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Spatiotemporal Patterns of Forest Changes in Korean Peninsula Using Landsat Images During 1990–2015: A Comparative Study of Two Neighboring Countries

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ABSTRACT Forest change in the Korean Peninsula related to different socioeconomic developments in North and South Korea and impacted on the regional environment. However, there was a lack of consistent information about forest changes, especially comparative knowledge of North and South Korea that support management and policymaking. We used the change object update method to generate the first object-based 30m land cover set for the peninsula and analyzed new observations of forest changes in North and South Korea from 1990-2000 to 2000-2015. Results showed that, in North Korea, annual forest loss increased from 142 $km^2 \cdot yr^{-1}$ to 257 $km^2 \cdot yr^{-1}$, and the total loss increased from 1,407 km^2 to 3,769 km^2. The elevation range where forest loss concentrated shifted from 100-300 m to 300-1,000 m. The conversion of forest to cropland increased from 1,256 km^2 to 3,910 km^2, indicating North Korea's forest eroded by agriculture expansion to ensure food security. By contrast, in South Korea, despite forest total loss increased from 338 km^2 to 513 km^2, annual loss remained at 34 $km^2 \cdot yr^{-1}$. The forest loss was concentrated at the elevation range of 0-300 m, which linked with built-up land expansion. Different public income and social developments drove distinct magnitude of forest loss in the two countries. Follow the Global Forest Observations Initiative, although forest loss might be underestimated for North Korea and overestimated for South Korea, our land change information equipped good overall accuracy ($\geqslant 0.94 \pm 0.031$). This study could provide useful implications for forest management and regional sustainable development.

INDEX TERMS Remote sensing, North Korea, South Korea, forest, sustainability.

I. INTRODUCTION

Forest ecosystems play a crucial role in soil formation, water regulation, climate control, etc. [1], [2] and provide vital habitat services for humans, animals, plants, and insects [3], [4].

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Continued loss of forest cover may lead to the intensification of various disasters such as floods [5], bio-sequestration loss [6], displaced wildlife [7], and financial loss [8], [9]. Reliable information on forest changes is thus of great help to international agencies, governments, and non-governmental organizations when making policies and investment decisions, and to scientists who provide decision support [10].

Although consensus on drivers of forest changes, accurate monitoring forest remains a challenge for further actions in some countries, obstructing global efforts on forest ecosystem protection [11], [12].

Socioeconomic development and human activities for subsistence are the main drivers for changing the forest. Socioeconomic development tends to recover forest [12], such as planting for environmental and commercial purpose, and spontaneous regeneration on abandoned agriculture land due to rural-to-urban migration. For example, thanks to China's massive forestation plan and economic development, the forest area in East Asia grown the fastest globally, although world forests lost 1.29 million hectares in 1990-2015 [13], [14]. However, in tropics that concentrates the underdeveloped countries [15], forest losses were too high to be offset by forest gains in other climate areas [16]. Timber harvesting and agricultural development were the primary drivers, resulting from financial purpose or lack of food and energy [17], [18]. Meanwhile, deforestation ultimately led to a loss of essential supplies of timber and medicines on which poor residents largely depend, as well as soil erosion and habitat degradation. Wealthy societies, however, could afford to renovate landscapes to improve ecological conservation. For example, China's forestation program not only improved soil erosion and wildlife habitat domestically [19] but also contributed greatly to forest C sequestration in East Asia [6]. For achieving more human well-being, local socioeconomic status should be taken into account to seek pathways for sustainable forest management, especially under the Reduced Emissions from Deforestation and Degradation (REDD+) scheme by the U.N. Framework Convention on Climate Change (UNFCCC).

After the Korean War ended in 1952, North and South Korea experienced different socioeconomic development. For eradicating poverty and ending hunger, increasing agricultural production has been one of the main tasks in North Korea [8]. Although North Korea has been attaching great importance to land protection since the 1990s [20], deforestation was still severe in the 2000s [21]. By contrast, South Korea was one of the largest economies worldwide and played a crucial role in trade globalization [22]. Despite years of efforts in forest restoration [6], [23]–[25], there were still some ecological problems such as biodiversity loss and non-native species invasion triggered by forestation activity in South Korea [22]. Therefore, the Korean Peninsula as the only place worldwide where hosts an underdeveloped country and a wealthy country [15], [22] is a study area of value to comprehend more about links between forest change and socioeconomic development. Besides, the peninsula forest ecosystem in the center of Northeast Asia is an irreplaceable ecological barrier between China, Russia, and Japan. However, there is lacking consensus on the trend of forest changes in the Korean Peninsula and differences between North Korea and South Korea, which cannot support eliminating potential challenges for local sustainability.

Reliable observations of forest changes are challenging in secretive societies such as North Korea. North Korea seldom disclosed forest and agriculture records [8]. Although South Korea officially released inventory data, it lacked statistics on conversions of forests with other land covers [26]. In this case, to break through the land boundary and observe the forest change, satellite remote sensing is the ideal choice. Among various remote sensing data, Landsat imagery with a spatial resolution of 30m and the longest record of the Earth's surface was frequently employed in mapping land cover [27], [28] and observing forest loss [17], [29]. Yet, few studies observed the forest loss in North Korea using the Landsat data, indicating discrepant results that loss of forest cover ranged from 0 to 12.8% during the 1990s [21], [30]. Findings on forest change for the entire peninsula were even rarer, which based on different data inputs and could thus be inaccurate [24], [31]. Because different data inputs were inconsistent in the mapping method and forest definition, the "real" forest extent and change cannot be captured. For example, [24] extracted tree cover in North and South Korea from AVHRR and MODIS tree cover maps. As the two satellites provided much coarser images, details of land changes were very likely to be neglected. Besides, consistent observations of forest changes throughout the peninsula from the 1990s to the mid-2010s have not yet taken place, and this gap needs to fill. Landsat data could gain more accurate observation and thus provide reliable forest information for the whole peninsula [10], [11].

In this study, we aim to generate consistent observations about forest changes in the Korean Peninsula using long-term Landsat images. Our specific objects are to (1) generate land cover maps for 1990, 2000, and 2015 using a change object updating approach, and (2) quantify spatiotemporal forest changes in North Korea and South Korea during 1990-2015. Besides, socioeconomic drivers of forest change have discussed qualitatively. For the first time, this study reports consistent and coherent information on forest changes for North and South Korea, shedding light on environmental management and policymaking for the Korean Peninsula.

II. MATERIALS AND METHODS

A. STUDY AREA

The Korean Peninsula locates in temperate East Asia, borders China and Russia, and is close to Japan (Figure 1). The land extent of the peninsula is about 225×10^3 km^2 and is covered mostly by forest and cropland. There is a mountain chain that continues from the north to the south in the peninsula, where the altitude and slope ranged from 0-2727 m and 0-78°, respectively. Two countries, North and South Korea, occupied the northern and southern parts, separated by the Demilitarized Zone (DMZ) in the central peninsula [22]. According to the Food and Agricultural Organization (FAO), there were 25×10^6 and 51×10^6 inhabitants in North and South Korea in 2015, respectively. About 82% of the South Korean population was living in urban areas compared to

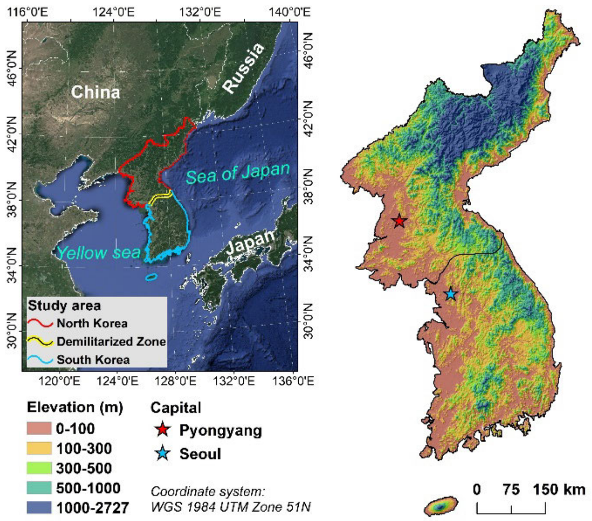

FIGURE 1. The location and topography of the Korean Peninsula.

61% in North Korea. South Korea as a high-income country, its Gross National Income (GNI) per capita was $27,405 in 2015 [15]. In contrast, North Korea was the only low-income country in East Asia with a GNI per capita of $652 in 2015.

B. LANDSAT AND REFERENCE DATA

A total of 96 Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) images from the year or near years of 1990, 2000, and 2015 were collected from https://glovis.usgs.gov. All images equipped good observations with cloud cover $< 5\%$. Among them, 72 growing season images for mapping in the software and 24 multi-season images for phenological reference to differentiate vegetation (Figure S1-S3). In the software ENVI 5.1, they were all georectified to Universal Transverse Mercator (UTM) coordinate system using the World Geodetic System 1984 (WGS84) datum.

The 30m digital elevation model (DEM) was downloaded from http://www.gscloud.cn to classify the elevation and slope for observing forest change at different landforms. High-resolution images from Google Earth were visually referenced when mapping land cover for 2000 and 2015 (Table S1). Besides, five 30m land cover or forest products were compared with our forest maps (Table 1) [21], [32]–[35].

C. METHODOLOGY FOR LAND COVER MAPPING

Through referenced land cover products [32], [34], we found that the peninsula shrub had a slight proportion and cannot be effectively distinguished from trees in the peninsula. Instead, shrubs were integrated into the forest category [30], and the forest did not require an explicit height of more than 5m [34]. The forest was defined as trees having obvious canopies, shadows, textures, etc., with the canopy cover of more than 10%, including coniferous forest, deciduous forest, and mixed forest. Forest changes include loss and gain as the

TABLE 1. Summary of six land cover or forest maps used for comparison in this study.

Publisher	Abbreviation	Period	Method
[34]	FROM-GLC	2010, 2015	Automatic classification
[35]	GLCF-VCF	2000, 2005, 2010	Supervised classification
[33]	GFC	2000-2017	Supervised classification
[32]	Globeland30	2000, 2010	POK-based method
South Korea's Ministry of Environment	LCMKP	1980, 1990, 2000	Unsupervised classification
This study	KP-LC	1990, 2000, 2015	Change object updating approach

results of inter-conversions between the forest and other land covers including grassland, wetland, water body, barren land, burned land, cropland, and built-up land [30], [31], [36].

The change object updating (COU) approach, an integration of updating approach and object-based image analysis (OBIA), was employed to map land cover [37]. The updating approach made multi-year land cover classification efficient [27], [28]. Based on OBIA, our COU method used visual interpretation to update land cover [38], which obtained complete land patches and boosted efficiency. The COU method is robust and suitable for forest change research [29] but applied to the Korean Peninsula for the first time in this study.

We first segmented the 1990 Landsat images to generate object layers for a basic land cover map classification (Figure 2). Because image segmentation we used, which is a built-in function of the software eCognition Developer 8.64, was performed based on similar spectral, texture, and topological features of similar pixel groups [29], enabled land patches intact. From visual inspections, a satisfactory match between image objects and land cover features was achieved when the scale, shape, and compactness parameter was set to 10, 0.1, and 0.8, respectively. Hereafter, the decision rule classifier was employed to label objects into land categories. Based on optical characteristics of land cover, optical indices were employed as rules, including normalized difference vegetation index ($NDVI$), enhanced vegetation index (EVI), normalized difference built-up index ($NDBI$), and normalized difference water index ($NDWI$).

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

$$EVI = 2.5 \times (NIR - RED)/(NIR + 6 \times RED - 7.5 \times BLUE + 1) \tag{2}$$

$$NDBI = (SWIR - NIR)/(SWIR + NIR) \tag{3}$$

$$NDWI = (NIR - GREED)/(NIR + GREED) \tag{4}$$

where $BLUE$, $GREED$, RED, NIR, and $SWIR$ correspond to bands 1 to 5 in the TM sensor and bands 2 to 6 in the OLI sensor, respectively. The index threshold was determined by repeated testing, and forest, built-up land, water body, and cropland could be extracted separately. The experts then manually modified the misclassified objects and generated a

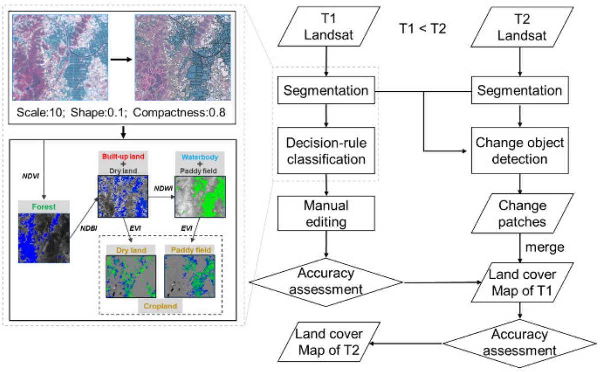

FIGURE 2. **The flowchart shows work steps of the change object updating approach.**

map for the year 1990 as a basis (LC90) for updating multi-year land cover.

Specifically, experts together segmented the Landsat images with the same path/row from 1990 and 2000 and visually searched change patches of land cover from 1990-2000. Then, the LC90 was merged with the change patches to map land cover for the year 2000 (LC00) [37]. Based on LC00, land cover for the year 2015 was generated through the same process. In the software ArcGIS 10.1, these land cover maps (KP-LC) were used for quantifying spatiotemporal forest changes.

D. TWO METHODS FOR ACCURACY ASSESSMENT

For a classic accuracy assessment, we randomly collected validation points from Landsat images (Figure S4). Each land cover map was equipped with 700 points of all land types and assessed by a confusion matrix (See supplemental materials for methods) [29].

We assessed the integrity of land change information with a robust statistical approach [39], following the guidance of the Global Forest Observations Initiative (GFOI) [40]. The step assessed the accuracy of four land strata (classes) includes forest loss, forest gain, unchanged forest, and unchanged other land covers during a period. First, a total of 3,000 points by stratified random sampling of Landsat images were used to compute the user's accuracy (UA) of North and South Korea during 1990-2000 and 2000-2015 (Figure S5). Hereafter, the UA was used to match the areal weight of land strata for design sampling. As a result, 1481 points were randomly selected and statistically allocated 20 times into different number groups of four land strata for assessing accuracy (See supplemental materials for details). The accuracy report includes overall accuracy (OA), UA, producer's accuracy (PA), and estimated area [39]. We employed GFOI estimates for the uncertainty analysis.

E. COMPUTATION OF FOREST CHANGE

Changed forest area (*CFA*) during a given period was computed by subtracting forest area of the earlier date from that of the later date, given by equation

$$CFA = FL\,(t_2) - FL\,(t_1) \tag{5}$$

where $FL\,(t_2)$ and $FL\,(t_1)$ are forest areal extent (km^2) at the later year (t_2) and earlier year (t_1), respectively.

As lengths of two study periods were inconsistent, the annual rate of forest change was calculated by an FAO method for a given period between t_2 and t_1.

$$ACR = 1/(t_2 - t_1) \times \ln\left(FL(t_2)/FL(t_1)\right) \times 100 \tag{6}$$

where ACR (in %·yr^{-1}) corresponds to the annual change rate of forest in a period. Hereafter, the computation of the annual deforest area (ADA, in km$^2\cdot$yr^{-1}) was possible. The ADA was assumed to decrease at an exponential rate over a period [41].

$$ADA = FL\,(t_1) \times \left(1 - e^{ACR}\right) \tag{7}$$

where the e denotes the natural base.

In the software ArcGIS 10.1, the conversion area (A_{ij}, in km^2) of land cover i to j in a period was spatially computed.

F. ANALYSIS DRIVERS OF FOREST CHANGE

As the core task of forest observations, we qualitatively analyzed socioeconomic drivers of forest changes. From http://www.fao.org, the economy, demography, and forestry data on which the analyses rely were collected. Besides, to link the forest change and economy, we selected low-income ($\leqslant$ \$1,025) and high-income ($\geqslant$ \$12,476) countries and their forest area data from 1990-2015 in the Global Forest Resources Assessment 2015 (FRA2015) [14], [15]. Forest change statistics were computed by expressions (5) and (6).

III. RESULTS AND ANALYSIS

A. ACCURACY ASSESSMENT

Land cover maps of the Korean Peninsula for 1990, 2000, and 2015 were generated by the COU approach (Figure 3). For three maps, accuracy matrices showed that commission error concentrated on grassland, wetland, and burned land, reflecting by the minimal UA was 0.56, 0.69, and 0.71, respectively (Table S2-S4). Besides, barren land, grassland, and wetland had higher omission errors, and their minimal PA was 0.74, 0.76, and 0.76, respectively. Nevertheless, the overall accuracy of these maps was greater than 0.90, laying a good foundation for data analysis.

The GFOI assessment showed that forest changes on the Korean Peninsula during 1990-2015 were well observed. For 1990-2000, the OA of land change in North and South Korea was 0.96 ± 0.023 and 0.94 ± 0.032, respectively (Table S5-S6). For 2000-2015, the OA of land change in North and South Korea was 0.95 ± 0.03 and 0.94 ± 0.031, respectively (Table S7-S8). There might be overestimation and underestimation in our observations. For example, the forest gain in 1990-2000 was underestimated, compared with the GFOI estimates (Figure 4). Nonetheless, because areal weight of forest gain in the two countries during 1990-2000 was small,

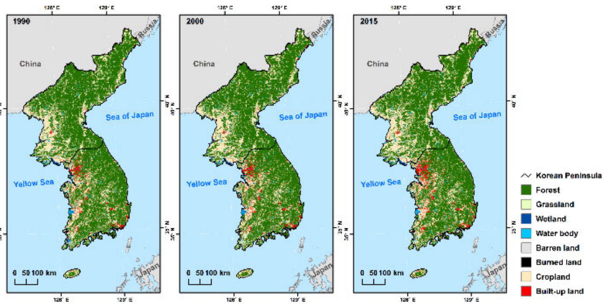

FIGURE 3. The land cover map of the Korean Peninsula generated from the COU approach.

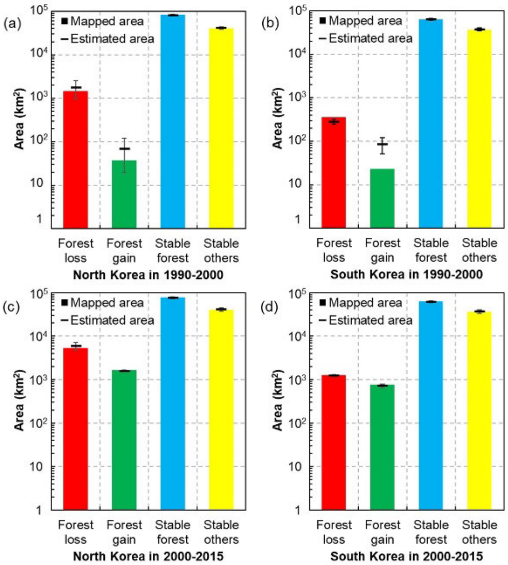

FIGURE 4. Comparison of the land change information in this study with GFOI estimates. The error bar of the estimates denotes a 95% confidence interval. Due to the large difference, the area was corrected based on the common logarithm. See Table S9 for values.

and the mapped area of other land strata was located in confidence intervals of the estimates, our maps equipped good usability.

B. SPATIOTEMPORAL PATTERNS OF FOREST CHANGES

Forest in the peninsula distributed widely other than western regions (Figure 3). The peninsula's forest cover decreased from 66.0% in 1990 to 65.2% in 2000, and then to 63.3% in 2015 (Table 2). In 1990-2015, North Korea lost 5,176 km^2 forest and far exceeded South Korea's 851 km^2. Forest loss in North Korea was 4.2 times higher than that of South Korea from 1990-2000, and it was 7.3 times in 2000-2015.

The forest area of North Korea changed dramatically in 1990-2015. The forest cover decreased from 67.9% in 1900 to 63.8% in 2015. The forest area decreased 1,407 km^2 in 1990-2000. In 2000-2015, 3,769 km^2 of the forest was further lost, which was 2.7 times as that of 1990-2000. Besides, the annual deforest area (ADA) in North Korea from 2000-2015 reached 1.8 times as that of 1990-2000. In contrast,

TABLE 2. The forest area and change in North Korea and South Korea in 1990-2015.

Year	Forest area (km^2)		Forest cover (%)			
	North Korea	South Korea	North Korea	South Korea		
1990	84,860	64,255	67.9	63.6		
2000	83,453	63,918	66.8	63.2		
2015	79,684	63,404	63.8	62.7		
Period	Changed forest area (km^2)		Annual change rate (%·yr^{-1})		Annual deforest area (km^2·yr^{-1})	
	North Korea	South Korea	North Korea	South Korea	North Korea	South Korea
1990-2000	-1,407	-338	-0.17	-0.05	142	34
2000-2015	-3,769	-513	-0.31	-0.05	257	34

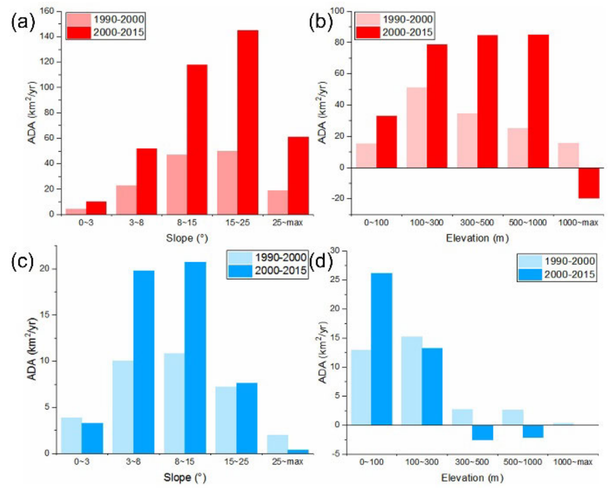

FIGURE 5. The annual deforest area (ADA) categorized by elevations and slopes in North Korea (a, b) and South Korea (c, d).

South Korea's forest cover decreased slightly (Table 2). The forest lost 338 km^2 in 1990-2000 and 513 km^2 in 2000-2015, respectively. However, ADA remained unchanged at 34 km^2 · yr^{-1} during the 25 years.

At different elevations and slopes, forest changes varied widely in North Korea and South Korea (Figure 5). In North Korea, the lost forest largely occurred in slopes of 8-25° from 1990-2015. In terms of elevation, forest loss mostly took place at altitudes of 100 to 300 m in 1990-2000. However, in 2000-2015, altitudes of 300-1,000 m became the most severely deforested place. Particularly, ADA at altitudes of 500-1,000 m increased sharply by 238% from 1990-2000 to 2000-2015.

By contrast, in South Korea, forest loss occurred mostly in slopes of 3-15° during 1990-2015. From 1990-2000 to 2000-2015, in slopes of 3-8° and 8-15°, ADA increased by 98% and 93%, respectively. In terms of elevation, the greatest forest loss concentrated in altitudes of 0-300 m for both periods. However, ADA at altitudes of 0-100 m increased by 102% in 2000-2015, which replaced altitudes of 100-300 m to become the most forest losing region.

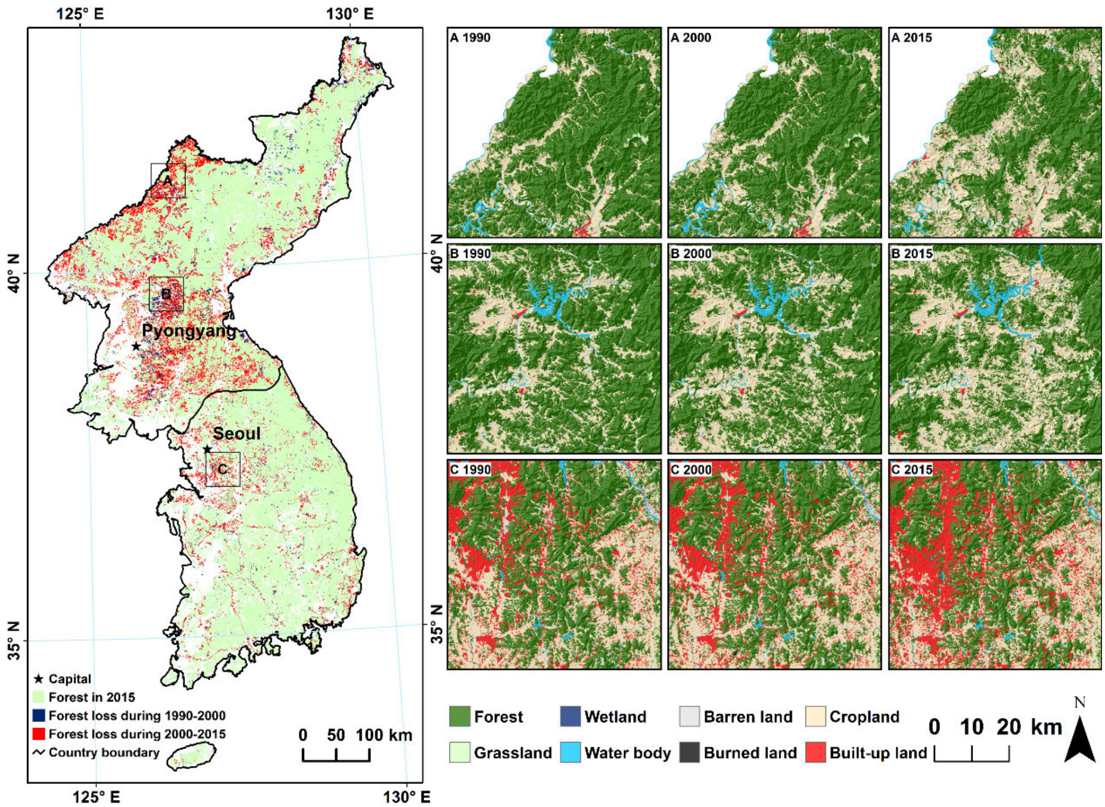

FIGURE 6. Spatial distribution of forest loss. Subsets A, B, and C are samples showing the conversion between the forest and other land covers.

C. LAND COVER CONVERSION AND FOREST LOSS

Forest loss in North Korea spatially concentrated in the central regions and northwestern borders (Figure 6). We presented land cover conversions during 1990-2015 in a dynamic flow (Figure 7), illustrating that the conversion of forest to cropland in North Korea was the most significant. Specifically, the area of forest loss to cropland increased from 1,256 km^2 in 1990-2000 to 3,910 km^2 in 2000-2015 (Table S10). The area of forest to built-up land decreased from 14 km^2 to 11 km^2.

Forest loss in South Korea distributed mostly in the northwestern region, surrounding the capital Seoul (Figure 6). Our results indicated that the built-up land (184 km^2) encroached the most on the forest, followed by cropland (106 km^2) in 1990-2000 (Table S10). In 2000-2015, built-up land encroached the most on the forest with 422 km^2, and the net conversion of forest to cropland was 195 km^2.

IV. DISCUSSION

A. REMOTELY SENSED FOREST CHANGE

1) COU APPROACH FOR FOREST CHANGE OBSERVATION

Some open-access land cover or forest cover products were used to observe forest changes in the Korean Peninsula [21], [30], [31], [42], but they have different results compared with our observation (Table 3). GFC's 2000 results have the most obvious differences with others. LCMKP's estimates of forest change for South Korea (approximately $+1.67 \times 10^3$ km^2) have the opposite trend of KP-LC. However, the South Korean forestry agency officially reported that the forest area decreased during the 1990s (approx. -0.54×10^3 km^2), having similar to our results [26]. Besides, KP-LC has a smaller estimate for South Korea than LCMKP, GLCF-VCF, and FROM-GLC. However, "most reliable" estimates of FRA2015 indicated that forest in South Korea decreased from 62.88×10^3 to 61.84×10^3 km^2 in 2000-2015 [10]. Such difference could result from different forest definition, local biomes, or mapping methods used [25], [43], [44]. The forest definition of each remotely sensed dataset is comparable [10], [43], and the Korean Peninsula does not have tall plants like in tropics [8], thereby we focus discussion below on differences of mapping methods.

Raster maps of six data mentioned were compared in three difficult-to-map locations (Figure 8). Pixel-based forest data, including GFC, FROM-GLC, GLCF-VCF, and LCMKP, has obvious land patch fragments, knowing as the salt-and-pepper noise (SPN). The SPN is usually due to classifier selection, parameter debugging, image preprocessing, input characteristics, etc., and causes information loss. For example, unsupervised classifier based LCMKP map significantly overestimates forest extent. Although the most accurate map generated by classifiers testing, SPN still exists in FROM-GLC [34]. In this regard, image segmentation prevented SPN [37]. For example, in Globeland30, forest patches are relatively complete because of the operation of image segmentation [32]. Nonetheless, forest extent in Globeland30 is

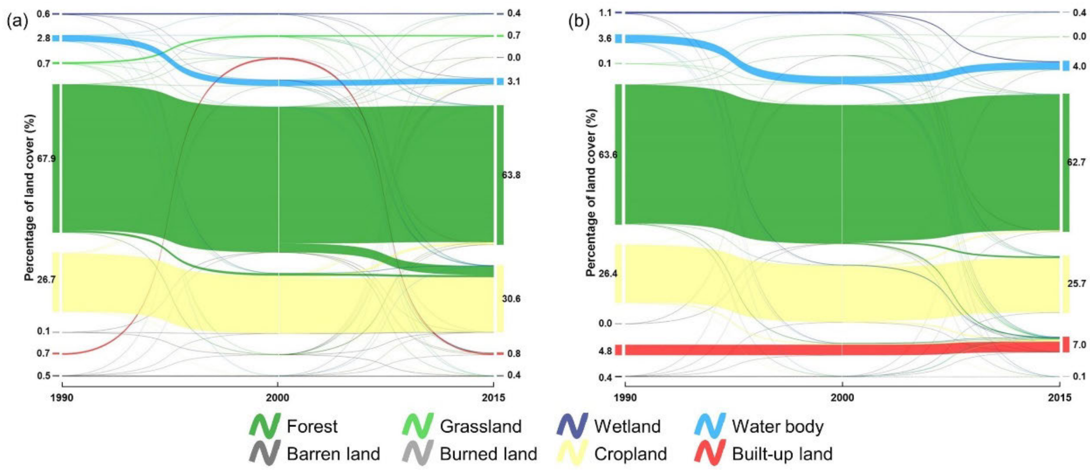

FIGURE 7. Sankey diagrams show total land cover conversions during 1990-2015 in (a) North Korea and (b) South Korea.

TABLE 3. The forest areal extent comparison between the KP-LC and reference data.

Year	Forest area (10^3 km^2) in North Korea			Forest area (10^3 km^2) in South Korea		
	KP-LC	Reference data		KP-LC	Reference data	
		Area	Name		Area	Name
1990	84.86	91.20	LCMKP	64.26	64.36	LCMKP
2000	83.45	91.19	LCMKP	63.92	66.03	LCMKP
		92.09	GLCF-VCF		77.57	GLCF-VCF
		58.93	GFC		57.10	GFC
		89.61	Globeland30		63.17	Globeland30
2015	79.68	79.07	FROM-GLC	63.40	65.14	FROM-GLC

Note: The forest area of LCMKP was quoted from [31]. In the GFC and GLCF-VCF, similar to the forest definition in this study, pixels with a canopy cover of more than 10% were considered as the forest.

inaccurate. An assessment work suggested that Globeland30, GFC, GLCF-VCF, and FROM-GLC have the overall accuracy of more than 93% in mountain forest [43]. However, although these four products provide global forest data, they are not accurate enough to analyze forest changes and impacts for the Korean Peninsula. These maps thus have to be calibrated for uncertainty in a particular region otherwise may bring erroneous forest information [44].

In contrast, KP-LC has complete forest patches (Figure 8) and high overall accuracy (Table S2-S4), which are the basis of reliable information on forest changes (Figure 4). The robust of the COU approach contributed to our maps. The application of the decision rule classifier allowed carefully debug spectral indices for better preliminary results. On the other hand, the image segmentation facilitated experts to manually modify the preliminary results carefully built on remote sensing knowledge, serving maps more accurate. Considering the low quality of current forest information for North Korea [10], for the first time, we mapped consistent and coherent land cover for 1990, 2000, and 2015. Therefore, forest changes between the two countries can be comparatively observed, which facilitates multilateral cooperation in environmental management and policy formulation on a peninsula scale.

2) UNCERTAINTIES OF LAND CHANGE INFORMATION

The GFOI method could provide reliable land change estimation based on maps and validation samples [39], [40].

TABLE 4. The forest change area of this study and GFOI estimates.

Period	Country	Forest change area (km^2)	
		KP-LC	GFOI
1990-2000	North Korea	-1,407	-1794 ± 777
	South Korea	-337	-348 ± 19
2000-2015	North Korea	-3,769	-4326 ± 1196
	South Korea	-514	-488 ± 20

Note: Negative sign denotes forest loss. See Table S10 for GFOI estimates.

In general, our observation underestimated the forest loss in North Korea (Table S9), as the GFOI estimates were -1794 ± 777 km^2 and -4326 ± 1196 km^2 for 1990-2000 and 2000-2015, respectively (Table 4). For South Korea, although the forest loss might be overestimated (Table S9), our observations still closed to the GFOI estimates (Table 4). Nonetheless, higher overall accuracy of land change encouraged us to analyze forest change based on KP-LC. These uncertainties could be limitations of forest definition, image quality, and validation point collection.

3) LIMITATIONS AND FUTURE WORK

The appropriate forest definition is a critical component for forest management [10]. For example, the official forest definition of South Korea is stricter than FRA [25], i.e., trees with the canopy cover > 30% and the height > 5 m in places > 0.5 ha. Such a definition is formulated for a forest inventory, and not suitable for long-term remote sensing observation

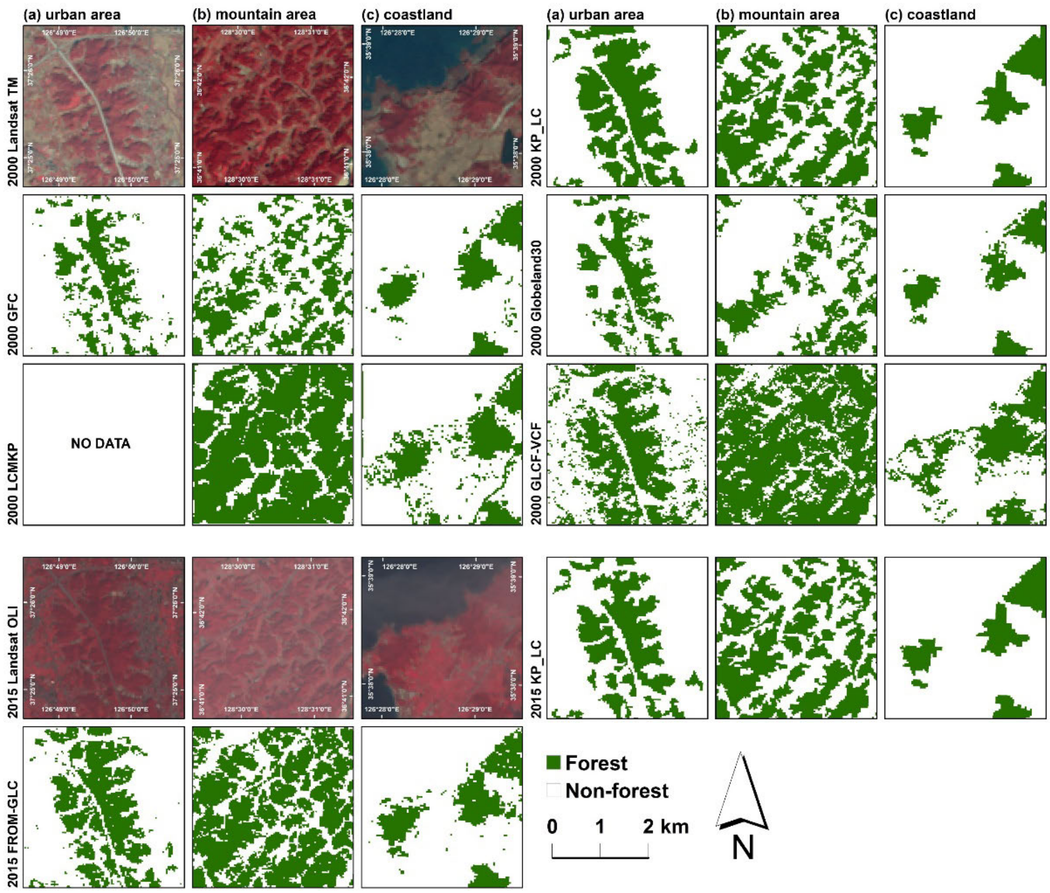

FIGURE 8. The zoom-in comparison of six forest maps across case landscapes. Landsat images displayed with the band combination of R = Red, G = NIR, and B = SWIR to highlight forest.

because the optical image cannot obtain the tree height information. Therefore, we defined the forest in a general way [10], [34] and did not classify the shrubs [30], which could be inconsistent with some national forest inventory.

Besides, because Landsat has a revisit period of 16-day, high-quality (or less-cloud-covered) images of the growing season have not always been sufficient. Clean images could only be collected from near years of the map year to ensure good observations (Figure S1), which may affect the temporal consistency of the resultant map. In this regard, data fusion of multiple sensors (e.g. ETM+ and OLI [45]) can enhance the temporal consistency of reliable observations. Moreover, without field surveys, microwave data (e.g. PALSAR [43]) could obtain tree structure information to meet special forest definitions of national or local concerns.

Although there may be some human error in the visual interpretation, the validation points collected from satellite images, a common practice [32], [34], are more likely to cause uncertainty in the accuracy report. Collecting verification points is a laborious task, and Landsat images have to be used to collect consistent validation points in this study [39]. If there were sufficient samples from field surveys and high-resolution images, the integrity of KP-LC could be more accurately assessed.

B. FOREST CHANGES AND DRIVERS IN KOREAN PENINSULA

Differences in spatiotemporal forest changes between North Korea and South Korea in 1990-2015 were significant. Although [30] reported that forest area remained almost unchanged in North Korea in the 1990s, we were consistent with more findings that deforestation was exacerbated in the 1990s [8], [21], [24] and encroached by cropland expansion [31], [36]. By contrast, South Korea's forest loss was mild and largely converted to built-up land (Figure S6) [31].

After the collapse of the Soviet Union, huge energy shortages [46] and growing agricultural populations (Figure S7) made the forest a free source of food, new arable land, and fuelwood [21], [36]. However, deforestation increased risks of landslides and floods due to sediment block water flow during the summer rain [8], [9]. Besides, the carbon sink lost significantly [6], [31]. Negative effects of deforestation could go beyond North Korea's territory because of shared forest communities of South Korea, China, and Russia. For example, the Changbai Mountain was home to endangered species includes Siberian tiger and Chinese merganser, but North Korea's deforestation significantly threatened habitat quality there [7], [47]. Although a series of forestation policies were formulated, results have never been reported yet [20]. This

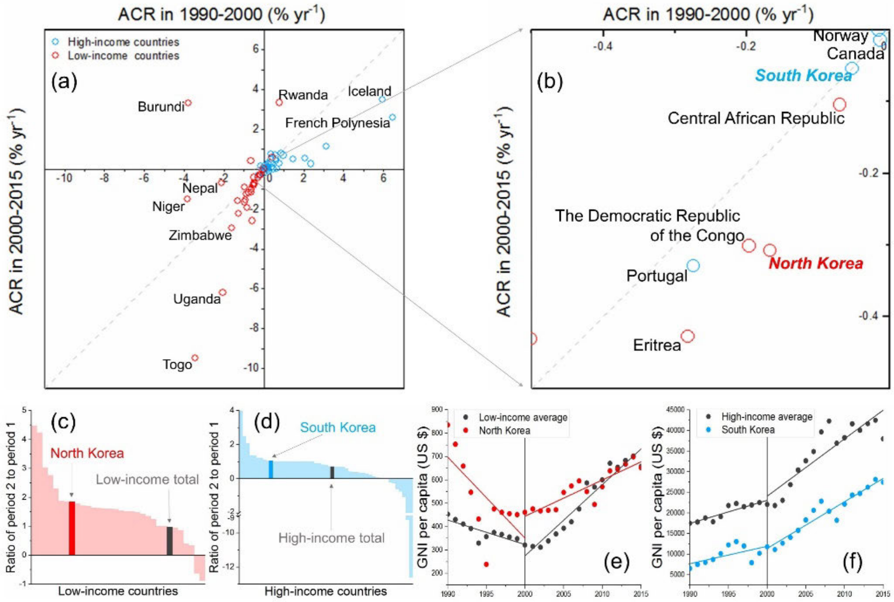

FIGURE 9. The annual change rate (ACR) categorized by public income. Positive and negative ACR represent areal increase and decrease, respectively. Period 1 and period 2 denote periods of 1990-2000 and 2000-2015, respectively.

study showed that deforestation has intensified and shifted to higher uplands, meaning the failure of forestation. In 2012, many stunting and wasting among children confirmed that the food shortage in North Korea remained severe [48]. Deforestation for cropland was inevitable.

The two-period ACR ratio suggested that North Korea's acceleration of deforestation was greater than 75% of low-income countries (Figure 9c). Nonetheless, North Korea received little attention, which may be masked by the rapid forest regrowth in East Asia [10]. Although low-income countries Burundi and Rwanda achieved forest regrowth [10] and [36] also reported that North Korea's forest started to regrowth in 2001, our observation showed that the deforestation exacerbated after 2000. North Korea could be unable to afford the forestation. North Korea's GNI per capita trend has been increasing slowly since 2000, but by 2008, it had fallen below the average of low-income countries (Figure 9e). North Korea enacted a 10-year reforestation plan in 2009, half of which was estimated to cost \$47 billion [49]. North Korea's GDP in 2015 was only \$28.5 billion. In China, for example, annual investment in all ecological projects never exceeded 0.37% of GDP after 1998 [13]. According to this standard, North Korea cannot achieve forest regrowth in the short run mainly due to financial constraints. Besides, whether soil fertility and water conditions of uplands can support to grow seedlings, due to years of tillage and deforestation, was questionable.

By contrast, South Korea's forest loss was relatively prominent in high-income countries (Figure 9d), which did not appear to be limited by the economy (Figure 9f), but rather policy-related. Numerous urban jobs created by the transformation of an agricultural country to an industrial power enabled rural people to lose at 100,840 per year (Figure S7b). Large areas of residential, recreational, industrial, and transport land thus were developed to meet the routine needs of urban people, and forestland became a crucial contributor to land structural adjustment [25]. The migration not only reduced the consumption of fuelwood significantly (Figure S7c) but made forest regrowth naturally in abandoned cropland [25]. Besides, the state-led National Forest Development Program (NFDP) entered the 3rd to 5th batch after 1990, aiming to maintain the national forest cover at roughly 64% and enhance ecosystem services [20], [50]. Therefore, water yield and soil loss were improved due to sustainable management [51], despite forest lost and timber production boosted (Figure S7f).

V. CONCLUSION

Different magnitude of forest changes between North Korea and South Korea were observed based on 30m land cover maps generated by a change object updating approach. This approach used image segmentation to avoid omission errors and map fragments, and improved accuracy by the integration of automatic classification and visual interpretation. Our study showed that, during 1990-2015, cropland expansion and built-up land expansion led to forest loss in North Korea and South Korea, respectively. Such conversions became more intense in the two countries. Despite forestation policies were formulated in North Korea, forest loss became sharper. Deforestation in North Korea thus required more attention but would not be easy to mitigate due to economic constraints. By contrast, despite the forest loss, South Korea's forestry policy placed emphasis on sustainable forest ecosystems. In the peninsula, forest changes indicated the need for reliable forest observation to respond to the emerging negative effects and to facilitate management. Future work should be considered conducting in a wider region, such as Northeast Asia because the peninsula's forest changes could bring potential effects to neighboring countries.

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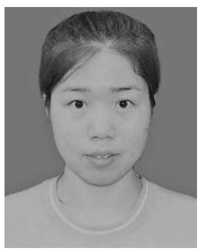

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