Master's Thesis of Landscape Architecture

Study of Deforestation in North Korea Using Google Earth Engine

Google Earth Engine을 이용한 북한의 산림 황폐화 연구

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Abstract

Deforestation destroys forest ecosystems and reduces the functions of forests, such as reducing water storage and supply and air pollution. The degradation of forests due to deforestation harms climate change response and air quality. North Korea is one of the world's three deforested areas, and according to the research results of the National Institute of Forestry and Science, about 28% of the forest has been degraded from the 1990s until recently. However, as there are no official statistics, it is necessary to accurately identify the current situation for future restoration. Unlike general deforestation, North Korea was caused by a shortage of food and energy resources due to economic difficulties. Forests were cleared into fields for food supply, and extensive deforestation was accelerated by indiscriminate logging for use as an energy source due to a lack of coal. Although North Korea has recognized the problem of deforestation and implemented related policies, it has not been effectively implemented due to the continuing economic difficulties and deterioration of relations with South Korea. Since deforestation in North Korea has a socio-economic impact on North Korea and the environment on the Korean Peninsula and in Northeast Asia, restoration is urgently needed. In addition, it is important to know the exact current status and scale of deforestation for effective restoration project support when relations with Korea improve in the future. Since North Korea is currently inaccessible and it is impossible to determine the current situation through field surveys, remote sensing using satellite imagery is the most effective method. In addition, since deforestation is not a short-term phenomenon, but a long-term phenomenon, it is necessary to analyze it in multiple periods. Therefore, in this study, the status of deforestation in North Korea for 20 years from 2000 to 2020 after the 1990s, when deforestation in North Korea began to intensify, was identified, and two research hypotheses were established and confirmed. This study aims to enable it to be used as basic data for systematic planning when conducting a restoration project in the future. To this end, land cover classification is carried out using the pixel-based supervised classification random forest method through Google Earth Engine, a geographic information platform in the United States, and based on this, change detection is performed to determine the extent of devastation in an area. We looked at the progress and how much the forest area had changed. As a result of the analysis, the proportion of forests in North Korea decreased by about 11.5% from about 72.5% of the total area to about 61% from 2000 to 2010. On the other hand, the ratio of cropland and bareland increased by about 7% and about 2%, respectively, indicating that the deforestation caused by reckless logging and clearing is serious. The regions with the most changes were Pyeongan-do, Hamgyeong-do, and Gangwon-do, and the region with the least change was Hwanghae-do. During 2010-2020, the proportion of forests in North Korea increased by about 1% from about 61% to about 62%, and the cropland also increased by about 3%. When the full-scale forest restoration project began in North Korea, the ratio of bareland decreased by about 4% and the ratio of the forest increased slightly. Hwanghae-do and Gangwon-do, Hamgyeong-do showed the largest change, and Pyeongan-do show the least change. Gangwon-do, Hamgyeong-do, has seen many changes in common over the past 20 years, and the analysis results show that clearing and logging took place a lot in this area.

Keyword : North Korea, Deforestation, Remote Sensing, Random Forest, Change Detection, Google Earth Engine(GEE)
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Chapter 1. Introduction

1.1. Study Background and Purpose of Research

Deforestation destroys forest ecosystems and impairs many functions, including water storage and supply, and their role as carbon sinks that can reduce air pollution and mitigate greenhouse gas emissions (Lim et al., 2019). Degradation of forest function due to deforestation occurs on a global as well as regional scale, and it has a negative impact on the global environment in terms of climate change response and air quality (Kim et al., 2017; Lee et al., 2018; Lim et al., 2018; Lim et al., 2019). Deforestation is mainly due to urbanization of forests and conversion to agricultural land.

North Korea is known to have the most degraded forests in the world, including being selected as one of the world's three major deforestation areas (Jin et al., 2016; Yoo and Kim 2015). According to a study conducted by the National Institute of Forest Science in Korea, about 28% of forests were degraded from the 1990s until recently. In addition, according to the 'Prospects for Environmental Climate Change in North Korea' conducted by the United Nations Environment Program (UNEP) in 2012 with data from the North Korean Ministry of Land, Infrastructure and Environment, about 14% of forests were degraded. However, as there are no official statistics, it is necessary to know the exact situation.

Unlike general deforestation, North Korea was caused by economic difficulties, food shortages, and rapid development. During the 'March of Suffering' period, extensive North Korean forests were converted into fields for food crop production and felled as firewood to replace fuel (Jin et al., 2016; Lim et al., 2017; Lim et al., 2019). Such indiscriminate logging not only brought about changes in the ecosystem but also reduced carbon absorption, and caused natural disasters such as large-scale floods and landslides (Jin et al., 2016; Lim et al., 2017; Park et al., 2009). Indiscriminate logging also affected the nutrient loss of forest soil and vegetation (Jin et al., 2016).

From the initial period after liberation, North Korea actively tried to use forests and underground resources that accounted for 80% of the country's land, resulting in extensive deforestation. In order to effectively use forest resources, the resources have been nationalized and the state has established a forest management system. In particular, since the 1990s, as the economic hardship became extremely severe, the reclaiming of terrace fields and paddy fields for food production expanded. In addition, as the production of coal, the main energy source in North Korea, began to decrease, indiscriminate firewood harvesting was made to supplement coal shortage, and forest restoration became impossible due to the self-regulation of deforestation. Thereafter, North Korea also recognized the problem of deforestation, implemented policies for their forest restoration in earnest, and continued efforts to restore forests, such as establishing restoration plans. At the 7th Party Congress held in May 2016, North Korean leader Kim Jong-un announced a project to complete forest restoration within 10 years, but the restoration was not carried out effectively due to continued economic difficulties and worsening relations with South Korea, which supported restoration. (Park, 2014; Kim et al., 2016; Lee et al., 2017).

Since deforestation in North Korea has a serious social and economic impact not only on North Korea but also on the environment on the Korean Peninsula and in Northeast Asia, restoration is urgently needed. In addition, it is necessary to continuously monitor the degraded forest in order to select a priority restoration area and establish a systematic restoration plan and management plan (Kim, 2018). Since North Korea is currently inaccessible, there is little data available and it is impossible to determine the current status and scale of deforestation through field surveys. In addition, access to forest-related data is limited, and it is difficult to accurately determine the extent of deforestation because data through field surveys and statistical surveys in North

Korea reported to international organizations are difficult to guarantee objectivity and accuracy (Lim et al., 2018; Choi an Um, 2012; Lee et al., 2019; Lee et al., 2017; Park, 2014; Kim, 2018). The best way to analyze special inaccessible areas like North Korea is remote sensing using satellite image data. The deforestation analysis using this method has the advantage of being able to analyze the change pattern according to a specific period in the area using the classification result of the image (Choi et al., 2017).

Since deforestation does not occur in a short period of time, but over a long period of time, it is important to look at multi-period data in order to examine deforestation more accurately. Therefore, in this study, using Landsat satellite imagery, the status of deforestation in North Korea for the past 20 years from 2000, when the deforestation in North Korea began in earnest, to 2020, after the forest restoration project in North Korea began in earnest, was identified, and the data was used to confirm two research hypotheses. The first hypothesis is that the main causes of deforestation in the two periods of 2000-2010 and 2010-2020 are different. The main causes of deforestation are reckless logging and clearing of cropland. However, as North Korea has been pursuing the 10-year national economic development strategy since 2011, we analyzed whether the causes of deforestation between 2010 and 2020 are actually different from those of the previous period. The second hypothesis is that the main causes of deforestation vary by major region. Since North Korea is divided into economic development zones, coal mining zones, and granary zones in each region, we want to confirm whether the main causes of deforestation actually differ by region. In addition, the research goal is to evaluate the extent of deforestation and whether the restoration project has been successful, and to create basic data for a systematic restoration project in the future. For this, the land cover in 2000, 2010, and 2020 were classified using the Random Forest, one of the machine learning methods, using the Google Earth Engine (GEE) platform of the United States to determine the location and using change detection to examine where and how much the forest has changed. In addition, we will examine how the forest area has changed by region in North Korea and identify the causes for deforestation during each period.

Although the diplomatic conflict between the two Koreas has intensified recently, the South has expressed its intention to unconditionally support North Korea’ s Forest restoration project (Park, Yoo, 2009). It is important to know the extent of deforestation in order to successfully carry out a deforestation project. It can also provide essential and basic information for prioritizing forest management, making decisions about the restoration of degraded areas, and developing systematic restoration plans.

Chapter 2. Literature Review

2.1. Deforestation of North Korea

North Korea's deforestation is a situation that is attracting attention not only on the Korean Peninsula but also around the world. As explained above, North Korea is one of the world's three most deforested areas. For this reason, numerous researches are being conducted in this issue. In Korea, various studies, such as papers and reports, on deforestation in North Korea are being conducted.

Han and Yoon (2007) studied the economic feasibility of afforestation CDM, one of afforestation projects, in order to restore deforested areas in North Korea. The CDM project is a reforestation project recognized by the Kyoto Protocol, and the economic feasibility of this project when applied to the North Korean region was examined. The potential target area to which afforestation CDM can be applied was estimated by using the results of North Korea's previous research on estimating the forest area. As a result, it is estimated that there are about 510,000 hectares of desolate areas in North Korea, and about 8,000 hectares in the Kaesong area are selected as an economic feasibility study area. The Afforestation CDM sets up to increase carbon fixation by artificially planting acacia tree, one of the major afforestation species in North Korea, and maintaining the artificially planted acacia tree for 20 years. The economic effectiveness was evaluated by analyzing administrative costs.

Park et al. (2011) conducted a study to establish a basic direction for restoring degraded forests in consideration of North Korea's economic and social conditions. This study examines the relationship between North Korea's economic crisis and deforestation, changes in forest policy and its limitations, and suggestions four directions for restoration. (A) After the collapse of North Korea's centralized planned economic system after 2000, support for forest restoration should proceed in consideration of various interests. (B) Since the forest restoration project has the characteristic that long-term participation of residents should be continued, it should be voluntarily encouraged to participate by allowing additional economic benefits to be obtained from the restoration site. (C) It is necessary to reduce dependence on forests through restoration projects and comprehensive development projects. (D) The system that can systematically manage forests while securing the labor required for short-term afforestation by utilizing the existing management system should be improved.

Table 1 below summarizes changes in the area of forests and agricultural land in North Korea. Looking at it, it can be seen that while the area of forests is gradually decreasing, the area of agricultural land has decreased and then increased again.

Table 1 Decrease in forest area (JH. Park, 2010 cited)

년도	산림(km^2)	농경지(km^2)	비고
1989	95,004	25,342	AVHRR 자료 이용
1996	81,830	21,030	북한발표자료, UNEP(2003)
2008	77,986	29,969	무립목지는(13,910km^2) 제외

Park et al. (2013) studied the status of forest use of North Koreans, which is closely related to deforestation in North Korea, and what kind of perception they have about forest restoration support. In this study, the researcher says that it is very important to understand the forest use patterns of the residents and establish a forest restoration plan according to the needs of the residents in the relevant area residents participate because the deforestation in North Korea is caused by the living environment of the residents. However, since conducting interviews with the residents were not feasible, this study was conducted by distributing questionnaires to North Korean defectors residing in South Korea, so this study was conducted through a questionnaire targeting North Korean defectors residing in South Korea. The survey was conducted in 2012, and it was conducted using direct survey and mail distribution and collection methods. 91.5% of the respondents said they had witnessed the mountain becoming increasingly desolated. This means that many North Koreans are aware of deforestation. In addition, the majority of respondents perceived the increase in devastation as a serious problem, and answered in favor of external restoration support. The most numerous feedbacks provided from North Koreans as a solution was to provide food as a plan to encourage resident participation.

Lee et al. (2015) conducted a study to examine the policy implications of deforestation in North Korea by analyzing the reporting characteristics of South Korean newspapers. This study examines how domestic newspapers deal with deforestation in North Korea, which is also receiving attention in Korea, and how this affects inter-Korean relations and various issues on related reports. For this purpose, 204 articles on deforestation in North Korea reported in six major domestic newspapers from 2001 to 2013 were analyzed. As a result, most newspapers recognized the seriousness of North Korea's deforestation problem and positively stated the need for South Korea's support for forest restoration. However, when conflicts with North Korea occurred, conservative newspapers appeared to write negative opinions about aid from South Korea. From an economic point of view, it was pragmatic, such as the South Korean government's burden of unification costs, responding to climate change, and securing carbon emission rights. Throughout the time, the articles' topic, focus, and frequency were impacted by the relationship between the two Koreas, it was found that the frequency, topic and focus of articles, and related topics change according to the relationship between the two Koreas.

Jeong et al. (2016) conducted a study to classify the attic, one of the major causes of deforestation in North Korea, using MODIS multi-period images. Terrace fields are causing aggravation of forest damage, which causes secondary damage such as landslides and avalanches when natural disasters occur. As the lost forest soil covers arable land or flows into rivers, flooding due to floods is also frequent. (FAO, 2010). To prevent the problems, a quantitative review is required for scientific and systematic forest restoration, and for this purpose, the overall distribution of degradation was confirmed through land cover classification using remote sensing. Using multi-period images of MODIS satellite imagery, land cover maps were constructed using indices such as NDVI, NDWI, and NDSI, and the classification accuracy was improved by classifying wasteland using slopes.

Most of the foreign papers related to deforestation in North Korea have been researched in Korea and published in foreign journals.

Jin et al. (2016) conducted a study to map deforestation in North Korea using a phenology-based multiple indices with a random forest algorithm. Classification using multiple indexes can overcome the disadvantages of existing pixel-based classification such as ISODATA or decision trees and existing deforestation mapping related to single images. The purpose of this study is to investigate a method for identifying deforestation areas in North Korea and to improve classification accuracy by using phylogenetic characteristics extracted with multiple indexes and random forest algorithms. Mapping of deforestation areas was performed using a random forest by merging NDVI, NDWI, and NDSI obtained using MODIS image data. As a result, the overall classification accuracy was 89.38%, and the corresponding Kappa coefficient was 0.87, confirming that the classification method used in this study has high accuracy.

Lim et al. (2017) studied the effects of deforestation on agricultural environmental variables in North Korean agricultural land. This study uses GEPIC (GIS-based EPIC model) and time-series land cover to estimate agricultural environmental variables in North Korean agricultural land and analyze the impact of deforestation. In order to understand changes in agricultural quality, wind erosion, water erosion, organic carbon loss, and runoff were selected as variables affecting the stability and productivity of arable land. According to the land cover map classified over the past 30 years, 75% of the forest was converted to arable land, and 69% of the converted arable land was originally forest, confirming that there is an important correlation between deforestation and increase in arable land. Despite the lack of verification data due to the inaccessibility to the area, qualitative and quantitative verifications were performed on the estimated variables to confirm that the results were reasonable.

As deforestation in North Korea has been recognized as an important problem on the Korean Peninsula, it has been confirmed that the issue has been continuously studied for a long period of time.

2.2. Random Forest using GEE

Google in the United States launched a new platform called Google Earth Engine (GEE) in December 2010 (US Geological Survey, 2010; Bar et al., 2020). This new geospatial analysis platform has provided more than 40 years of satellite imagery online to scientists and researchers worldwide to analyze real-time changes in the Earth's surface (Houseman et al., 2015; Bar et al., 2020). GEE has millions of servers around the world and the scientific community uses parallel processing to rapidly analyze trillions of images (Dong et al., 2016; Bar et al., 2020). GEE provides an analysis method using various powerful algorithms such as regression and classification for geospatial data using JavaScript-style code.

Random forest method is one of the analysis methods used by GEE. Random forest is one of ensemble techniques that increases the accuracy of analysis by combining multiple decision trees. It conducts analysis through learning and is applied and utilized in various research fields.

In this study, domestic and foreign studies using random forests on the US GEE platform were examined.

Overseas, the random forest technique using GEE is actively being used.

Bar et al. (2020) detected wildfires in the western Himalayas using Landsat 8 and Sentinel-2 images for the period 2016-2019 in GEE. Machine learning algorithms such as random forest, SVM, and CART were used for fire patch identification, and algorithm comparison analysis was performed between machine learning techniques in areas burned by forest fires. The reflectance of the fire-sensitive spectral band was analyzed by comparing the time before and after the fire and using the contrast. In addition, classification and analysis were performed using differential spectral indices, such as normalized combustion rate, normalized vegetation index, normalized water index, and short-wave infrared rays, as auxiliary data to improve classification accuracy. As a result of classification, the overall accuracy of CART and RF were high at 97-100%, and the classification accuracy of SVM was slightly lower. GEE has been extensively used to run the entire classification, not only from the analysis images, but also from the collection of training samples to the assessment of accuracy.

Gu et al. (2020) proposed a new river turbidity measurement model based on the random forest ensemble technique using GEE. In this study, a new error minimization-based pruning algorithm that deletes bad random forest values according to dynamic thresholds after generating all possible basic random forests by maximizing the adjusted spectral information was used to prevent from using the bad random data samples. The final measurement result of river turbidity was calculated by aggregating the random forest data preserved after pruning using the additive averaging method solved by normalized linear regression. As a result, it has been proven that the model proposed in this study is superior to other models.

Zhou et al. (2020) used GEE and a machine learning algorithm, Random Forest, to identify potential impacts over different times for grazing indicator estimation. In addition to random forest, machine learning algorithms were compared after analyzing all other candidate algorithms. As sampling data for random forest, time (year, month, day) data was used. Although this study found that temporally relevant training data improved predictions, they say that training data do not have to be precisely temporal data for predictions to be temporally relevant. We also concluded that it is better to use training data of all possible times to be the best random forest prediction map.

Bey et al. (2019) conducted a research on the detection and evaluation of land use and land cover change (LULCC) using the Zambezia region of Mozambique as a study site. For this evaluation, a new evaluation methodology was established using both standard and continuous training and validation data obtained from the Collect Earth software within the GEE. After that, the suitability of five pixel-based synthesis techniques was investigated to overcome the disadvantages of Landsat satellite imagery, which cannot use data with clouds. A pixel-based composite was used to classify land use over the three periods 2006, 2012, and 2016 and characterize land use changes based on the spectral and texture characteristics of the Landsat data.

Teluguntla et al. (2018) used the random forest algorithm in GEE to analyze arable land in Australia and China. For the analysis of arable land, Landsat data from 2013-2015 were used and continent-scale mapping was performed. Each band was synthesized and analyzed over 4−6 time zones over a one−year period using the median for various agroecological regions in Australia and China. Overall classification accuracy exceeded 94% in both Australia and China.

Gumma et al. (2020) analyzed the range and region of agricultural land in South Asia such as India and Pakistan using GEE and random forest algorithm. For analysis, Landsat satellite images with a resolution of 30 m were used. The temporal range is 2013−2015, and 10 times were synthesized to remove the effect of clouds, and three periods were analyzed: summer, winter, and monsoon climate period. As the sample data for the random forest, 2179 spatially well−dispersed reference training data from 5 agroecological zones (AEZs) in South Asia were used. The map accuracy was developed using 1185 independent validation data. The producer accuracy was 89.9%, the user accuracy was 95.3%, and the overall accuracy was 88.7%.

2.3. Change Detection

Change Detection captures spatial changes in satellite imagery at multiple times due to man−made or natural phenomena. This is very important for remote sensing, environmental change monitoring, and land use and land cover change detection. Satellite images for change detection are used by acquiring images of various resolutions such as 5m, 10m, and 30m (Asokan & Anitha, 2019). Various methods for change detection have been developed over a long period of time, and since they are still under development, there are many related studies and the methods used are also diverse.

In this study, domestic and foreign studies using various change detection were examined.

In Korea, Kim and Park (2001) used change detection techniques to investigate forest fragmentation in urban areas in North Korea. Forest fragmentation patterns were investigated and analyzed in terms of changes in forest area and landscape structure in Pyongyang and Nampo for about 20 years from 1979 to 1998. For forest fragmentation investigation, the NDVI values of Landsat MSS and Landsat TM were used, and for a more accurate analysis, the modified Cluster-Busting algorithm was used to simply divide the forest into forest and non-forest regions.

Lee et al. (2007) quantitatively analyzes the trend of forest damage through secular change analysis, which is a method of classifying land cover using satellite imagery and extracting areas that have changed from forests to areas other than forests through land cover classification. To this end, land cover classification data were created using Landsat TM and Landsat ETM+ satellite image data in April, May, September, and October of three periods (1980s, 1990s, and 2000s) since the 1980s. Using this method, the degree and condition of damage in the Baekdu-daegan region was identified, and the spatial characteristics of the area where the forest was damaged by time were identified to establish trends

Also, active research is being conducted abroad. Housman et al. (2018) presented three algorithms and Operational Remote Sensing (ORS) to detect and augment real-time forest disturbance (RTFD) with the US Insect and Disease Survey (IDS) using both Landsat and MODIS satellite imaging data.

Feng et al. (2018) conducted a rough uncertainty analysis of RoF (Rotation Forest) and multi-time high-resolution remote sensing images to solve the problems related to the extraction and analysis of scale and data with object-based change detection (OBCD) to describe an object-based approach to change detection. In experiments with two pairs of real high-resolution remote sensing datasets, the proposed approach was used as a training sample as the identified altered or unchanged objects were automatically selected and were not feasible because they outperform the conventional method in terms of change detection accuracy.

Woodcock et al. (2019) looked at the paradigm shift from simple change detection to monitoring through remote sensing. In this study, after the advent of the freely available Landsat data, the use of medium-resolution satellite imagery for time-series analysis could not only provide new information about the timing of changes, but also improve the quality and accuracy of information derived from remote sensing. Through this, author explains that the paradigm is shifting from simple change detection to being able to monitor changes with remote sensing.

Sapucci et al. (2021) used unsupervised change detection techniques to analyze the land cover of Atlantic forests in space and time. Research has been conducted to support the biodiversity and conservation of the Atlantic forests and the economic decision-making of public and private agents. This study investigated the effectiveness and practical feasibility of a distinct unsupervised change detection approach to reveal the spatial and temporal dynamics of the study site over a 40-year period. Various change detection approaches such as CVA and PCA-KM frameworks were taken and appropriately adapted for use in Landsat images. As a result of the analysis, continuous change was confirmed in the study site, and CVA was confirmed as the best mode to map change detection.

Chapter 3. Materials and Methods

3.1. Study Area and Materials

3.1.1. Study Area

The study site is North Korea (Figure 1). North Korea is located in the northern part of the Korean Peninsula, surrounded by rivers and seas bordering China and Russia, and covers an area of about 123,138 km². North Korea, like South Korea, has four distinct seasons. 80% of North Korea's land consists of forests. In the northern and eastern regions there are mountain ranges with peaks on plateaus above 2000 m. Indiscriminate deforestation is taking place due to food and energy shortages, and the trend of deforestation is clearly visible (Schoene et al., 2007; Jin et al., 2016).

Figure 1 Study Area

3.1.2. Materials

As the physical access to North Korea is limited, remote sensing using satellite image data was used to classify deforestation. The satellite image data used for classification are Landsat TM, Landsat ETM+, and Landsat OLI, which are medium-resolution satellite images with a spatial resolution of 30 m and a temporal resolution of 16 days launched by the National Aeronautics and Space Administration. It has been launched consecutively since 1972.

Landsat TM, Landsat ETM+, and Landsat OLI used in this study are satellites 5, 7, and 8 and have values between 0 and 255. There are 7 bands for Landsat TM, 8 for Landsat ETM+, and 11 for Landsat OLI. Each band has different wavelength information and characteristics (Table 2, 3, 4). The observation width of the Landsat TM, Landsat ETM+, and Landsat OLI images is, and about 14 Landsat images are needed to include all the North Korean parts (Figure 2).

Since forests have different vegetation vitality depending on different seasons, it is important to classify them using data from all seasons except winter and rainy season for accurate classification. Therefore, images from April, May, June, September, and October were selected and used to analyze the North Korean region, excluding the winter and rainy seasons of 2000, 2010, and 2020. For data construction and analysis, Google Earth Engine (GEE), an American geographic information analysis platform, was used.

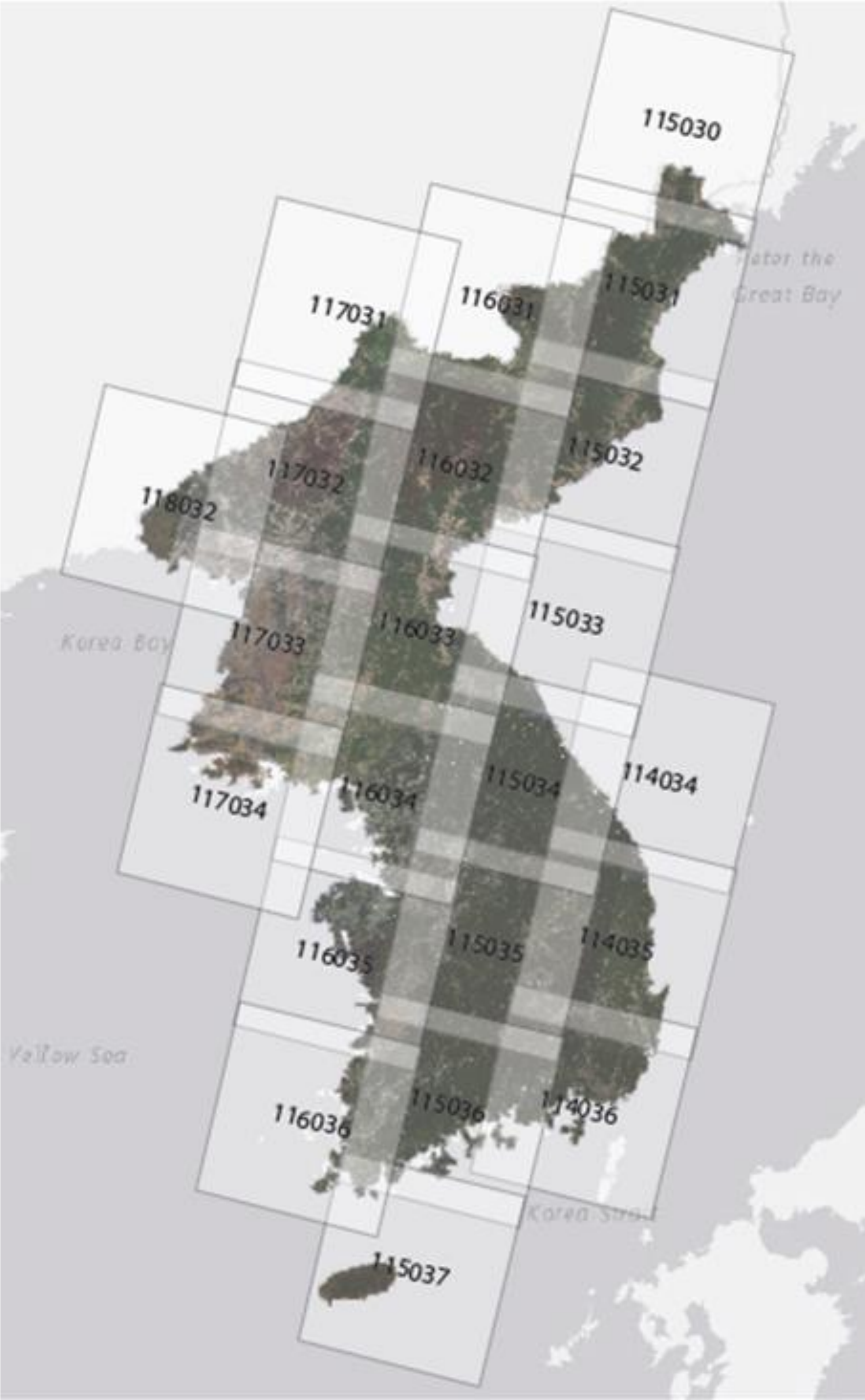


Figure 2 Location and number of Landsat data tiles corresponding to the

Table 2 Spectral characteristics of Landsat TM bands and their spatial resolution (USGS)

Band	Wave-length (㎛)	Nominal Spectral Location	Principal Application	Spatial Resolution (m)
1	0.45-0.52	Blue	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation	30
2	0.52-0.60	Green	Emphasizes peak vegetation, which is useful for assessing plant vigor	30
3	0.63-0.69	Red	Discriminates vegetation slopes	30
4	0.76-0.90	Near Infrared	Emphasizes biomass content and shorelines	30
5	1.55-1.75	Short-wave (Mid) Infrared	Discriminates moisture content of soil and vegetation; penetrates thin clouds	30
6	10.4-12.5	Thermal Infrared	Thermal mapping and estimated soil moisture	120
7	2.08-2.35	Short-wave (Mid) Infrared	Hydrothermally altered rocks associated with mineral deposits	30

Table 3 Spectral characteristics of Landsat ETM+ bands and their spatial resolution (USGS)

Band	Wave-length (μm)	Nominal Spectral Location	Principal Application	Spatial Resolution (m)
1	0.45-0.52	Blue	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation	30
2	0.52-0.60	Green	Emphasizes peak vegetation, which is useful for assessing plant vigor	30
3	0.63-0.69	Red	Discriminates vegetation slopes	30
4	0.76-0.90	Near Infrared	Emphasizes biomass content and shorelines	30
5	1.55-1.75	Short-wave (Mid) Infrared	Discriminates moisture content of soil and vegetation; penetrates thin clouds	30
6	10.4-12.5	Thermal Infrared	Thermal mapping and estimated soil moisture	60/30
7	2.08-2.35	Short-wave (Mid) Infrared	Hydrothermally altered rocks associated with mineral deposits	30
8	0.52-0.90	Panchromatic	Sharper image definition	15

Table 4 Spectral characteristics of Landsat OLI bands and their spatial resolution (USGS)

Band	Wave-length (μm)	Nominal Spectral Location	Principal Application	Spatial Resolution (m)

1	0.43–0.45	Coastal	Coastal and aerosol studies	30
2	0.45–0.51	Blue	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation	30
3	0.53–0.59	Green	Emphasizes peak vegetation, which is useful for assessing plant vigor	30
4	0.64–0.67	Red	Discriminates vegetation slopes	30
5	0.85–0.88	Near Infrared (NIR)	Emphasizes biomass content and shorelines	30
6	1.57–1.65	Short-wave (Mid) Infrared (SWIR) 1	Discriminates moisture content of soil and vegetation; penetrates thin clouds	30
7	2.11–2.29	Short-wave (Mid) Infrared (SWIR) 2	Improved moisture content of soil and vegetation; penetrates thin clouds	30
8	0.50–0.68	Panchromatic	Sharper image definition	15
9	1.36–1.38	Cirrus	Improved detection of cirrus cloud contamination	30
10	10.60–11.19	TIRS 1	Thermal mapping and estimated soil moisture	100
11	11.50–12.51	TIRS 2	Improved thermal mapping and estimated soil moisture	100

3.2. Methods

3.2.1. Dataset and Pre−processing

The Landsat TM, Landsat ETM+, and Landsat OLI satellite images used in the analysis are artificial satellites launched by NASA in the United States. The brightness value of satellite imagery is influenced by many factors, such as distance from the sun, elevation angle, and atmospheric conditions, depending on the timing of the satellite image. In addition, since it inherently contains a geometric error, image correction through preprocessing is required (Hong et al., 2008).

In this paper, image correction was performed through two pre−processing processes. The first process is called radiation correction; it normalizes brightness values based on one image (Heo & FitzHugh, 2000), was performed. The second process is called atmospheric correction. It is performed to remove errors caused by atmospheric scattering, absorption, and refraction caused by problems such as various reflective characteristics of the earth's surface and water vapor in the atmosphere.

In this paper, image acquisition, pre−processing, and analysis were simultaneously performed using the GEE platform. The setting of classification items using satellite images can be vary used differently depending on the research purpose and application. Anderson et al. (1976) classified nine categories, such as urban areas, urbanized dry areas, cropland, pastures, forests, wetlands, bareland, tundra, and ice caps, which are widely used. Most of them are modified and used by Hong et al. (2008)

In this study, the total land cover was divided into a total of 5 areas including urban area, agricultural area, forest area, bare area, and water area in consideration of various factors such as classification items of previous studies and Landsat image resolution used for analysis, and classification using visual reading and random forest. The items were set and analyzed (Table 4).

Table 5 Land-cover classifications and standard colors by using the Landsat images

Classification		Color Code			
		R	G	B	Color
Urban	100	255	0	0	
Cropland	200	238	233	7	
Forest	300	42	75	45	
Bareland	600	89	206	202	
Water	700	6	2	250	

3.2.2. Random Forest using GEE

The Random Forest (RF) algorithm is a machine learning method, in which a random forest classifier constructs several uncorrelated random decision trees that are bootstrapped and aggregated to classify a data set using the prediction modes of all decision trees. The random forest classifier is a more powerful method than a single decision tree and is easier to implement compared to many other advanced classifiers such as SVM (Pelletier et al., 2016; Xiong et al., 2017a). In the study of Breiman (2001), a randomly selected dataset is constructed from the training data and an ensemble of a decision tree is formed by searching an arbitrary subspace in the given data using bagging applied to the algorithm. The node is best partitioned by minimizing the correlation between. Also, it is useful to quantitatively measure the contribution of each variable to the classification result and evaluate the importance of each variable (Teluguntla et al., 2019).

Pixel-based random forests are generally very useful for classifying remote sensing data without being subject to data noise and overfitting. It can also successfully handle high data dimensions and, in general, it achieves higher accuracy compared to other approaches such as maximum likelihood, single decision trees (Chan and Paelinckx, 2008), and single-layer neural networks (Belgiu and Drăguţ, 2016; Lawrence et al., 2006; Na et al., 2010; Teluguntla et al., 2019). The random forest classifier available in GEE uses the following six input parameters: A) number of classification trees, B) number of variables used in each classification tree, C) minimum leaf population, D) bagging ratio of input variables per decision tree, E) out-of-bag (OOB) mode, F) pseudo It is a random seed variable for constructing a decision tree. As the number of trees increases, the overall accuracy of classification increases without overfitting (Breiman, 2001).

In this study, Landsat time series data with a spatial resolution of 30 m and a temporal resolution of 16 days were used for land cover classification using a pixel-based supervised classification approach on the GEE platform. For the temporal range, data from April, May, June, September, and October except for the rainy season and winter in 2000, 2010, and 2020 were used. The analysis was performed using the data collected from the above methods.

Sample data for learning the random forest classifier is difficult to obtain data through on-site verification and investigation due to the nature of North Korea, which is an inaccessible region. Classifier was trained by taking 50-110 points, and it was set to repeat 500 times. The learned cover data is a total of five types: urbanization area, agricultural area, forest area, bare area, and water area.

3.2.3. Change Detection

Change Detection captures spatial changes in satellite imagery at multiple times due to man-made or natural phenomena. This is very important for remote sensing, environmental change monitoring, and land use and land cover change detection. Satellite images for change detection use images collected at different spatial resolutions and different times, such as 5 m, 10 m, and 30 m (Asokan & Anitha, 2019). Various methods for change detection have been developed over a long period of time, and since they are still under developed, there are various related studies and methods.

In this study, change detection was performed using the categorical change detection method of the ArcGIS program.

Categorical raster data is raster data that represents a class or category for each pixel, used in GIS to represent land cover, land use, and other zone information such as risk levels. In order to detect changes in three periods: 2000-2010, 2010-2020, and 2000-2020, change detection was performed using the results of random forest classification by year. In addition, in order to examine the causes of deforestation by region, the ArcGIS program was used to extract them by region and then analyzed them.

Chapter 4. Results and Discussion

4.1. Results of Random Forest

In this study, the land cover map of North Korea was analyzed by using the random forest method of the US GEE platform to analyze the Landsat satellite image images in April, May, June, September, and October of 2000, 2010, and 2020. GEE's 'Smile Random Forest' was used for the random forest code, and the 'Validation error Matrix' and 'Validation overall accuracy' were used for the accuracy verification code. For 2000, we used Landsat TM data, for 2010, we used Landsat ETM+ data, and for 2020, we used Landsat OLI data. Sample data corresponding to the corresponding land cover was selected by 50-110, and data learning was set to repeat 500 times and analyzed.

Since the access to North Korea is prohibited, on-site verification is not feasible, so the sample data was selected by looking at satellite images in 2000 and 2010 in Google Earth Pro, and in 2020 by looking at satellite images in Google Earth Engine. Land cover was divided into five categories: urban area, forest, cropland, water, and bareland. For urban, water, and bareland, 50-100 sample data were selected, and data forests and cropland with seasonal changes were selected. 60-110 pieces were selected.

After selecting sample data and running random forest analysis, accuracy verification was performed. As a result, the Validation Accuracy of 2000 was 0.8529, and the Kappa Coefficient was 0.8154, which was classified with relatively high accuracy. (Figure 3). In 2010, the accuracy of land cover classification was 0.8975 and the Kappa coefficient was 0.8709 (Figure 4). In 2020, the accuracy of land cover analysis was 0.9432 and the Kappa coefficient was 0.9286, which was classified with very high accuracy (Figure 5).

As the result of land cover classification in 2000, forest accounted for the most at about 72.5%, followed by cropland and bareland with about 15% and about 11%, respectively. The urbanization area showed a very small ratio of about 1.5%. As a result of land cover classification in 2010, about 61% was forest, about 22% cropland, and about 13% bareland. It can be seen that the ratio of forest decreased and the ratio of cropland and bareland increased. This means that the area of forest has decreased and the area of cropland has increased significantly. The urbanization area showed no difference in the ratio at about 1.5%, and the water showed a slight increase in the ratio to about 2%. This was confirmed to be the effect of a newly created artificial reservoir in Gangwon-do (Figure 9). As a result of land cover classification in 2020, the proportion for forest increased to about 62% and about 25% for cropland. The urbanization area also showed a slight increase in the ratio to about 2%. There was no change in the ratio of water body to 2%, and the ratio was slightly decreased to about 9% in open water. It is predicted that the increase in forests and the decrease in the ratio of bareland are due to the forest restoration projects that North Korea has been implementing out since 2015. However, the increase in the proportion of cropland in North Korea indicates that the restoration projects are not yet successful.

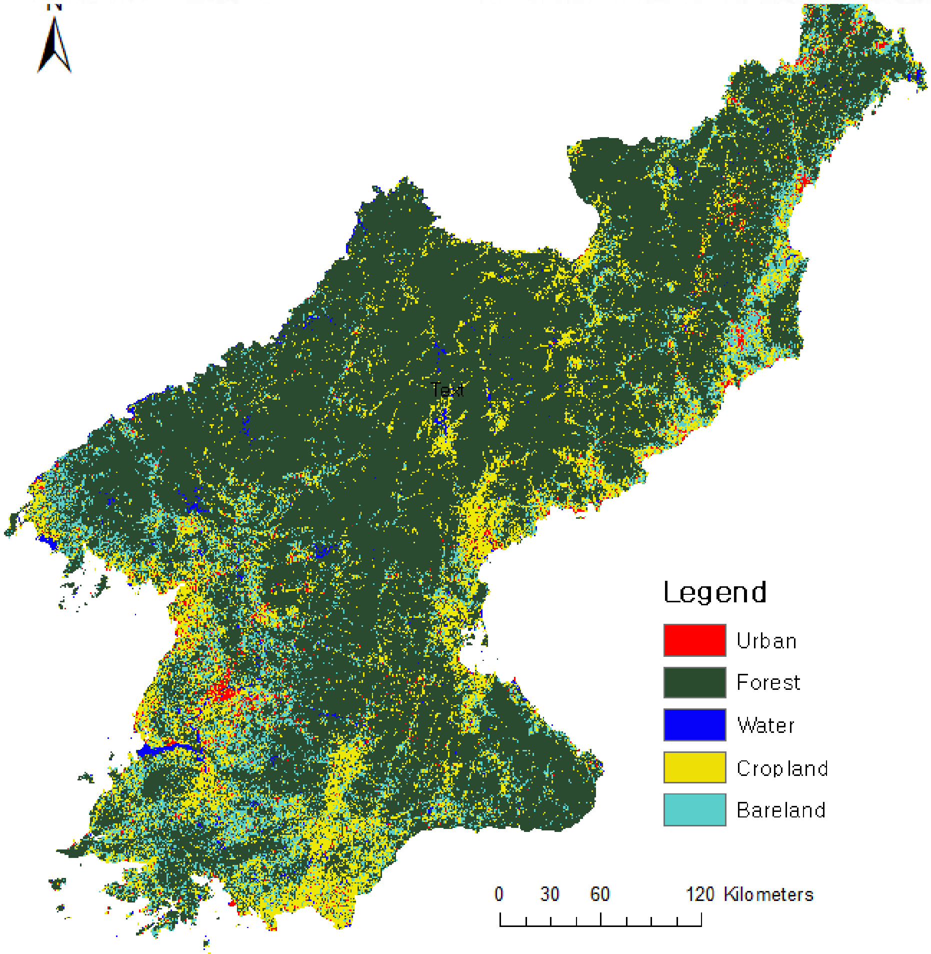


Figure 3 Land-cover classification result using the Random Forest (2000)

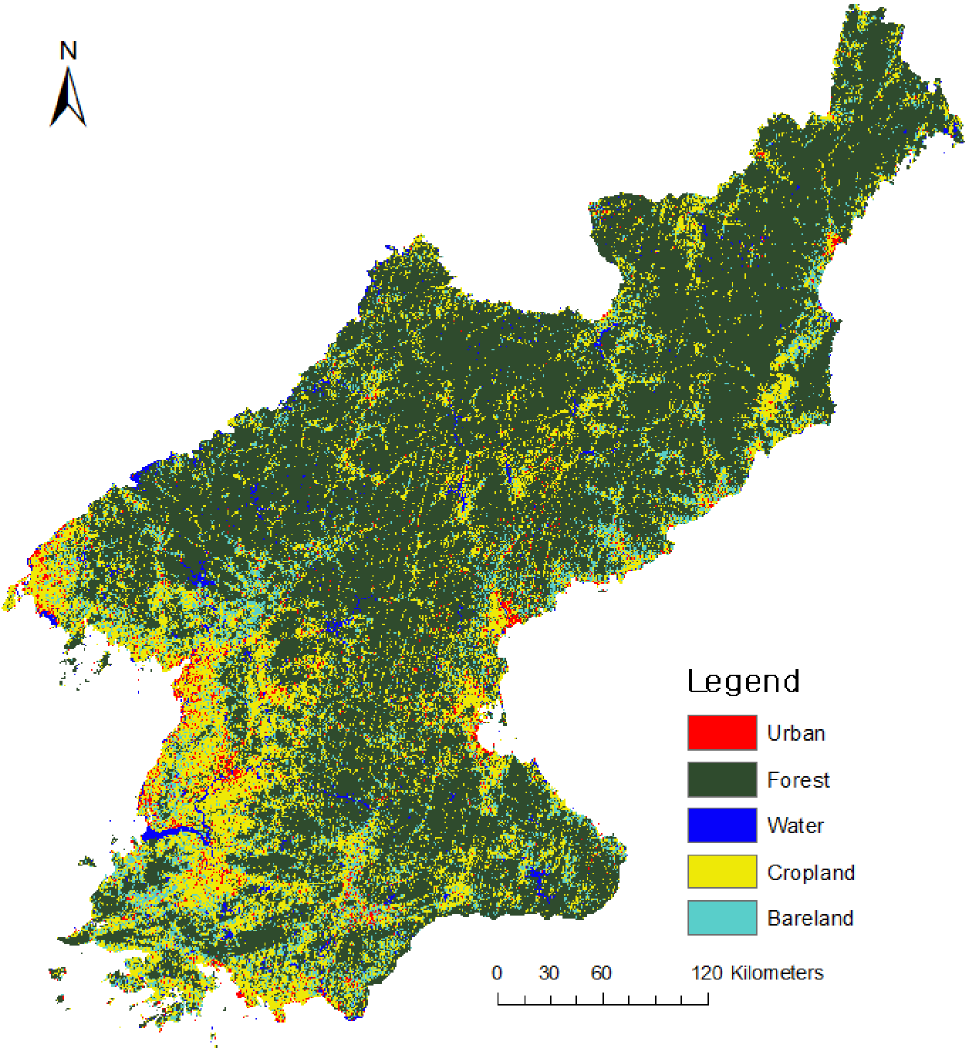


Figure 4 Land-cover classification result using the Random Forest (2010)

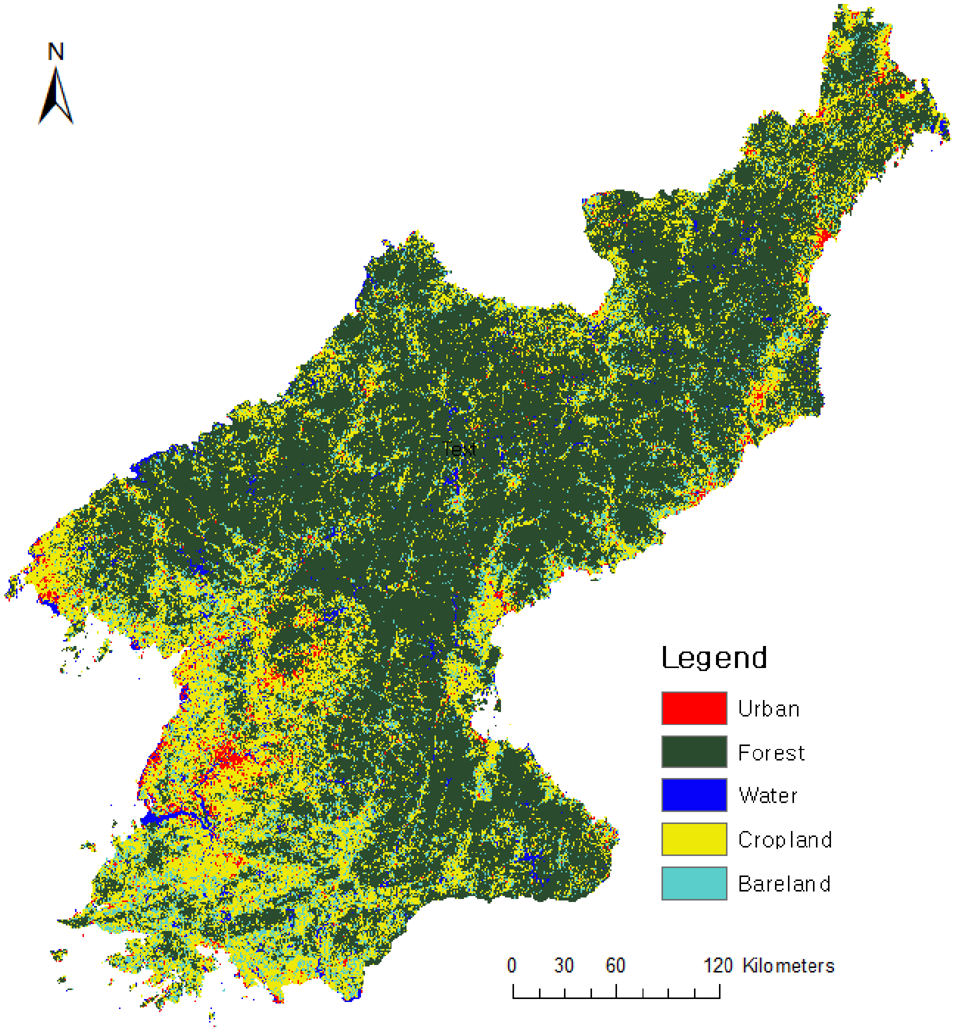


Figure 5 Land-cover classification result using the Random Forest (2020)

4.2. Results of Change Detection

4.2.1. 2000-2010

From the data obtained via random forest land cover classification, from 2000 to 2010, the proportion of forests is decreased about 11.5%. From 2000 to 2010, the ratio of farmland and bare land increased about 7% and 13%, respectively. Reckless logging and clearing of Terrace fields for the energy and food shortages are the main causes of deforestation in North Korea during this the period of 2000-2010. The proportion of water bodies also increased from about 1% to 2%. The data collected from random forest analysis and satellite images indicate that the construction of artificial reservoirs contributed to the increase of the proportion of water bodies in that region.

In addition to the change in the coverage ratio, change detection was conducted to find out the region that had changes in the past. (Figure 7). Based on the results of the random forest analysis, we looked at the areas where the change occurred. In Figure 7, during 2000 and 2010, the areas marked in dark red indicate areas with significant changes, areas marked in dark green indicate areas with little change, and areas marked in white indicate no change at all. Looking at the results of the analysis, the regions with significant changes in 2000-2010 are Pyeongan-do, Pyongyang, Hamgyeongnam-do, and Gangwon-do. Looking at the results of random forest analysis, it can be seen that forests have changed a lot to cropland in the regions where the change is significant. The region where little change occurred was in Hamgyeongbuk-do.

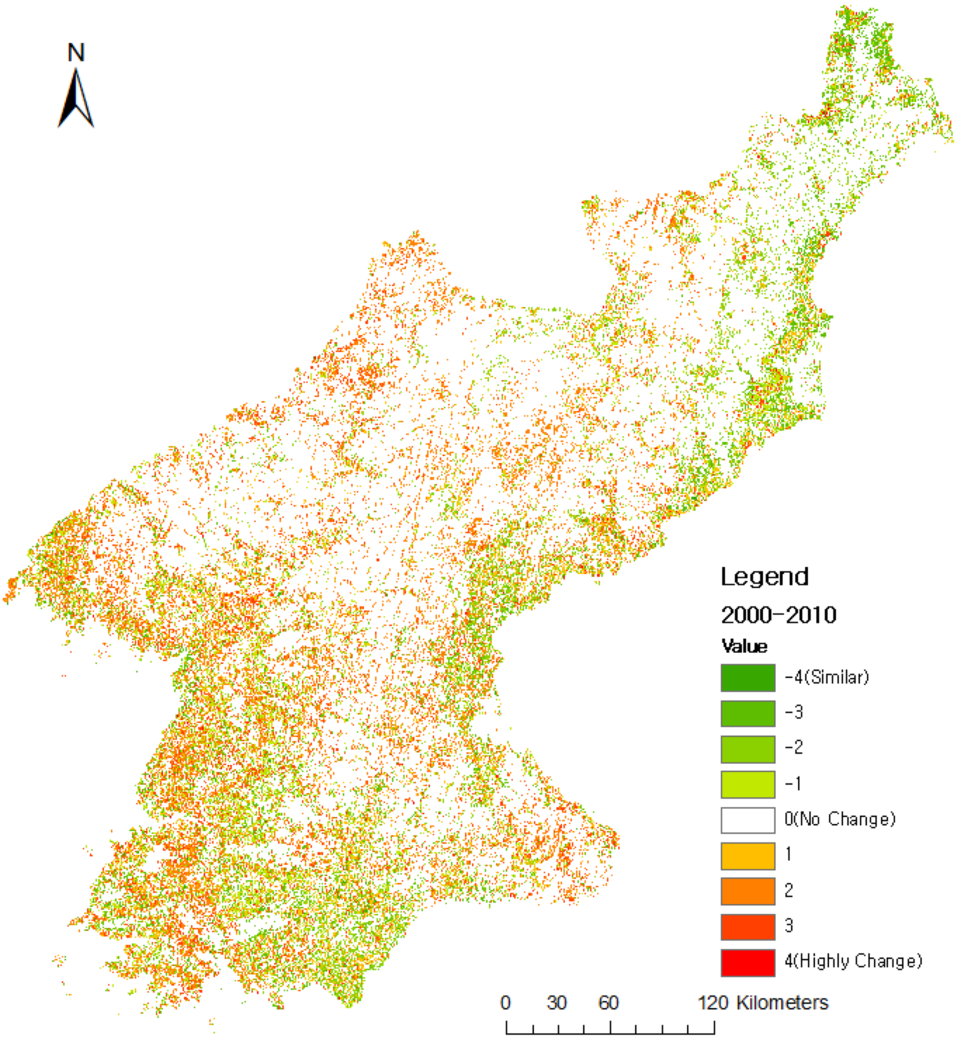


Figure 6 2000-2010 change detection result

4.2.2. 2010-2020

As a result of random forest land cover classification, the forest ratio in 2020 increased by about 1% from about 61% to about 62% compared to 2010. The proportion of cropland also increased by about 3% from about 22% to about 25%. It was found that the proportion of bareland decreased by about 4% from about 13% to about 9%. In addition, the proportion of urbanized areas also increased by 0.5% from 1.5% to 2%, which was found to have increased not only with the progress of urbanization but also with the development of industrial complexes (Figure 11,13). The increase in the proportion of forests by about 1% and the decrease in the proportion of bareland by about 4% seems to be due to the result of North Korea’s Forest restoration combat project (Lee et al., 2017) announced in February 2015. However, the proportion of cropland also increased by 3%, indicating that forests are still being degraded due to reclamation. It can be seen that the main cause of deforestation during the period 2010-2020 is slightly different from the period 2000-2010, as industrialization and urbanization are added due to North Korea's 10-year national economic development strategy from 2011.

Change Detection was performed to examine regional changes between 2010 and 2020 (Figure 8). Based on the results of the random forest analysis, we looked at the areas where the change occurred. Figure 8 is the result of examining the changes in 2000 and 2010. As with the previous 2000-2010 results, the areas marked in dark red indicate areas with significant changes, and areas marked in dark green indicate areas with little change, white areas indicate regions where no change has occurred.

Looking at the results of the analysis, it was found that North Pyongan-do, Pyongyang, Hengyang-do, and Gangwon-do were the regions where changes occurred significantly in 2010-2020. In contrast to the result of little change in Hwanghae-do from 2000 to 2010, it can be seen that large changes occurred in Hwanghae-do between 2010 and 2020. Contrary to the 2000-2010 results, there was almost no change occurred in Pyeongannam-do.

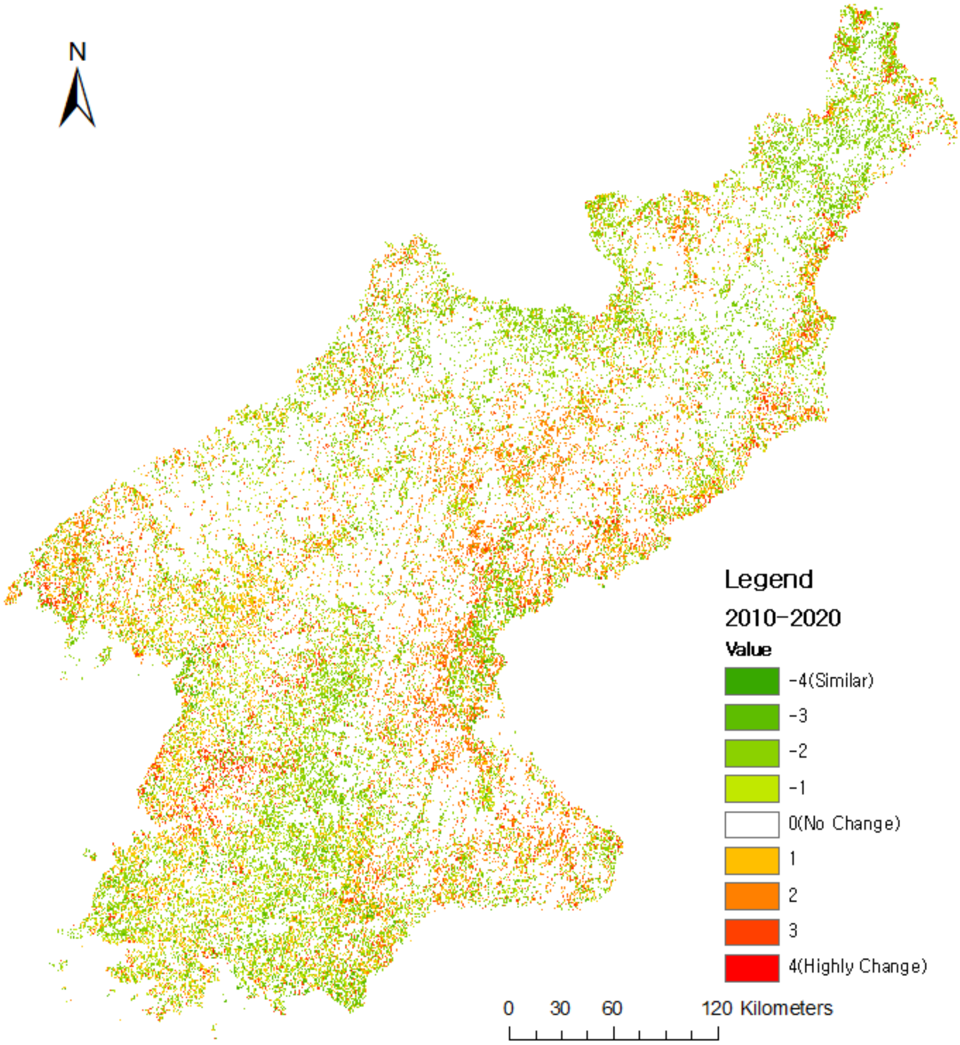


Figure 7 2010-2020 change detection result

4.2.3. 2000-2020

Change detection analysis was performed in 2000 and 2020 to examine the overall change over the 20-year period from 2000 to 2020 (Figure 9). As a result of the analysis, there was a change in the whole of North Korea, and the regions where the change occurred significantly were Pyeongan-do, Hamgyeong-do, and Hwanghae-do. In Figure 8, it can be seen that the red areas are evenly distributed throughout North Korea. Thus, it can be concluded that land cover changes have occurred throughout North

Korea over the past 20 years.

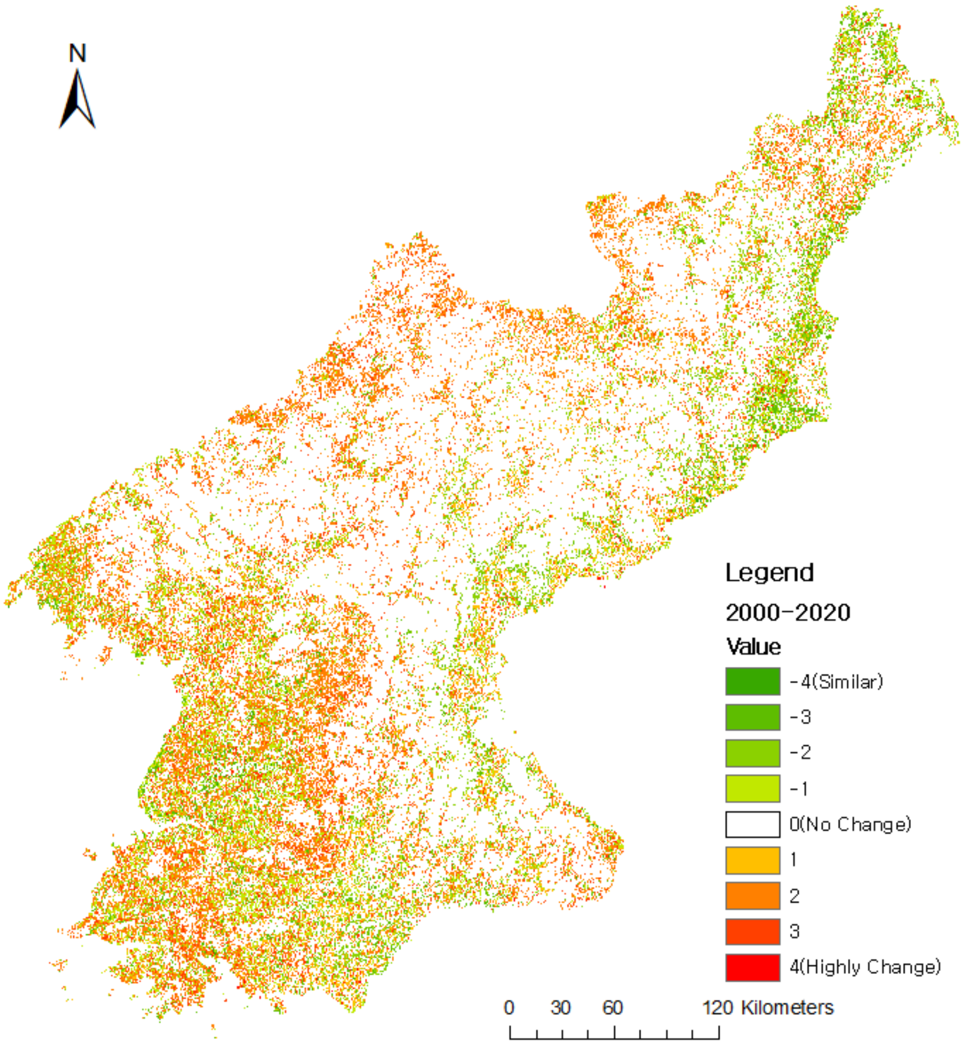


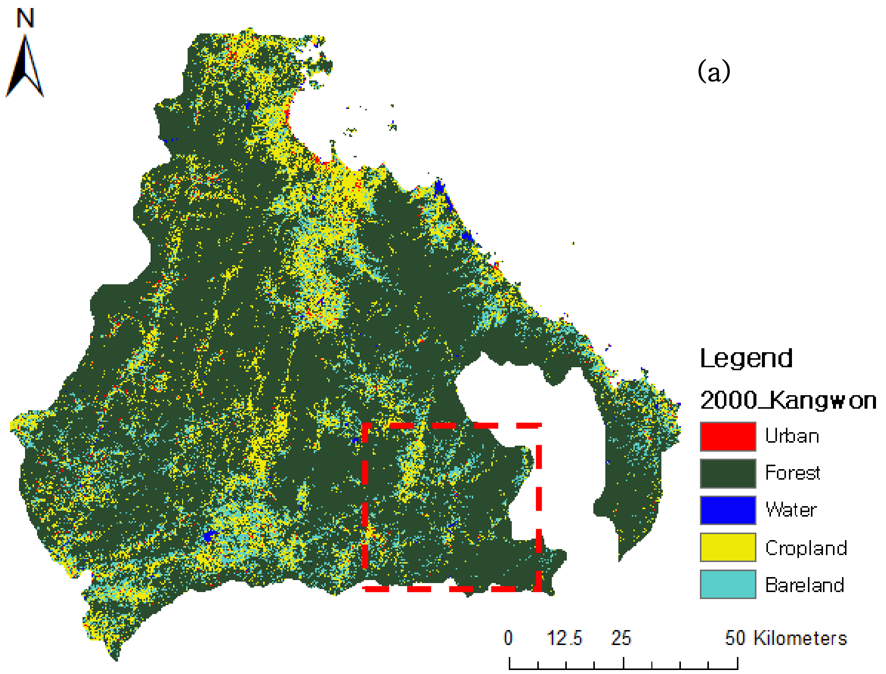
Figure 8 2000-2020 change detection result

4.2.4. Regional Results

During the period of the study from 2000 to 2020, we examined in detail which parts and how the changes occurred mainly in the areas where the results of change detection occurred a lot. First, the Gangwon-do region was examined (Figure 9). The most notable change in the region was the creation of a large artificial reservoir between 2000 and 2010. The red dotted line in Figure 9 indicates that, during 2000, a large artificial reservoir was created in the region consisting of forest, cropland, and bare land.

In Pyeonganbuk-do, industrialization, urbanization, and agricultural landization caused widespread deforestation across the entire region (Figure 10).

Pyeongyang, the capital of North Korea, is notable for its urbanization and rapid agricultural land reclamation. There is also a spot where it is partially bare. The figure indicates that the urban part of Pyongyang has grown gradually over the past 20 years, and the agricultural land reclamation has occurred extensively in the area around it (Figure 11). In case of Pyeongannam-do and Pyeonganbuk-do, it was confirmed that forest damage due to industrialization is in progress because coal mines are located extensively in the outskirts (Figure 11, 12; Yang et al., 2020; National Academy of Forest Sciences, 2018).


N
(a)
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Urban
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Cropland
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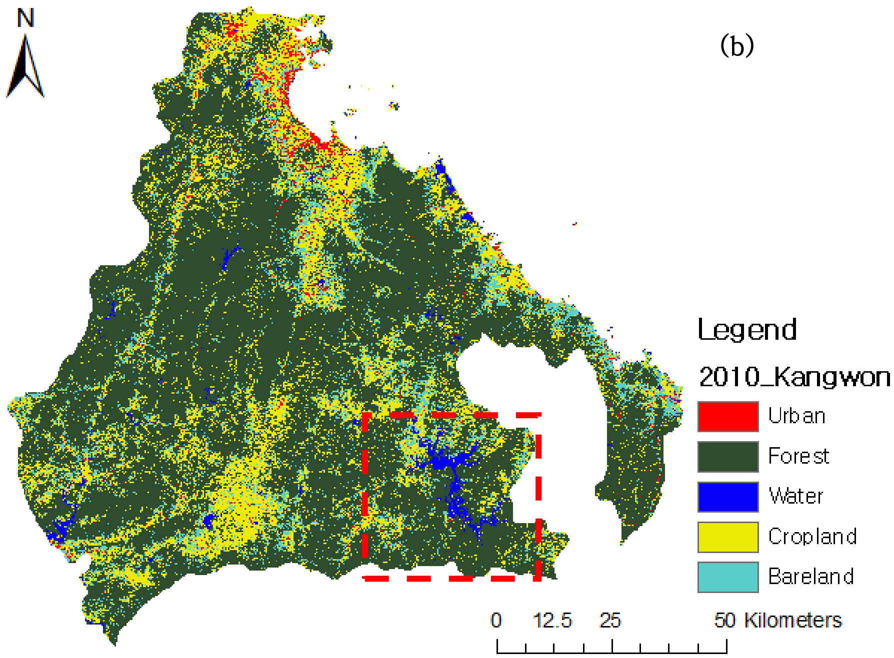
0 12.5 25 50 Kilometers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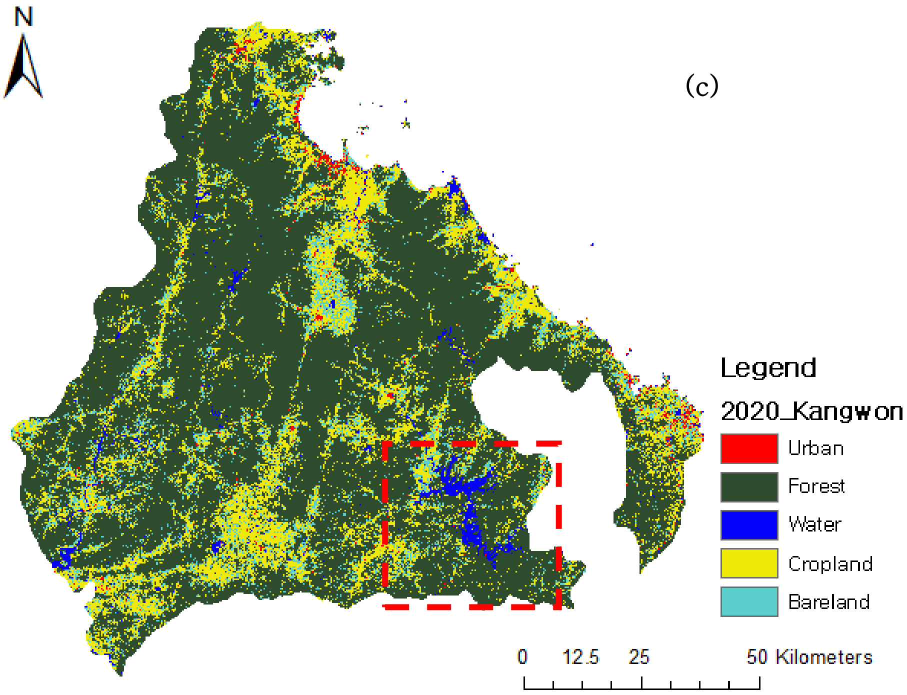
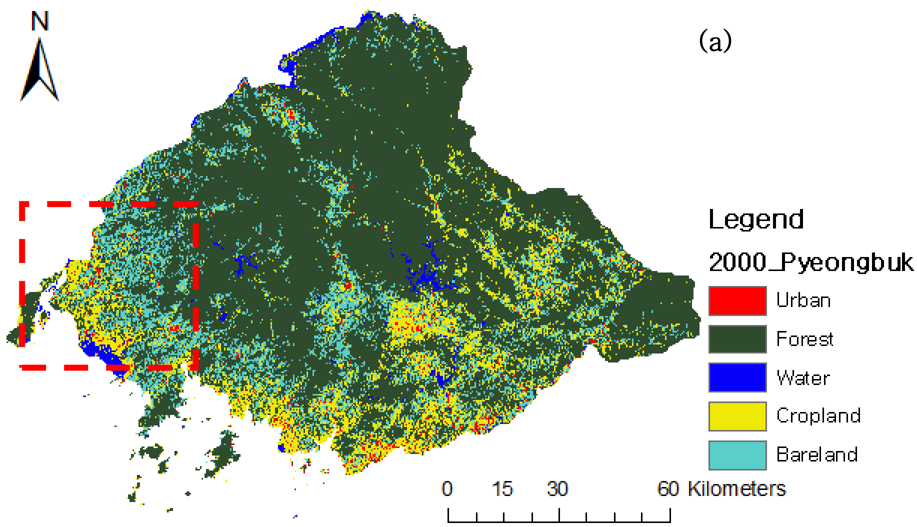


Figure 9 Result of classification of land cover in Gangwon-do (a) Gangwon-do in 2000 (b) Gangwon-do in 2010 (c) Gangwon-do in 2020 (Change of land cover to artificial reservoir in red dashed line)



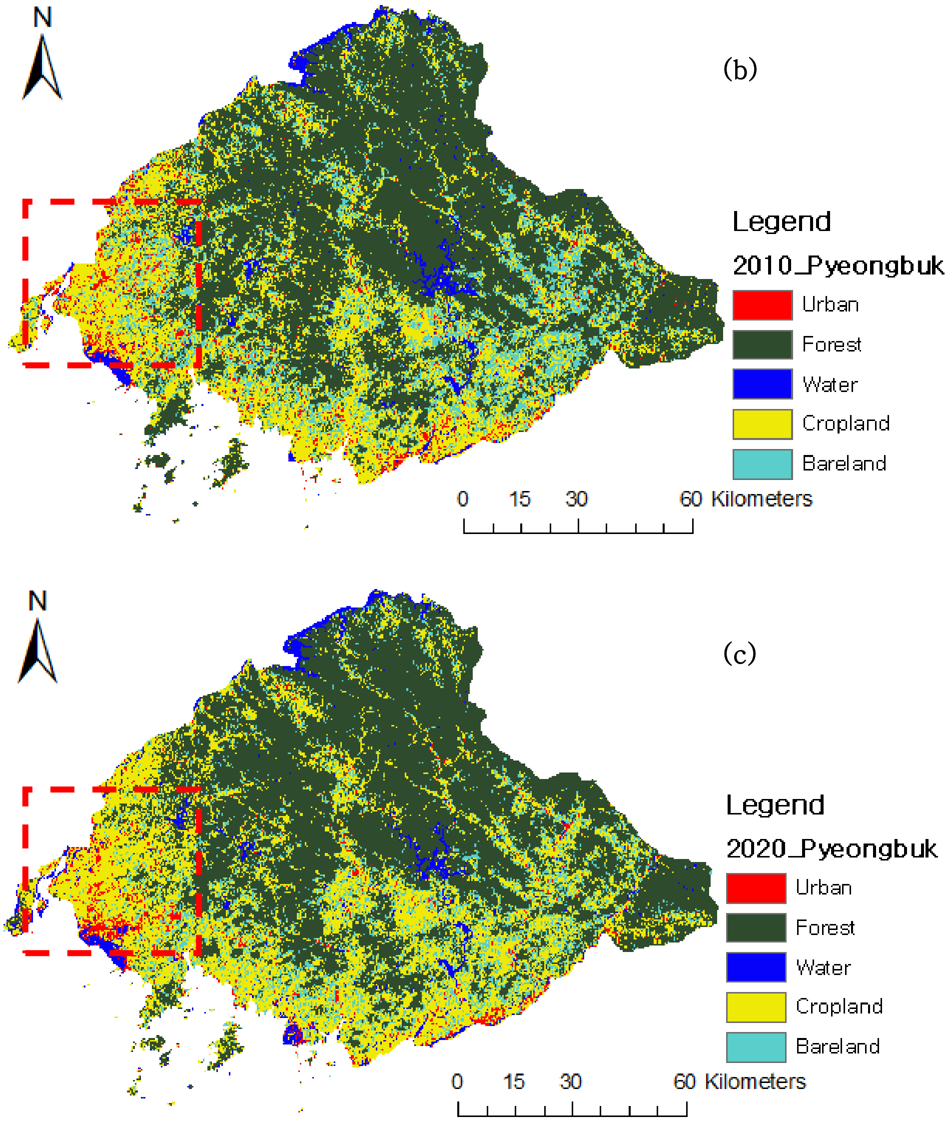
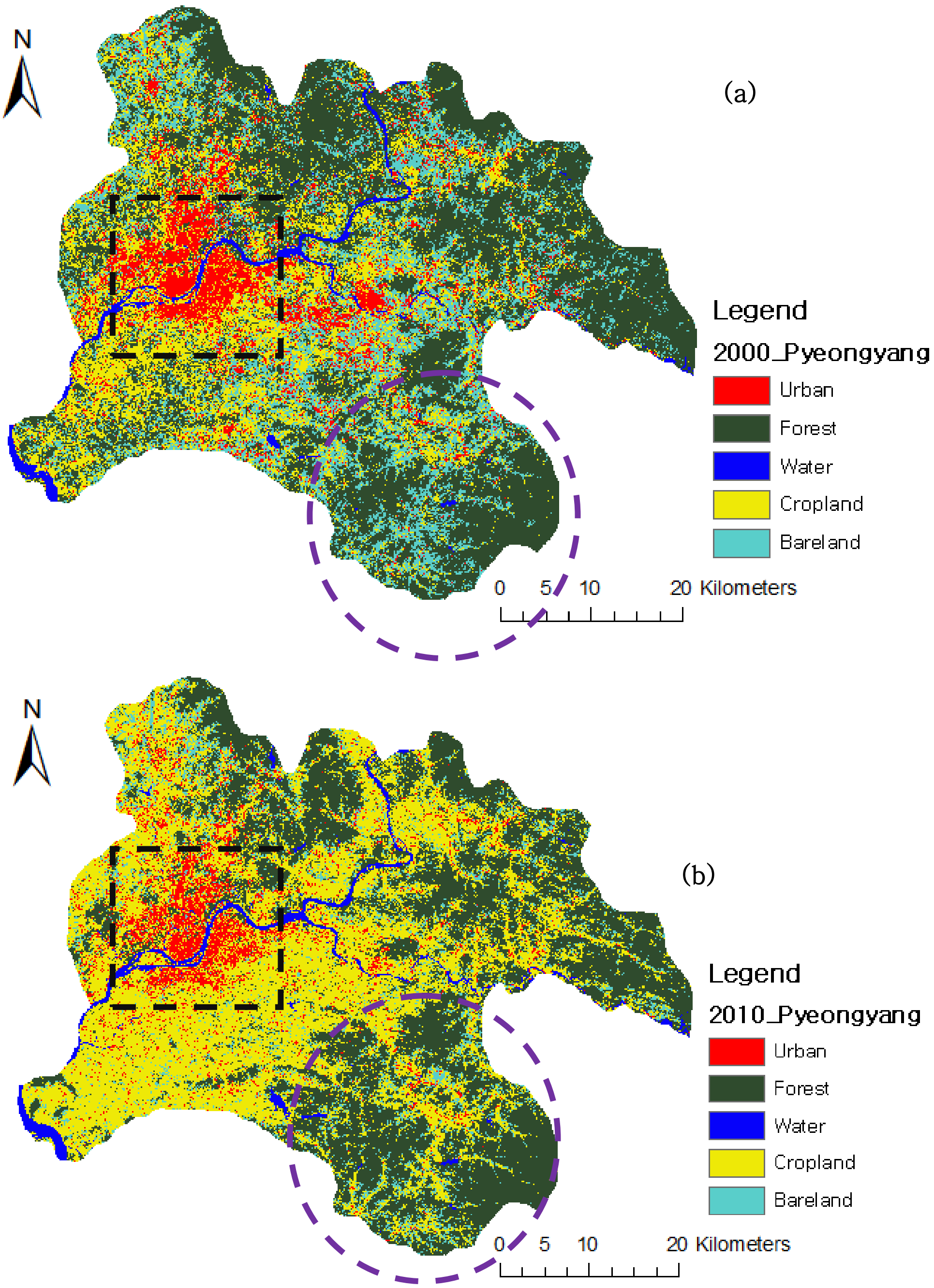


Figure 10 Result of classification of land cover in Pyeonganbuk-do (a) Pyeonganbuk-do in 2000 (b) Pyeonganbuk-do in 2010 (c) Pyeonganbuk-do in 2020 (Change of land cover to cropland in red dashed line)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2000_Pyeongyang
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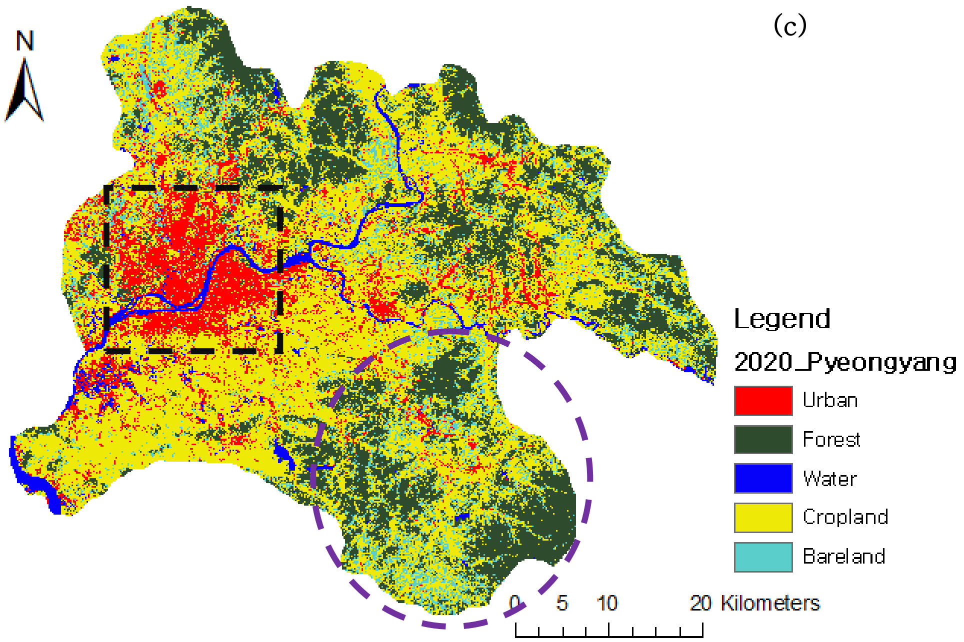
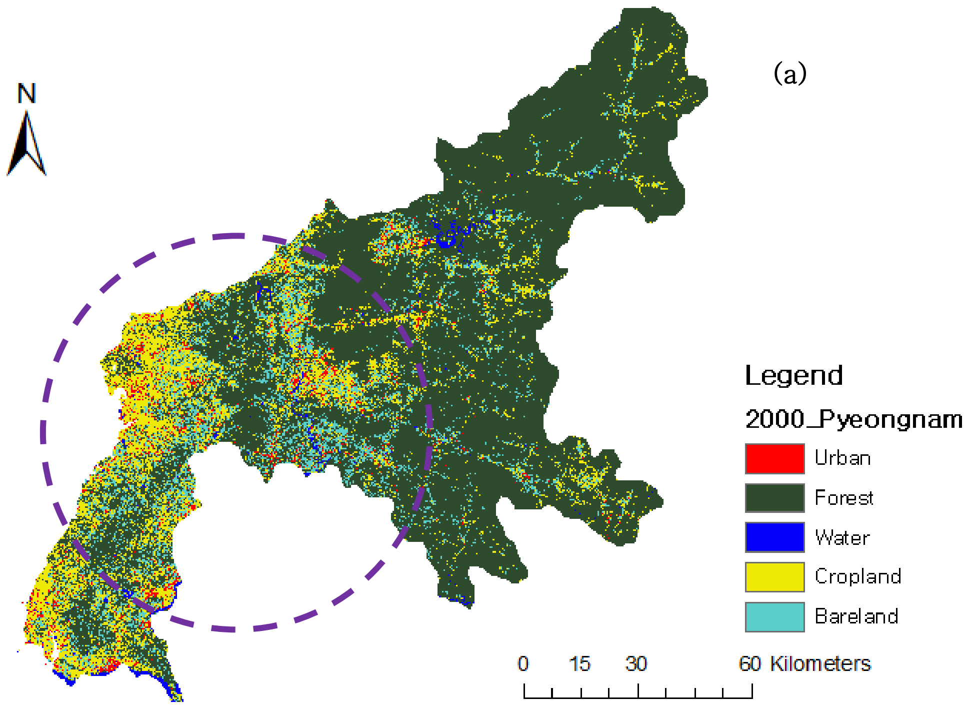
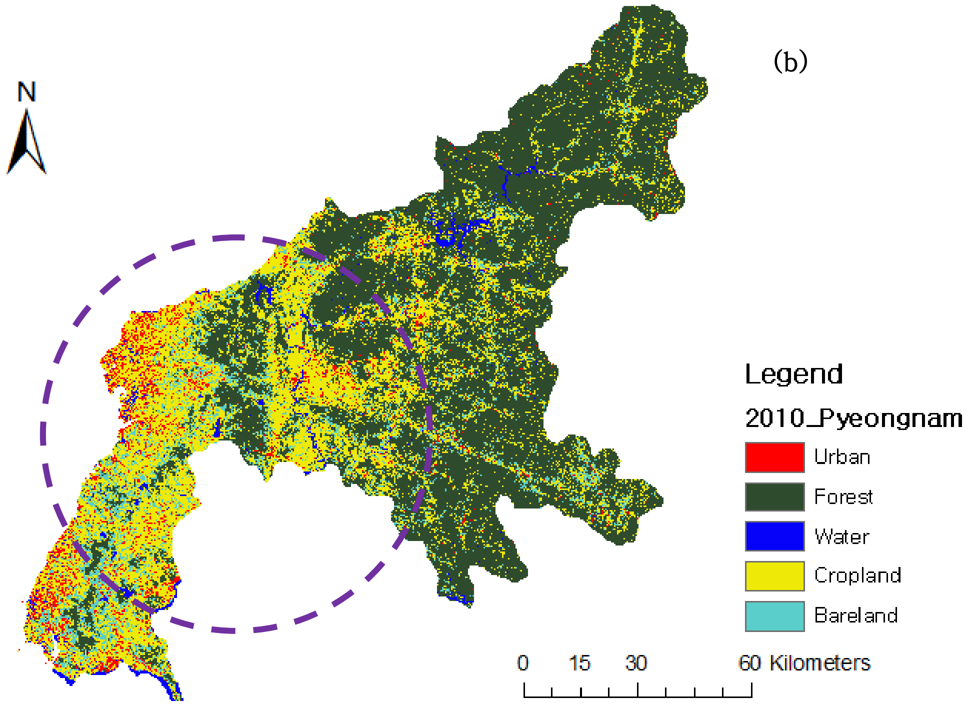


Figure 11 Result of classification of land cover in Pyeongyang (a) Pyeongyang in 2000 (b) Pyeongyang in 2010 (c) Pyeongyang in 2020 (Change of land cover to urbanization in black dashed line, Change of land cover to cropland and bareland in purple dashed line)





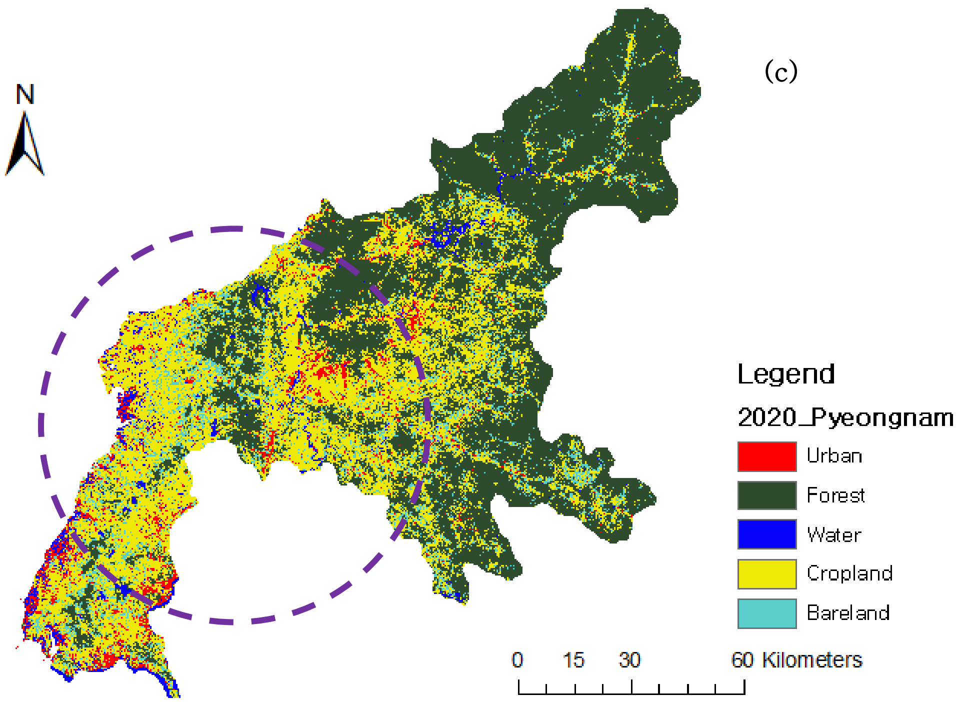


Figure 12 Result of classification of land cover in Pyeongannam-do (a)

Pyeongannam-do in 2000 (b) Pyeongannam-do in 2010 (c) Pyeongannam-do in 2020 (Change of land cover to cropland and urbanization in purple dashed line)

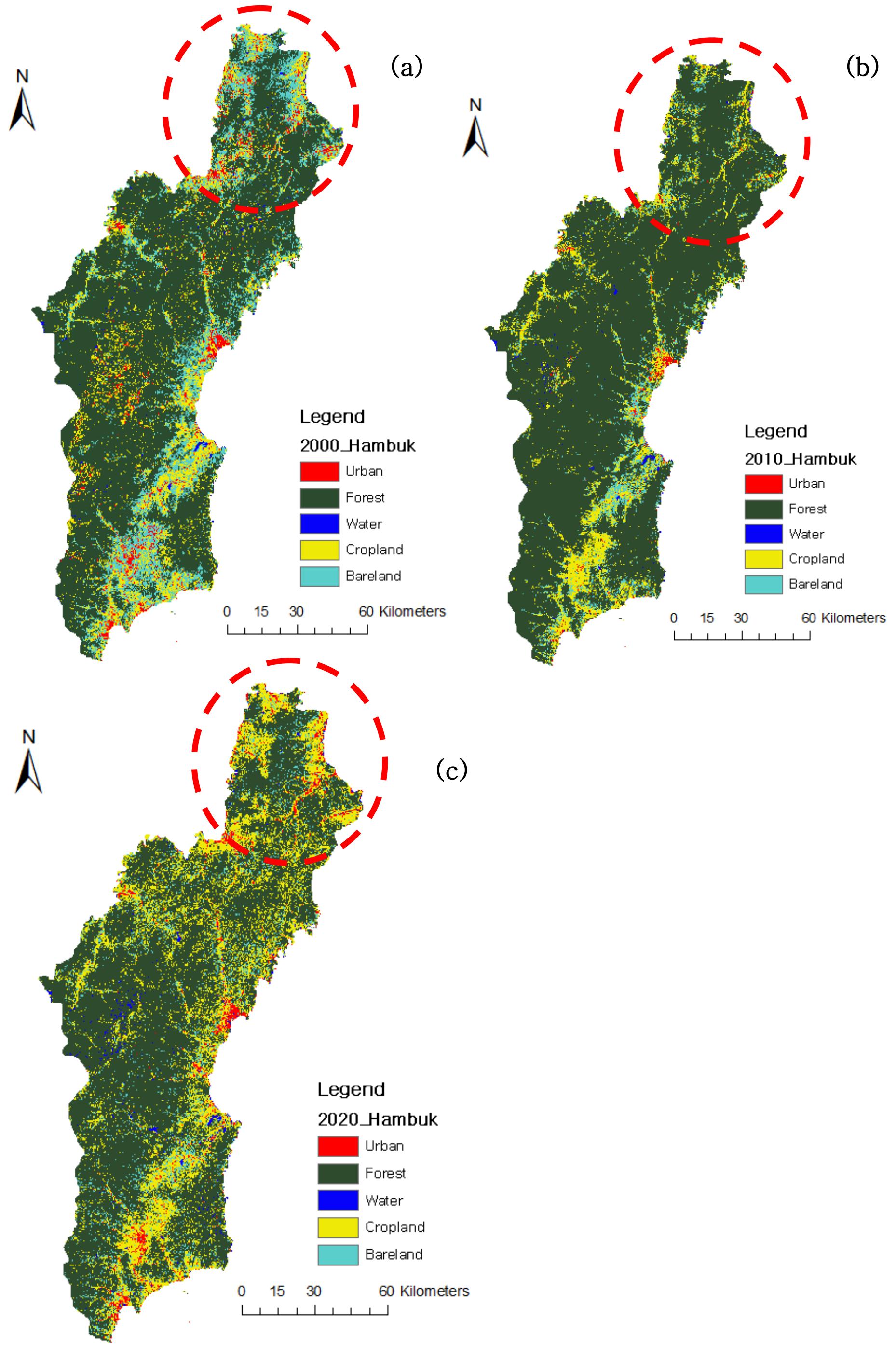
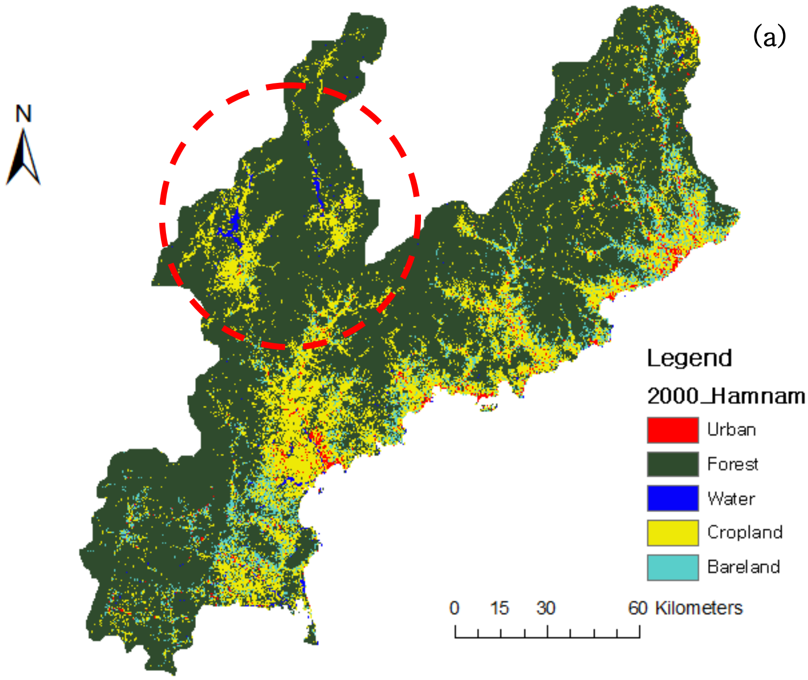


Figure 13 Result of classification of land cover in Hamkyeongbuk-do (a) Hamkyeongbuk-do in 2000 (b) Hamkyeongbuk-do in 2010 (c) Hamkyeongbuk-do in 2020 (Change of land cover to urbanization in red

dashed line)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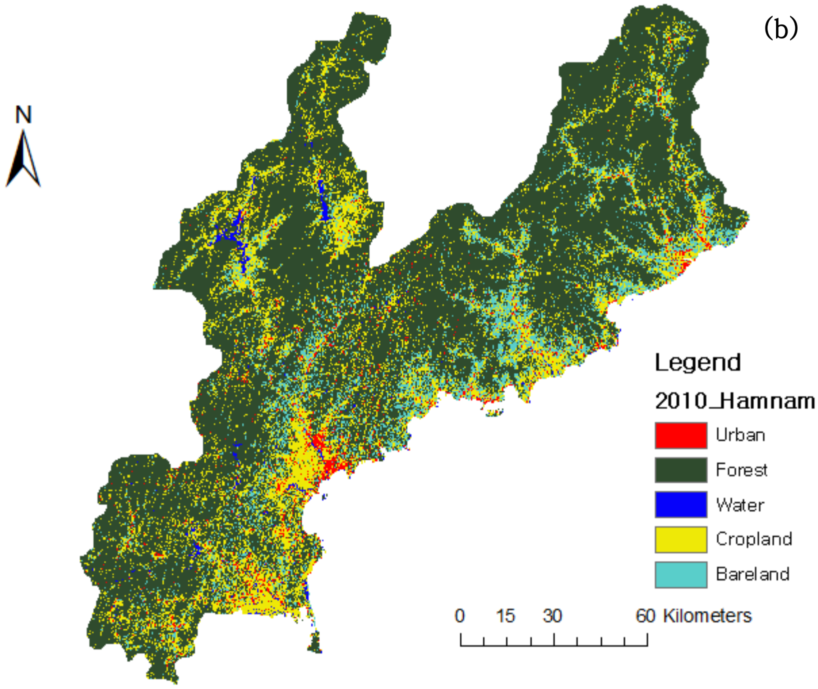
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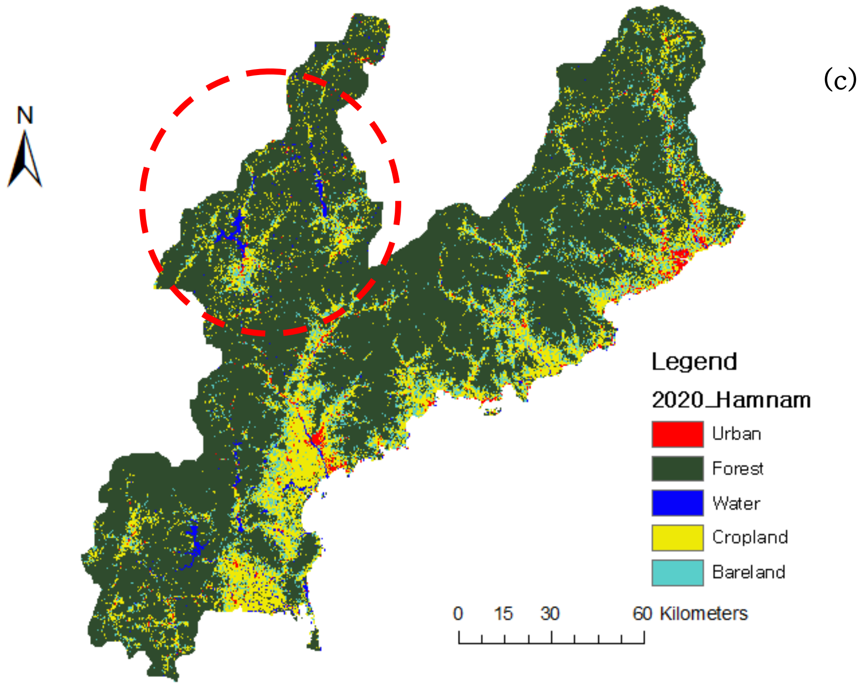
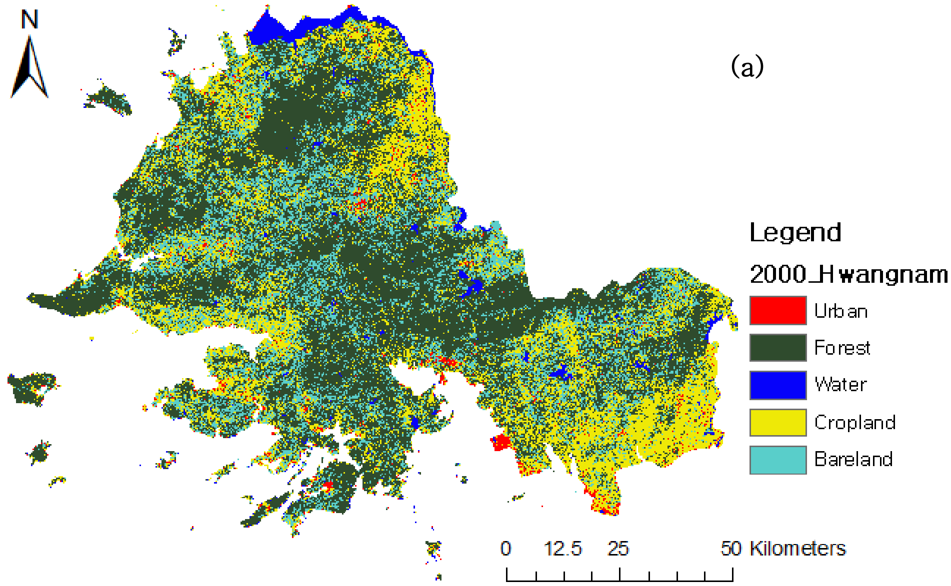
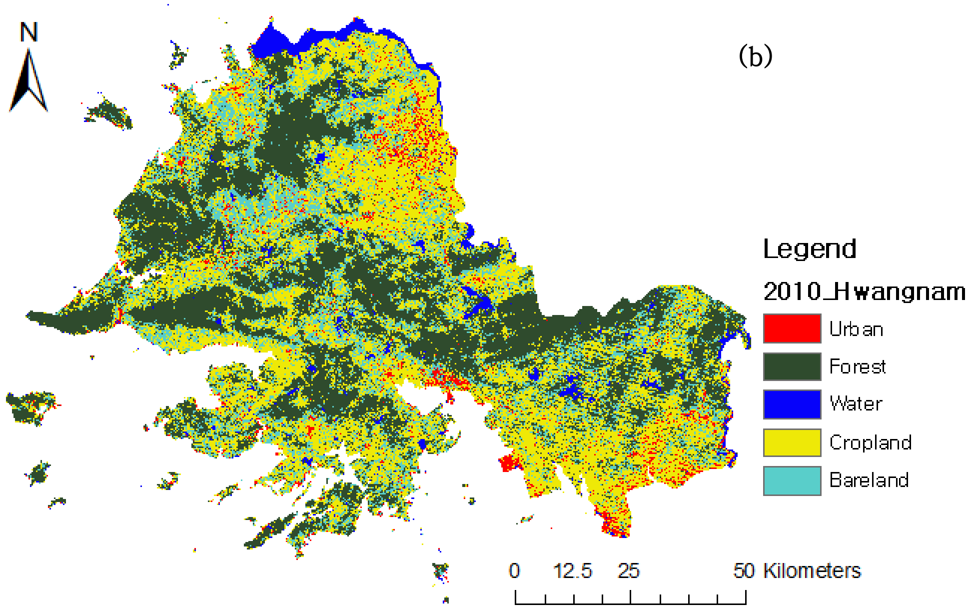


Figure 14 Result of classification of land cover in Hamkyeongnam-do (a) Hamkyeongnam-do in 2000 (b) Hamkyeongnam-do in 2010 (c) Hamkyeongnam-do in 2020 (Change of land cover to reforestation in red dashed line)





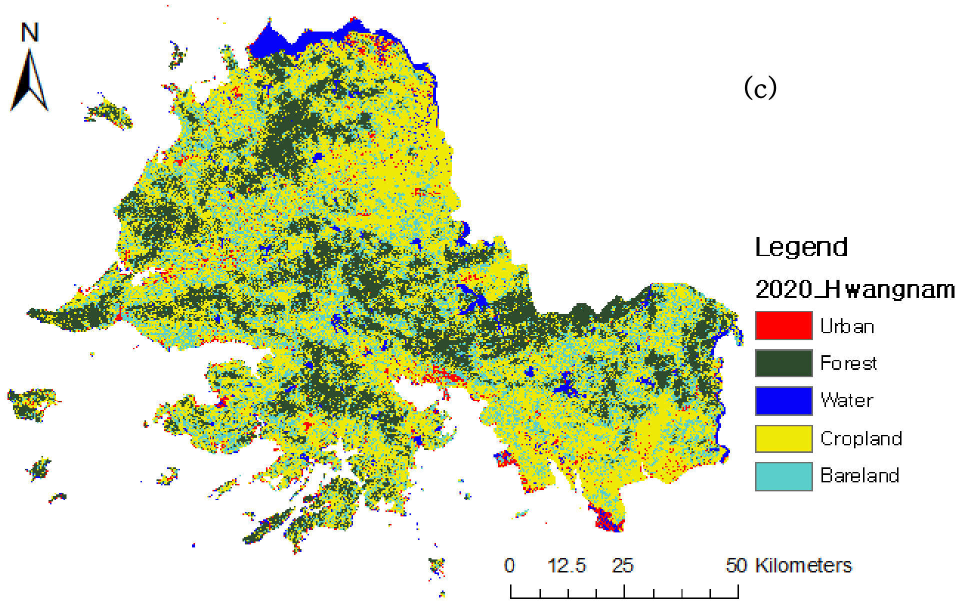
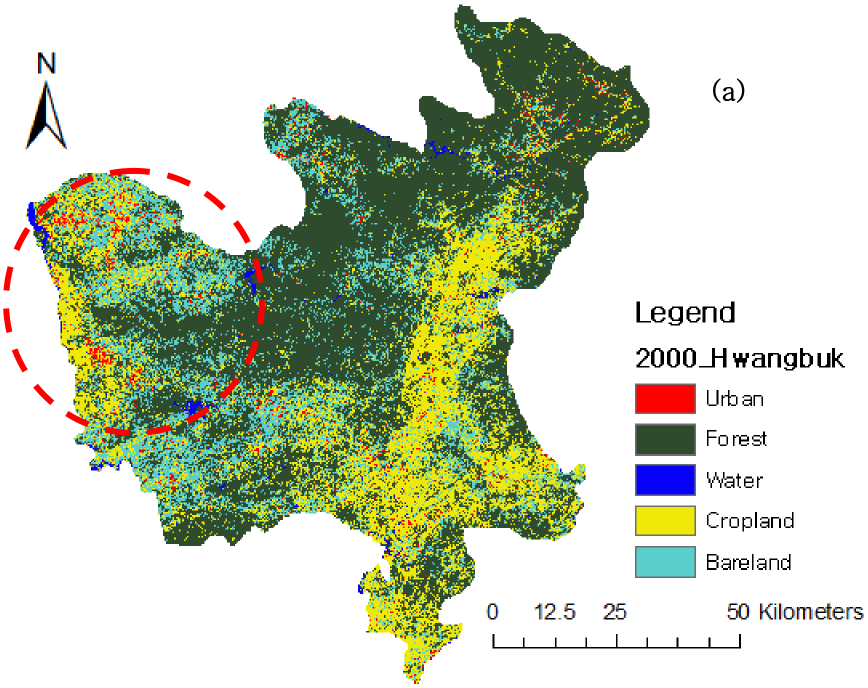


Figure 15 Result of classification of land cover in Hwanghaenam-do (a) Hwanghaenam-do in 2000 (b) Hwanghaenam -do in 2010 (c) Hwanghaenam -do in 2020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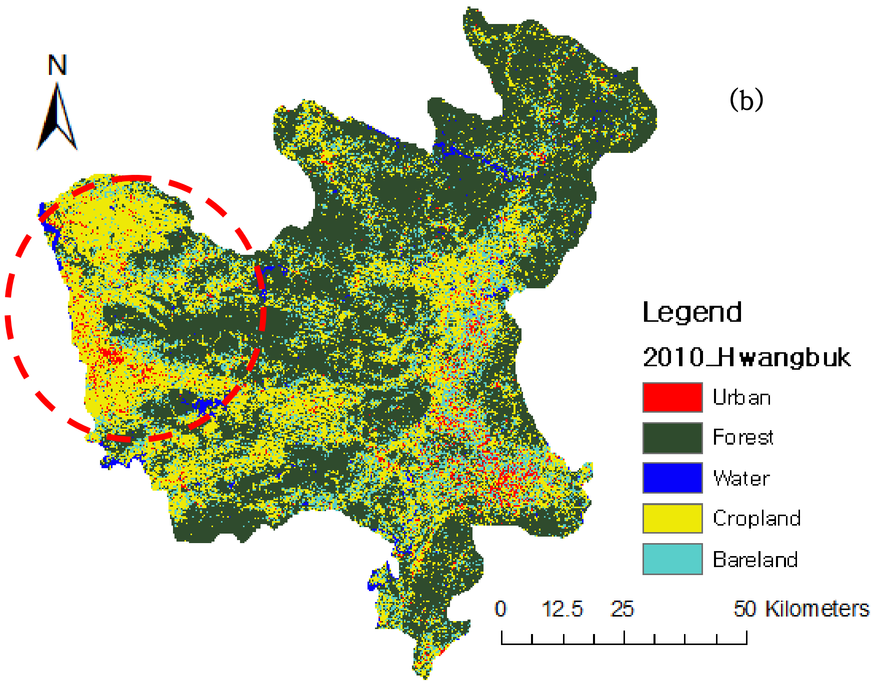
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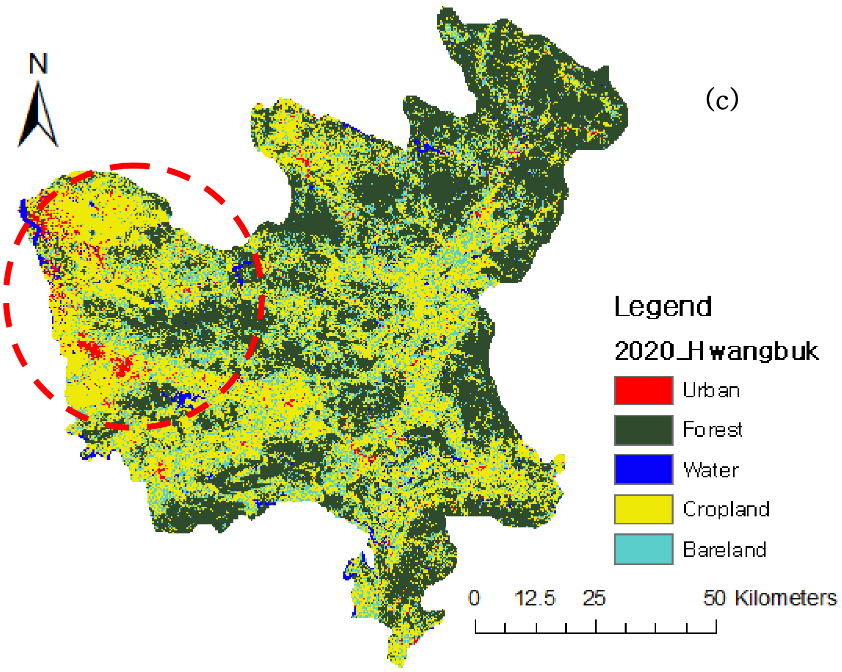

Figure 16 Result of classification of land cover in Hwanghaebuk-do (a) Hwanghaebuk-do in 2000 (b) Hwanghaebuk -do in 2010 (c) Hwanghaebuk -do in 2020 (Change of land cover to cropland and urbanization in red dashed line)

4.3. Discussion

In this study, using the GEE platform, the status, scale, and cause of deforestation in North Korea for 20 years in 2000, 2010, and 2020 were identified, and the causes of deforestation were analyzed by region. For the analysis, Landsat TM, ETM+, and OLI data of April, May, June, September, and October were used. Radiation and atmospheric correction were performed prior to analysis to prevent errors. Since forest areas and cropland can be classified differently by season, multi-period images were used for analysis. A pixel-based supervised classification was classified using a random forest classifier, and it was classified into a total of five types of cover: urbanization area, agricultural area, forest area, bare area, and water area. Sample data for machine learning was selected by visually checking from satellite image maps of Google

Earth Pro and GEE, and 50-110 sample points were selected and trained for each cover and year. It was repeated 500 times, and the overall classification accuracy was about 85% or more and the maximum was 94%, and the Kappa coefficient was about 81% or more and the maximum classification accuracy was 92%.

The proportion of forest decreased by about 11.5% during the decade from 2000 to 2010, while the proportion of cropland and bareland increased by about 7% and 2%, respectively. This supports the results of previous studies that North Korea's deforestation has become more severe since the 1990s (Lee et al., 2017). This is interpreted as a result of deforestation caused by reckless deforestation and clearing of agricultural land (Jin et al., 2016; Lim et al., 2017; Lim et al., 2019). Looking at by region, it can be seen that clearing of agricultural land especially occurred in Hwanghae-do and Pyeonganbuk-do (Figures 10, 15, 16), and industrialization and urbanization occurred more in Pyongyang, Pyeongannam-do, and Hamgyeongbuk-do than in other areas (Figure 11,12,13).

Also, looking at the results for 10 years from 2010 to 2020, the proportion of forests increased by about 1%, and it was confirmed that forest areas were restored in some areas (Figure 14). This can be interpreted as the result of the restoration project carried out continuously in North Korea, and supports the results of previous studies that forest restoration was successful in some areas of Hamgyeongbuk-do (Yang et al., 2020; Daily NK, Jun 25, 2021). However, as the percentage of cropland has still increased by 3%, it can be interpreted that cropland reclamation is being carried out at the same time as the forest restoration project (Yang et al., 2020). By region, forests have been restored in Hamgyeongbuk-do, Pyeongannam-do, and some areas of Pyeongyang (Figure 10, 11, 14; Daily NK, June 24, 2021; Yang et al., 2020), although It was confirmed that serious cropland reclamation was still taking place in Pyeongannam-do and Hwanghae-do (Figures 10, 15, 16).

Since most studies related to forest restoration and policies in North Korea do not have research results on forest area after 2018, the significance of this study is that it can serve as a basic data for the most recent status and causes of deforestation in North Korea. However, since auxiliary data such as vegetation index and slope, which can improve the accuracy of the random forest classification result, were not used, it is necessary to perform a more accurate analysis by using auxiliary data in the future.

Chapter 5. Conclusion

In this study, pixel-based supervised classification random forest classification was performed using Landsat satellite image data for 20 years from 2000 to 2020 using GEE, a geographic information platform. In addition, change detection analysis was conducted to identify areas that were deforested. In this study, two hypotheses were established. The first is that the main causes of deforestation in North Korea during the two periods 2000-2010 and 2010-2020 will be different, and the second is that the causes of deforestation will be different by region. The results confirmed that the first hypothesis was partially correct. As explained in the previous research results, the main causes of deforestation in North Korea are reckless deforestation and clearing of agricultural land due to lack of food and fuel. Reckless deforestation and clearing of agricultural land are identified as the main causes during the periods of 2000-2010 and 2010-2020. In addition, urbanization and industrialization were further identified as the other causes during the period of 2010-2020. There were no significant development projects in North Korea during the period 2000-2010, and during the period of 2010-2020, it was confirmed that other causes were added due to North Korea's 10-year national economic development project that started in 2011.

The second hypothesis confirmed that the causes of deforestation vary slightly according to regional characteristics. In Pyongyang, the capital of North Korea, devastation caused by urbanization was the main cause, and in the densely populated

Hwanghae–do region, the main cause was the clearing of agricultural land. In Pyeongannam–do and Pyeonganbuk–do, urbanization and clearing of agricultural land were the main causes, and in Hamgyeongbuk–do, where the Rajin–Seonbong Special Economic Zone is located, industrialization was the main cause. As North Korea plans to continuously carry out regional development projects throughout North Korea (CEO NEWS, Jun 25, 2021), the causes of deforestation will vary from region to region. Therefore, in the case of future restoration projects, it is necessary to establish a restoration plan suitable for the characteristics of each region.

As such, deforestation is taking place throughout North Korea, but through the analysis results, it was possible to confirm that the forest was restored in some areas. As the deforestation in North Korea becomes more severe, the North Korean government recognizes the seriousness and aggressively calls it a 'forest restoration battle project'. The restoration project is being carried out by planting trees (Yang et al., 2020; Daily NK, Jun25, 2021; KBS). However, there is a limit to mobilizing residents to plant trees, and North Koreans do not actively participate due to difficulties in their livelihoods. In addition, as tensions between the two Koreas continue, South Korea's support for the North Korean Forest restoration project is not smooth, so the restoration project is progressing slowly. (Park and Yu, 2009; Lee et al., 2010; Lee et al., 2017; Heo, 2020; VOA, Jin 25, 2021). In addition, the results of the study confirmed that there are regions where deforestation and forest restoration are in progress concurrently. Despite the high level of desire to restore forest, deforestation continues in North Korea and this study can be used as a basic data to support successful restoration projects in the future.

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Abstract(국문)

산림 황폐화는 산림 생태계를 파괴하며 물 저장 및 공급과 대기오염을 줄이는 등 산림이 가지고 있는 기능을 저하시킨다. 황폐화로 인한 산림의 기능 저하는 기후변화 대응 및 대기질 측면에서 부정적인 영향을 미치게 된다. 북한은 세계 3개 산림 황폐지역으로 1990년대부터 최근까지 산림의 약 28%가 황폐화되었다는 국립 산림 과학원의 연구결과가 있다. 하지만 공인된 통계는 없어 추후 복원을 위해서는 정확한 현황 파악이 필요한 실정이다. 일반적인 산림 황폐화와는 달리 북한은 경제적인 어려움으로 인한 식량 부족과 에너지 자원의 부족으로 발생하였다. 식량 공급을 위하여 산림은 밭으로 개간되었고, 석탄의 부족으로 인하여 에너지원으로 사용하기 위한 무분별한 벌목이 진행되어 광범위함 산림 황폐화가 가속화되었다. 산림 황폐화의 문제점은 북한에서도 인식하여 관련 정책을 진행하는 등의 노력을 하였지만, 지속되는 경제난과 한국과의 관계 악화로 인하여 효과적으로 이루어지지 않고 있다. 북한의 산림 황폐화는 북한뿐 아니라 한반도의 환경과 동북아에 사회 경제적으로 영향을 주고 있기 때문에 복원이 시급한 상황이며 추후 한국과의 관계가 개선되었을 때 효과적인 복원 사업 지원을 위해서는 정확한 현황과 규모를 파악하는 것이 중요하다. 북한은 현재 접근 불가 지역으로 현장조사를 통한 현황 파악이 불가능하기 때문에 위성영상을 사용한 원격탐사가 가장 효과적인 방법이다. 또한 산림 황폐화는 단기간에 나타나는 현상이 아니라 장기간에 걸쳐 진행되는 현상이기 때문에 다중시기로 분석할 필요가 있다. 따라서 본 연구에서는 북한의 산림 황폐화가 심화되기 시작한 1990년대 이후인 2000년부터 가장 최근인 2020년까지 20년 동안의 북한 산림 황폐화 현황을 파악하는 것을 기본으로 두 가지 연구 가설을 세워 리를 확인하고, 황폐화 진행이 얼마나 되었는지, 복원사업의 성과가 있었는지 살펴보고자 한다. 이를 통해 추후 복원 사업을 진행할 때, 체계적인 계획을 세울 수 있는 기초자료로 쓸 수 있도록 하는 것이 연구 목표이다. 이를 위하여 미국의 지리정보 플랫폼인 Google Earth Engine을 통하여 픽셀 기반 감독 분류 랜덤 포레스트(Random Forest) 방법을 사용하여 토지 피복 분류를 진행하고, 이를 기반으로 Change Detection(변화 감지)을 하여 어느 지역에서 황폐화가 진행되었는지, 산림 면적이 얼마나 변화하였는지 살펴보았다. 분석을 진행한 결과, 2000년-2010년 동안 북한의 산림 비율은 전체 면적의 약 72.5%에서 약 61%로 약 11.5% 정도 감소한 것으로 나타났다. 이와 반면에 농지와 나지의 비율은 각각 약 7%, 약 2% 증가한 것으로 나타나 무분별한 벌채와 개간으로 인한 산림 황폐화가 심각하다는 것을 보여준다. 변화가 가장 많이 나타난 지역은 평안도, 함경도, 강원도 지역으로 나타났으며, 변화가 가장 적게 나타난 지역은 황해도 지역으로 나타났다. 2010년-2020년 동안의 북한의 산림 비율은 약 61%에서 약 62%로 약 1%정도 증가하였으며, 농지도 약 3% 증가하였다. 이와 반면에 나지 비율은 약 4% 감소하여 본격적인 산림 복원 사업을 시작한 2016년 이후 산림 비율이 약간 상승하고 나지

비율이 감소하였으나 농지 비율이 증가한 것으로 보아 산림 복원이 성공적으로 이루어지지 않았으며, 무분별한 개간 또한 지속되고 있다는 것을 보여준다. 변화가 가장 크게 일어난 지역은 황해도, 함경도 강원도 지역으로 나타났으며, 변화가 가장 적게 일어난 지역은 평안도 지역으로 나타났다. 20년 동안 공통적으로 변화가 많이 일어난 지역은 함경도 강원도로, 분석결과를 통해 이 지역에서 개간과 벌채가 많이 일어났음을 알 수 있다.

주요어 : 북한, 산림 황폐화, 원격탐사, 랜덤 포레스트(RF), Change Detection, GEE(Google Earth Engine)
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