Findings and lessons learned from pilot applications of statistical geospatial indicators for drought monitoring in Kazakhstan and South Korea

Korea University

Woo-Kyun Lee,

Sea Jin Kim, Soo Jeong Lee, Jiwon Kim, Eunbeen Park, Sugyeong Park, Altynay Shaimerdenova

Content

1. Development of statistical geospatial indicators (index)
2. Existing drought indicators (index)
3. Decision supporting tool
4. Repository for spatial data
5. Satellite derived vegetation indices
6. Fire susceptibility indices
7. Suggestions

1. Development of statistical geospatial indicators (index)

Question (3)

Your view or suggested **approach** on development or application of statistical geospatial indicators (index) for drought monitoring and early warning

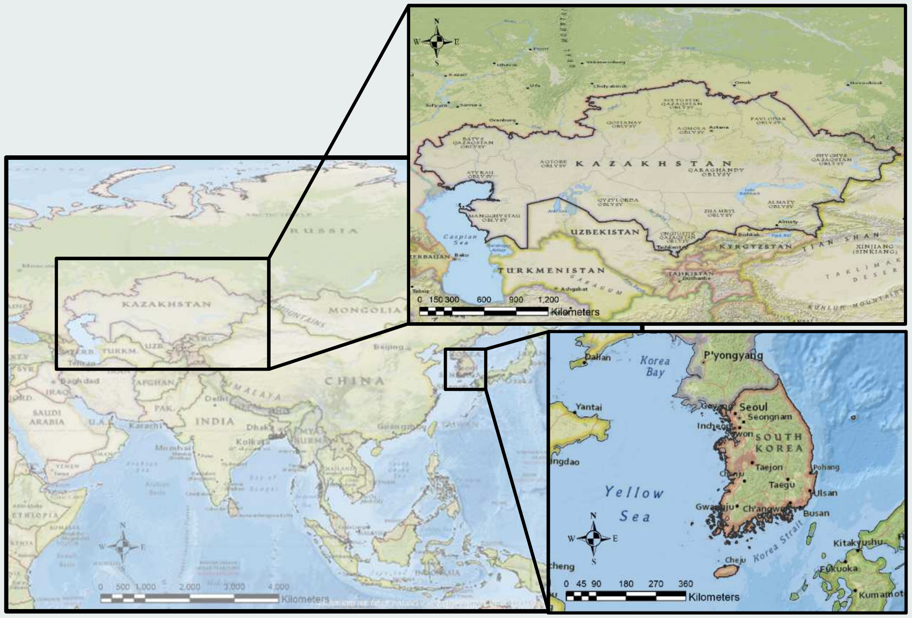
1. Development of statistical geospatial indicators (index)

A. Objective of the research

- The research objective is to develop a set of statistical geospatial indicators and assess disaster risk (vulnerability) to prepare adaptive pathways for Disaster Risk Reduction (DRR).

B. Research area

- Kazakhstan
- South Korea (as reference)



1. Development of statistical geospatial indicators (index)

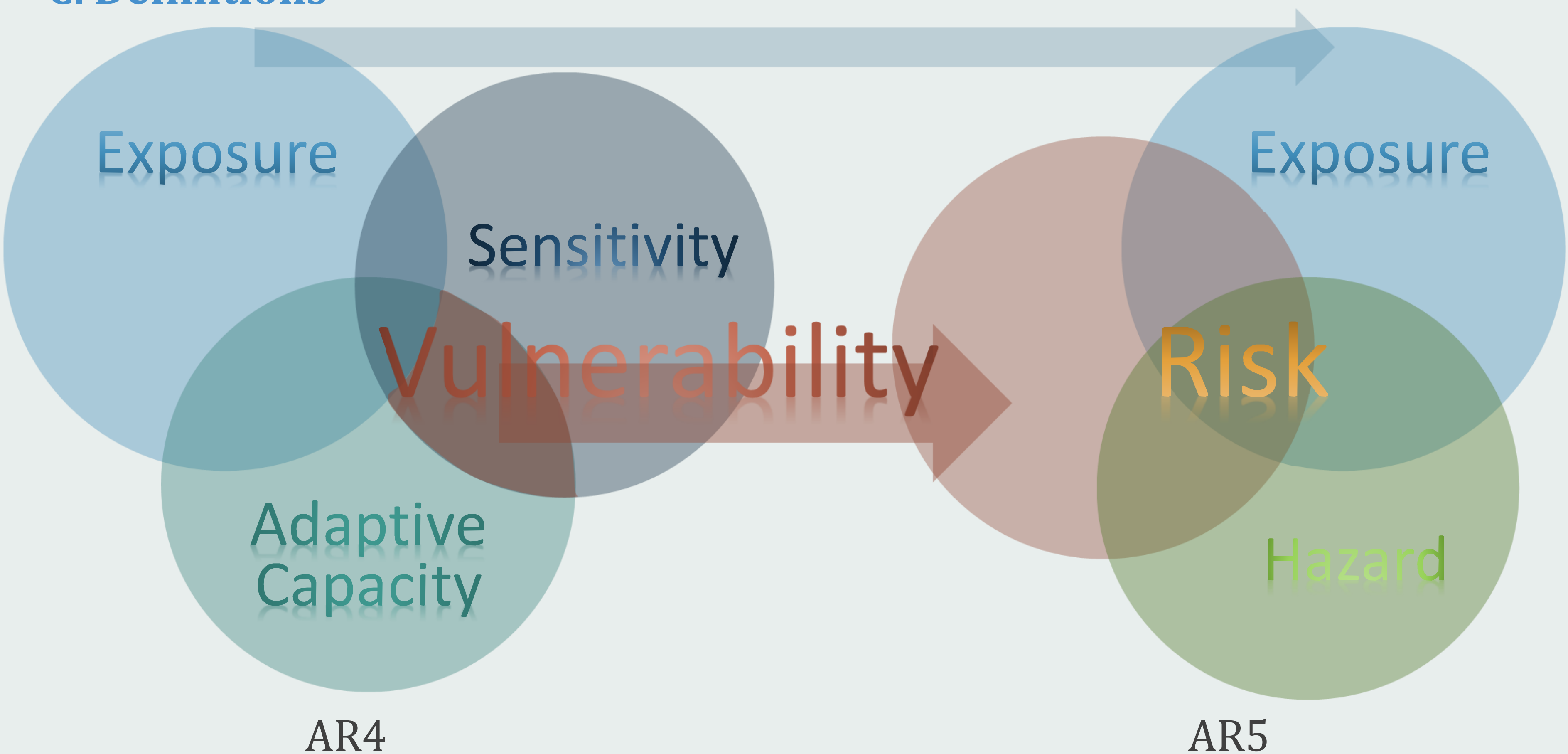
C. Definitions

- We assessed "disaster risk" using the concept of "vulnerability", as outlined by the Intergovernmental Panel on Climate Change (IPCC).

Term	Definition from IPCC
Vulnerability	"The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes"
Exposure	"The nature and degree to which a system is exposed to **significant climatic variations**"
Sensitivity	"The degree to which **a system is affected**, either adversely or beneficially, **by climate-related stimuli**"
Adaptive capacity	"**The ability of a system to adjust to climate change** to moderate potential damages, to take advantage of opportunities, or to cope with the consequences"

1. Development of statistical geospatial indicators (index)

C. Definitions



1. Development of statistical geospatial indicators (index)

C. Definitions

High Vulnerability (Drought) → High Risk (Disaster)

↑ Hazard Exposure

- Human
- Fauna
- Flora
- Soil
- Water

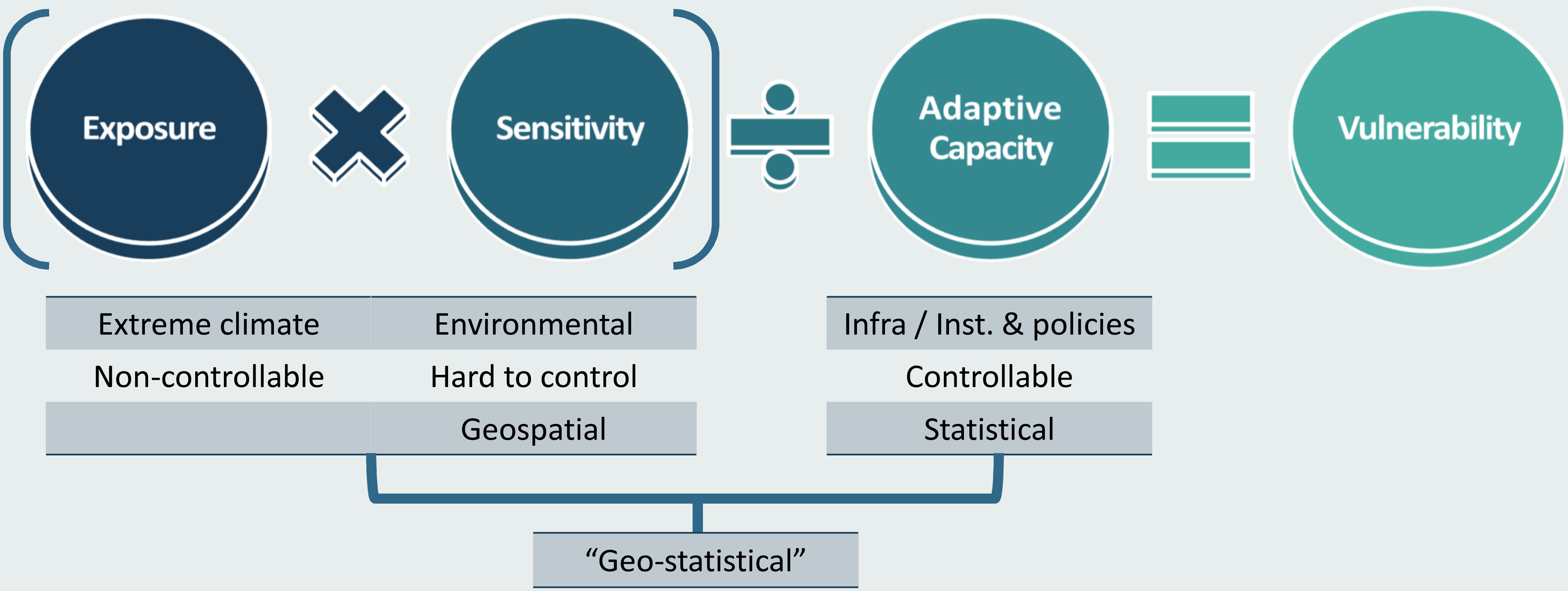
1. Development of statistical geospatial indicators (index)

D. Method

- To develop geo-statistical indicators for assessing vulnerability, we first selected indicators related to exposure, sensitivity and adaptive capacity through literature reviews.
- Then we prepared vulnerability indices and maps by computing the exposure, sensitivity and adaptive capacity indicators.
- These methods are based on Geographic Information System (GIS) technology which prepares data into spatial forms and analyzes them statistically.

1. Development of statistical geospatial indicators (index)

D. Method



1. Development of statistical geospatial indicators (index)

D. Method

Step 1

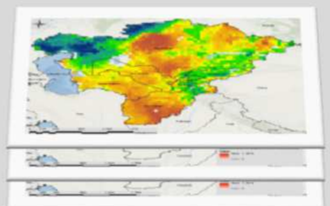
Exposure, Sensitivity
(Geo-spatial) Indicators

Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Exposure	Annual precipitation (mm)	0	0	Choi et al. (2009) Jung et al. (2010)
Sensitivity				

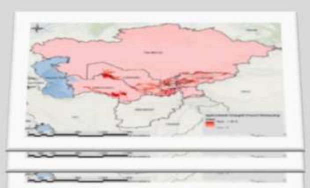
Adaptive Capacity
(Statistical) Indicators

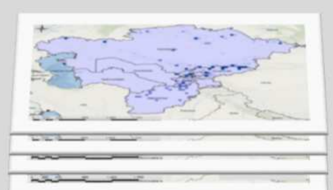
Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Adaptive Capacity				

Step 2

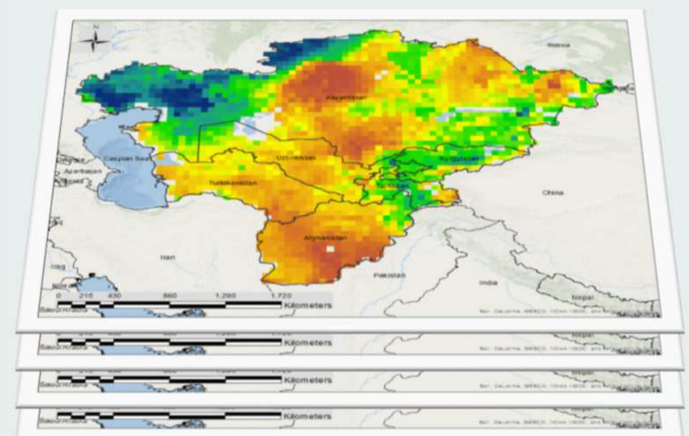


Exposure, Sensitivity Map





Adaptive Capacity Map
(Infrastructure / Institutions and Policies)



Vulnerability Map

2. Existing drought indicators (index)

Question (5)

Can we use any good existing drought indicators (index) in Central Asia?
Is it good enough to use?

2. Existing drought indicators (index)

A. Literature review -> Only Climate Indicators

Drought

Index	Indicator	Equation	Description	Reference
Palmer Drought Severity Index (PDSI)	temperature, precipitation	$X_i = X_{i-1} + \left(\frac{Z_i}{3}\right) - 0.103X_{i-1} = 0.897X_{i-1} + \left(\frac{Z_i}{3}\right)$ X: drought index , Z: moisture anomaly index , i: months	An indicator to estimate relative dryness and that has been widely adopted in the USA for long-term drought monitoring	Palmer (1965)
Keetch-Byram Drought Index (KBDI)	precipitation, temperature	$dQ = \frac{[800 - Q]\,[0.968 \exp(0.0486T) - 8.30]\,d\tau}{1 + 10.88 \exp(-0.0441R)} \times 10^{-3}$ Q: Moisture deficiency , T: Daily maximum temperature , R: Mean annual precipitation, dr: Time increment	An indicator of soil moisture deficit because it is directly related to drought stress on crops	Keetch and Byram (1968)
Precipitation or Percent of Normal Precipitation	precipitation		A simple indicator used all over the world / An indicator that uses simple calculation to identifying various impacts of droughts	
Standardized Precipitation Index (SPI-n)	precipitation	It uses monthly precipitation aggregates at various time scales. For a 3-month time scale, the precipitation accumulation from month j − 2 to month j is summed and attributed to month j. Next follows the normalization procedure, in which an appropriate probability density function is first fitted to the long-term time series of aggregated precipitation. Then the fitted function is used to calculate the cumulative distribution of the data points, which are finally transformed into standardized normal variates.	A statistical indicator that is used to identify a precipitation shortage by comparing the total precipitation received at a particular location during a period of n months with the long-term rainfall distribution for the same period of time	McKee et al (1993)
Standardised Precipitation-Evapotranspiration Index (SPEI)	precipitation, potential evapotranspiration	The Standardized Precipitation Evapotranspiration Index (SPEI) is an extension of the widely used Standardized Precipitation Index (SPI). The SPEI is designed to take into account both precipitation and potential evapotranspiration (PET) in determining drought.	An indicator for determining the onset, duration and magnitude of drought conditions based on climatic data to identify the impact of increased temperatures on water demand and is an extension of SPI	Vincente-Serrano et al. (2010)
Surface Water Supply Index (SWSI)	reservoir storage, streamflow, snowpack, precipitation	The index is calculated by combining pre-runoff reservoir storage (carryover) with forecasts of spring and summer streamflow which are based on current snowpack and other hydrologic variables.	An indicator calculated at the basin level used for water supply forecasting and is an extension of PDSI since it adds additional information including water supply data	Shafer and Dezman (1982)
Bhalme and Mooley Drought Index (BMDI)	precipitation	$I_k = 0.50I_{k-1} + (M_k/48.55)$ I: Drought intensity , M: moisture anomaly index , k: current month	An indicator that requires only precipitation data and it may be considered as a simplified version of PDSI	Bhalme and Mooley (1980)

2. Existing drought indicators (index)

B. Drought index (developed)

Drought

$$\begin{aligned}&\boldsymbol{Agricultural\ Drought\ Vulnerabilty\ Index}\\&= [(1 - PDSI) \times (1 - TWI) \times (Agriculture\ value\ added) \times (Drainage\ class\ (high))]\\&\div [(Dam\ storage\ capacity) \times (Improved\ water\ source)\\&\times (Land\ designated\ for\ agricultural\ promotion) \times (Agricultural\ water\ location)\\&\times (Budget\ per\ capita) \times (Disaster\ management\ fund)]\end{aligned}$$

Description

This index is developed to see the potential impact of drought on agriculture by its value, water source, local governments' financial commitment to disaster management, including the meaning of meteorological drought.

2. Existing drought indicators (index)

C. Availability of indicators

Drought

Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Exposure	Annual precipitation (mm)	O	O	Choi et al. (2009) Jung et al. (2010)
	Palmer Drought Severity Index (PDSI)	O	O	Sivakumar et al. (2010)
	Standardized Precipitation Index (SPI)	O	O	Łabędzki and Bąk (2014)
Sensitivity	Population density	O	O	Oh et al. (2012) Swain and Swain (2011)
	Cultivated area	O	O	Kim et al. (2013) Jang (2006)
	Topographic Wetness Index (TWI)	O	O	Muukkonen et al. (2015) Zhang et al. (2011)
	Drainage class	O	X	Quiring and Ganesh (2010)
	Agricultural value added/GDP (%)	O	O	Iglesias et al. (2009)

2. Existing drought indicators (index)

C. Availability of indicators

Drought

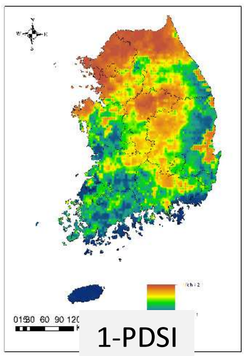
Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Adaptive Capacity	GDP per capita	O	O	Cheng and Tao (2010) Wu et al. (2013)
	Population with access to improved water (% of total)	△	O	Iglesias et al. (2009)
	Available reservoir storage of farm dams	O	△	Oh et al. (2012)
	Number of reservoirs	O	O	Cancelliere et al. (1998).
	Agricultural water location	O	△	Yi et al. (2004)
	Disaster management fund	O	X	Kim (2010) Park (2008) Lee et al. (2017)
	Land designated for agricultural promotion	O	X	Park (2006)
	Annual budget per capita	O	O	This study

2. Existing drought indicators (index)

D. Indicator maps (1)

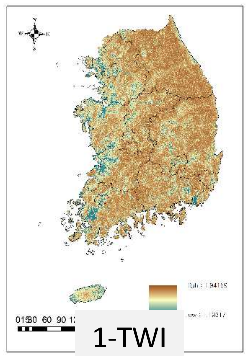
2015 – Observation **Drought**

Exposure

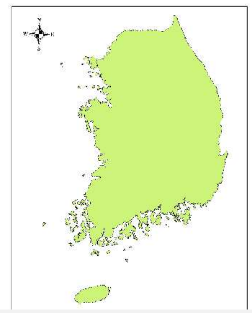


1-PDSI

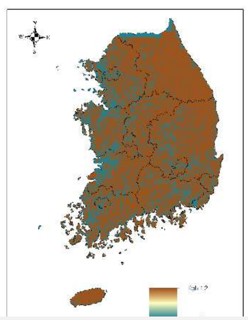
Sensitivity



1-TWI



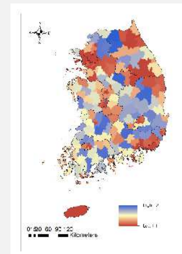
Agriculture value added

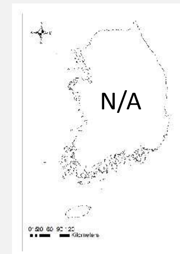


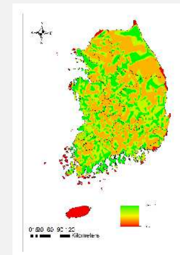
Drainage class (high)

Adaptive Capacity

Improved water source





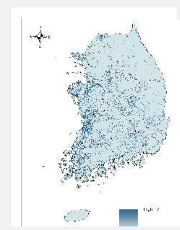


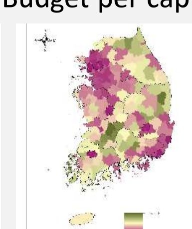
Dam storage capacity

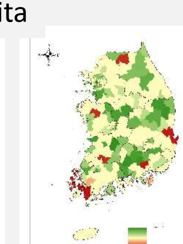
Agricultural water location

→ Infra

Budget per capita







Land designated for agricultural promotion

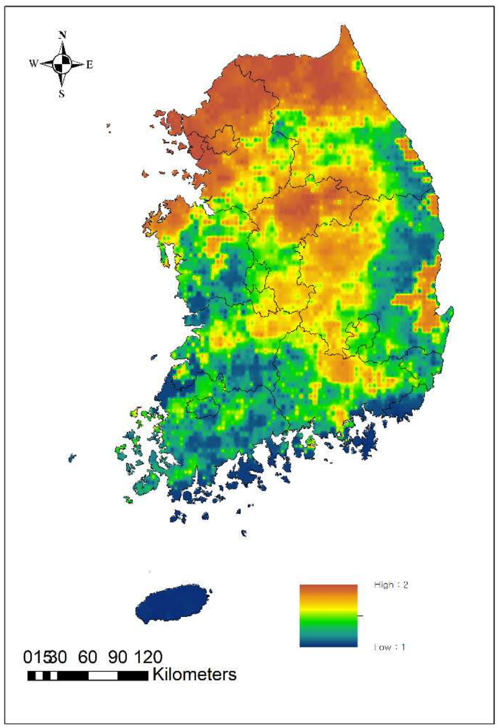
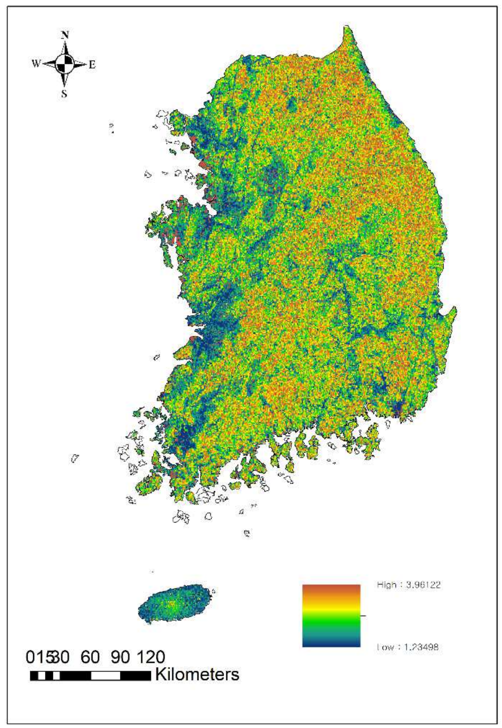
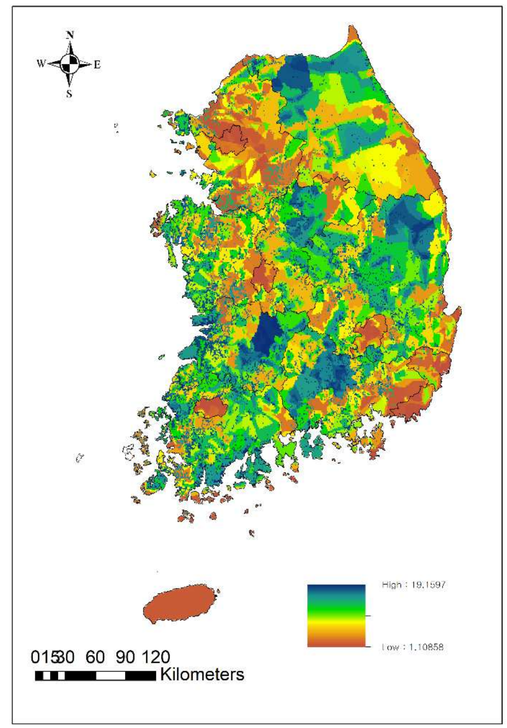
Disaster management fund

→ Inst. & Policies

2. Existing drought indicators (index)

E. Integrated indicator maps (1)

2015 – Observation **Drought**

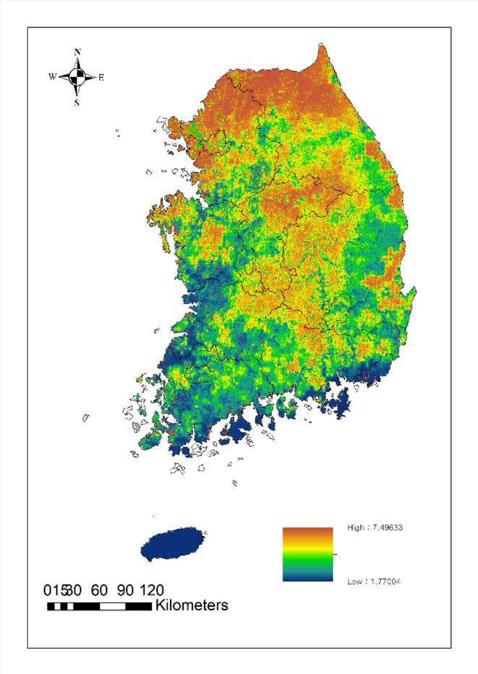
Exposure	Sensitivity	Adaptive Capacity
		

2. Existing drought indicators (index)

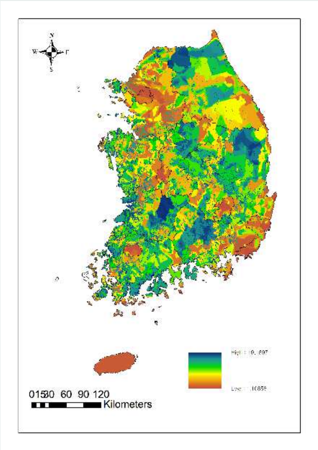
F. Vulnerability map (1)

2015 – Observation
1km*1km

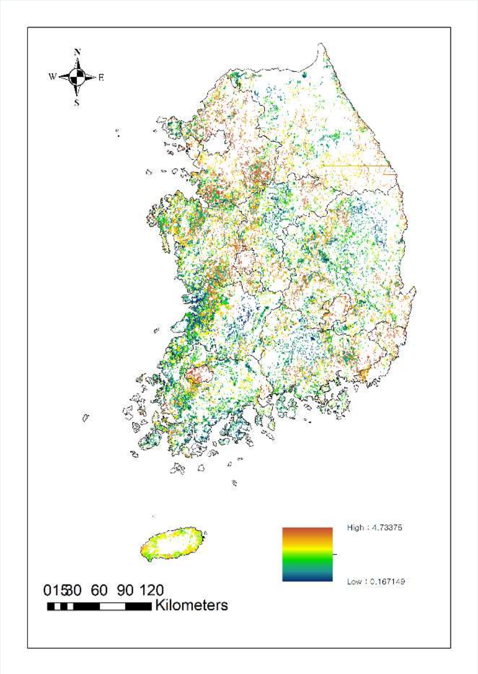
Drought



Exposure*Sensitivity



Adaptive Capacity



Vulnerability

2. Existing drought indicators (index)

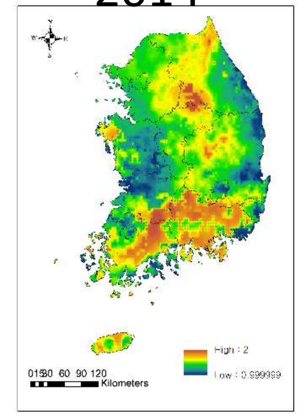
G. Exposure's yearly variability

2014-2018 – Observation

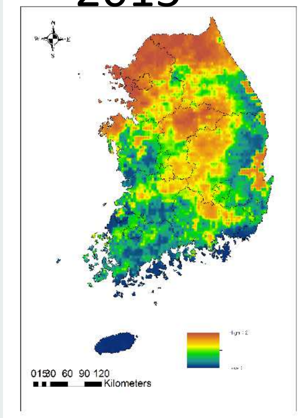
Drought

1-PDSI → Exposure variability by year is 'LARGE'

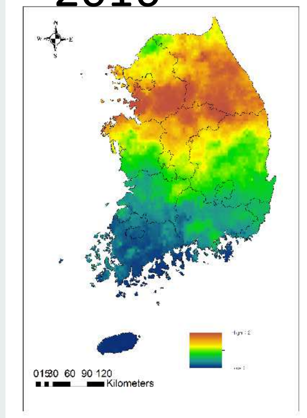
2014



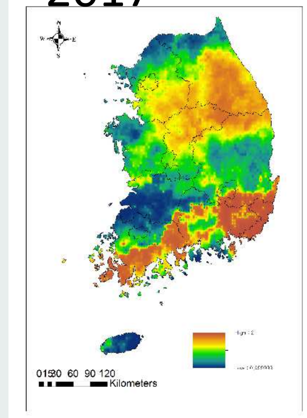
2015



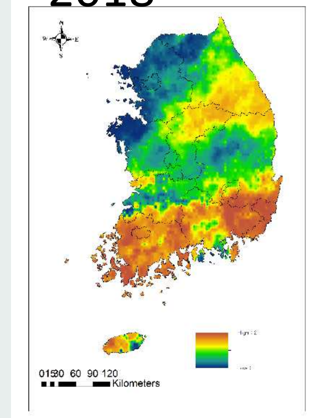
2016



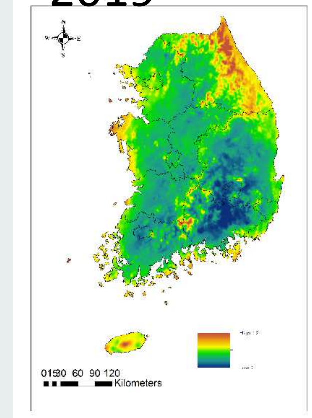
2017



2018



2019

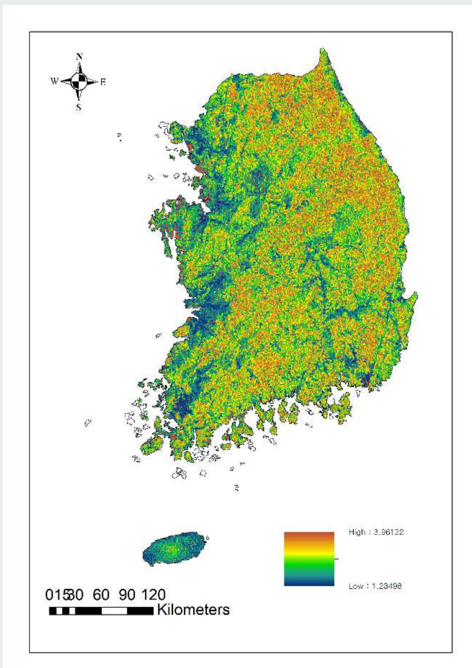


2. Existing drought indicators (index)

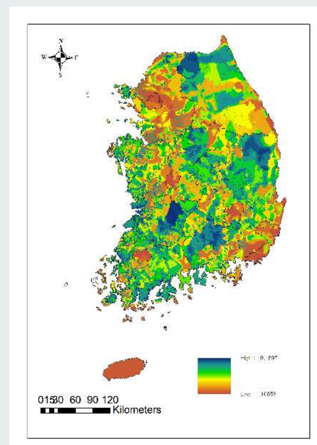
H. Vulnerability map by S and AC

2015 – Observation
1km*1km

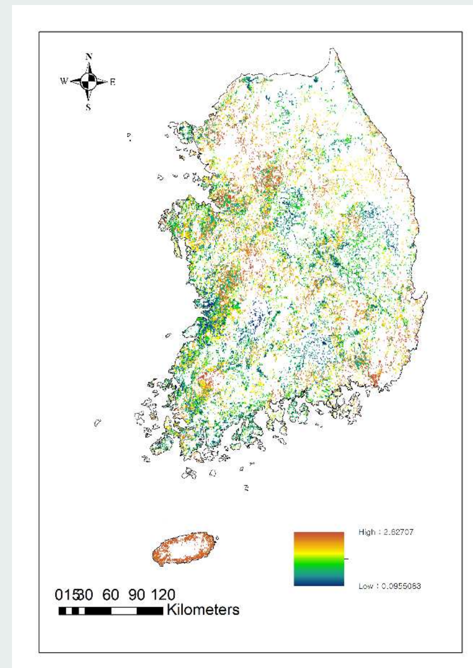
Drought



Sensitivity



Adaptive Capacity



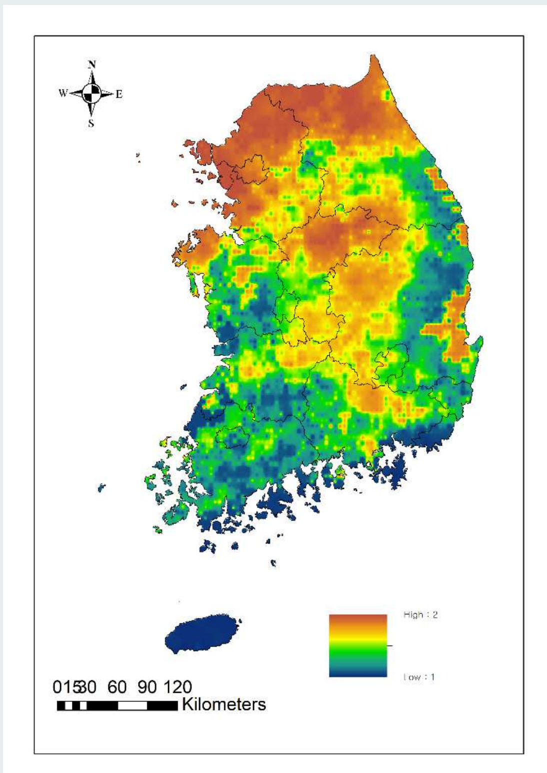
Vulnerability

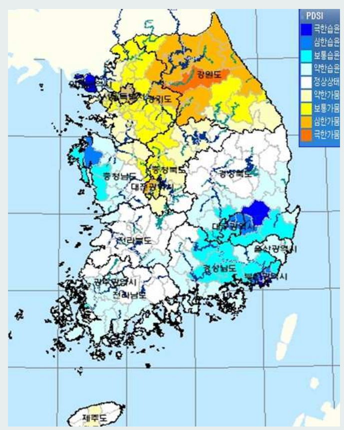
2. Existing drought indicators (index)

I. Comparison

2015 – Observation **Drought**

(1-PDSI) of 2015





↑ 2014 accumulated precipitation

Average: 700 mm,
50% of precipitation compared to the year before,
Extreme drought

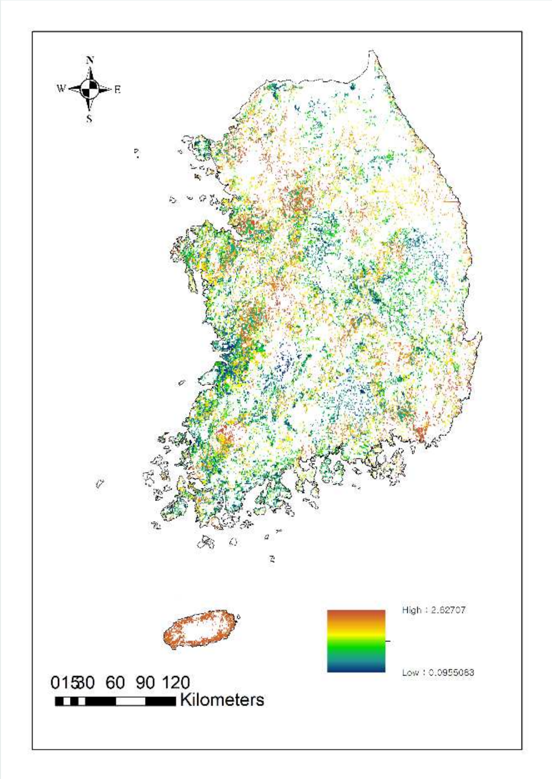
←PDSI of Feb 9, 2015 from K-water

2. Existing drought indicators (index)

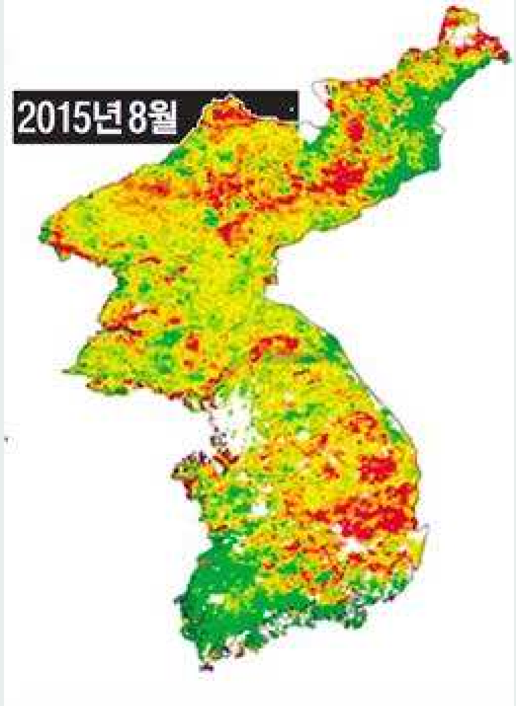
I. Comparison

2015 – Observation **Drought**

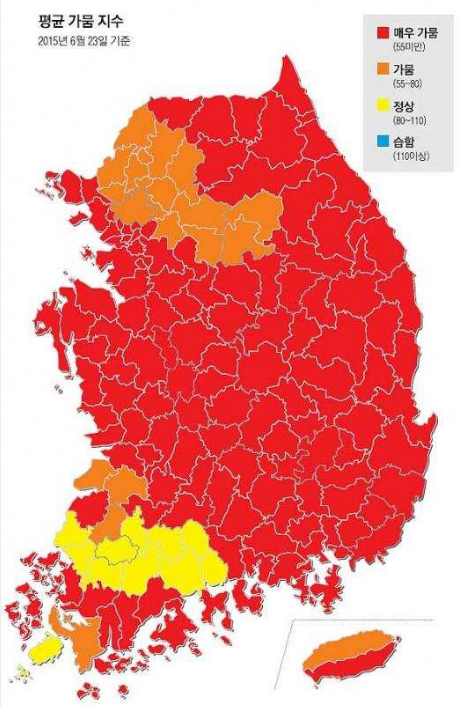
Vulnerability of 2015



Drought of Aug, 2015 from RS (Choi et al.)



Average drought index of June 23, 2015 from Ministry of Public Safety and Security



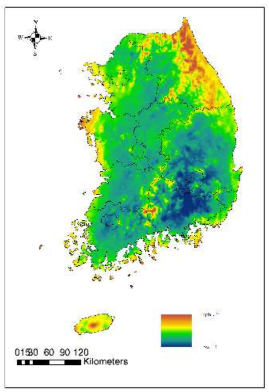
2. Existing drought indicators (index)

D. Indicator maps (2)

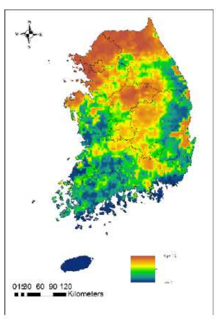
2019 – **Prediction**

Drought

Exposure

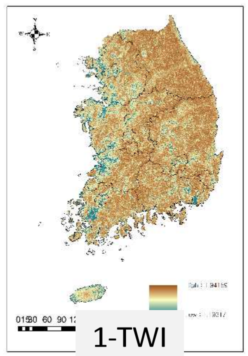


1-PDSI
(2019)

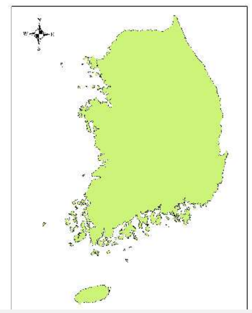


1-PDSI
(2015)

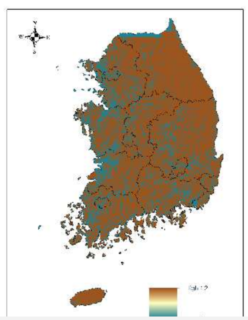
Sensitivity



1-TWI



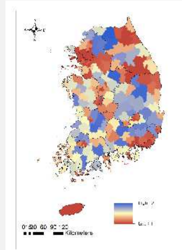
Agriculture value added

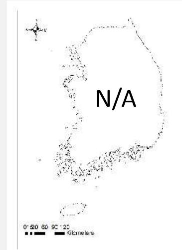


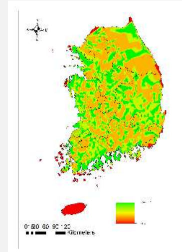
Drainage class (high)

Adaptive Capacity

Improved water source





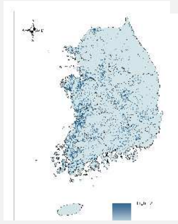


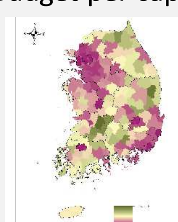
Dam storage capacity

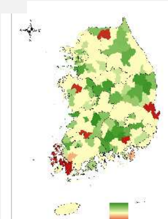
Agricultural water location

→ Infra

Budget per capita







Land designated for agricultural promotion

Disaster management fund

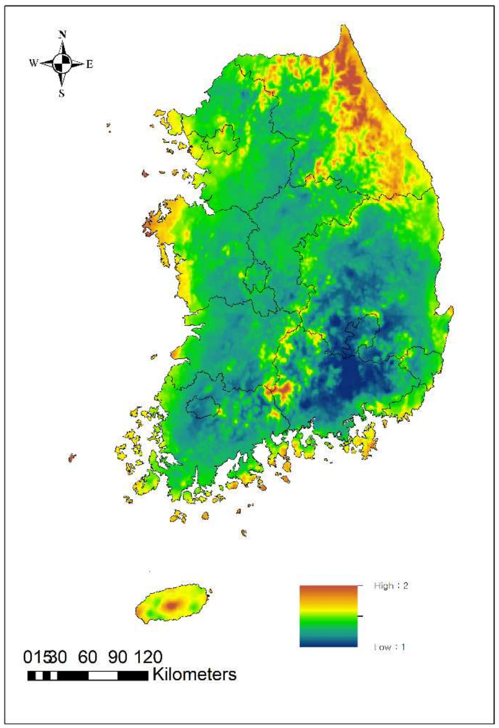
→ Inst. & Policies

2. Existing drought indicators (index)

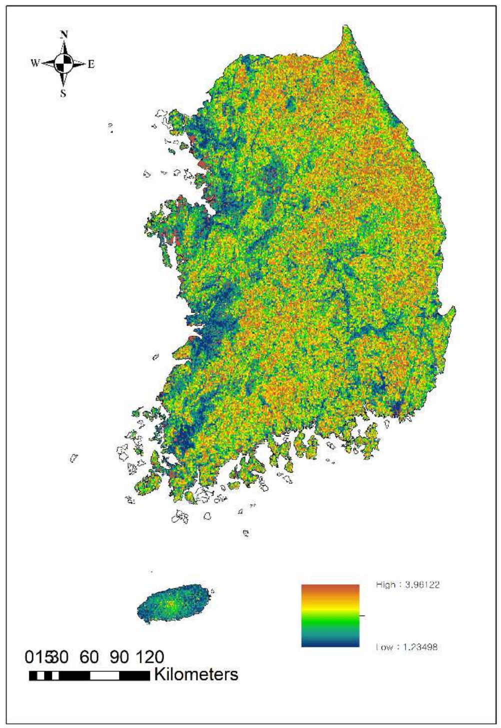
E. Integrated indicator maps (2)

2019 – Prediction **Drought**

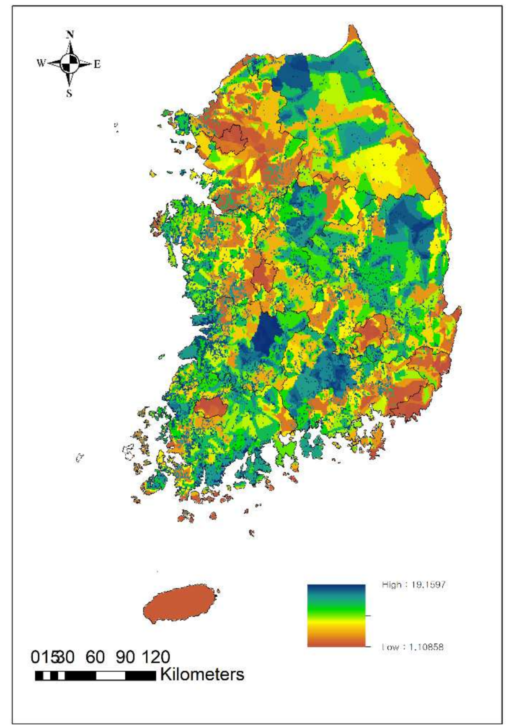
Exposure



Sensitivity



Adaptive Capacity

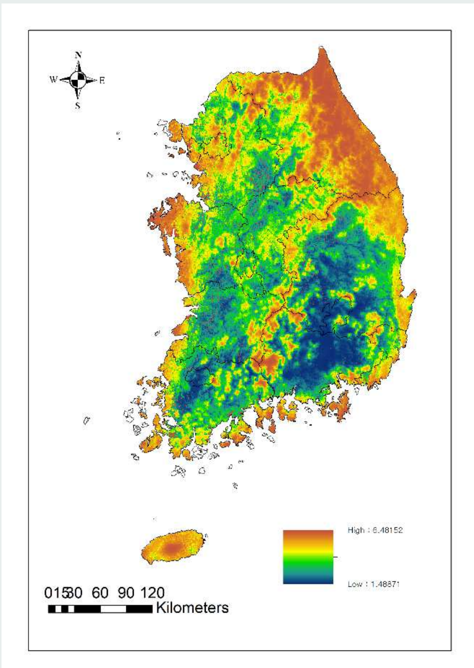


2. Existing drought indicators (index)

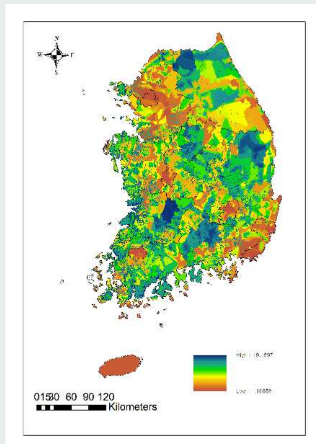
F. Vulnerability map (2)

2019 – Prediction
1km*1km

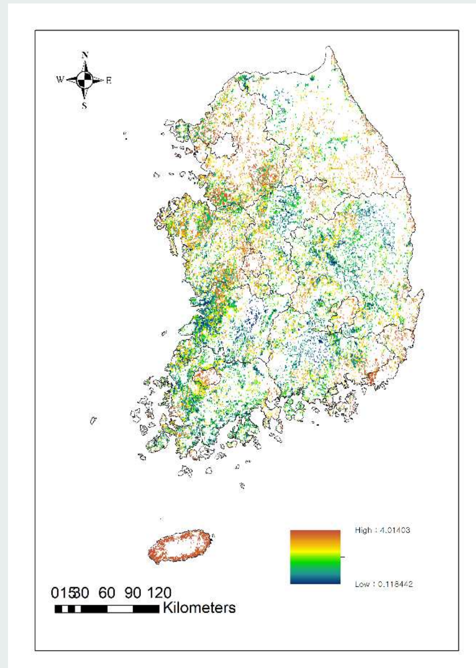
Drought



Exposure*Sensitivity

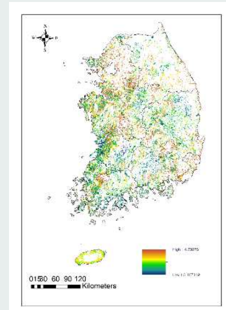


Adaptive Capacity



Vulnerability

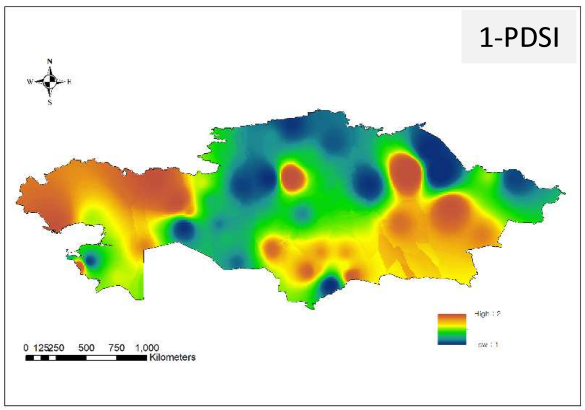
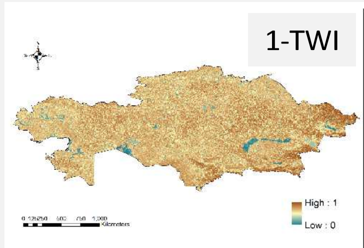
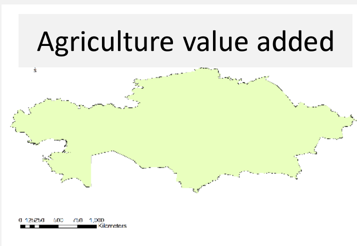
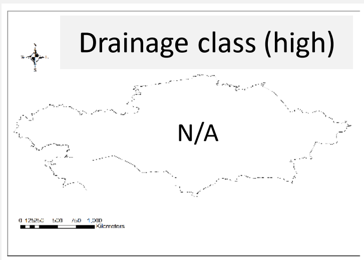
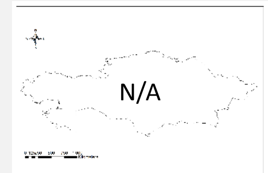
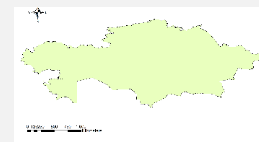
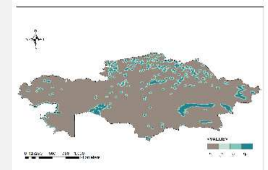
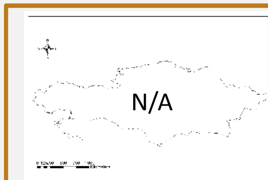
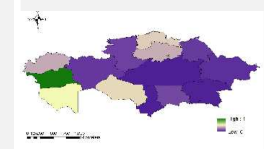
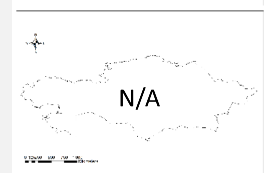
2015



2. Existing drought indicators (index)

D. Indicator Maps (3)

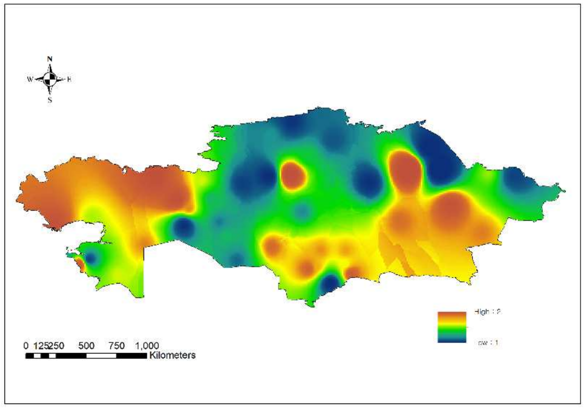
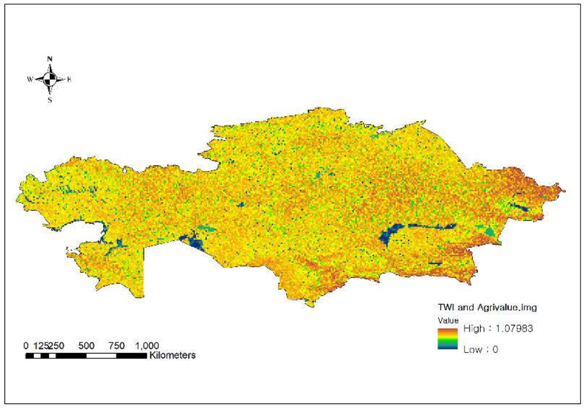
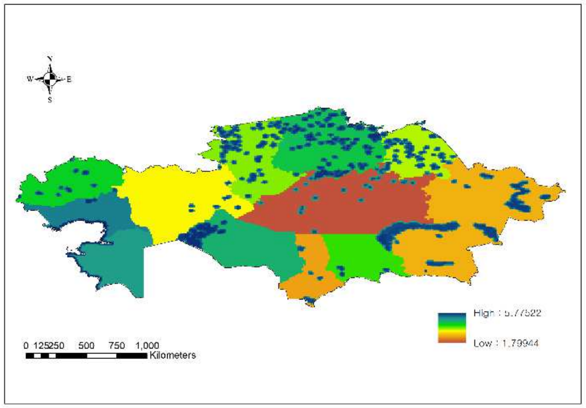
2015 – Observation **Drought**

Exposure	Sensitivity	Adaptive Capacity
	  	← Dam storage capacity  Improved water source   ← Agricultural water location (all lakes and reservoirs) → Infra ← Land designated for agricultural promotion  Budget per capita   ← Disaster management fund → Inst. & Policies

2. Existing drought indicators (index)

E. Integrated indicator maps (3)

2015 – Observation | **Drought**

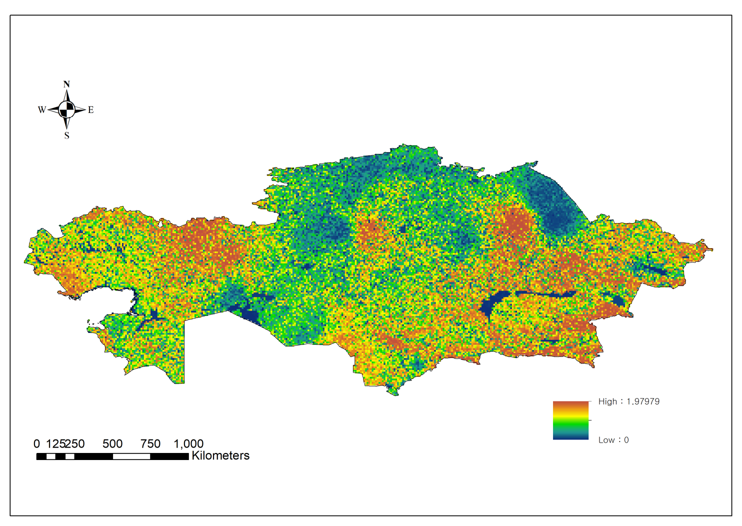
Exposure	Sensitivity	Adaptive Capacity
		

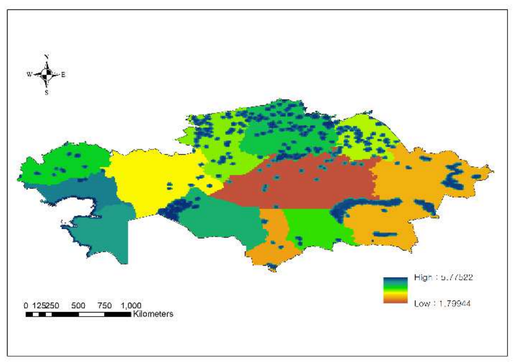
2. Existing drought indicators (index)

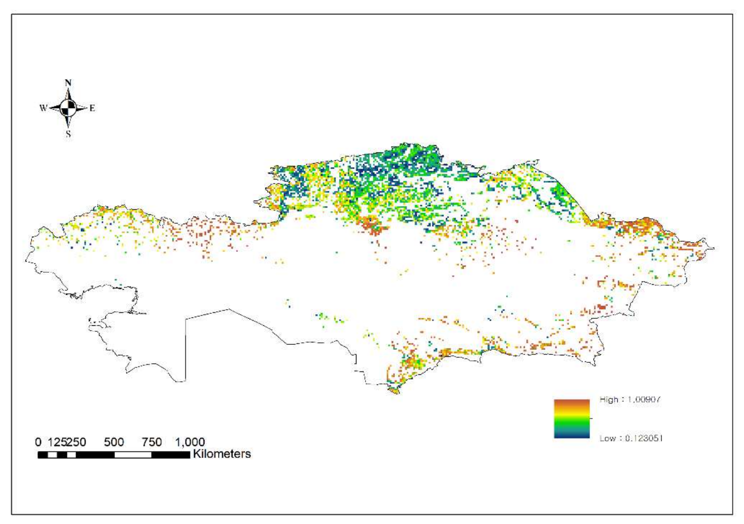
F. Vulnerability map (3)

2015 – Observation
10km*10km

Drought







(Agricultural area)

Exposure*Sensitivity

Adaptive Capacity

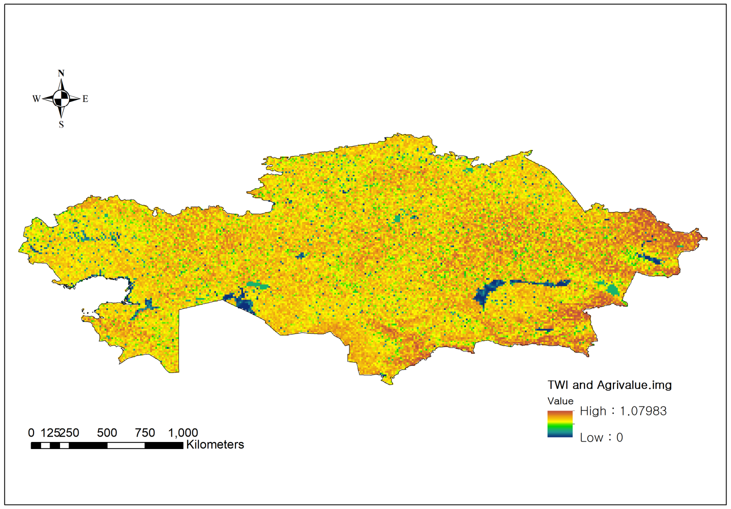
Vulnerability

2. Existing drought indicators (index)

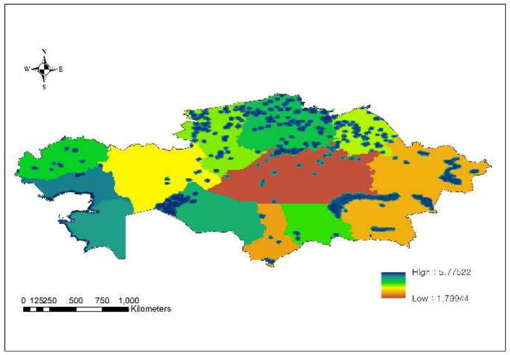
H. Vulnerability map by S & AC (3)

2015 – Observation
10km*10km

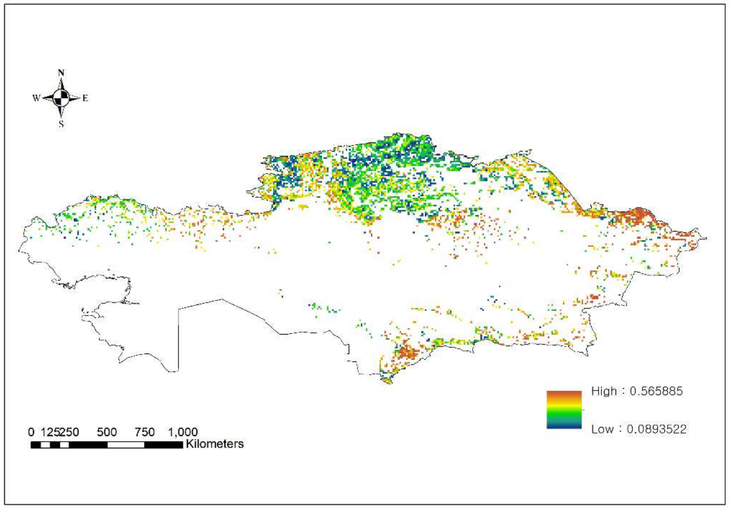
Drought



Sensitivity



Adaptive Capacity



(Agricultural area)

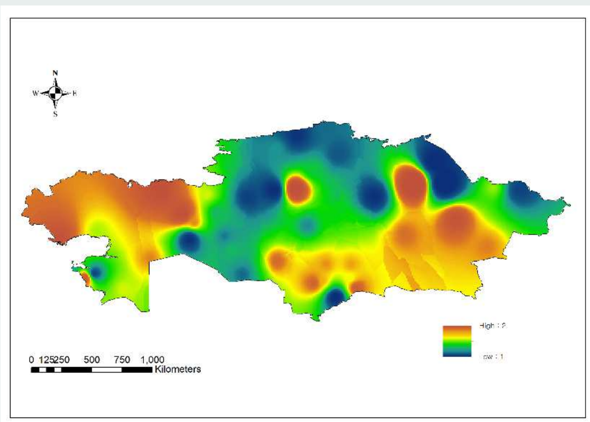
Vulnerability

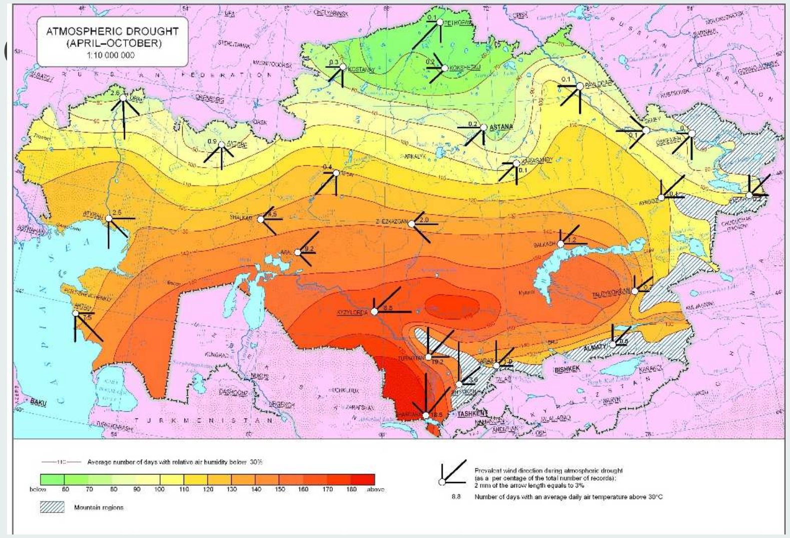
2. Existing drought indi

H. Comparison

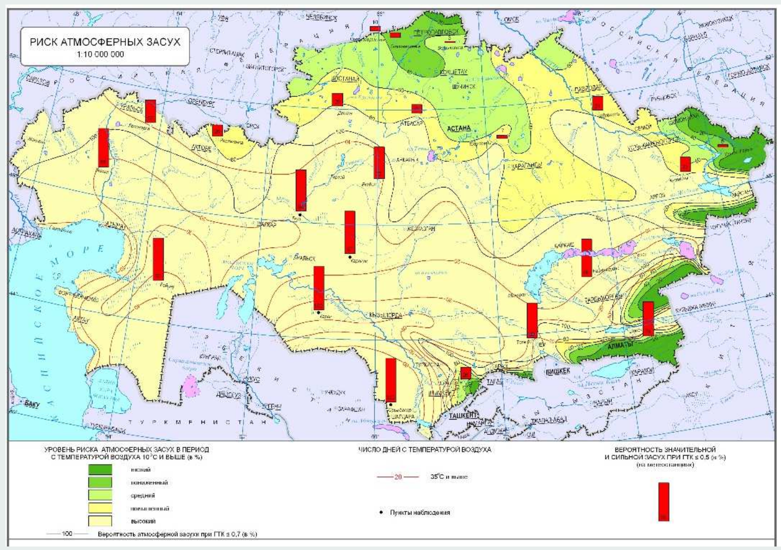
Drought

(1-PDSI) of 2015





Atmospheric drought
- Mainly from air humidity below 30%
- Average year



The risk of atmospheric drought from hydrothermal index
- (red bar) Probability of drought from hydrothermal index
- Average year

3. Decision supporting tool

Question (4)

How can we develop a user friendly decision supporting tool, which can use statistics data and geospatial data for drought monitoring and early warning?

3. Decision supporting tool

A. Concept

Criteria for Vulnerability Index	Sector for Adaptive Measures	Indicator for Adaptive Measures
Exposure (extreme climate) (non-controllable)		
Sensitivity (hard to control)	Environmental	Geospatial
Adaptive capacity (controllable)	Socio-economic	Statistical

Technology and Policy for CC/DRR/SDGs

Technology

GIS & RS

Infrastructure

Institution and Policy

3. Decision supporting tool

B. Adaptive Pathways

- To support decision-makers and take actions to reduce vulnerability/risk that is assessed by previous research steps, developing adaptive pathways is necessary.
- Vulnerability maps are classified into three phases through an optimization method called ‘natural breaks (Jenks)’:
  - High vulnerability (HV)
  - Medium vulnerability (MV)
  - Low vulnerability (LV)
- The Adaptive Pathways are developed towards DRR:
  - Risky Pathway (Level 0): Taking no action at all
  - Passive Pathway (Level 1): HV → MV
  - Active Pathway (Level 2): HV → MV & MV → LV
  - Full Pathway (Level 3): HV → LV & MV → LV

3. Decision supporting tool

B. Adaptive Pathways

Risky Pathway Level 0	Passive Pathway Level 1	Active Pathway Level 2	Full Pathway Level 3
Taking no action al all	High vulnerability ⇩ Medium vulnerability	High vulnerability ⇩ Medium vulnerability & Medium vulnerability ⇩ Low vulnerability	High vulnerability ⇩ Low vulnerability & Medium vulnerability ⇩ Low vulnerability

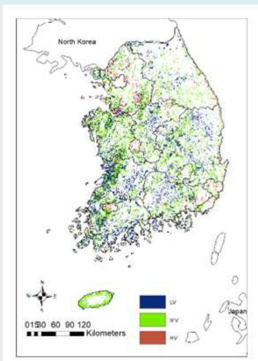
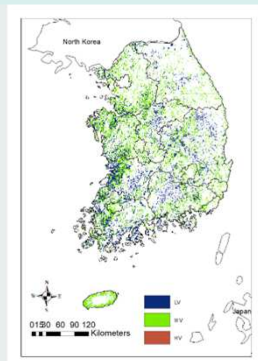
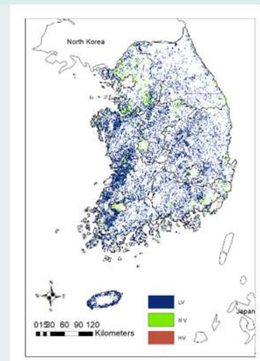
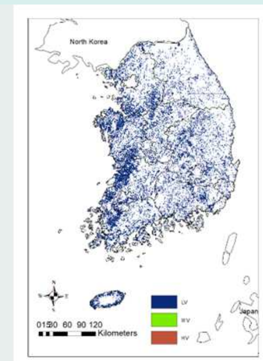
3. Decision supporting tool

Example of South Korea

B. Adaptive Pathways

Drought

Agricultural Drought Vulnerability Index

Risky Pathway (no action)	Passive Pathway (HV→MV)	Active Pathway (HV→MV, MV→LV)	Full Pathway (HV→LV, MV→LV)
			

Class	Risky Pathway		Passive Pathway		Active Pathway		Full Pathway	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
LV	9,782	40.5	9,782	40.5	22,159	91.8	24,132	100
MV	12,377	51.3	14,350	59.5	1,973	8.2	0	0
HV	1,973	8.2	0	0	0	0	0	0
Sum	**24,132**	**100**	**24,132**	**100**	**24,132**	**100**	**24,132**	**100**

3. Decision supporting tool

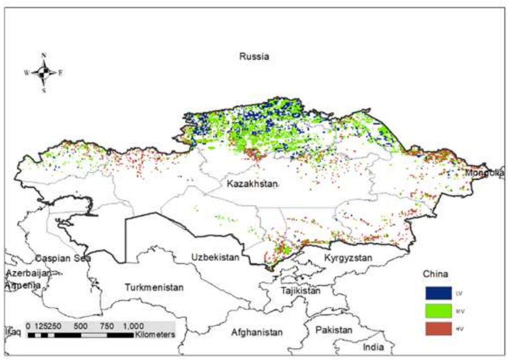
Example of Kazakhstan

B. Adaptive Pathways

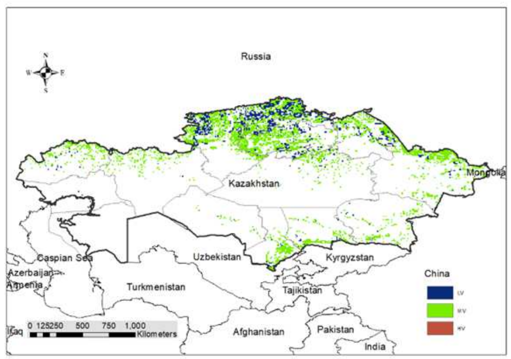
Drought

Agricultural Drought Vulnerability Index

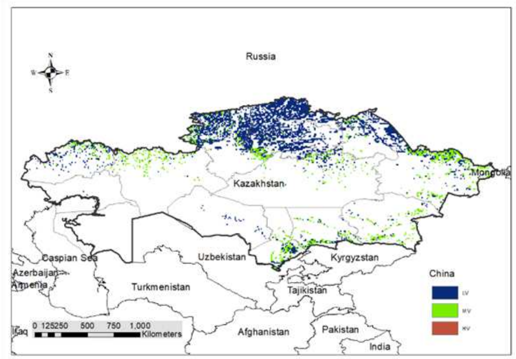
Risky Pathway
(no action)



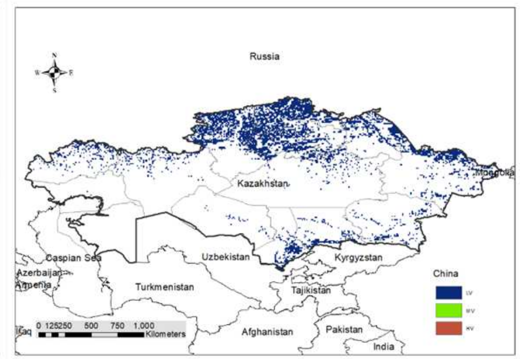
Passive Pathway
(HV→MV)



Active Pathway
(HV→MV, MV→LV)



Full Pathway
(HV→LV, MV→LV)



Class	Risky Pathway		Passive Pathway		Active Pathway		Full Pathway	
	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
LV	107,800	21.2	107,800	22.2	353,000	72.7	485,300	100
MV	245,200	50.5	377,500	77.8	132,300	27.3	0	0
HV	132,300	27.3	0	0	0	0	0	0
Sum	**485,300**	**100**	**485,300**	**100**	**485,300**	**100**	**485,300**	**100**

4. Repository for spatial data

Question (6)

How to develop a repository for spatial data in a pilot country?

4. Repository for spatial data

A. Availability of indicators

Drought

Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Exposure	Annual precipitation (mm)	O	O	Choi et al. (2009) Jung et al. (2010)
	Palmer Drought Severity Index (PDSI)	O	O	Sivakumar et al. (2010)
	Standardized Precipitation Index (SPI)	O	O	Łabędzki and Bąk (2014)
Sensitivity	Population density	O	O	Oh et al. (2012) Swain and Swain (2011)
	Cultivated area	O	O	Kim et al. (2013) Jang (2006)
	Topographic Wetness Index (TWI)	O	O	Muukkonen et al. (2015) Zhang et al. (2011)
	Drainage class	O	X	Quiring and Ganesh (2010)
	Agricultural value added/GDP (%)	O	O	Iglesias et al. (2009)

4. Repository for spatial data

A. Literature review and available indicators

Drought

Category	Indicator	Availability		Reference
		South Korea	Kazakhstan	
Adaptive Capacity	GDP per capita	O	O	Cheng and Tao (2010) Wu et al. (2013)
	Population with access to improved water (% of total)	△	O	Iglesias et al. (2009)
	Available reservoir storage of farm dams	O	△	Oh et al. (2012)
	Number of reservoirs	O	O	Cancelliere et al. (1998).
	Agricultural water location	O	△	Yi et al. (2004)
	Disaster management fund	O	X	Kim (2010) Park (2008) Lee et al. (2017)
	Land designated for agricultural promotion	O	X	Park (2006)
	Annual budget per capita	O	O	This study

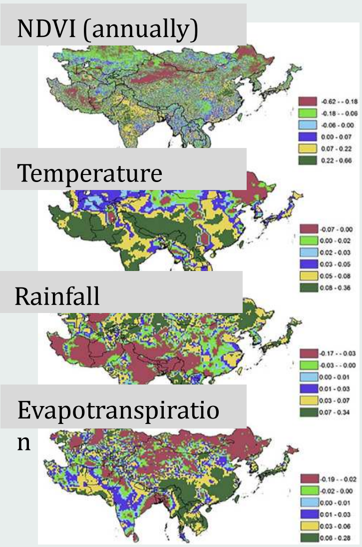
5. Satellite derived vegetation indices

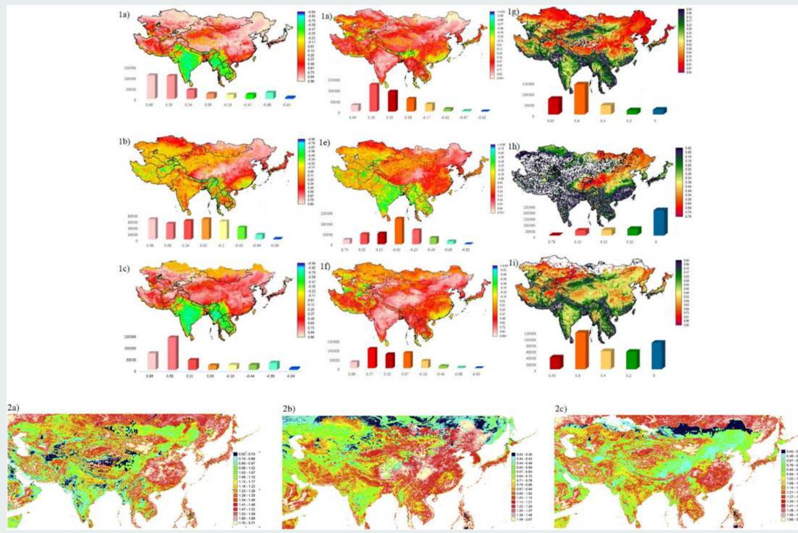
Question (1)

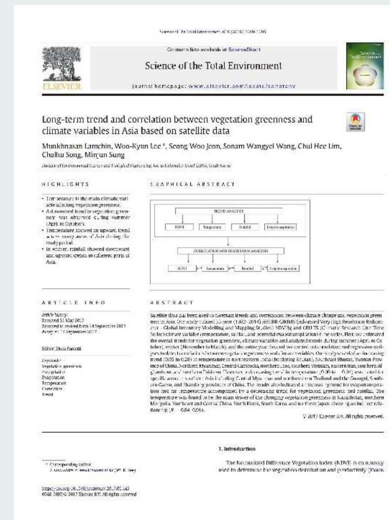
What is your view on assessing satellite derived vegetation indices to apply in a pilot country in Central Asia?

5. Satellite derived vegetation indices

- Case 1: Long-term trend and correlation between vegetation greenness and climate variables in Asia based on satellite data






Science of the Total Environment

Long-term trend and correlation between vegetation greenness and climate variables in Asia based on satellite data

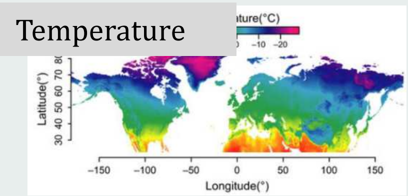
→ An increasing trend for evapotranspiration and air temperature accompanied by a decreasing trend for vegetation greenness and rainfall

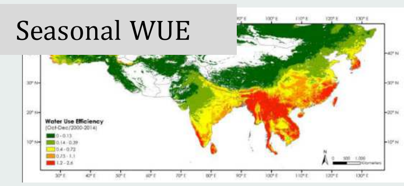
→ The vegetation greenness and temperature shows indirect relationship in Kazakhstan, northern Mongolia, Northeast and Central China, North Korea, South Korea, and northern Japan (R=0.84-0.96)

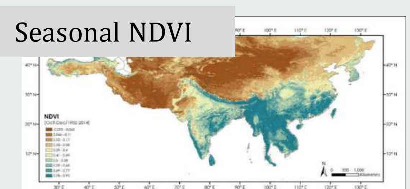
Lamchin, M., Lee, W. K., Jeon, S. W., Wang, S. W., Lim, C. H., Song, C., & Sung, M. (2018). Long-term trend and correlation between vegetation greenness and climate variables in Asia based on satellite data. Science of The Total Environment, 618, 1089-1095

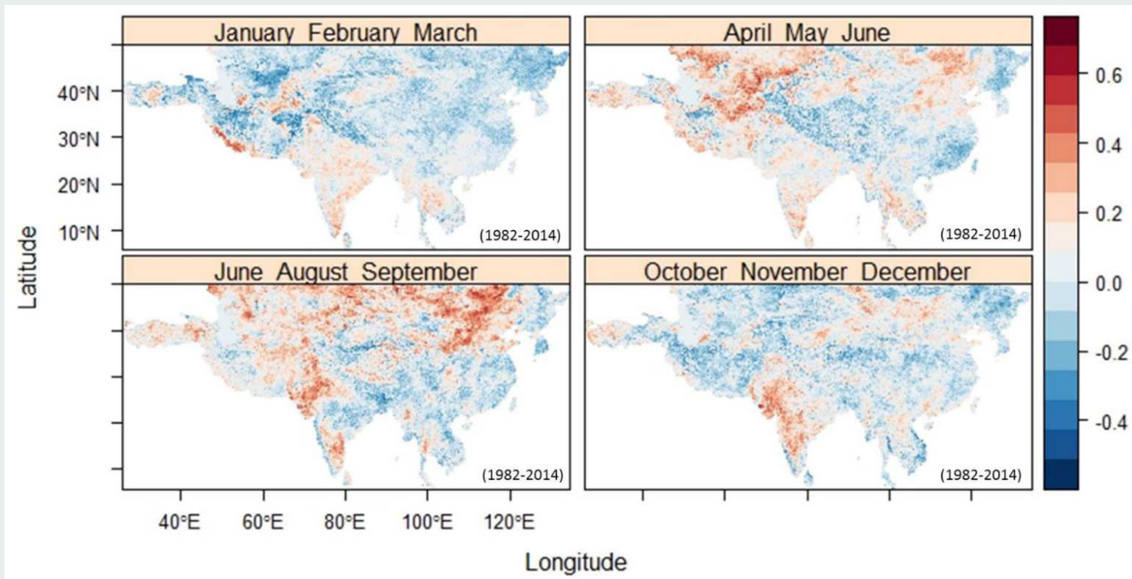
5. Satellite derived vegetation indices

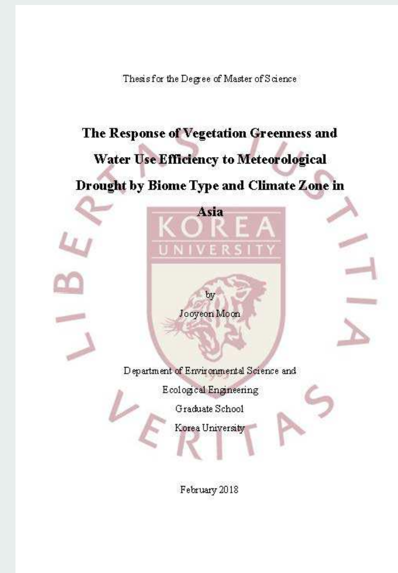
- Case 2: The response of vegetation greenness and water use efficiency to meteorological drought by biome type and climate zone in Asia











Thesis for the Degree of Master of Science

The Response of Vegetation Greenness and Water Use Efficiency to Meteorological Drought by Biome Type and Climate Zone in Asia

by
Jooyeon Moon

Department of Environmental Science and Ecological Engineering
Graduate School
Korea University

February 2018

→ The grassland ecosystems in 28 to 44 latitude zones are most sensitive to precipitation fluctuation which were supported by a strong positive correlation between SPI and NDVI.

Moon, J. (2018). The response of vegetation greenness and water use efficiency to meteorological drought by biome type and climate zone in Asia. Thesis for the degree of master of science , Korea University, Seoul

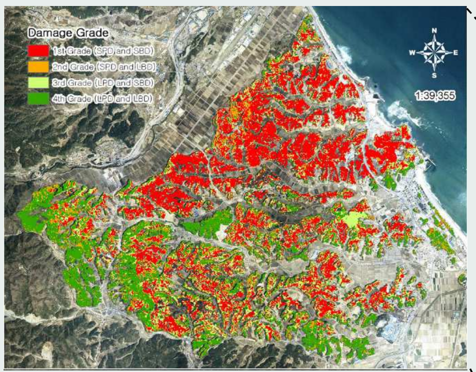
6. Fire susceptibility indices

Question (2)

How can we approach to design a fire susceptibility index for fire risk monitoring?

6. Fire susceptibility indices

- Case 1: Evaluation for Damaged Degree of Vegetation by Forest Fire using LiDAR and a Digital Aerial Photograph



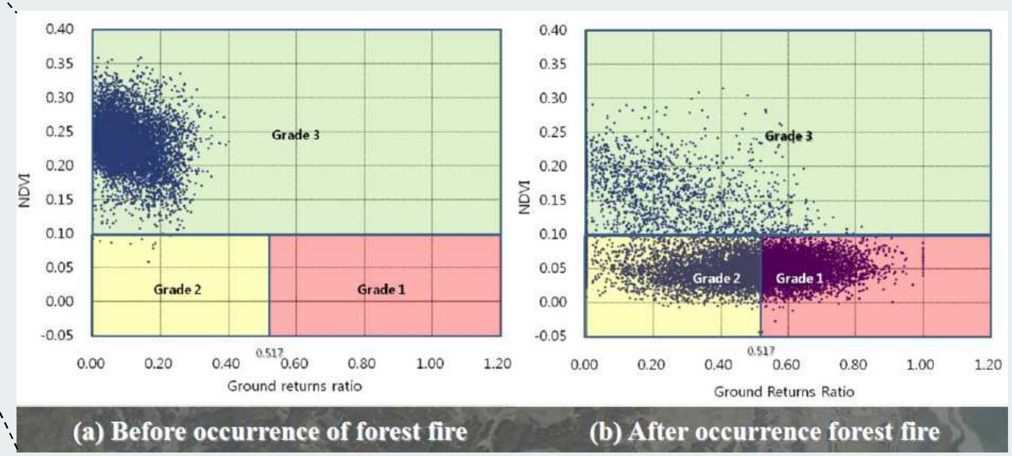
[Grading of area damaged by forest fire]

First grade: High physical damage with high biological damage

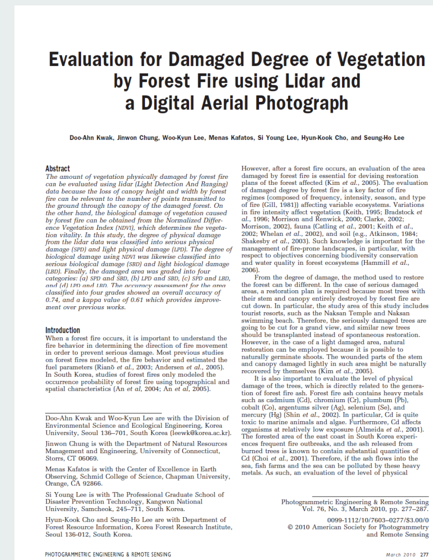
Second grade: High physical damage with low biological damage & low physical damage with high biological damage

Third grade: low physical damage with low biological damage

Before forest fire: Low GRR, High NDVI
After forest fire: High GRR, Low NDVI



Most of the data exist in the third grade area before the forest fire, but the wildfire occurs and the points (GRR and NDVI) move to the second grade and the third grade area from the beginning to the end

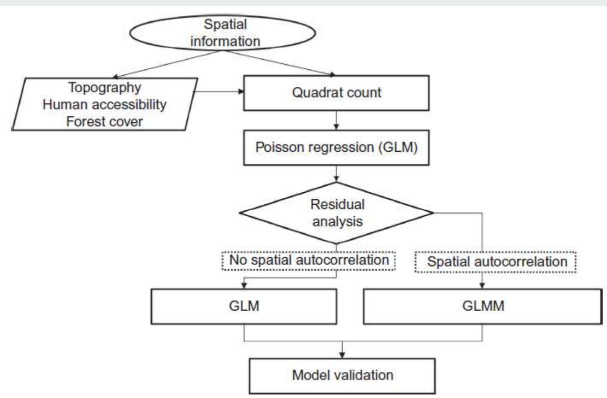


Evaluation for Damaged Degree of Vegetation by Forest Fire using Lidar and a Digital Aerial Photograph

Kwak, D. A., Chung, J., Lee, W. K., Kafatos, M., Lee, S. Y., Cho, H. K., & Lee, S. H. (2010). Evaluation for damaged degree of vegetation by forest fire using Lidar and a digital aerial photograph. Photogrammetric Engineering & Remote Sensing, 76(3): 277-287

6. Fire susceptibility indices

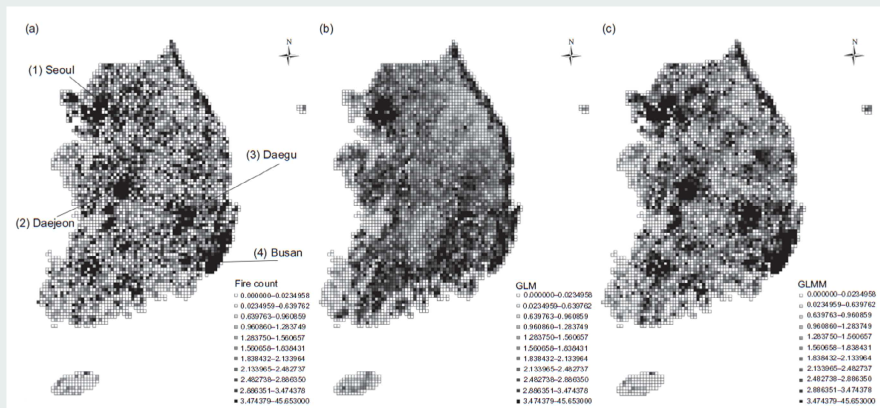
- Case 2: Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea



Observed Fire count

GLM

GLMM



This article was downloaded by: [Korea University]
On: 03 October 2012, At: 18:57
Publisher: Taylor & Francis
Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK

International Journal of Geographical Information Science

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tgis20

Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea

Hanbin Kwak [a] , Woo-Kyun Lee [a] , Joachim Saborowski [b] , Si-Young Lee [c] , Myoung-Soo Won [d] , Kyo-Sang Koo [d] , Myung-Bo Lee [d] & Su-Na Kim [a]

[a] Department of Environmental Science and Ecological Engineering, Korea University, Seoul, Republic of Korea

[b] Chair of Ecoinformatics, Biometrics and Forest Growth and Chair of Ecosystem Modelling, Georg-August-University Göttingen, Göttingen, Germany

[c] Department of Disaster Prevention and Safety Engineering, Kangwon National University, Samcheck-si, Gangwon-do, Republic of Korea

[d] Division of Forest Disaster Management, Korea Forest Research Institute, Seoul, Republic of Korea

Version of record first published: 20 Feb 2012.

To cite this article: Hanbin Kwak, Woo-Kyun Lee, Joachim Saborowski, Si-Young Lee, Myoung-Soo Won, Kyo-Sang Koo, Myung-Bo Lee & Su-Na Kim (2012): Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea, International Journal of Geographical Information Science, 26:9, 1589-1602

To link to this article: http://dx.doi.org/10.1080/13658816.2011.642799

PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: http://www.tandfonline.com/page/terms-and-conditions

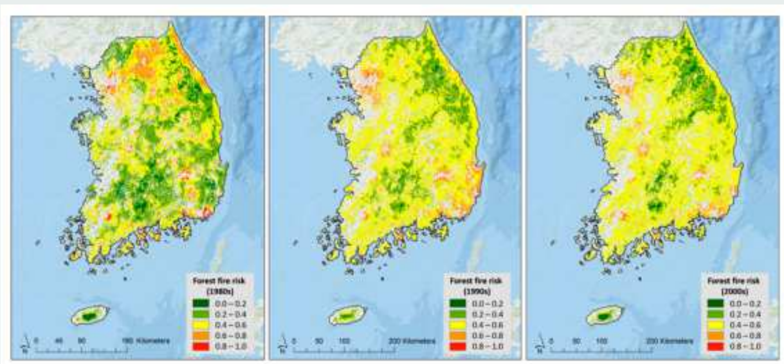
Pearson correlation: 0.4088 → Pearson correlation: 0.6267

→ Spatial autocorrelation improves fire prediction results

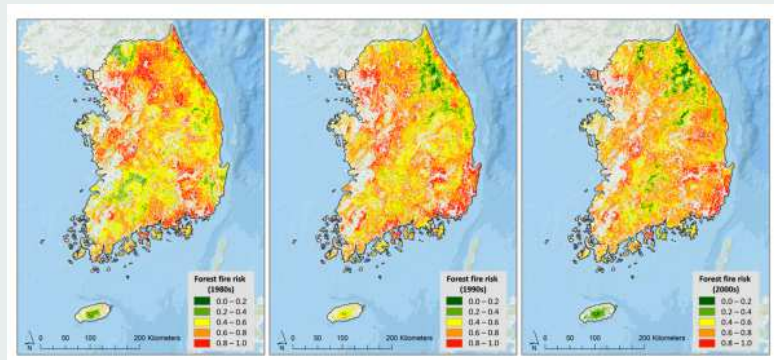
Kwak, H., Lee, W. K., Saborowski, J., Lee, S. Y., Won, M. S., Koo, K. S., ... & Kim, S. N. (2012). Estimating the spatial pattern of human-caused forest fires using a generalized linear mixed model with spatial autocorrelation in South Korea. International Journal of Geographical Information Science, 26(9): 1589-1602

6. Fire susceptibility indices

- Case 3: Multi-Temporal Analysis of Forest Fire Probability Using Socio-Economic and Environmental Variables using Maxent and Random Forest



Forest fire probability during the 1980s, 1990s, 2000s using Maxent analysis



Forest fire probability during the 1980s, 1990s, 2000s using Random Forest analysis

remote sensing

MDPI

Article

Multi-Temporal Analysis of Forest Fire Probability Using Socio-Economic and Environmental Variables

Sea Jin Kim [1,2], Chul-Hee Lim [1,3], Gang Sun Kim [4], Jongyeol Lee [3,5], Tobias Geiger [2], Omid Rahmati [6], Yowhan Son [1] and Woo-Kyun Lee [1,*]

1 Department of Environmental Science and Ecological Engineering, Korea University, Seoul 02841, Korea; bluegulcy@gmail.com (S.J.K.); limpossible@korea.ac.kr (C.-H.L.); yson@korea.ac.kr (Y.S.)
2 Potsdam Institute for Climate Impact Research, 14412 Potsdam, Germany; geiger@pik-potsdam.de
3 Institute of Life Science and Natural Resources, Korea University, Seoul 02841, Korea; dlwhdduf89@korea.ac.kr
4 Department of Land and Water Environment Research, Korea Environment Institute (KEI), Sejong 30147, Korea; gskim@kei.re.kr
5 Center for Climate Technology Cooperation, Green Technology Center, Seoul 04554, Korea
6 Young Researchers and Elites Club, Khorramabad Branch, Islamic Azad University, Khorramabad 6817816645, Iran; orahmati68@gmail.com
* Correspondence: leewk@korea.ac.kr; Tel.: +82-2-3290-3016

Received: 31 October 2018; Accepted: 1 January 2019; Published: 6 January 2019

check for updates

Abstract: As most of the forest fires in South Korea are related to human activity, socio-economic factors are critical in estimating their probability. To estimate and analyze how human activity is influencing forest fire probability, this study considered not only environmental factors such as precipitation, elevation, topographic wetness index, and forest type, but also socio-economic factors such as population density and distance from urban area. The machine learning Maximum Entropy (Maxent) and Random Forest models were used to predict and analyze the spatial distribution of forest fire probability in South Korea. The model performance was evaluated using the receiver operating characteristic (ROC) curve method, and models' outputs were compared based on the area under the ROC curve (AUC). In addition, a multi-temporal analysis was conducted to determine the relationships between forest fire probability and socio-economic or environmental changes from the 1980s to the 2000s. The analysis revealed that the spatial distribution was concentrated in or around cities, and the probability had a strong correlation with variables related to human activity and accessibility over the decades. The AUC values for validation were higher in the Random Forest result compared to the Maxent result throughout the decades. Our findings can be useful for developing preventive measures for forest fire risk reduction considering socio-economic development and environmental conditions.

Keywords: forest fire; probability; disaster risk reduction; Maxent; socio-economic; multi-temporal analysis; spatial analysis

1. Introduction

Analysis of forest fire probability is important in disaster risk reduction (DRR) because it provides means for preventing and managing forest fires. The most direct cause of forest fires that occur in South Korea, where approximately 65% of the land is covered by forest, is human activity [1–3]. Most of these forest fires, caused by human negligence, waste incineration, stubble burning, and discarded cigarettes, are considered to be accidental. While human activity directly causes most forest fires in South Korea, climatic, meteorological and environmental conditions cannot be disregarded, as they contribute to the ignition, combustion, and spread of accidental forest fires [4,5]. According to the Korea Forest

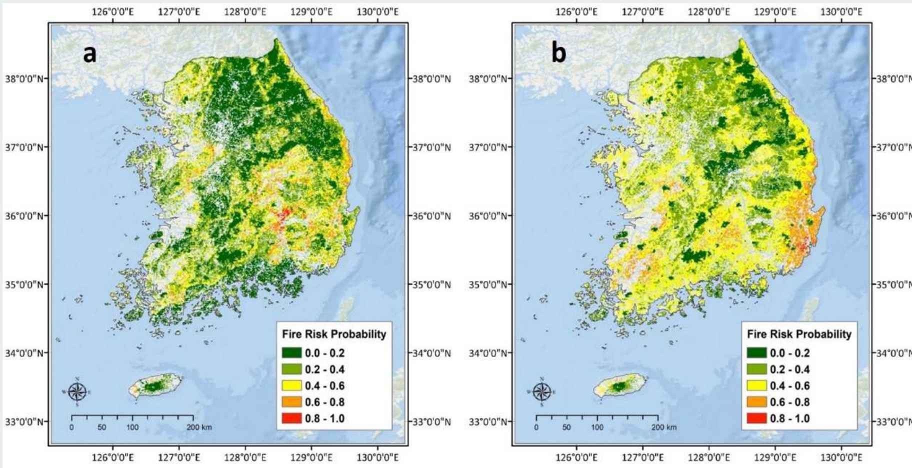
→ Socio-economic variables affect substantially to the occurrence of South Korean forest fire from both Maxent and Random Forest analyses.

→ Regions near cities are prone to forest fire due to the large population.

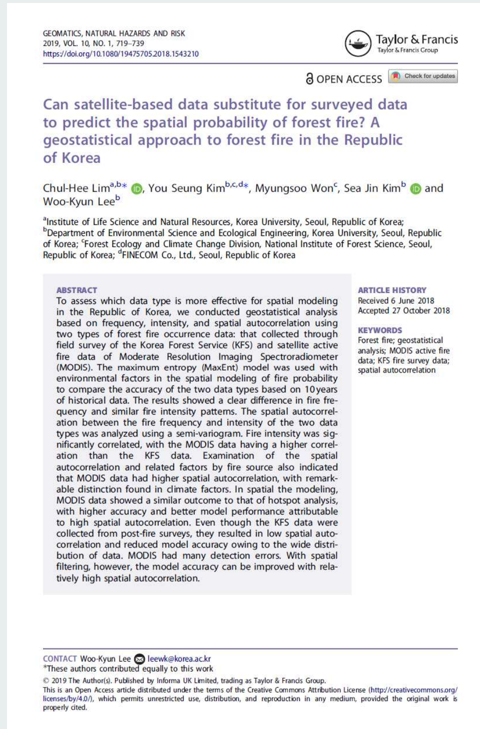
Kim, S., Lim, C. H., Kim, G., Lee, J., Geiger, T., Rahmati, O., ... & Lee, W. K. (2019). Multi-temporal analysis of forest fire probability using socio-economic and environmental variables. Remote Sensing, 11(1), 86.

6. Fire susceptibility indices

- Case 4: Can satellite-based data substitute for surveyed data to predict the spatial probability of forest fire? A geostatistical approach to forest fire in the Republic of Korea



Satellite Data based Results **Ground Data based Results**



GEOMATICS, NATURAL HAZARDS AND RISK
2019, VOL. 10, NO. 1, 719–739
https://doi.org/10.1080/19475705.2018.1543210

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

Can satellite-based data substitute for surveyed data to predict the spatial probability of forest fire? A geostatistical approach to forest fire in the Republic of Korea

Chul-Hee Lim[a,b*], You Seung Kim[b,c,d*], Myungsoo Won[c], Sea Jin Kim[b] and Woo-Kyun Lee[b]

[a]Institute of Life Science and Natural Resources, Korea University, Seoul, Republic of Korea; [b]Department of Environmental Science and Ecological Engineering, Korea University, Seoul, Republic of Korea; [c]Forest Ecology and Climate Change Division, National Institute of Forest Science, Seoul, Republic of Korea; [d]FINECOM Co., Ltd., Seoul, Republic of Korea

ABSTRACT
To assess which data type is more effective for spatial modeling in the Republic of Korea, we conducted geostatistical analysis based on frequency, intensity, and spatial autocorrelation using two types of forest fire occurrence data: that collected through field survey of the Korea Forest Service (KFS) and satellite active fire data of Moderate Resolution Imaging Spectroradiometer (MODIS). The maximum entropy (MaxEnt) model was used with environmental factors in the spatial modeling of fire probability to compare the accuracy of the two data types based on 10 years of historical data. The results showed a clear difference in fire frequency and similar fire intensity patterns. The spatial autocorrelation between the fire frequency and intensity of the two data types was analyzed using a semi-variogram. Fire intensity was significantly correlated, with the MODIS data having a higher correlation than the KFS data. Examination of the spatial autocorrelation and related factors by fire source also indicated that MODIS data had higher spatial autocorrelation, with remarkable distinction found in climate factors. In spatial the modeling, MODIS data showed a similar outcome to that of hotspot analysis, with higher accuracy and better model performance attributable to high spatial autocorrelation. Even though the KFS data were collected from post-fire surveys, they resulted in low spatial autocorrelation and reduced model accuracy owing to the wide distribution of data. MODIS had many detection errors. With spatial filtering, however, the model accuracy can be improved with relatively high spatial autocorrelation.

ARTICLE HISTORY
Received 6 June 2018
Accepted 27 October 2018

KEYWORDS
Forest fire; geostatistical analysis; MODIS active fire data; KFS fire survey data; spatial autocorrelation

CONTACT Woo-Kyun Lee leewk@korea.ac.kr
*These authors contributed equally to this work

→ Satellite-based forest fire occurrence data can substitute for surveyed data to predict the spatial probability using machine learning model.

Lim, C. H., Kim, Y. S., Won, M., Kim, S. J., & Lee, W. K. (2018). Can satellite-based data substitute for surveyed data to predict the spatial probability of forest fire? A geostatistical approach to forest fire in the Republic of Korea. Geomatics, Natural Hazards and Risk.

7. Suggestions

7. Suggestions

A. Limitation

- Two year project - too short.
  - The approach on developing disaster-related geo-statistical indices are developed.
- Demand and interest from the member States are high enough.
- Securing data from member States is critical for future projects.

7. Suggestions

B. Future cooperative events

- Asia Resilience Center (ARC) Conference
  - Special Symposia: Interoperable Pathway for Achieving Water-Food-Ecosystem Security and Climate Change Adaptation in Mid-Latitude Region
  - Oct. / Nov. 2019: Asia Resilience Center Conference Scheduled

http://arc.ojeri.org/

7. Suggestions

B. Future cooperative events

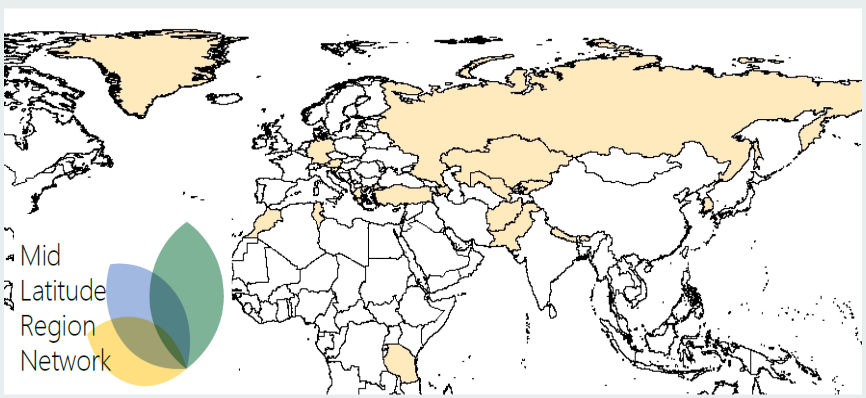
- Asian Conference on Remote Sensing 2019
  - Oct. 13, 2019. (Sun) – Oct. 18, 2019. (Fri)
  - Daejeon Convention Center, Daejeon City, Korea

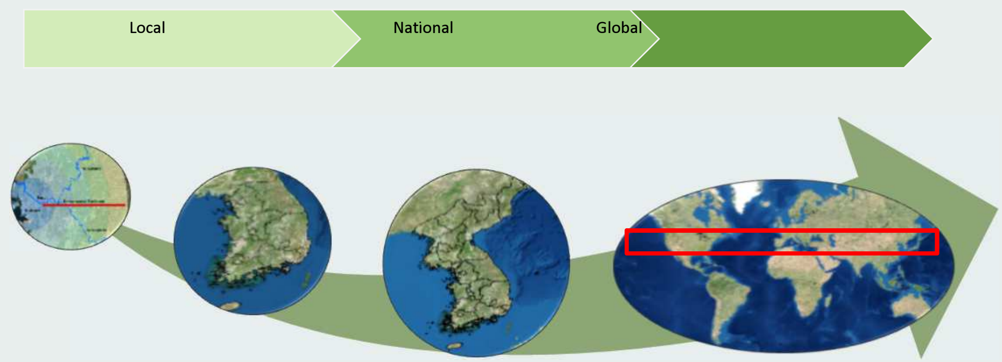
7. Suggestions

B. Future cooperative events

- Initiative on Mid-Latitude Region Network (MLRN)
  - Water-Food-Ecosystem resilience under the SDGs framework in the region
  - Expert Group Meeting (EGM) since 2014
  - 40 members across 18 countries*

* Afghanistan, Austria, Azerbaijan, Bhutan, Germany, Greece, Kazakhstan, Kyrgyzstan, Morocco, Nepal, Pakistan, Russia, Slovenia, South Korea, Tunisia, Turkey, Tanzania, Uzbekistan





http://mlrnetwork.org

Thank You

Prof. Woo-Kyun Lee
leewk@korea.ac.kr

Research Staffs: Sea Jin Kim, Soo Jeong Lee, Jiwon Kim,
Eunbeen Park, Sugyeong Park, Altynay Shaimerdenova