information for the adaptation process. Key information is derived from the meteorological numerical model and the atmospheric environmental models and projects climate data for the years 2000, 2020, 2050, and 2100.

2.3. Statistical Analysis Approach

Jhang (2006) analyzed drought vulnerability for agricultural sectors at si-gun level through Principle Component Analysis on factors such as land use, water resource development, terrestrial soil, and agricultural weather (Drought Vulnerability Index for Paddy).

Kim (2010) collected and tested regional socio-economic data to calculate the sensitivity and adaptability indices needed to calculate the vulnerability of climate change. To examine climate change impacts, Kim calculated the climate change exposure index, sensitivity, and adaptive capability index based on the 12 indicators selected for the agricultural sector, forestry sector, and ecosystem sector, along with various vulnerable areas. The climate change vulnerability index is then calculated by combining the three indices.

Kim et al. (2012a, 2012b) selected proxy variables for vulnerability assessment by classifying proxy variables into three categories: climate change exposure, sensitivity, and adaptive capability based on the precedence of a climate change vulnerability assessment by si-do.

Early studies suggested that analyzing a country and all of its industry as a single unit is accurate enough and the vulnerability variables were selected in rather intuitive manners. With the passage of time, it was proven that microscopic analysis is more accurate than

macroscopic analysis. Also, variables were tested using quantitative analyses such as principle analysis and correlation tests, proving added statistical analysis improves accuracy. Application of time-dynamic data also proves its superiority over single year data analysis. There had been different attempts and approaches but it can be said that those approaches were never combined in a single study.

Chapter 3. Data and Variables

3.1. Variables and Data Description

The concept of climate change vulnerability considers exposure, sensitivity, and adaptive capabilities as its core variables. Exposure refers to the degree of change in the climate itself, represented by the frequency and intensity of extreme weather events. Sensitivity refers to factors that are impacted at a greater level by the frequency of extreme weather events. Lastly, adaptive capability indicates how capable a region is of recovering from extreme weather events or even natural disasters. Each index takes multiple proxy variables as sub-variables.

The proxy variables used in this study are referenced from the research of Kim et al. (2012a) and Kim et al (2012b), which are dedicated to developing appropriate proxy variables for vulnerability analysis in the agriculture sector of South Korea. All data was collected for 160 si-gun, over a period of 10 years, between 2006 and 2015.

The terms do, si, and gun used in this research are Korean administrative territorial division units, each referring to region, city, and county respectively. There are eight do, one special city, six metropolitan cities, one special autonomous city, and one special autonomous island. Eight do (region) are then divided to 77 si (cities) and 77 gun (counties). When si-do are put together it refers to the eight do, special cities, and metropolitan cities while si-gun refers to the seventy-seven cities (si) and seventy-seven gun (county) under the eight do (region), making a total of one hundred and sixty-three samples. This research, however, omits Ullengdo[2] in Gyeongsangbuk-do and Goseong-gun in Gangwon-do because they are outliers geographically. Also, Jeju-si and Seoguipo-si in the Special Autonomous Island of Jeju is considered as a single sample, making the total number of si-gun subject to analysis one hundred and sixty. All romanization of si-do and si-gun names follow the official rules declared by the National Korean Language Institute[3]

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2) Ullengdo in Gyeongsangbuk-do is a gun. “Do” at the end means island in Korean

3) National Korean Language Institute (국립국어원) https://www.korean.go.kr/front/roman/romanList.do?mn_id=98

The climate change exposure index is represented by the frequency and intensity of extreme weather events. The exposure index consists of measures of rain, drought, temperature, wind, and snow; all of which consist of 14 weather variables, each representing the frequency and intensity of extreme weather events. All weather-related data was collected from the Korea Meteorological Administration (KMA). The daily data used in the research was recorded at 140 observation points scattered all around Korea for a period of ten years period. Each climate variable was interpolated using the Ordinary Kriging interpolation method on a 1 km*1 km grid, then the average value for each si-gun was calculated to obtain daily weather values of the si-gun, from which extreme weather events are calculated based on appropriate definitions.

Interpolation is a widely used method to process weather-related data including rain, temperature, snow and wind variables. Wind variables, in particular, require more intricate interpolation models; however, since this research only requires non-directional wind speed, the ordinary Kriging Interpolation model is not only

acceptable but as good as other widely used models (Luo et al., 2008).

For extreme temperature events, the threshold is set at 25℃ and 33℃. Extreme event variables for low temperatures were removed from the analysis since reported related damage is substantially low. Additionally, record and future projection suggest that temperature rise and heatwaves are the main issues in regards to temperature. For heatwave frequency, the number of days with a maximum temperature of 25℃ and 33℃ and above were used while the average temperature of maximum temperature above 25℃ and 3 3℃ is calculated for intensity.

For precipitation variables, the maximum precipitation level in a 24 hour period and average precipitation over 80 mm in a 24 hour period are used as intensity variables while the maximum number of consecutive rainy days and number of accumulated rainy days are used for frequency. For drought variables, “over 21 days without precipitation” and “over 30 days without precipitation” were used as both intensity and frequency variables. As for wind variables, maximum momentary

wind speed and maximum wind speed was considered since it is difficult to gather wind occurrence data due to the characteristics of wind. The threshold for snow extreme event was set at 5 cm. The number of snowy days and depth data was collected to represent the intensity and frequency of extreme events.

For sensitivity variables, agricultural factors including cultivated areas for paddy and field crops, number of farms, and farmer population were used. All data was extracted from the Korea Agricultural Area Database between the years 2006 and 2015 at si-gun level. Cultivated areas were specified into paddy and field crops since they are expected to have a different degree of, and kind of, impact from extreme weather events. Farmer population was also included under the assumption that the population would be directly proportional to damage costs from extreme weather events. All data was extracted from the Agricultural Area database from Korean national statistics. For adaptive capabilities, government spending on agricultural infrastructure development for each region was used. Variables used in this research are presented in the table

below (table 3-1).

<Table 3-1> List of Vulnerability Variables(Independent Variables)

Category	Sub-category	Proxy variables	
Climate Change Exposure (CC)	Heat-stress	Daily temperature over 25℃ (average temp)	Heat Stress
		Daily temperature over 25℃ (# of days)	
		Daily average temperature of 33℃ and above (average temp)	Heatwaves
		Daily average temperature of 33℃ and above (# of days)	
	Flood	Number of rainy days over 80mm	Flood Frequency
		Max. continuous rain (mm)	Flood Intensity
		Max. rain in 24hr period(mm)	
	Drought	Over 21 days of no rain (days)	Drought Stress
		Over 30 days of no rain (days)	
	Wind	Average momentary wind speed above 20m/s	Wind Damage
		Average wind speed above 20m/s	
	Snow	Snowfall depth over 5cm in 24 hrs (depth)	Snow
		Snowfall depth over 5cm in 24 hrs (# of days)	
Sensitivity (SS)	Agricultural Factors	Cultivated area (Paddy)	Sensitive Land Area
		Cultivated area (Field)	
		Farmer population (#)	Sensitive Population
		Number of Farms (#)	
Adaptive Capability (AC)	Gov. Support	Government spending in agricultural infrastructure (cost)	Regional Infra-structure
		Government spending in agricultural infrastructure (area)	

Damage cost from extreme weather events is used as a dependent variable to determine the relationship between vulnerability variables as well as to calculate accurate weights. Regression analysis uses the damage cost from extreme weather events as the dependent variable and conducts a panel data analysis. All variables from the original vulnerability model are taken as independent variables. Damage cost data was acquired at the si-gun level, between the years 2006 and 2015, from the Korean Disaster Annual Report. Only damage data from the agricultural sector is extracted for the analysis. Damage cost only includes damages to the agricultural sector, and is the sum of issues created by floods, storms, heavy snow, and wind damage.

Finally, to test the appropriateness of the models, a correlation test was conducted to determine different vulnerability results and productivity variables. Rice production data was taken from the annual Korean crop production report. The data regarding production quantity per crop area, farm, and the population is used, and presented in (Table 3-2).

<Table 3-2> Dependent Variable and Productivity Variables

Dependent Variable	Extreme Event Damage	Flood, storm, wind, damage from natural disaster in agricultural industry (cost)	Damage Cost
Testing Variables	Productivity	Rice production per crop area (ton/ha)	Production per Area
		Rice production per farm (kg/farm)	Production per Farm
		Rice production per population (kg/person)	Production per Population

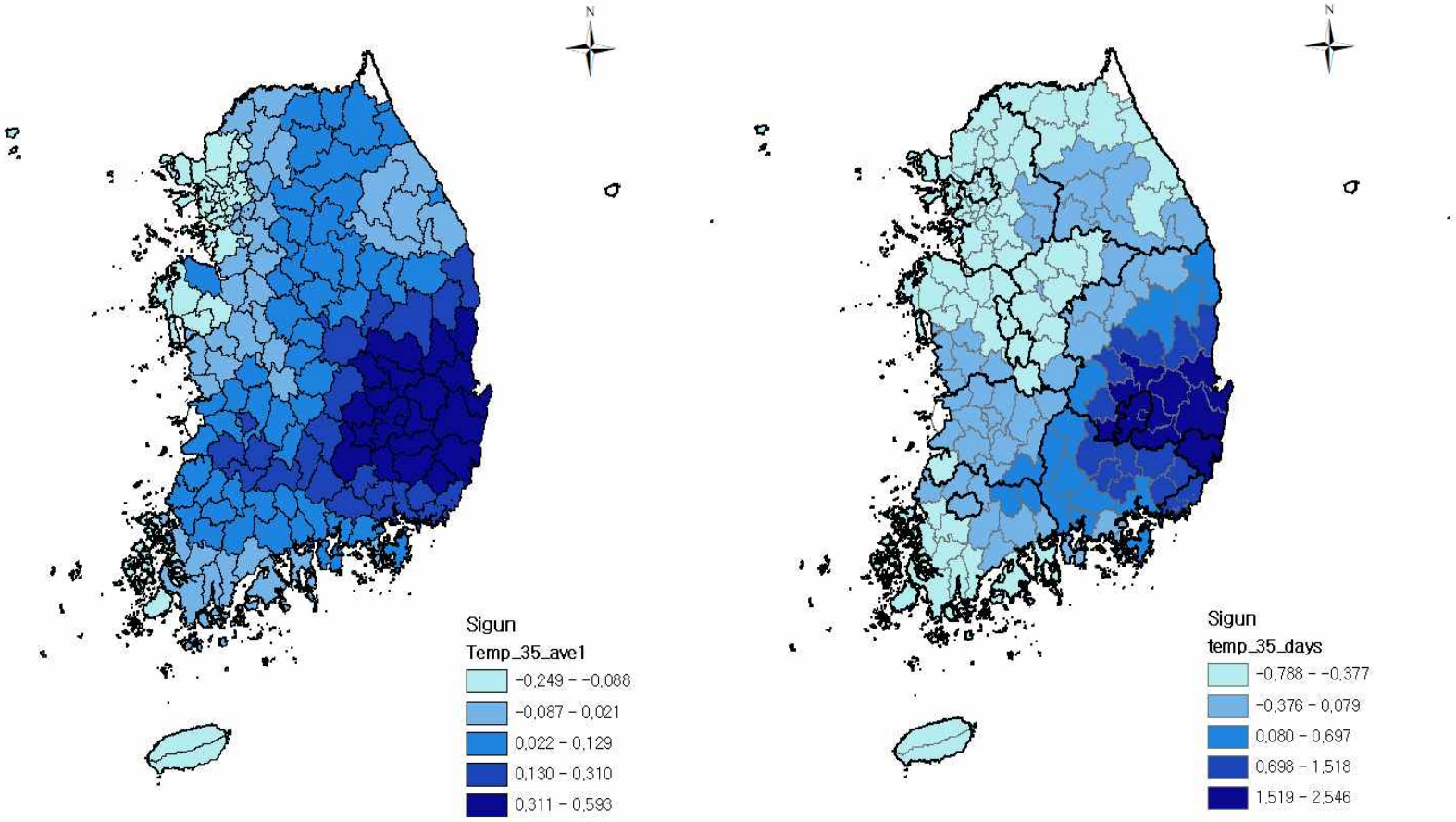
3.2. Data Summary

Temperature-related climate change exposure levels tend to be particularly high in the southeastern regions of Gyeongsangbuk-do and Gyeongsangnam-do. As for heatwave variables, max. temperature above 33℃, Pohang-si (0.59), Yeongcheon-si (0.59), Gyeongju-si (0.58), Gyeongsan-si (0.57), and Daegu-si (0.52) scored the highest. As for a number of days with a heatwave, Yeongcheon-si (2.55), Gyeongsan-si (2.45), Daegu-si (2.21), Gyeongju-si (2.14), and Cheongdo-gun (2.10) scored the highest (See table). Spatial distributions are shown in (figure 3-1).

<Table 3-3> Heatwave Duration and Intensity

Rank	Si-gun	Value	Rank	Si-gun	Value
1	Pohang-si	0.593	1	Yeongcheon-si	2.546
2	Yeongcheon-si	0.590	2	Gyeongsan-si	2.446
3	Gyeongju-si	0.581	3	Daegu-si	2.214
4	Gyeongsan-si	0.567	4	Gyeongju-si	2.143
5	Daegu-si	0.523	5	Cheongdo-gun	2.099
156	Incheon-si	-0.249	156	Jeju-do	-0.781
157	Seosan-si	-0.219	157	Seosan-si	-0.720
158	Tae'an-gun	-0.198	158	Cheongju-si	-0.718
159	Gimpo-si	-0.193	159	Asan-si	-0.716
160	Jeju-do	-0.174	160	Wando-gun	-0.705

<Figure 3-1> Heatwave Intensity and Duration



The number of days with rain over 80mm was used as flood frequency variable. Jeju-do(7.5) and Yeonggwang-gun (3.653) had the highest score out of all si-gun. Their number is quite large even comparing them to the third highest si-gun. Osan-si, Sokcho-si, Gunpo-si, Gyeryong-si, and Anyang-si scored the lowest, all with - 0.315.

<Table 3-4> Number of Rainy Days Over 80mm

Rank	Si-gun	Score
1	Jeju-do	7.503
2	Yeonggwang-gun	3.653
3	Shin'an-gun	1.960
4	Mu'an-gun	1.700
5	Yeong'am-gun	1.278
156	Osan-si	-0.315
157	Sokcho-si	-0.315
158	Gunpo-si	-0.315
159	Gyeryong-si	-0.315
160	Anyang-si	-0.315

Unlike other extreme weather events, rain events show notable differences between the two variables. This indicates that areas exposed to a large quantity of rain over a prolonged period of time do not necessarily have a high quantity of rain in a short period of time. For

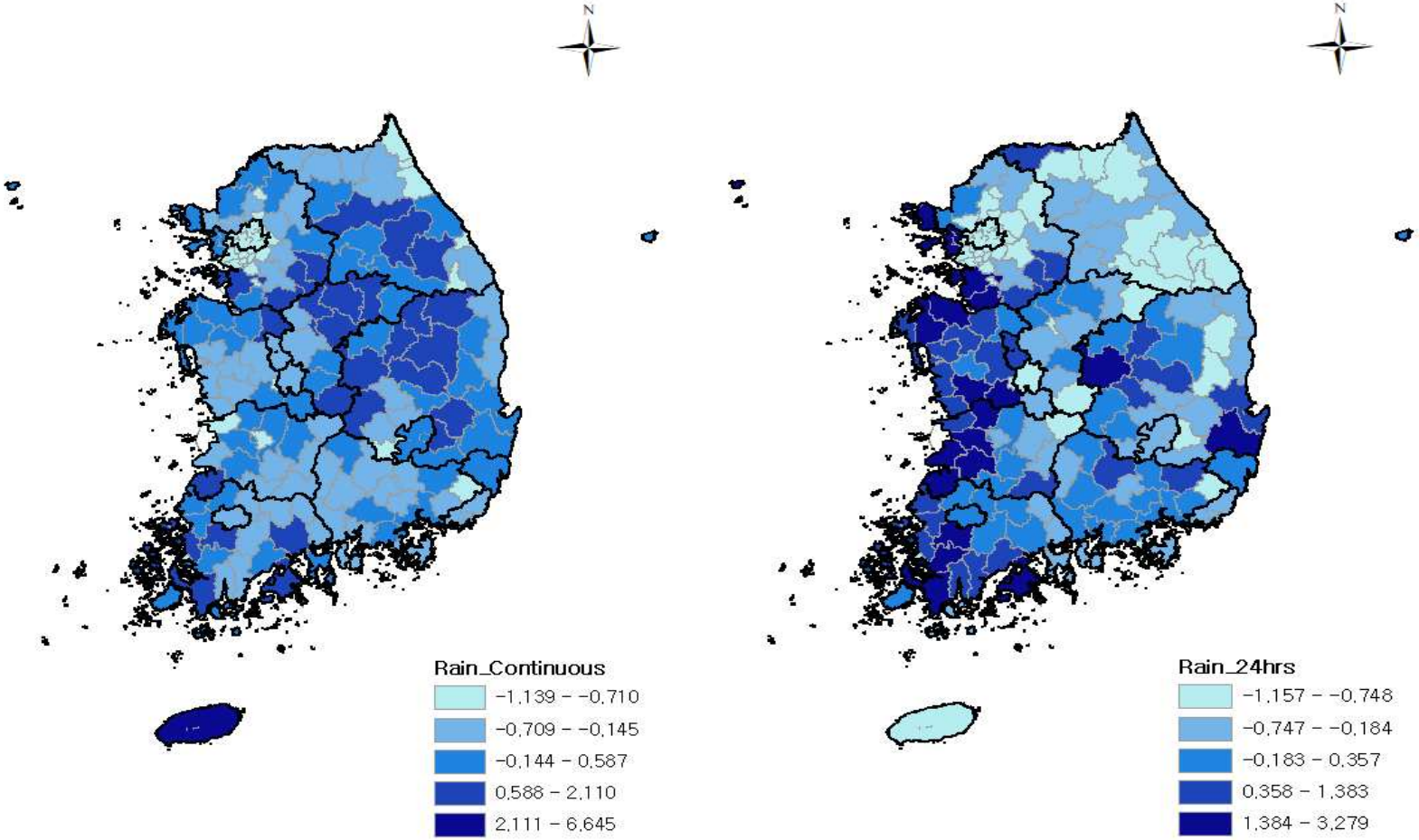
continuous rain variables, Southern Jeonra-do region and Jeju-do had the highest score while the rest of the highly exposed areas are clustered in central regions.

Intensive rainfall takes max. continuous rain and max. rain in 24 hours as its variables. As for max. continuous rain, Jeju-do(6.645), Andong-si(2.11), Haenam-gun(1.834), Sanju-si(1.647), and Gochang-gun(1.457) scored the highest. It was observed that regions on the west coast of Korea had the most severe rain, a majority of them scoring over 2.0. Ginjae-gun (3.28), Haenam-gun (3.19), Dangjin-si (3.06), Seosan-si (2.96), Iksan-si (2.67), and Yeongam-gun (2.10) had the highest scores in the category.

<Table 3-5> Max. Continuous Rain, Max. Rain in 24hrs

Rank	Si-gun	Score	Rank	Si-gun	Score
1	Jeju-do	6.645	1	Gimje-si	3.279
2	Andong-si	2.110	2	Haenam-gun	3.189
3	Haenam-gun	1.834	3	Dangjin-si	3.055
4	Sangju-si	1.647	4	Seosan-si	2.957
5	Gochang-gun	1.457	5	Iksan-si	2.661
156	Osan-si	-1.104	156	Hanam-si	-1.149
157	Sokcho-si	-1.114	157	Gwacheon-si	-1.154
158	Gunpo-si	-1.120	158	Guri-si	-1.157
159	Gyeryong-si	-1.128	159	Anyang-si	-1.157
160	Anyang-si	-1.139	160	Taebaek-si	-1.157

<Figure 3-2> Max. Rain (Continuous, 24 Hours)

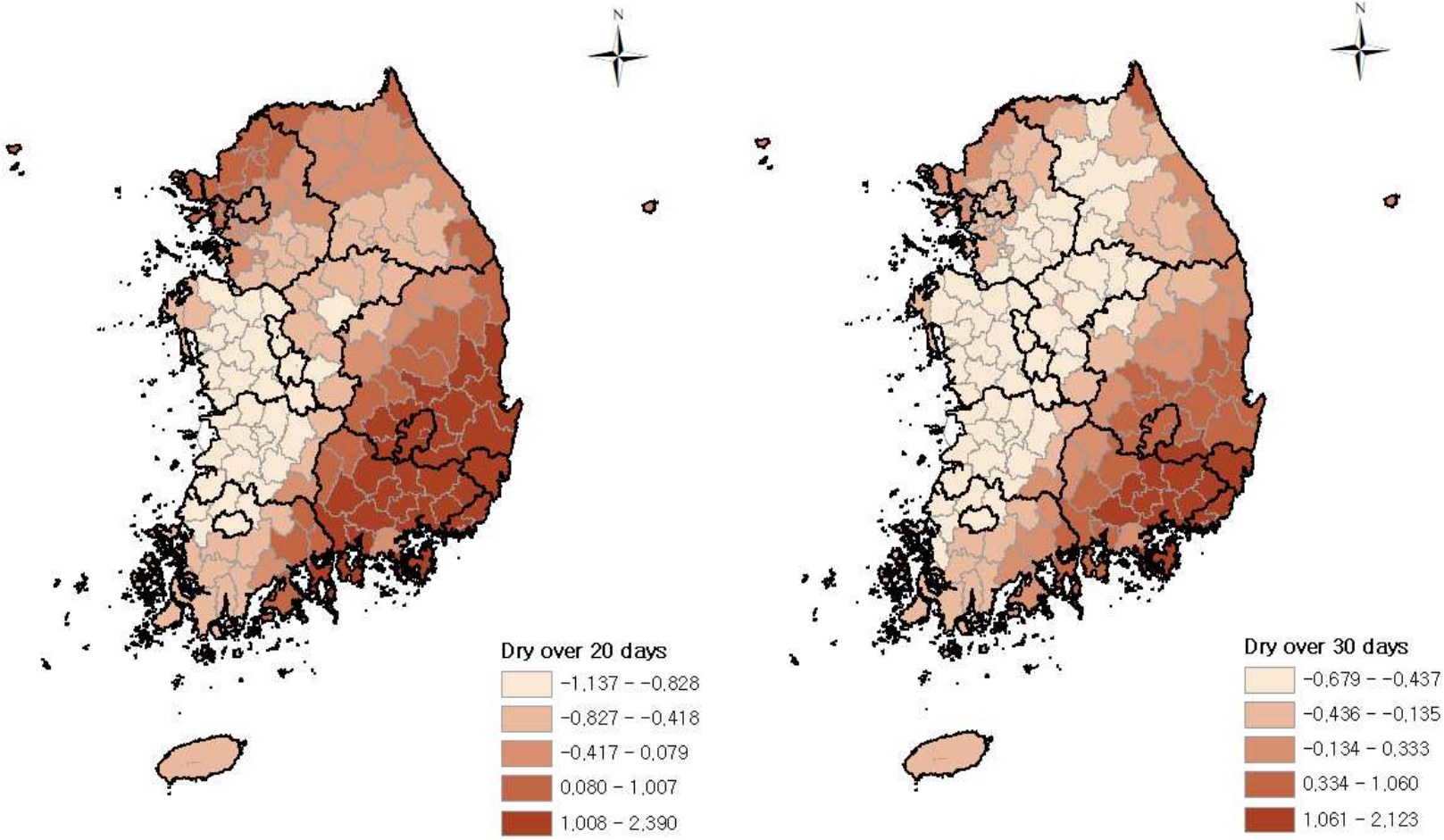


To represent drought variables, continuous number of days without rain over 21 days and over 30 days are used. Both of them show somewhat similar results. For over 21 days without rain variable, Busan-si (2.390), Yansan-si (2.353), Gimhae-si (2.346), Miryang-si (2.233), and Changwon-si (2.120) scored the highest while Busan-si(2.123) Gimhae-si (1.904), Yangsan-si(1.828), Changwon-si (1.613), and Miryang-si (1.562) scored the highest. In the analysis both variables were not significant. This could be because most si-gun are somewhat ready with the water reserves and it may require a more intricate model to calculate drought index.

<Table 3-6> Days without Rain (Over 21 Days, Over 30 Days)

Rank	Si-gun	Value	Rank	Si-gun	Value
1	Busan-si	2.390	1	Busan-si	2.123
2	Yangsan-si	2.353	2	Gimhae-si	1.904
3	Gimhae-si	2.346	3	Yangsan-si	1.828
4	Miryang-si	2.233	4	Changwon-si	1.613
5	Changwon-si	2.120	5	Miryang-si	1.562
156	Gochang-gun	-1.103	156	Jeongeup-si	-0.630
157	Jeonju-si	-1.125	157	Anseong-si	-0.633
158	Bu'an-gun	-1.125	158	Hongseong-gun	-0.634
159	Gimje-si	-1.125	159	Gochang-gun	-0.648
160	Jeongeup-si	-1.137	160	Bu'an-gun	-0.679

<Figure 3-3> Days with No Rain (Over 20 days, Over 30 days)

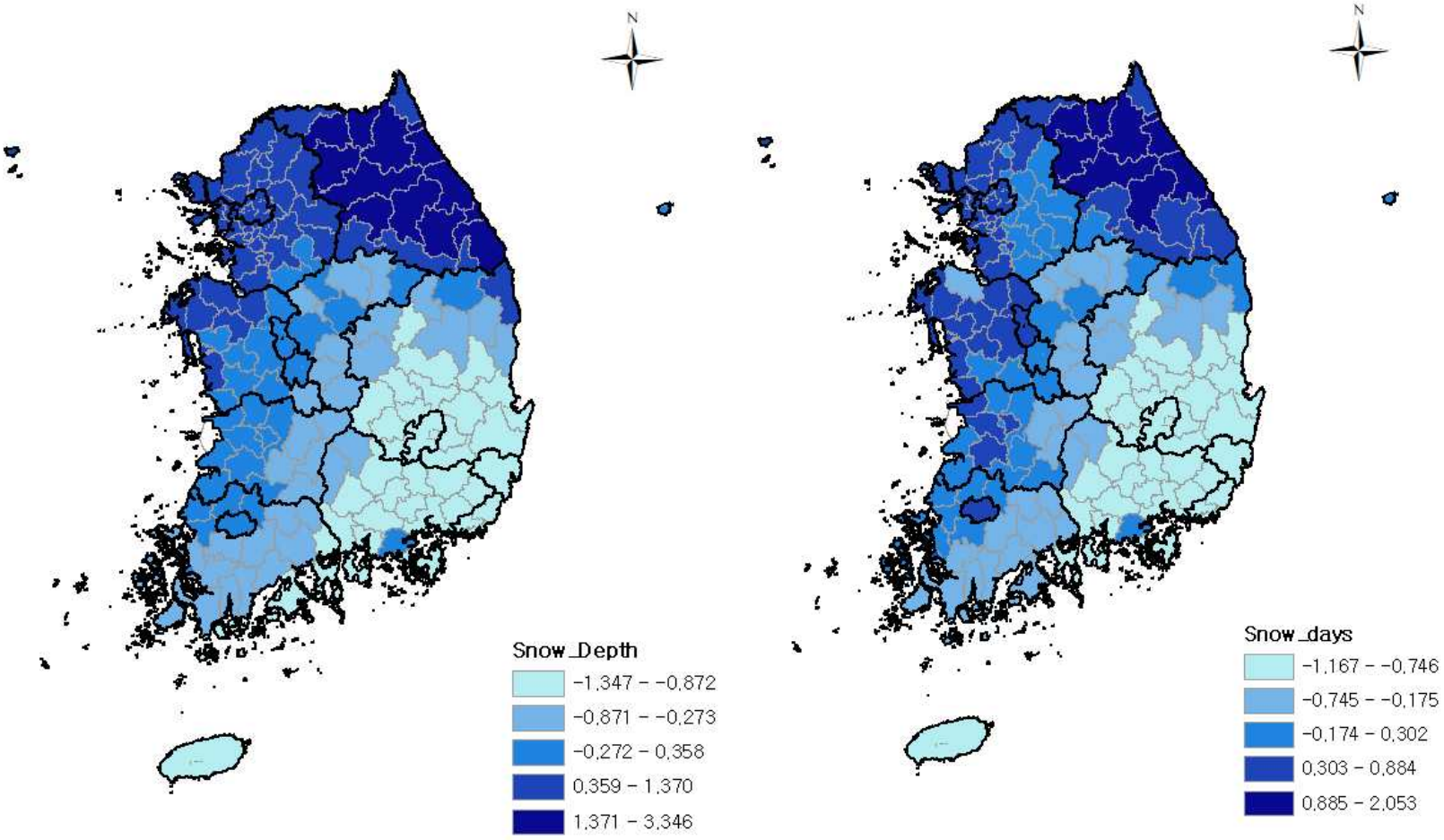


The snowfall variable was also a significant part of the analysis. 5 cm snow in a 24 hour period was set as the threshold for an extreme event. For average depth of snow over 5 cm, Gangwon-do area scored the highest, followed by si-gun on the northwest coast. The highest snowfall scores were from Gangneung-si (3.33), Sokcho-si (3.28), Yangyang-gun (3.06), Pyeongchang-gun (2.48), Injae-si (2.44), and Yanggu-gun (2.41). As for number of days with snow over 5 cm, Sokcho-si (2.053), Gangneung-si (1.680), Yangyang-gun (1.673), Yanggu-gun (1.438), and Inje-gun(1.387) scored the highest. Southern regions seemed to be almost unaffected by snow extreme events.

<Table 3-7> Snowfall over 5cm (Depth, # of Days)

Rank	Si-gun	Value	Rank	Si-gun	Value
1	Gangneung-si	3.346	1	Sokcho-si	2.053
2	Sokcho-si	3.296	2	Gangneung-si	1.680
3	Yangyang-gun	3.070	3	Yangyang-gun	1.673
4	Pyeongchang-gun	2.486	4	Yanggu-gun	1.438
5	Inje-gun	2.450	5	Inje-gun	1.387
156	Pohang-si	-0.915	156	Miryang-si	-1.127
157	Gimcheon-si	-0.969	157	Busan-si	-1.133
158	Goheung-gun	-0.991	158	Tongyeong-si	-1.144
159	Gwangyang-si	-0.992	159	Gimhae-si	-1.144
160	Hadong-gun	-1.052	160	Geoje-si	-1.167

<Figure 3-4> Over 5cm Snow in 24 Hours (Depth, # of Days)

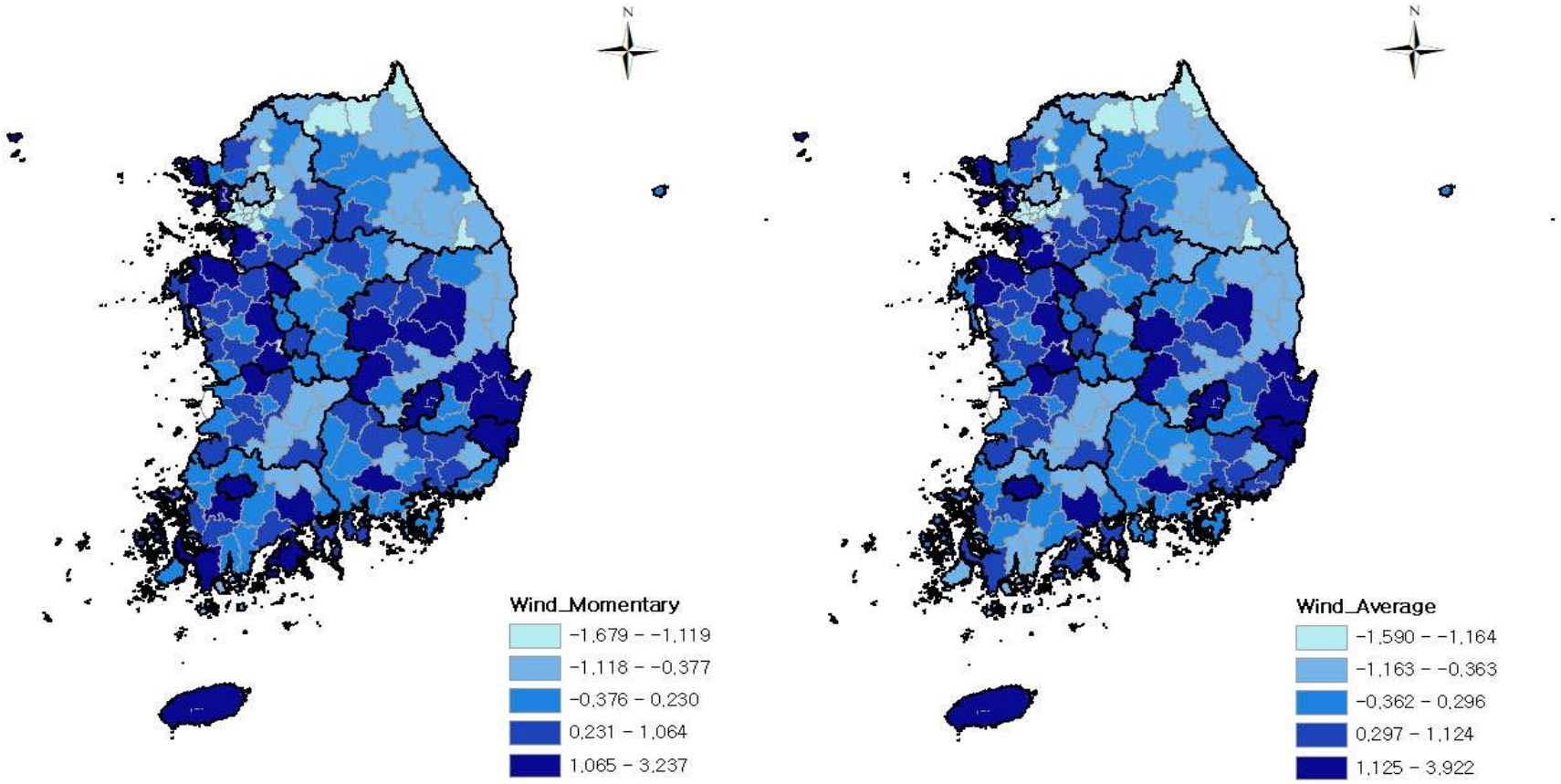


Momentary wind speed and average wind speed show somewhat similar results. Jeju-do (3.237), Daegu-si (2.309), Sangju-si (2.236), Gyeongju-si (2.121), and Andong-si (2.003) scored the highest, while for average wind speed, Jeju-do(3.922), Daegu-si(2.769), Hwaseong-si(2.050), and Gyeongju-si(1.956) scored the highest. The areas with high wind speed are Jeju-do (3.94), Daegu-si (2.79), Hwasung-si (2.07), Gyeongju-si (1.97), and Jinju-si (1.93). In the case of Jeju, the max. rainfall in 24 hours was very low while maximum continuous rainfall and the number of days with over 80 mm rainfall as well as wind speed score were exceptionally high, indicating that Jeju-do suffers from many storm-related extreme events.

<Table 3-8> Windspeed over 20m/s (Momentary, Average)

Rank	Si-gun	Value	Rank	Si-gun	Value
1	Jeju-do	3.237	1	Jeju-do	3.922
2	Daegu-si	2.309	2	Daegu-si	2.769
3	Sangju-si	2.236	3	Hwaseong-si	2.050
4	Gyeongju-si	2.121	4	Gyeongju-si	1.956
5	Andong-si	2.003	5	Jinju-si	1.910
156	Taebaek-si	-1.638	156	Gwacheon-si	-1.556
157	Gwacheon-si	-1.651	157	Guri-si	-1.560
158	Gyeryong-si	-1.653	158	Gyeryong-si	-1.576
159	Guri-si	-1.653	159	Taebaek-si	-1.582
160	Gunpo-si	-1.679	160	Gunpo-si	-1.590

<Figure 3-5> Wind Speed over 20m/s (Momentary Speed, Average Speed)

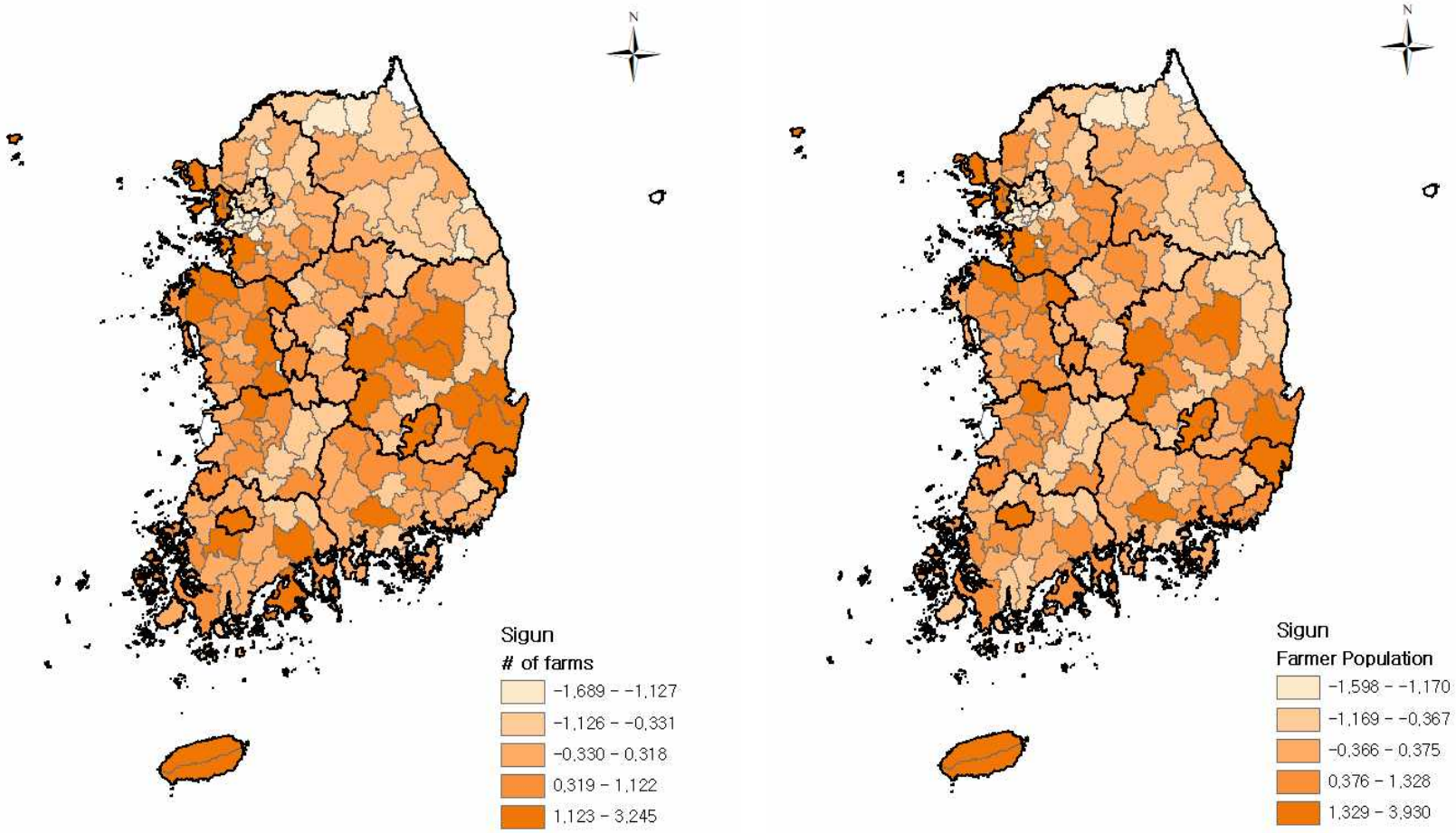


The number of farms and the farmer population was used to represent the sensitivity of the region. Originally, both rice paddy and field areas were included. However the field areas were removed from the analysis due to a multicollinearity issue and the paddy area did not seem to have a statistically significant relationship with the damage cost. For number of farms Jeju-do (3.245), Chungju-si (2.57), Daegu-si (2.313) Jinju-si (2.21, 2.23), and Gyeongju-si (2.26) scored highest.

<Table 3-9> Number of Farms and Farmer Population

Rank	Si-gun	Value	Rank	Si-gun	Value
1	Jeju-do	3.245	1	Jeju-do	3.930
2	Daegu-si	2.313	2	Daegu-si	2.774
3	Sangju-si	2.240	3	Hwaseong-si	2.053
4	Gyeongju-si	2.124	4	Gyeongju-si	1.958
5	Andong-si	2.006	5	Jinju-si	1.913
156	Taebaek-si	-1.649	156	Gwacheon-si	-1.564
157	Gwacheon-si	-1.661	157	Guri-si	-1.568
158	Gyeryong-si	-1.663	158	Gyeryong-si	-1.584
159	Guri-si	-1.664	159	Taebaek-si	-1.590
160	Gunpo-si	-1.689	160	Gunpo-si	-1.598

<Figure 3-6> Number of Farms and Farmer Population



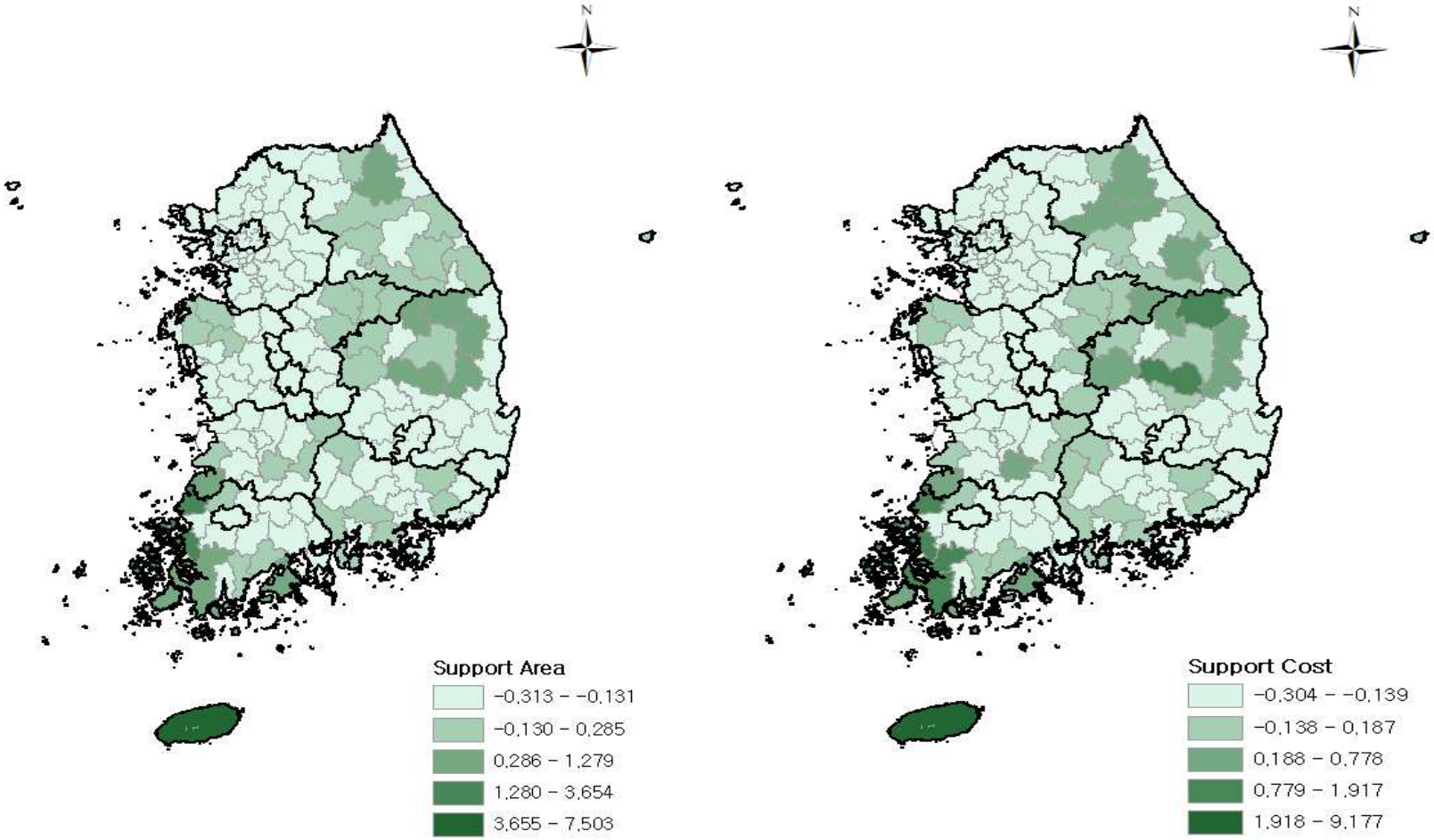
As for the adaptive capability variable, the measurement of government spending on infrastructure for field crops was used. Daegu(-0.31), Chungju(-0.31), Gyeongju(-0.3), Hwasung(-0.29), and Incheon(-0.29) had the lowest gov. spending. It should be noted that Jeju-do takes a large portion of total government spending.

<Table 3-10> Government Support (Area, Cost)

Rank	Si-gun	Value
1	Jeju-do	7.503
2	Yeonggwang-gun	3.654
3	Shin'an-gun	1.960
4	Mu'an-gun	1.701
5	Yeong'am-gun	1.279
156	Gwangmyeong-si	-0.313
157	Gwacheon-si	-0.313
158	Guri-si	-0.313
159	Gyeryong-si	-0.313
160	Gunpo-si	-0.313

Rank	Si-gun	Value
1	Jeju-do	9.177
2	Shin'an-gun	1.917
3	Mu'an-gun	1.695
4	Yeong'am-gun	1.115
5	Yeonggwang-gun	1.041
156	Gwangmyeong-si	-0.304
157	Gwacheon-si	-0.304
158	Guri-si	-0.304
159	Gyeryong-si	-0.304
160	Gunpo-si	-0.304

<Figure 3-7> Government Support(Area, Cost)



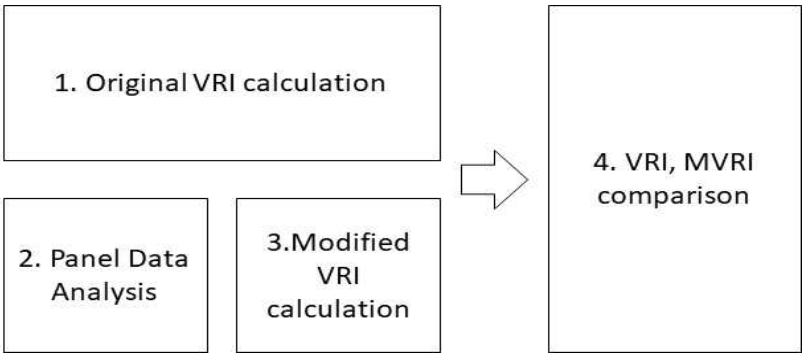
Chapter 4. Model Description

4.1. Analysis Procedure

The two primary goals in this research are to prove that 1) multi-year data analysis is more accurate than single year analysis due to the time-dynamic nature of climate change, and 2) variables that are weighted by regression results provide more accurate vulnerability than the original vulnerability model. For such, three different versions of models with three different time specifications are calculated and compared.

First, three different models are calculated with single year data (2015). The regional vulnerability is calculated using the original vulnerability model to determine VRI. Then regression analysis is conducted to obtain coefficient values to be used as weights for each variable. Lastly, only statistically significant values are selected and calculated into two different versions of the vulnerability model (MVRI 1 & 2), using coefficient values as weights (See figure 4-1).

<Figure 4-1> Analysis Procedure



4.2. Model Specifications

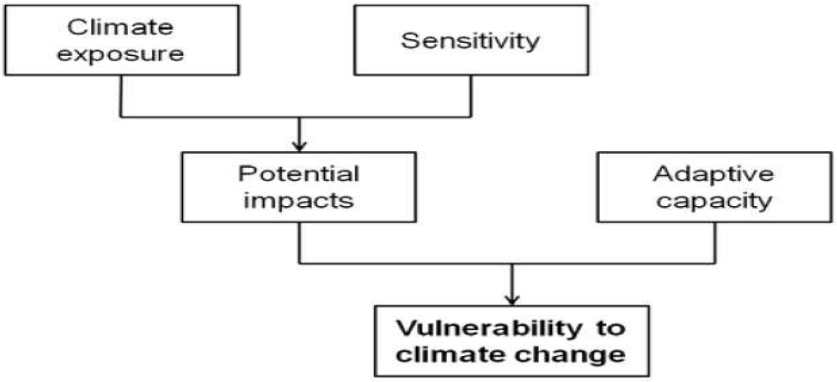
The IPCC model (Original model) attempts to analyze regional climate change vulnerability by building a vulnerability-resilience index consisting of three key categories: exposure, sensitivity, and adaptive capacity in an attempt to reduce potential risks and costs of climate change (Fusser and Klein, 2006; Go, 2009). Scores for the three categories (climate change exposure, sensitivity index, and adaptive capability) are determined by calculating the arithmetic average of generalized variables in each category. All variables are generalized using the z-score method. The IPCC's Climate Change Vulnerability Resilience Index Model is expressed in (1).

(1) $VRI_i^t = (CCE_i^t + SI_i^t/2) - AC_i^t)/2$

Where $CCE_i^t = \sum_{i=1}^{n_1} Z_i^t/n_1$, $SI_i^t = \sum_{i=1}^{n_2} Z_i^t/n_2$, and (4) $AC_i^t = \sum_{i=1}^{n_3} Z_i^t/n_3$

The potential impact is calculated by obtaining an average value of CC and sensitivity. The Vulnerability-Resilience index is then obtained by calculating the average potential impact and adaptive capacity.

<Figure 4-2> IPCC Vulnerability Resilience Model



The Modified Vulnerability-Resilience Model (MVRI & MVRI2) conducts regression analysis between the region's damage cost and specified vulnerability variables. Doing so would provide the following

advantages: increased accuracy from using statistically significant variables and applying appropriate weight to the variables. Since the data consists of both cross-section and time-series data, a Houseman Test and panel data analysis is conducted. Regression analysis uses natural disaster damage costs in the agricultural sector as its dependent variables and uses proxy variables for the three categories as independent variables. One hundred and sixty samples with 10 years of data from 2006 and 2015 were subjected to analysis. The model is expressed in formula (6).

(6) $$y_{it} = \alpha + \beta_0 CCE_{it} + \beta_1 SI_{it} + \beta_2 AC_{it} + u_i + \epsilon_{it}$$

Panel data analysis results are then applied to two different versions of the vulnerability model: MVRI1 and MVRI2. MVRI1 still uses the original vulnerability model, where variables are first calculated into the three categories before finally determining the vulnerability, giving more weight to adaptive capability (as seen in formula (7).

(7) $MVRI1_i^t = (CCE_i^t + SI_i^t/2) - AC_i^t)/2$

Where, $wCCE_i^t = \sum_{i=1}^{n_1} w_i^t Z_i^t / n_1$, $wSI_i^t = \sum_{i=1}^{n_2} w_i^t Z_i^t / n_2$, and

$wAC_i^t = \sum_{i=1}^{n_3} w_i^t Z_i^t / n_3$

MVRI2 model weights the variables individually, rather than using the original model where averages are taken for the three categories. This is shown in (11).

(11) $MVRI2_i^t = (\sum_{i=1}^{n} w_i^t Z_i^t)/n$

Chapter 5. Analysis Results

5.1. Regression Analysis Results

Panel data regression was conducted to utilize coefficient values for weights. Prior to panel data analysis, a Hausman Test was conducted to test whether or not the data is suitable for fixed or random effect analysis. The resulting value was 32.17, and PROB>chi2 = 0.0095, indicating that the data is subject to fixed effect panel data analysis. The analysis took the damage cost of the si-gun as the dependent variable and the variables from the vulnerability model as independent variables. Regression analysis results showed that most of the statistically significant climate variables are consistent with theoretical expectations. The results of this analysis are presented in <Table 5-1>.

<Table 5-1> Fixed Effect Panel Data Analysis Results

Categories	Sub categories	Variables	Coefficient (Std. err)
Climate Change Exposure (CCE)	Heatstress	Daily max. temperature above 25℃ (# of days)	-0.146 (0.0846)
		Daily max. temperature above 25℃ (average)	-0.409*** (0.0620)
		Daily max. temperature above 33℃ (# of days)	0.125*** (0.0476)
		Daily max. temperature above 33℃ (average)	0.553*** (0.0580)
	Flood	Average rain over 80mm	-0.0548 (0.0473)
		Max. rain in 24hrs	0.151*** (0.0532)
	Drought	Non-precipitation over 31days	-0.00861 (0.0246)
	Snow	Max. continuous snow	0.128* (0.0482)
		Max. snow in 24hrs	-0.0601 (0.0452)
	Wind	Average wind speed over 20m/s	0.125* (0.0699)
		Max. momentary wind speed over 20m/s	-0.110 (0.0700)
Sensitivity (SI)	Agricultural Variables	# of farms	1.096*** (0.404)
		Farmer population	1.130*** (0.376)
		Rice Paddy Area	0.249 (0.313)
Adaptive Capability (AC)	Government Support	Gov. spending on Infrastructure (Area)	0.00540 (0.0865)
		Gov. spending on Infrastructure (cost)	-0.221** (0.0896)
		Constant	1.72e-09 (0.0229)
		Observations	1,600
		Number of si-gun	160

note : ***, **, * are significant at 1%, 5%, 10% level respectively

Average temperatures that reached a daily maximum temperature above 25℃ were significant. However, the number of days with a maximum temperature of 25℃ was not statistically significant at the 99% level. This seems to be because a temperature of 25℃ and above is considered warm weather rather than an extreme event and tends to not overlap with most wind/rain extreme events. However, heatwave variables (max. temp. over 33℃) both showed a positive relationship and were statistically significant at the 95% level. This means the magnitude of damage is highly related to both the intensity and duration of a heatwave. However, the average instances of daily temperatures of 33℃ and higher have a significant and positive relationship with the damage cost. This is consistent with the theory that increases in heatwaves tend to increase overall precipitation and related extreme events including flooding and storms (Min et al., 2011).

Maximum daily rainfall did not show any statistical significance, while maximum precipitation levels in a 24-hour period did. This is due to the characteristics of modern anti-flood measures having discharge thresholds

that can control flooding unless the threshold is surpassed within a given amount of time. The threshold for rainfall related damage differs region by region since their flood control infrastructure already reflects the climate conditions; therefore, it can be assumed that the occurred flood damage is an extreme event that surpassed normal precipitation levels.

In the case of drought variables, none showed any significance. This could be because the analysis included days without precipitation, which includes drought during winter time, during which time there are relatively fewer crops to be damaged. Drought also seems to require a more complicated index/scoring to accurately reflect drought-induced damages. There are many studies dedicated to analyzing drought vulnerabilities found as well.

As for wind variables, it was expected that momentary wind speed would cause more damage than average wind speed in similar assumptions, such as the precipitation. However, the results are different from the expectations. This seems to be because momentary wind speed can be very difficult to detect. The analysis

conducted in this research shows that average wind speed is significant and positively related to damage cost. However, wind variables may require a different approach, as drought variables did.

For sensitivity variables, it was expected that a larger number of farms, farmer population, and cultivated areas would result in more damage, in the case of extreme events. The results are consistent with the expectations as both the number of farms and the farmer population were significant at 99% level and were positively related to damage cost. As for the cultivated area, paddy area was not significant. This is possibly due to the nature of paddy farming being more resistant to heavy rainfall or heat and being the most cared after agriculture in South Korea; substantial adaptation measures would have taken place already. In the analysis, the field crop variable was not included because its correlation value with government support value was over 0.8, besides which, the variance inflation factor value was over 10 and caused multicollinearity.

Government spending on infrastructure variables indicated that the area subject to spending was not

significantly related. However the amount of budget was significant and had a negative relationship with damage cost. Intuitively, government spending should be in a negative relationship with damage cost since better infrastructure would mean the higher capacity to cope with natural disasters, resulting in lower damage cost, to which the result was consistent.

5.2. Results Comparison

Three model versions (VRI, MVRI1, and MVRI2) are calculated using three different time specifications: single year, 10-year average, and 10-year time weighted average[4] to make a total of nine vulnerability results for each region. The models are then compared with regional cumulative damage cost, disaster frequency, and average damage cost to determine which model with time specification reflects the reality most accurately.

The correlation test result suggests that the best model specification is the first version of the Modified Vulnerability Model, which takes both individual weights from regression analysis and the original model's

4) Progressively more weights applied

weights. When compared with production per area, in all time specifications, MVRI1 shows the highest correlation. The top correlation is the single year result of MVRI1 (MVRI1_15) with a correlation value of -0.387, which is then followed by the time-weighted average and the 10-year average of MVRI1, showing -0.367 and -0.340 respectively. MVRI1 shows the highest score for production quantity per farm and per population variables as well as for a 10-year average and time-weighted average, showing -0.281 and -0.286 respectively (see table 5-2).

<Table 5-2> Correlation Test Results (Model Comparison)

Time Specification	Model Specification (Variable Name)	Production per Area	Production per Farm	Production per Population
Single year	Original Model (VRI_15)	0.047	0.081	0.059
	Modified ver. 1 (MVRI1_15)	-0.387	0.075	0.058
	Modified ver. 2 (MVRI2_15)	-0.357	0.215	-0.205
10 year average (`06~`15)	Original model (VRI_ave)	0.195	0.085	0.069
	Modified ver. 1 (MVRI1_ave)	-0.340	-0.357	-0.337
	Modified ver. 2 (MVRI2_ave)	-0.283	-0.281	-0.300
Time weighted average (`06~`15)	Original model (VRI_TWM)	-0.225	0.072	0.053
	Modified ver. 1 (MVRI1_TWM)	-0.367	-0.330	-0.308
	Modified ver. 2 (MVRI2_TWM)	-0.276	-0.286	-0.305

In terms of time specifications for the original model, the 10-year average showed the strongest correlation. The relationship was hypothesized to be a negative one. However it was positively related to the original model. MVRI1 showed the highest correlation with productivity variables with a 10-year average time specification while MVRI2 showed the highest correlation value for time-weighted average. However, with all things considered, MVRI1 with a 10-year average value had the highest correlation value overall and was negatively related to productivity variables (See table 5-3).

<Table 5-3> Correlation Test Results (Time Specification Comparison)

Model Specification (Variable Name)	Time Specification	Production per Area	Production per Farm	Production per Population
Original model (VRI)	Single year	0.047	0.081	0.059
	10 year average	0.195	0.085	0.069
	Time weighted average	-0.225	0.072	0.053
Modified ver. 1 (MVRI1)	Single year	-0.387	0.075	0.058
	10 year average	-0.340	-0.357	-0.337
	Time weighted average	-0.367	-0.330	-0.308
Modified ver. 2 (MVRI2)	Single year	-0.357	-0.215	-0.205
	10 year average	-0.283	-0.281	-0.300
	Time weighted average	-0.276	-0.286	-0.305

5.3. Regional Climate Change Vulnerability

Based on the results comparison, it can be said that MVRI1 is the best out of the three model versions and the 10-year average was overall the best time specification. This indicates that weighting variables based on panel data regression analysis does help to improve the model. Additionally, it can be argued that the multi-year average of vulnerability results are better than single year results.

Finally, regional vulnerabilities are calculated using MVRI1 and the 10-year average value of vulnerability results, which is shown in (figure 5-1). The result is classified using natural breaks as all other figures in this research.

Final results indicate that vulnerabilities can vary even among neighboring si-gun within the same si-do. This supports the idea that finer scope analysis can portray more accurate results than macro analysis. Si-gun with the highest vulnerability and their subscores are shown in (Table 5-4).

Southern regions of Korea were relatively more vulnerable than northern regions. On average,

Chungcheongnam-do seemed to be the most vulnerable region. However it does not have any of the most vulnerable si-gun. Jeju-do (1.156), Hapcheon-gun (0.833), Pohang-si (0.473), Daegu-si (0.412), Busan-si (0.442), and Gyeonju-si (0.429) were the most vulnerable si-guns of Korea.

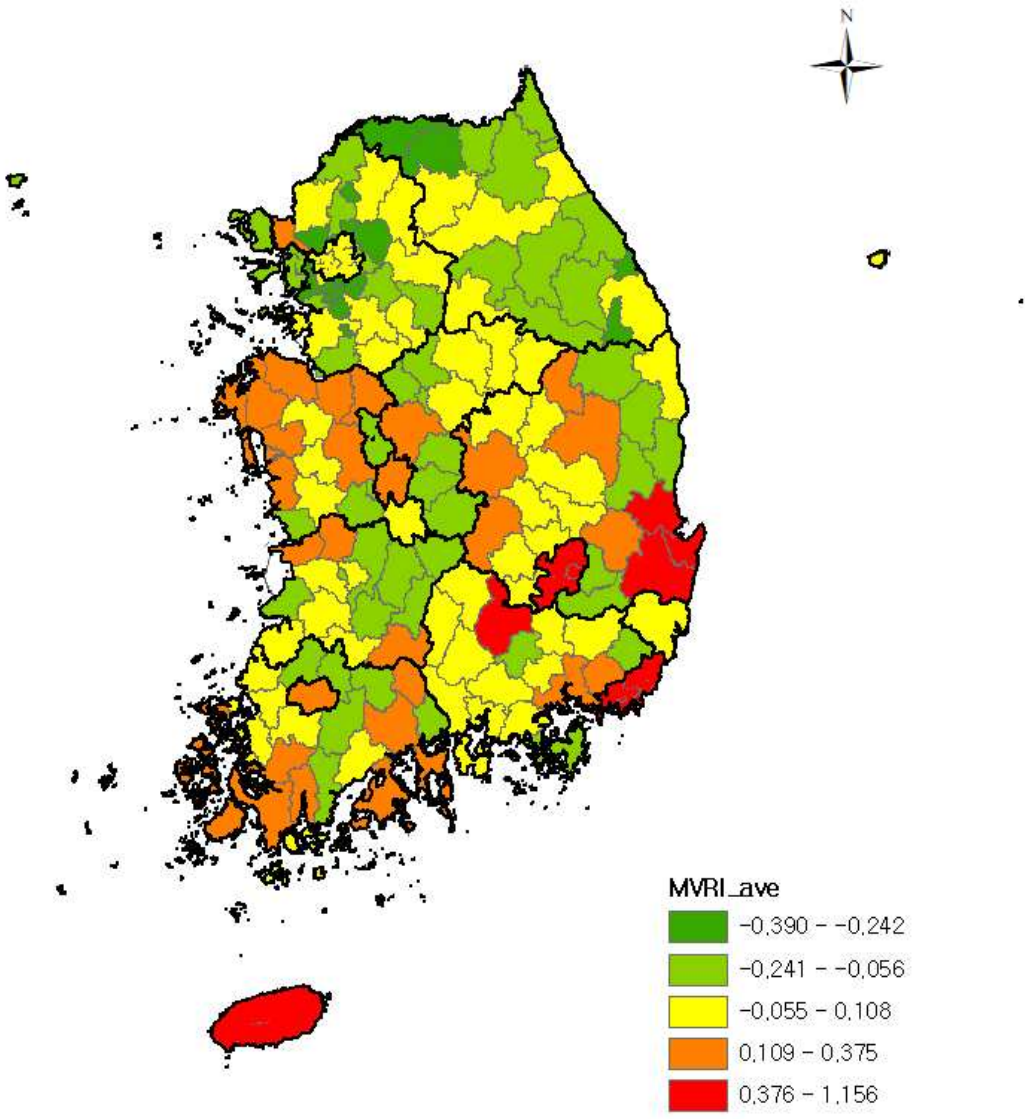
Jeju-do had the lowest score for government support with the score of -2.028, which is negatively related to vulnerability. However, Jeju-do also had one of the highest, if not the highest exposure and sensitivity scores. Jeju-do has the highest number of farms and farmer population in all the si-gun, being 3.556 and 4.441 respectively. Additionally, although Jeju-do doesn't seem to suffer from intensive heatwave events, having low scores on the intensity and duration of a heatwave. However, Jeju has the highest score for maximum wind speed, maximum continuous rain, and duration of intense rain. Hapcheon-gun and other si-do in Gyeongsang-do, on the other hand, have different factors for vulnerability. They have a moderate to high sensitivity score, and rain, wind, or snow-related scores are low. Government support is extremely low while heatwave intensity and duration scores are the highest among si-gun.

<Table 5-4> Top Most Vulnerable Regions and Vulnerability Factors

Si-gun	MVRI	Heatwave Intensity	Heatwave Duration	Rain	Wind	Snow	Farms	Farmer Population	Gov. Support
Jeju	1.155	-0.174 (-0.022)	-0.781 (-0.432)	-1.155 (-0.175)	3.922 (0.490)	-1.056 (-0.135)	3.245 (3.556)	3.93 (4.441)	9.177 (-2.028)
Hapcheon	0.833	0.354 (0.044)	1.307 (0.723)	0.627 (0.094)	0.296 (0.037)	-1.16 (-0.148)	0.693 (0.759)	0.293 (0.331)	-0.304 (0.067)
Pohang	0.473	0.593 (0.074)	1.917 (1.060)	0.640 (0.096)	1.306 (0.163)	-0.915 (-0.117)	1.541 (1.688)	1.307 (1.476)	-0.285 (0.062)
Daegu	0.455	0.523 (0.065)	2.214 (1.224	-0.210 (-0.031)	2.769 (0.346)	-1.148 (-0.146)	2.313 (2.535)	2.774 (3.134)	-0.304 (0.067)
Busan	0.442	0.216 (0.027)	1.097 (0.606)	-0.282 (-0.042)	0.429 (0.053)	-1.267 (-0.162)	0.131 (0.143)	0.427 (0.482)	-0.304 (0.067)
Gyeongju	0.429	0.581 (0.073	2.143 (1.185)	1.792 (0.270)	1.956 (0.244)	-1.137 (-0.145)	2.124 (2.327)	1.958 (2.212)	-0.304 (0.067)
Gimcheon	0.375	0.245 (0.031)	0.697 (0.385)	0.142 (0.0214)	1.485 (0.185)	-0.969 (-0.124)	1.757 (1.925)	1.486 (1.679)	-0.241 (0.053)

Note : Values in parenthesis is variable score weighted by respective coefficient values.

<Figure 5-1> Regional Vulnerability(MVRI1, 10yr average)



Chapter 6. Conclusions

The results of this research suggest that when climate change vulnerability analysis is conducted, it is more accurate to utilize time dynamics and regression analysis. Regression analysis not only allowed a more accurate selection of variables, but it also provided more accurate weights compared to the original model.

Additionally, it provided a more clear picture of the relationship between extreme weather event damage and each of the variables considered in the study. Models with weights were more accurate than the original model in all categories and time specifications.

Furthermore, it seems reasonable for future analysis to use si-gun as its scope since vulnerability varies even amongst the same si-do. This is because, although some neighboring si-gun shared similar vulnerability levels, they were often from a different si-do. It can be said that with an improved data set and more testing on the models used, the principles suggested in this research can provide more accurate and actionable ways to approach climate change vulnerability and adaptations.

The model suggested in this study(MVRI1) offers some advantages, in that variables can be individually tested with damage cost to show relationships in more accurate ways. This makes it possible to profile each regions' vulnerabilities more accurately. Locale-specific adaptation policies can be crafted from the analysis results. In preceding studies, different si-do showed different levels and causes of vulnerabilities, and the results suggest that even within the same si-do area, si-guns tend to show different factors of vulnerability. Therefore, a finer scope with a more specific analysis can aid in more effective policy making.

The data collection process had various limitations. The study was originally intended to analyze 30 years of data; as the definition of climate change refers to the statistical change of weather in the past 30 years. However, due to a number of mismatches in either timeline or regional scale, the analysis lost many variables. Many data points that were available in the si-gun level were not available in si-do level and most si-gun data was close to nonexistent before the year 2000. No limitations were found for obtaining exposure

variables since all of the data was available daily at every observation point. However, sensitivity and adaptive capability variables were not easily found.

Similar limitations were observed from preceding studies where Yoo et al. (2008) were able to obtain data for 40 proxy variables to apply the IPCC climate change vulnerability model, while Hwang (2016) was only able to obtain 22 variables applying the same model. This mismatch is due to the scope of research where Yoo's work took si-do as the scope of the analysis while Hwang attempted an analysis of si-gun only in Gangwon-do area, suggesting a lack of availability in the data when the analysis is conducted at a finer scope.

For agricultural sensitivity data, agricultural business registration information may provide accurate information in all level of analysis. However, the database is relatively young, providing only two years of available data yet. It will surely become useful in the future, as more consistent data accumulation takes place. Also, it was difficult to obtain variables to compare research results, other than data on the natural disaster damage cost of the agricultural sector.

As was shown in the research, even though further studies are required for completion of the vulnerability model, a combination of different approaches does lead to a more accurate assessment of climate change vulnerabilities, and can provide a sound founding data for climate change adaptation related policy making, such as on-going projects like "Establishment of Comprehensive Climate Change Impact and vulnerability Assessment Infrastructure" and "Climate Change Vulnerability Assessment and Mapping by Lot Number," conducted by the Department of Environment, Korea, or "Assessment of Climate Change Vulnerability and Impacts of Korean Agricultural Sector" conducted by the Ministry of Agriculture, Korea.

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Abstract (Korean)

국 문 초 록

한국 농업의 지역별 기후변화 취약성 평가

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최근 전지구적으로 발생하고 있는 기후변화는 보다 강렬하면서 빈번한 극한 기상현상을 수반하고 있으며, 이는 인간활동에 의해 발생하고 있어 앞으로도 심화될 전망이다. 한국은 아직 극한의 자연재해는 겪지 않았으나 온도 상승, 강우량과 패턴 변화 등 기후변화 자체는 전 세계 평균보다 더 빠르게 진행되고 있다. 기후변화는 전반적으로 부정적인 영향을 끼칠 것으로 예측되며 이에 대한 적절한 적응이 필요한 시점이다.

이에 지역별 기후변화 평가는 기후변화 적응의 적절한 척도로 연구되고 있으며 특히 하향식 정책 수립을 위한 전망을 제공하는데 도움이 된다. 또한 상대적으로 취약한 지역 및 해당 지역의 취약성 요인을 탐지함으로써 기후변화 대응 관련정책 수립 시 근거자료로 활용될 수 있다.

정확한 기후변화 취약성 평가 모델의 구축을 위해 다양한 접근방식의 시도가 있었다. 연구결과들을 요약하자면 기후변화 취약성 분석을 위해서는 취약성 요소들의 지역적, 산업적 특성에 관한 공간적, 그리고 시간적 관계를 반영해야 하며 정성적 보다 정량적 분석이 시행되어야 함을 강조하고 있다. 각자 다른 특성들의 반영이 분석의 정확성을 증가시키는 것으로 입증되었지만 대부분 한 동시에 여러 가지의 접근법을 적용하기보다 개념적 접근, 공간분석, 회귀분석이나 주성분 분석 등을 포함하는 통계분석 등 한 가지의 접근법에 집중해 왔다.

이에 따라 본 연구는 기존 취약성 평가방법들을 활용하여 한국농업의 지역별 기후변화 취약성을 좀 더 정확하게 평가하고자 하였다. 이를 위해 본 연구는 회귀분석을 통해 취약성 요소들과 지역별 피해함수들 간의 관계를 파악 하고 분석결과로 주어지는 계수를 가중치로 사용하여 모델을 개선하고자 했다. 회귀분석의 종속 변수로는 기후극한현상으로 인해 발생한 시군별 농업분야의 자연재해 피해액을 사용하였고 독립변수로는 열파, 홍수, 가뭄, 태풍, 폭설등을 포함하는 노출도 변수들과 농업면적과 농업인구를 포함하는 민감도 변수, 그리고 정부투자금액을 사용했다. 또한 수정된 모형이 기존 취약성 모형보다 현실을 더 반영하는지 확인하기 위해서 시군별 정곡생산성 변수와 상관성 분석을 실시했다.

분석결과 기존연구에서 사용된 대리변수들이 모두 기후변화로 인해 발생한 비용과 통계적으로 유의미한 관계를 가진 것은 아닌 것으로 나타났지만 변수 간 이론적 관계는 잘 반영된 것으로 나타났다. 또한 가중치를 주어 계산한 모형들과 기존 모형의 결과치를 시군의 정곡 생산성 변수들과 상관관계 분석을 진행한 결과 가중치를 주어 계산한 결과치의 10년 평균치가 가장 큰 상관관계를 가지고 있는 것으로 나타났다.

종합적으로, 정성적인 접근만으로 대리변수를 선정하고 취약성 분석을 진행하는 것 보다 회귀분석을 통한 가중치를 부여함으로써 모형에 현실성이 더 부여되는 것으로 나타났다. 또한 단년도 데이터의 분석 뿐 아니라 결과 값 역시 다년도 평균을 보는 것이 더 정확한 것으로 나타났다. 따라서 본 연구의 분석결과는 시계열 자료의 분석, 대리변수들 간 관계 파악을 통한 가중치 부여 등이 정확한 기후변화 취약성 평가의 정확도를 높인다는 논의를 뒷받침하고 있다. 따라서 본 연구의 결과는 취약성 파악 뿐 아니라 미래 예측치를 대입하여 취약성을 예측하는 등 현재 진행되고 있는 환경부의 “지번단위 기후변화 영향별 취약성 평가 지도 작성 및 배포”나 농림부가 추진하는 “농업부문 기후변화 영향 및 취약성 평가”와 같은 정책 수립을 위한 기초자료로 활용될 수 있을 것으로 기대된다.

주요어 : 기후변화 적응, 기후변화 취약성, 극한현상, 농업 생산성, 패널자료 분석

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