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Application of the domain adaptation method using a phenological classification framework for the land-cover classification of North Korea

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ABSTRACT

Efforts to achieve carbon neutrality are global, encompassing a wide range of factors. For the estimation of greenhouse gas emissions from the agriculture, forestry, and other land use (AFOLU) sector, the Intergovernmental Panel on Climate Change has proposed an advanced method that requires Approach 3, the highest level of suggested method, of activity data. Accordingly, we propose a phenological classification framework (PCF) that can perform land-cover classification by training the climatic repeatability of the annual cycle using a U-Net deep learning model. Additionally, the domain adaptation (DA) method can be applied to classify areas with insufficient data. We applied these methods to classify North Korea (i.e., using South Korean data), with an accuracy of 81.31%; overall this effort culminated in the simultaneous classification of the Korean Peninsula. Domain distribution comparison showed that the results for the two regions were similar. The PCF and DA methods proposed in this study allow for annual production of a land-cover map and change matrix, regardless of the presence or absence of data. The application of these methods is expected to provide a scientific basis for policy decisions that can facilitate the global attainment of carbon neutrality.

1. Introduction

Global warming and climate change, mainly caused by carbon emissions, have prompted efforts to achieve carbon neutrality (Chen, 2021; Korea Forest Service, 2021; Liu et al., 2022a). Carbon neutrality entails reducing human-made carbon dioxide emissions while increasing its uptake to decrease net emissions to zero, thereby preventing further carbon emissions(Tan et al., 2022; Wu et al., 2022). Land-based carbon neutrality is crucial to achieve this goal (W.K. Lee, 2022a, 2022b). Effective land monitoring is necessary to achieve land-based carbon neutrality. A land-cover map is the most suitable means of achieving this goal. The map enables the estimation of carbon emissions in the agriculture, forestry, and other land use (AFOLU) sector based on the guidelines specified by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2006). The impact of land-cover conversion on emissions can be estimated through the continuous generation of a land-cover map and matrix for a specific region. The IPCC also suggests the use of land-cover maps prepared using remote sensing as effective tools for estimating greenhouse gases (GHGs) (Ibnoaf et al., 2006; IPCC, 2006; Kathryn Bickel et al., 2006). The South Korean government recently emphasized on cooperation with North Korea's forestry departments as forests of both countries function as carbon sinks (Korea Forestry Service, 2021; Korea Research Institute for Human Settlements, 2022). To achieve carbon neutrality, North Korea's land must be managed as a sink. However, at present, deforestation is progressing owing to energy and food inadequacy in Noth Korea, leading to a reduction in carbon sink areas (Heo, 2020; Kim et al., 2021a). Therefore, it is necessary to develop a method that can enable effective collection and monitoring of land information in North Korea, since the data can then be subsequently used to estimate greenhouse gas inventories to achieve carbon neutrality.

Land-cover classification is based on establishing specific reflectance properties for various land-cover types, and thus, the status of the land surface is an important variable (Azzari and Lobell, 2017; Townshend

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et al., 1991). In temperate regions with seasonal climates, Earth's revolution causes changes in climate characteristics throughout the year, resulting in different vegetation states on the ground surface (Nguyen and Henebry, 2019; Schwartz, 2003; Townshend et al., 1991). This process is known as vegetation phenology, and its characteristics vary depending on the type of vegetation (Motohka et al., 2010). These changes in climatic characteristics create variations in the land surface over time, which are important factors for classification based on satellite imagery. As satellite imagery captures the state of the land surface at the time of acquisition of the image, it is a critical variable that can affect classification results, especially in seasonal climate regions (Gómez et al., 2016; Kim et al., 2021b). Vegetation phenological characteristics have been used to effectively classify land-cover (Jin et al., 2016; Kim et al., 2021a, 2021b; Zhang et al., 2017). In this study, we propose a phenological classification framework (PCF) that utilizes phenological characteristics of vegetation in satellite imagery and a deep learning model to effectively collect land surface information by mapping land-cover.

The use of deep learning models has become prevalent across various scientific fields. Specifically, these models have demonstrated exceptional performance in image classification. Consequently, numerous researchers are employing these models for land-cover classification and extraction of ecological information (Capinha et al., 2021; Jagannathan and Divya, 2021; Kırbaş and Çifci, 2022; Passah and Kandar, 2023). The U-Net model, a type of convolutional neural network (CNN), is a deep learning algorithm that performs classification through supervised learning (Ulmas and Liiv, 2020). The model was trained using both training and validation data, and classification was performed based on these data (Kattenborn et al., 2021). Consequently, the availability of labeling data is crucial for U-Net model applications. However, in North Korea, there is no official land-cover map based on national-scale field surveys, and satellite imageries alone are insufficient for land-cover mapping (S.H. Lee et al., 2014). Therefore, previous studies have applied various classification methods that do not require precise labeling data, such as object-based classification, unsupervised learning, and semi-supervised learning (Jin et al., 2016; Kwak et al., 2017; S. H. Lee et al., 2014; Zhang et al., 2017). Unlike in previous studies, here we use domain adaptation (DA), which transfers information from a source to a target domain thereby facilitating the application of the PCF to North Korea. In this study, we set South Korea and North Korea as the source and target domains, respectively.

Jin et al. classified deforested areas in North Korea using a phenology-based multi-index and the Random Forest algorithm (Jin et al., 2016). Specifically, they used visually interpreted data and accessible on-site survey data as labeling data, achieving an accuracy of 89.38%. However, a limitation of their study is that a 250 m resolution does not adequately capture the patch-like nature of rice paddy, a compactly dispersed form, in North Korea. Therefore, Kim et al., 2021a utilized “pseudo-labeling” using Sentinel-2 based phenological normalized difference vegetation index (NDVI), which is one of the semi-supervised learning methods to overcome the lack of labeling data in North Korea and secured a classification accuracy of 84.8%. They effectively represented the landforms of North Korea using a 10 m resolution; however, pseudo-labeling is characterized by a high uncertainty, and reference data are unavailable for verification (Kim et al., 2021a; Vatsavai et al., 2005). They further conducted accuracy verification through visual interpretation using Google Earth Pro, revealing limitations arising from the interpreter's subjectivity during this process, which compromised objectivity. Therefore, it is necessary to apply a method that can allow for the collection of high-level land information using high-resolution remote sensing data, while ensuring both classification accuracy and verification objectivity for North Korea.

In this study, phenological satellite imagery (PSI) data were generated using four bands of Sentinel-2 satellite imagery with a high spatiotemporal resolution, and thus, changes in vegetation were reflected every two months. The PCF leverages high-resolution PSI through the use of deep learning, allowing the model to be trained using various labeling methodologies, depending on data availability. As a labeling methodology, the DA was used to overcome the lack of data in North Korea, transferring the precise land-cover map of South Korea to North Korea. The applicability of DA was validated through various comparison tests, yielding an accuracy of 81.31% for South Korea and North Korea, respectively. Owing to the nature of utilizing deep learning models, it is challenging to precisely identify significant variables via PCF. However, indirect validation was made possible through the use of the source and target domains, respectively. In addition, based on the results obtained, this method is sufficient for accurate land analysis. Therefore, PCF can potentially serve as an effective means for continuous monitoring of ecosystem information.

In this study, we apply PCF in the context of land monitoring, proving its applicability in North Korea, using Sentinel-2 data and the DA method. Even though the Sentinel-2 data and DA method were the primary focus, the main strength of PCF lies in its ability to adapt satellite imagery data and labeling methods according to data availability. This study shows that PCF is an effective methodology for monitoring land-use and land-cover changes, leveraging remote sensing and contributing to the pursuit of land-based carbon neutrality.

2. Materials and methods

2.1. Study area

The study area covers the entire Korean Peninsula that consists of South Korea and North Korea. The Korean Peninsula is situated in Eastern Asia, with geographical coordinates ranging from 33°N to 43°N and 124°E to 132°E and occupying an area of 22,074,800 ha (Fig. 1a). The Korean Peninsula is located within a mid-latitude temperate climate zone and is encircled by the sea on three sides, thereby exhibiting a temperate climate and four distinct seasons (Yim and Kira, 1975). The topography of the Korean Peninsula has a higher elevation in the northeast with forests and mountainous terrain and has a lower elevation in the southwest with flat agricultural land, particularly rice paddies, which serve as the staple food crop (Y.H. Park, 2015). The climate of the Korean Peninsula is relatively uniform across regions, with the temperature rising gradually from north to south because of latitude.

South Korea is situated in the southern part of the Korean Peninsula, between 37° N and 43° N (latitude) and 124° E and 130° E (longitude), as depicted in Fig. 1b. The country spans an area of 10,020,800 ha with 65% of its territory comprising mountainous and forested regions. The administrative divisions of South Korea comprise of eight provinces, one capital city, six metropolitan cities, one self-governing city, and one self-governing province. The mean elevation of the country stands is 282 m a.s.l. Geographically, South Korea is characterized by high elevation terrain in the east and low elevation in the west. The climatic features of the region, which are typical of the Korean Peninsula, have led to the development of rice paddies in the south and west.

North Korea encompasses the northern portion of the Korean Peninsula (Fig. 1c) and is geographically situated between latitudes 37° N and 43° N and longitudes 124° E and 130° E. The country covers an area of 12,054,000 ha, 80% of which is mountainous. The administrative districts consist of nine provinces, one capital city, and three special cities. The average altitude in North Korea is 440 m, with high elevation in the northeast and low elevation in the southwest. As a result, rice paddies have developed in the west. However, owing to limited agricultural technology and food supply, much of the agriculture is carried out by reclaiming forests and clearing slopes, leading to deforestation and destruction of many forests (KREI, 2013).

2.2. Phenological classification framework

We propose the PCF as a method for effectively utilizing continuously accumulated big data of satellite imagery for land monitoring. PCF

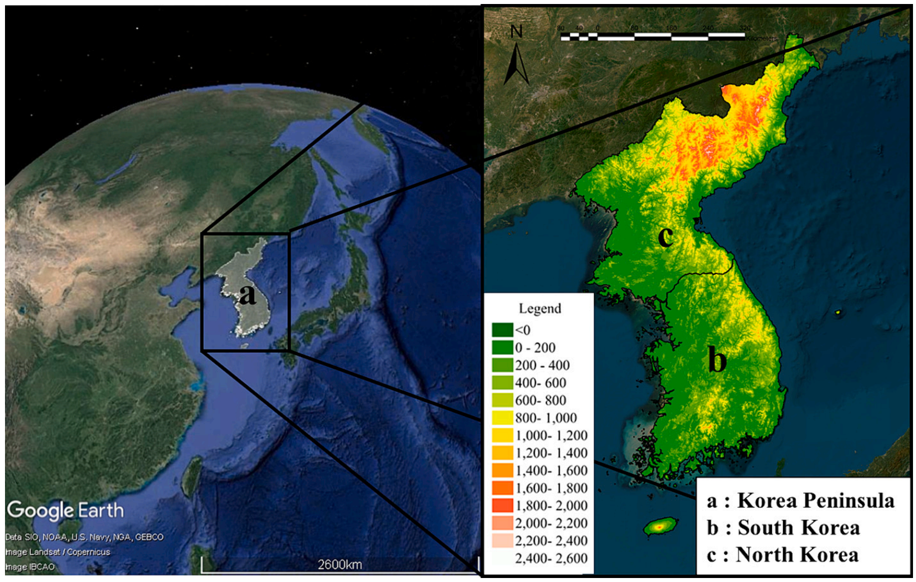

Fig. 1. Study Area: (a) the Korean Peninsula (b) South Korea. (c) North Korea.

employs a deep learning model that uses PSI, which is a chronologically arranged time-series, to classify land-cover maps. The observation of phenology through satellite imagery has been the subject of numerous studies since 1973 (Dethier et al., 1973; Jin et al., 2016; Kim et al., 2021a; Nguyen and Henebry, 2019; Zhang et al., 2017). Vegetation phenology can be observed using satellite imageries acquired several times at the same location. Therefore, it is easy to observe phenological differences according to changes in vegetation using remote sensing data such as near-infrared (NIR) bands or NDVI. This framework leverages PSI, a chronologically arranged time-series satellite imagery, to reflect the phenological characteristics of vegetation and contrast non-vegetated areas of the land surface (Fig. 2). The global climate has regional characteristics that are repeated according to an orbital cycle of one year. As a result, phenological characteristics are reflected in the PSI that is collected at specific intervals throughout the year based on the temporal resolution of the satellite.

The PCF consists of three sequential parts: PSI generation, labeling, and classification. The PSI generation part produces satellite imagery to train the model, which reflects the phenological characteristics of vegetation on the land surface. PSI data are defined as satellite imagery with appropriate intervals that have had cloud cover removed to accurately reflect these characteristics. The length of the appropriate interval may vary depending on the temporal resolution or observation width of the satellite. The labeling part determines the labeling methodology for training the deep learning model. In the classification part, a deep learning model was trained based on the results of previous steps. The target PSI, which has the same format as the trained PSI, can be classified using the trained model. Here, the format refers to the spatial resolution and spectral band used, interval in PSI, and chronological order of each band. If satellite imagery accumulates owing to continuous satellite observations, the PSI can also be continuously generated, and classification can be continued using the model. This enables PCF land monitoring.

Consistent criteria are important for classification. The PCF ensures the consistency of classification criteria by using the model after it is trained. By utilizing the resulting land-cover series, changes in the land surface and cover can be spatially tracked and used in various decision-making processes. Fig. 3 summarizes the PCF process. The PCF reflects time-series information through PSI to the U-Net model and CNN-based algorithms that do not analyze the time series. This approach leverages time-series information to resolve errors caused by the acquisition time of satellite imagery and simultaneously enhances the model accuracy by increasing input data (Kim et al., 2021b; Yuan et al., 2020).

In this study, DA, using data of South Korea, was used as the labeling method. In addition, the performance of the model was improved by increasing the amount of data using visible and near-infrared (VNIR) imageries from Sentinel-2 instead of NDVI as the PSI.

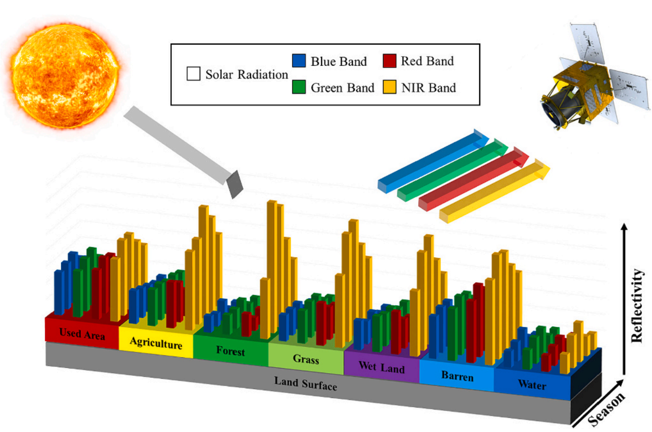

Fig. 2. Graphical representation of the concept of phenology based on satellite imagery.

2.3. Datasets

We employed Sentinel-2 satellite imagery as PSI for the use of PCF (Table 1). Additionally, since Sentinel-2 satellite imagery has a higher resolution (i.e., 10 m) than other satellite imagery, it is ideal for generating PSI.

We used a sub-class land-cover map provided by the Ministry of Environment in South Korea for training a deep learning-based PCF model. The sub-class land-cover map was generated through visual interpretation based on high-resolution (1 m) aerial photographs, ensuring an accuracy above 90%. Given that the sub-class land-cover map is in vector data format in the shapefile, it was converted into raster data with a resolution of 10 m to facilitate subsequent labeling. The sub-class land-cover map undergoes partial updates on an annual basis (Table 1).

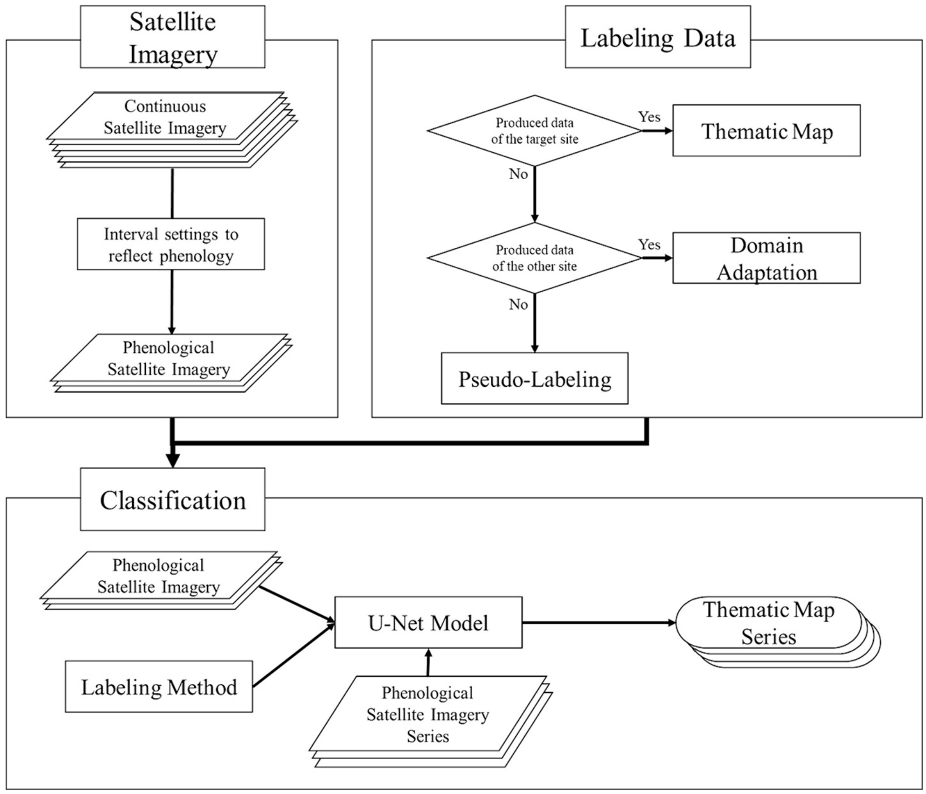

Fig. 3. Structure of phenological classification framework.

Table 1
Spatial datasets for PCF of this study.

	Sentinel-2 Satellite Imagery	Sub-Class Land-Cover Map	Converted Sub-Class Land-Cover Map as Label
Saptial Resolution	10 m	1 m	10 m
Temporal Resolution	5 days	Partial Update by 1 Year	Partial Update by 1 Year

2.4. Domain adaptation from South Korea to North Korea

We used DA to overcome North Korea's data insufficiency using data from South Korea. DA is a methodology that applies existing labels from the source domain to the target domain even if it has never been trained (Ben-David et al., 2006; Daumé, 2009). In the field of remote sensing, when training data of a target area are insufficient, the DA methodology is used to overcome data insufficiency (Tuia et al., 2016). DA is primarily a process wherein information and knowledge obtained from the source domain (e.g., the training data) are leveraged for predictions and classifications in the target domain (e.g., the test data domain). In this process, the model is fine-tuned to perform in the context of the source domain by learning from data rooted in the source domain. Subsequently, this adapted model is applied to the data in the target domain to extend its capabilities for making accurate predictions or classifications in that domain as well. The applicability of such inter-domain shifts is contingent upon the absence of substantial differences between domains. In cases where significant disparities exist between domains, domain generalization is necessitated to mitigate the effects of these differences. For instance, in cases where there is a substantial geographical separation leading to significant differences in spectral characteristics owing to variations in the acquisition timing of satellite imagery or when the acquisition years are entirely distinct, domain generalization becomes imperative to mitigate the differences between domains. While DA typically requires domain generalization for effective information transfer across domains, this study deviates from this norm. In this study, domain generalization was omitted by leveraging satellite imagery collected during the same period, thereby minimizing differences between domains. We trained the U-Net model using the official sub-class land-cover map of 1 m resolution of South Korea to classify North Korea. Through this process, the model learns information from satellite imagery labeled with land-cover data from South Korea and transfers this information to classify North Korea using satellite imagery alone. The technique of learning and classifying unlabeled regions into labeled regions in computer science, is known as unsupervised domain adaptation (X. Liu et al., 2022b). Therefore, to be more precise, this study utilized unsupervised domain adaptation; however, it adopted an approach based on domain adaptation rather than deep learning techniques for collecting ecological information. Hence, it is generically referred to as DA. DA can facilitate the creation of a highly accurate model through the use of more reliable labeling (i.e., instead of using pseudo-labeling). In addition, by classifying South Korea and North Korea using the same model, the classification result can be validated using the result of South Korea such that objectivity can be secured rather than visual interpretation using random points, according to the method of Kim et al. (2021a) (Kim et al., 2021a).

In this study, the DA method was applied to the same classifications from South and North Korea. Therefore, there is a need for similarities between land-cover and environmental characteristics (Persello and Bruzzone, 2012; Tuia et al., 2016, 2021). From this perspective, the classification of North Korea using labeling data from South Korea, derived from the DA method, is suitable because of their ecological and environmental similarities rooted in a shared geographical proximity (Kong, 2002; Lee, 1994; Park and Lee, 2019). Furthermore, considering the utilization of phenological characteristics by PCF, geographical proximity is particularly suitable for the application of DA, as it induces identical phenological characteristics of two countries. In addition, the

Sentinel-2 satellite used in this study continuously observes the land surface while rotating around Earth's orbit (Spoto et al., 2012). The Korean Peninsula is included in two observation swaths of Sentinel-2. Because two satellites observe one after another, the temporal resolution is high, and the number of satellite imageries are sufficient. Therefore, applying DA using the Sentinel-2 satellite has advantages of a frequent acquisition time (Wang et al., 2022). Based on these environmental similarities, the Ministry of the Environment of South Korea has applied South Korea's classification to North Korea (The Ministry of Environment, 2018). Consequently, it was confirmed that the same classifications could be applied to both South and North Korea.

The reason for considering the suitability of DA for classifying North Korea is the availability of well-established labeling data in South Korea, particularly the sub-class land-cover map. To apply the DA, it is necessary to have a source and target domains for training and classification, respectively (Persello and Bruzzone, 2012; Tuia et al., 2016, 2021). The quality of labeling data is crucial for the classification of satellite imagery using deep learning because the performance and results of the model depend on it. Thus, South Korea, which generates high-accuracy land-cover maps using national budgets, is a suitable source domain for classifying North Korea using the DA method. An example of a precisely produced sub-class land-cover map for South Korea is shown in Fig. 4a. The sub-class land-cover map includes all sub-classes that are part of the higher-level macro classes, enabling its conversion to a macro-class land-cover map, as shown in Fig. 4b. Fig. 4a and b show the same data—Fig. 4a has 41 sub-classes, and Fig. 4b has 7 macro-classes, i.e., the two sets of data have different display formats. Therefore, considering precise labeling data and environmental similarity, DA is a suitable labeling methodology for overcoming data insufficiency in North Korea.

In addition, the macro-class items of South Korea's land-cover map satisfied similar items of the AFOLU sector in the IPCC Guidelines for national GHGs inventories (IPCC, 2006). Therefore, if land-cover classification and monitoring are performed using data from South Korea, changes in emissions of GHGs can be estimated and monitored continuously.

2.5. Generation of PSI of Sentinel-2 VNIR imagery and model training

Sentinel-2 satellite imagery from 2019 was obtained as a time series using Google Earth Engine (GEE) to capture the phenological characteristics of vegetation in satellite imagery. However, owing to the limitations of a single observation swath of Sentinel-2, the entire Korean Peninsula was not covered, and cloud cover was common because of the temperate climate. To address this issue, the GEE cloud removal and mosaic algorithms were utilized to generate as many cloud-free satellite imageries of the entire peninsula as possible (Fig. 5). Each series was composed of satellite imageries with median value composition algorithm of GEE, acquired over a 2-month period to account for the temporal resolution of Sentinel-2. Series 1–5 span March to April, May to June, July to August, September to October, and November to December, respectively. The median value composition algorithm was used to mitigate the impact of confounding variables (e.g., winter snow cover) in the Korean Peninsula, which experiences seasonal climates, as well as monsoon clouds. Imageries from January and February were omitted because they were susceptible to analytical errors caused by snow cover in North Korea (Kim et al., 2021a). In the context of Series 1 and 5, some snow cover is visible snow cover in North Korea as well. However, for the purpose of utilizing big data, both of these series were

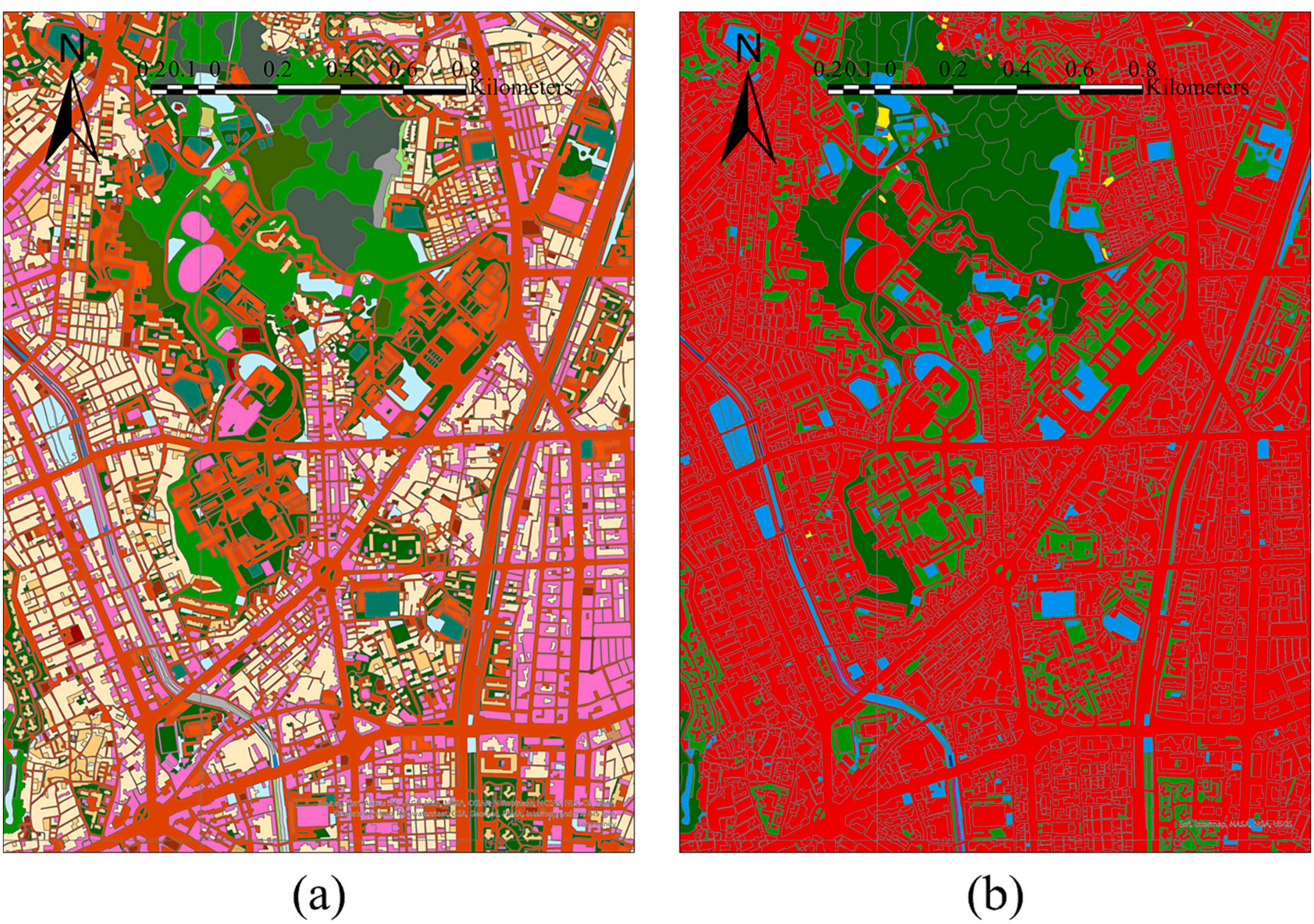

Fig. 4. Sub-class land-cover map of South Korea. (a) Sub-class of land-cover map. (b) Macro class of land-cover map.

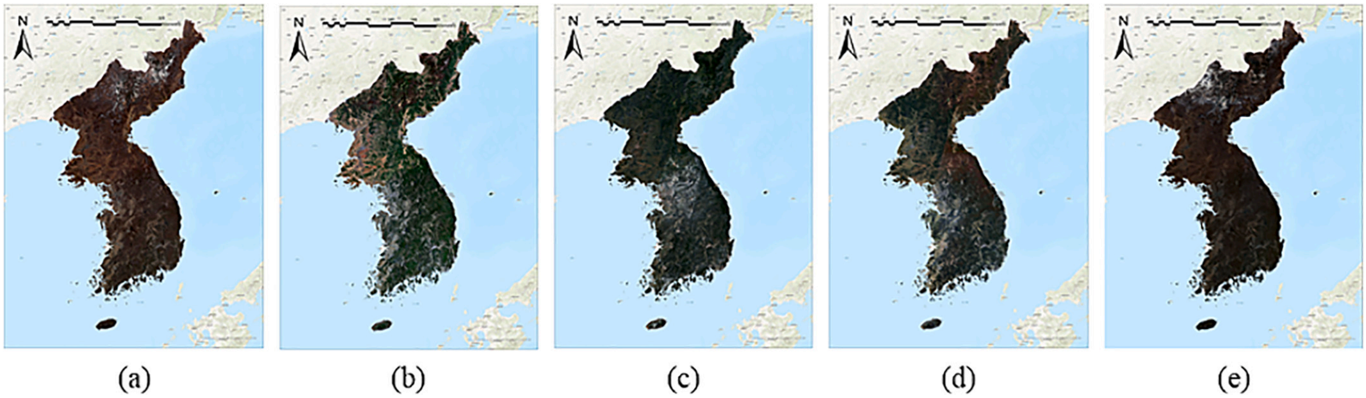

Fig. 5. Phenological Sentinel-2 satellite imageries of 2019 generated by GEE: (a) *series 1*; (b) *series 2*; (c) *series 3*; (d) *series 4*; (e) *series 5*.

not excluded but rather utilized. The generated satellite imageries were composited into a single imagery in chronological order as a PSI. Each scene contained four bands of VNIR, resulting in 20 layers in the PSI with a repeating sequence of blue, green, red, and NIR bands.

To generate training data for the PCF, 16,660 grid cells with a resolution of 2560 m were created in South Korea. This resolution was selected because the training unit of the U-Net model was 256 pixels, and 2560 m contains 256 pixels of Sentinel-2 with a 10 m resolution. Fig. 6a and b show the extracted results, where 8330 cells (half of the total) were randomly extracted as a mask for training data in Fig. 6a, and 3,332 cells (20% of the total) were randomly extracted as a mask for validation data in Fig. 6b. The PSI was extracted from Fig. 6a and b to prepare input data for model training. The sub-class land-cover map of South Korea can be transformed into a macro-class land-cover map by converting all sub-class items into macro-class items (Fig. 4). This conversion process resulted in the production of a completely converted sub-class land-cover map of South Korea, as shown in Fig. 6c. Additionally, the year of generation of the sub-class land-cover map was 2019, which is the same time as that of the Sentinel-2 satellite imagery used for the PSI. The existing macro-class land-cover map, despite its availability, is not suitable for training Sentinel-2 satellite imagery with difference in spatial resolution of 30 m to 10 m. If the resolution of the label data is higher, information loss in the satellite imagery will occur. However, since the resolution of the sub-class land cover map is 1 m, it can be converted to 10 m and applied. Moreover, the accuracy, guaranteed by the Korean government, of the macro-class land-cover map was lower (over 75%) than that of the sub-class land-cover map (95%). Because label data is the correct answer data for training, it is more appropriate to use data with high accuracy. Consequently, the converted sub-class land-cover map was used for labeling the training and validation data.

3. Results

3.1. *Classification results and discussion of accuracy*

Fig. 7 illustrates the results of the classification of the entire Korean Peninsula in 2019 using PCF, trained by PSI of Sentinel-2, and the DA method labeled by converted sub-class land-cover maps. Fig. 7a represents the full extent of the Korean Peninsula; Fig. 7b depicts Seoul, the capital of South Korea; and Fig. 7c displays Pyongyang, the capital of North Korea. The comparison between Fig. 6c and 7a for South Korea reveals that the spatial distribution of land-cover is similar, with forests covering most of the land and agricultural land being distributed around the western regions, whereas the developed regions are located around metropolitan cities, such as Seoul and Busan. Similarly, in the case of

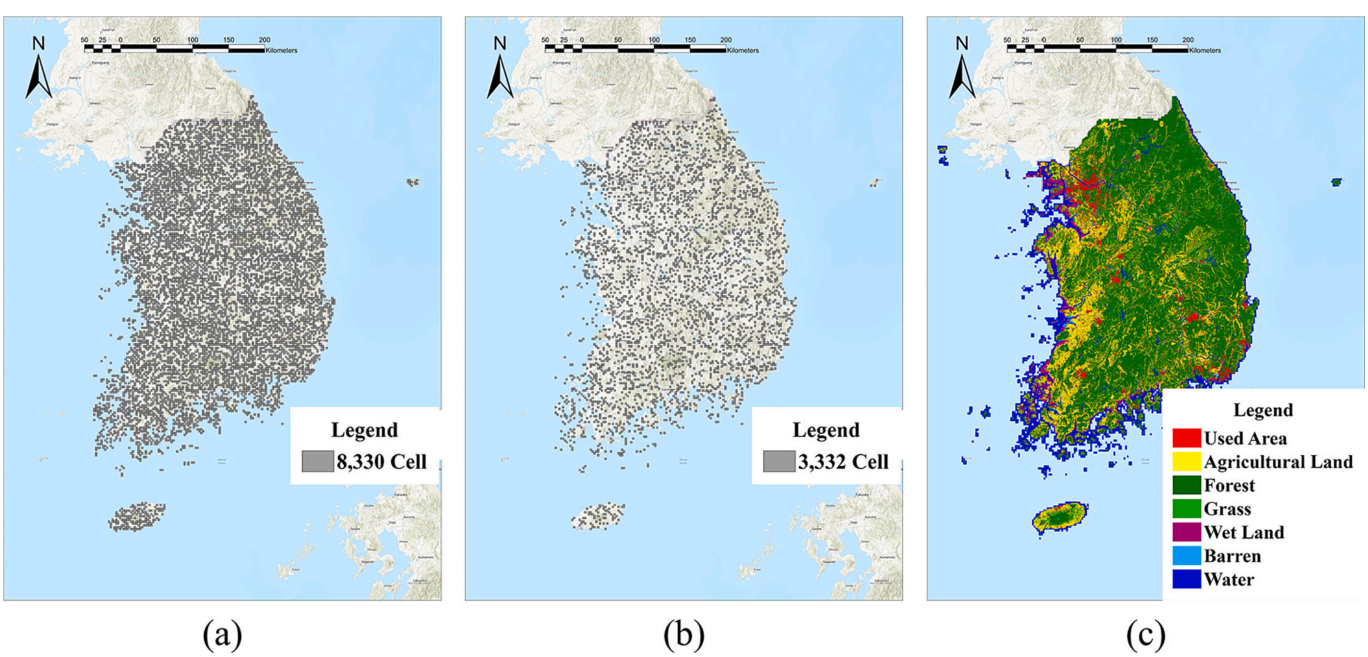

Fig. 6. Model training data: (a) training mask; (b) validation mask; (c) converted sub-class land-cover map as label.

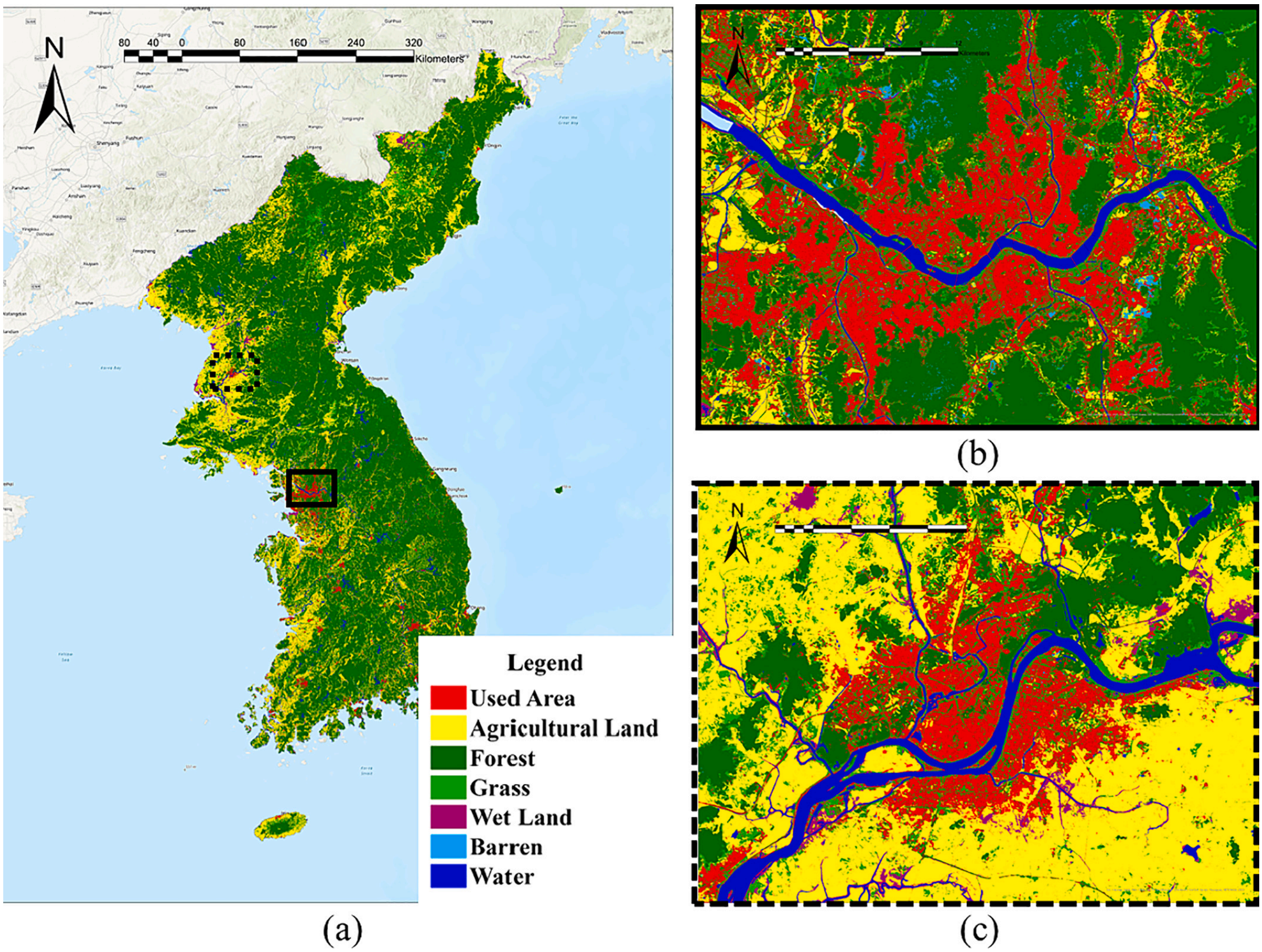

Fig. 7. Results of PCF using PSI of Sentinel-2 and DA method for 2019: (a) Korean Peninsula; (b) Seoul of South Korea; (c) Pyongyang of North Korea.

North Korea, a comparison of Fig. 7a with Fig. A1 the spatial distribution of land-cover is similar, with dominant forest coverage. Agricultural land is distributed to the southwest. Used areas are concentrated in the capital city, Pyongyang. Grassland is present in the northeastern high mountains.

To evaluate the classification accuracy, 990 random points were generated to create a confusion matrix. The confusion matrix for the classification results of this study (Fig. 7a) and converted sub-class land-cover map (Fig. 6c) are presented in Table 2. The total accuracy was 81.31%, and the kappa value was 0.6813 for South Korea region. The 95% confidence interval for the accuracy of 81.31% is 79.83% to 82.79%. Considering the classification of the seven classes, the total accuracy was found to be high (Landis and Koch, 1977). Producer's accuracy (PA) ranged from 10% to 98%, with an average of 54%. The range of user's accuracy (UA) was 20% to 92%, with an average of 58%. The producer's accuracy evaluation showed omission error in the used area class. Of the 70 points, 28 were properly classified, and 23 were classified as grass. This indicates that the used area class of the converted sub-class land-cover map includes green spaces in the city, such as public parks and street trees. As a result, green spaces in the city were classified as grass classes. In Fig. 6c, the used area classes and grass classes were mixed in Seoul. The converted sub-class land-cover map closely

Table 2
Confusion matrix for phenological land-cover classification of South Korea.

		Converted sub-class land-cover map								
		Used Area	*Agri-land*	*Forest*	*Grass*	*Wet land*	*Barren*	*Water*	Total	UA
Phenological Classification Result	*Used Area*	**28**	0	0	3	0	6	0	37	76%
	Agri-land	9	**137**	2	12	4	5	0	169	81%
	Forest	6	11	**571**	27	0	4	0	619	92%
	Grass	23	31	6	**46**	4	9	1	120	38%
	Wet land	1	2	0	2	**2**	1	2	10	20%
	Barren	3	0	2	1	1	**3**	0	10	30%
	Water	0	0	1	1	2	3	**18**	25	72%
	Total	70	181	582	92	13	31	21	**990**	
	PA	40%	76%	98%	50%	15%	10%	86%		**81%**

Accuracy: 81.31%. Kappa value: 0.6813.

resembles land-use classified according to the state of use, whereas the phenological classification in this study closely resembles land-cover classified according to the state of actual cover. Therefore, the 60% omission error of the used area was significantly higher than the 24% commission error, resulting in the highest error value difference among all the results. PA and UA indicate a low accuracy for wet land and barren classes, which are the two classes with the lowest accuracy in common, owing to the lack of training data and unstable state of cover, unlike water. Although non-water characteristics do not appear on the surface of water, vegetation can grow in barren areas because of the lack of management, making it difficult to distinguish from the surface of grass. In the case of wet land, there is a possibility of confusion, as there are cases where water is filled and drained or aquatic plants and wetland vegetation grow on the surface.

The DA methodology was originally to circumvent cross-domain transfer, allowing for the validation of model accuracy based on assessments conducted in South Korea. However, in this study, to verify the applicability of DA between South and North Korea, 500 random points were generated in North Korea, and accuracy validation was conducted through visual interpretation using Google Earth Pro and ESRI basemaps. This validation approach yielded an accuracy and Kappa Value of 89.00% and 0.8117 in the North Korea, respectively. Notably, South Korea exhibited an accuracy lower than that of North Korea (i.e., 81.31% vs. 89.00%). This difference can be attributed to variations in land cover proportions between the two regions, with North Korea having a smaller area. In addition, these accuracies were impacted by the verification points for land cover, such as used area and barren and wet lands, which were associated with lower accuracy in South Korea. Furthermore, it is important to note that the accuracy validation was not conducted through manual data-based verification; instead, it relied solely on high-resolution images. Consequently, the accuracy assessment may vary depending on the observer, potentially resulting in high or low evaluations. Despite differences in the validation methods, citing the accuracy of the model observed in South Korea is sufficiently justified, as it exhibited a high accuracy in North Korea.

The proportions of areas based on land cover for South Korea are shown in Table 3 and is compared with the converted sub-class land-cover map of South Korea, 2020 WorldCover map of the European Space Agency (ESA), and land-cover map prepared using Sentinel-2 satellite imagery. The proportions of areas based on land cover for North Korea are shown in Table 4 and are compared with the macro-class land-cover map and 2020 WorldCover map. In the case of WorldCover, only maps for 2020 were provided; therefore, this study used maps from 2020 onward. WorldCover of ESA has 11 classes different from South Korea such as tree cover, shrubland, grassland, cropland, built-up, bar/sparse vegetation, snow and ice, permanent waterbodies, herbaceous wetlands, mangroves, moss, and lichen. Among these classes, snow and ice, mangroves, moss, and lichen do not exist on the Korean Peninsula, and the other eight classes were reclassified according to the classification criteria of Korea as follows: built-up to used area, cropland to agricultural land, tree cover and shrubland to forest, grassland to grass, herbaceous wetland to wet land, bare/sparse vegetation to barren, and permanent waterbodies to water. WorldCover was used as a reference for evaluating the classification of North Korea because it is produced using Sentinel-2 satellite imagery with a 10 m resolution. According to the ESA, the average classification accuracy of WorldCover is 74.4% (Van De Kerchove et al., 2021).

Table 3
Area-wise proportions of phenological land-cover classification and comparison in South Korea.

Macro class	Phenological classification	Converted sub-class land-cover map	WorldCover of ESA (ha)
Used Area	392,790 (4%)	675,324 (7%)	710,504 (7%)
Agricultural Land	1,714,205 (17%)	1,817,605 (18%)	1,556,780 (16%)
Forest	6,335,014 (63%)	5,911,982 (59%)	6,638,638 (68%)
Grass	1,207,881 (12%)	970,116 (10%)	313,706 (3%)
Wet Land	94,518 (1%)	162,479 (2%)	10,197 (< 1%)
Barren	72,929 (< 1%)	307,968 (3%)	363,337 (4%)
Water	259,630 (3%)	232,247 (2%)	214,558 (2%)
Total Area	**10,076,697**	**10,077,721**	**9,807,720**

Table 4
Area-wise proportions of phenological land-cover classification and comparison in North Korea.

Macro-class	Phenological Classification	Macro-class Land-cover map	WorldCover of ESA (ha)
Used Area	65,789 (<1%)	201,404 (2%)	116,948 (1%)
Agricultural Land	2,534,527 (21%)	3,072,785 (25%)	2,662,431 (21%)
Forest	8,026,667 (65%)	8,503,797 (70%)	8,045,199 (64%)
Grass	1,217,172 (10%)	27,224 (< 1%)	1,201,341 (10%)
Wet Land	167,532 (1%)	38,020 (< 1%)	10,521 (< 1%)
Barren	34,597 (< 1%)	150,632 (1%)	281,809 (2%)
Water	210,886 (2%)	166,835 (1%)	241,920 (2%)
Total Area	**12,257,170**	**12,160,697**	**12,560,169**

In South Korea, many used areas of the converted sub-class land-cover map are classified as grass. The areas of used area and grass according to the phenological classification were 392,790 and 1,207,881 ha, respectively, whereas the corresponding values for the converted sub-class land-cover map were 675,324 and 970,116 ha, respectively. Although the areas differ, their sum is similar at approximately 1,600,000 ha. Notably, the used area for the converted subclass land-cover map in the confusion matrix is classified as grass, which lends credence to these results. Additionally, the low PA of the wet land and barren areas in the confusion matrix indicates a similar trend in the difference in area by class, as shown in Table 3. A comparison of these results with those obtained from WorldCover of the ESA highlights the differences in area distribution owing to differences in the initial classification criteria and the target year of the original satellite imagery used.

To explain the error between the used area and grass, Fig. 8 compares the satellite imagery used for the classification, reference data, and phenological classification results of the metropolitan area of South Korea. For the PSI of Sentinel-2, natural color combinations and false color combinations were used to identify vegetation areas, whereas the converted sub-class land-cover was used for labeling. Satellite imagery with a high resolution of 1 m provided by ESRI ArcGIS Pro and WorldCover of the ESA were also used as reference data. Commonly used area, including vegetated areas, tended to be classified as grass. Comparing label data and converted sub-class land-cover with the results of this study, the used area and the mixed area with grass tended to be classified as grass, which seems to reflect the characteristics of the U-net that classifies the surrounding area. The used area in the labeling data classified as grass appeared to have a red color in the false color combination. Fig. 8c shows that the area was trained as grass, but the actual surface was more vegetated and classified as forest. Compared with the ESA's WorldCover, the results of this study are close to the labeling data and better reflect the actual surface conditions.

In the case of North Korea, the area of WorldCover is similar to the land-cover map than to the macro-class land-cover map (Fig. 9). Fig. 9a, b, and c show that surface vegetation characteristics are better reflected, and the vegetated and non-vegetated areas are more accurately distinguished owing to the 10 m resolution of the Sentinel-2 satellite imagery. Notably, roads or artificial structures in the used area in the actual image were better reflected in the results of phenological classification and

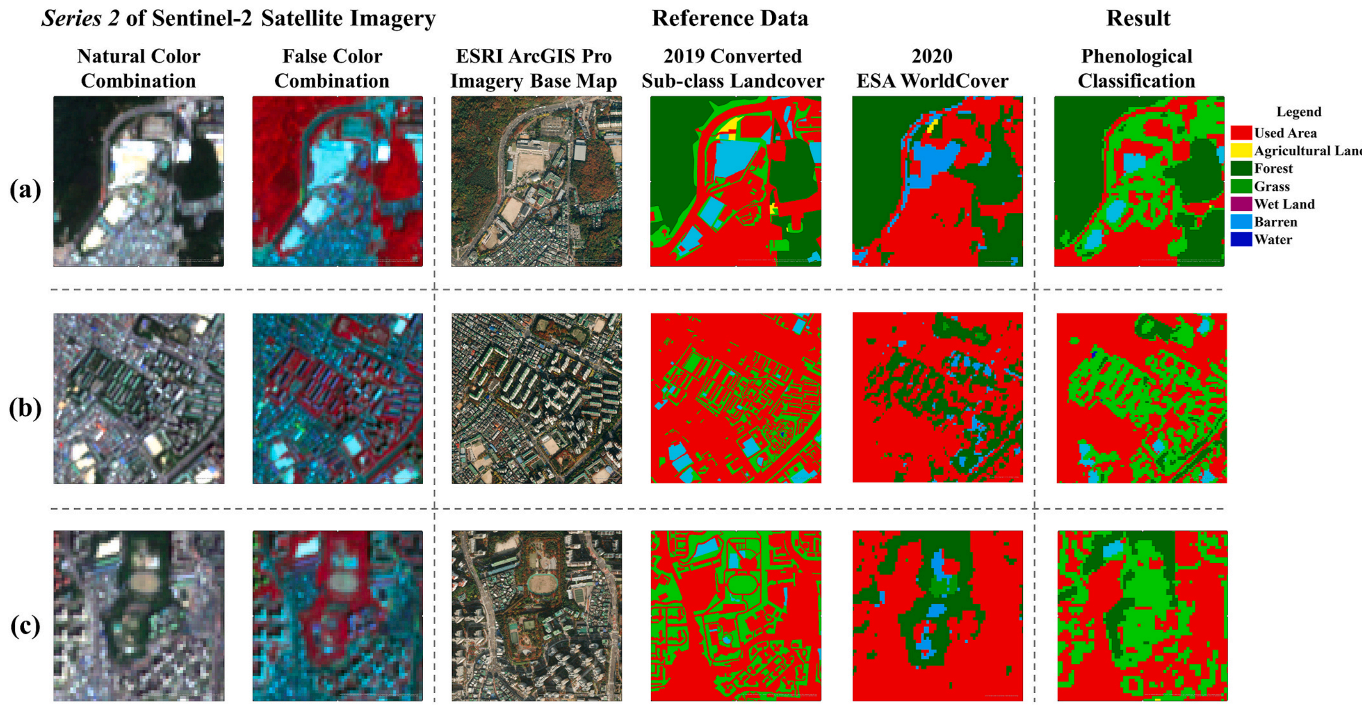

Fig. 8. Comparison of results of PSI, reference data, and phenological classification: (a) Seoul city Songpa district; (b) Seoul city Seongdong district; (c) Seongnam city Sujeong district.

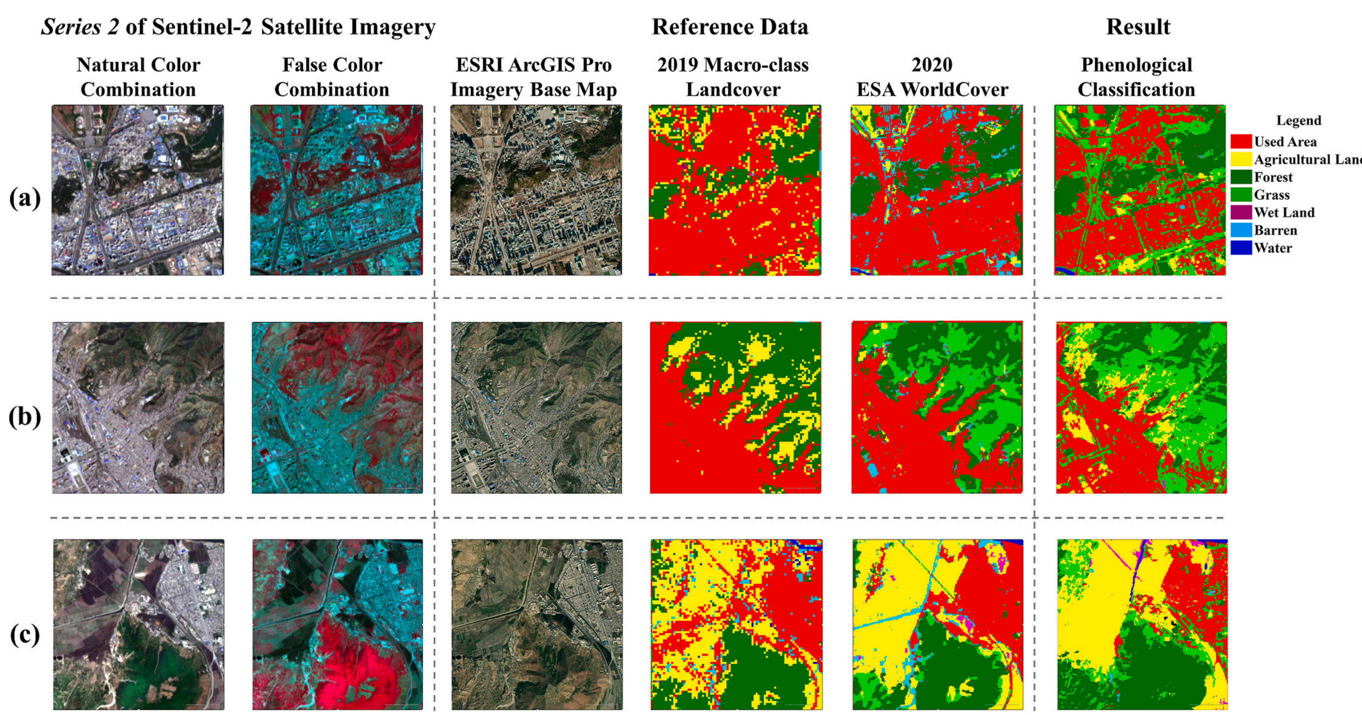

Fig. 9. Comparison of results of PSI, reference data, and phenological classification: (a) Pyongyang city; (b) Rason city; (c) Muncheon county.

WorldCover. Furthermore, compared to WorldCover, the results of phenological classification exhibited greater sensitivity in classifying areas composed of vegetation, such as green areas in the used area.

3.2. Comparison of spectral characteristics in the Korean peninsula

In this study, land-cover was classified using the phenological characteristics of the land surface and DA methods. As such, the phenological reflection characteristics according to land-cover based on spectral bands of both South Korea (source domain) and North Korea (target domain) were analyzed using spatial statistics that calculating mean value of all pixels in each landcover types (Fig. 10). In the phenological classification results the mean value for each land-cover type was extracted and listed through spatial statistics using the original satellite imagery. Fig. 10a illustrates the phenological reflection characteristics according to land-cover using the spectral bands in South

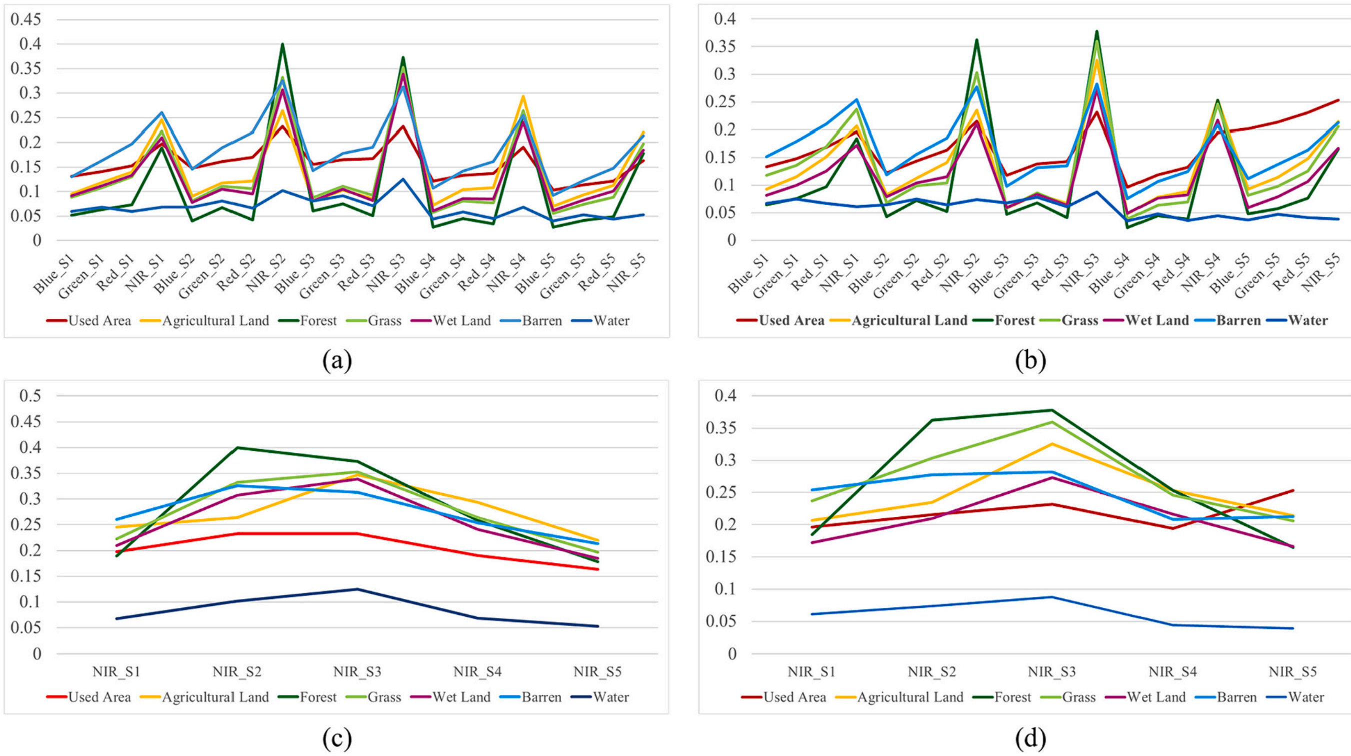

Fig. 10. Phenological spectral reflectance based on land cover: (a) VNIR of South Korea; (b) VNIR of North Korea; (c) NIR of South Korea; (d) NIR of North Korea.

Korea, whereas Fig. 10b depicts those in North Korea. Fig. 10c and d shows the phenological reflection characteristics according to the land-cover of the NIR band, which exhibited the greatest difference between the two domains. Furthermore, increasing input data using the VNIR imagery of four scenes for each series, compared to using the NDVI imagery of one scene, enhanced the accuracy of the classification model. A comparison of Fig. 10a and b indicates that each land-cover type shows a time series change pattern for each spectral band are similar. Notably, non-vegetative land-covers, including barren, water and used area, exhibited common features with insignificant changes according to the series. The minor differences in each series were attributed to variations in the amount of solar radiation depending on the acquisition time of satellite imagery. Moreover, the high outlier value observed in series 5 in the used area was attributed to snow cover in the northern region during winter. In this section, Fig. 5 shows the snow cover (in white) in North Korea, in series 1 and 5 (particularly 5). When considering the classification results and their respective accuracies, it appears that the impact of snow cover is negligible. However, due to the nature of deep learning models, it can be challenging to ascertain the importance of certain variables (i.e., referred to as series in this study) during modeling. Therefore, additional research is needed to analyze the impact of snow cover or to perform modeling while excluding certain series in order to yield a clearer understanding of their influence. The land-cover types with the most vegetation, such as agricultural land, forest, and grass classes, also displayed similar characteristics at the two target sites. As demonstrated in Fig. 10c and d, in the case of agricultural land, the NIR reflectivity increased during series 3, indicating active growth owing to cultivation. Conversely, in the case of forest, the NIR reflectivity increased dramatically during series 2, indicating an increase in the number of leaves along with the opening of the leaves. However, the value changed slightly depending on the phenology in the case of grass, unlike the other two classes. Consequently, using the same model and methods for both target sites resulted in similar phenological reflection characteristics according to the land cover of each band.

4. Implications of PCF application with domain adaptation

We conducted this study based on the premise that land-cover classification using remote sensing data, machine learning, and deep learning, as demonstrated in various studies, can contribute to policy development through the collection of ecological information (Jagannathan and Divya, 2021; Prasai et al., 2021; Yuh et al., 2023). This study represents an effort to classify the Korean Peninsula, especially North Korea, through PCF, and the phenological characteristics of vegetation were used to overcome the limitation of classification error caused by the acquisition time of satellite imagery in seasonal climate regions. To address previously highlighted issues tied to the classification of North Korea, we combined PCF and DA. This study addressed the error of classification results due to resolution, as proposed by Jin et al. (2016), by utilizing 10 m resolution Sentinel-2 satellite imagery (Jin et al., 2016). In addition, unlike the pseudo-labeling methodology of Kim et al. (2021a), since there is a source domain, the resultant classification results can be verified using this method (Kim et al., 2021a). Through this approach, we were able to address the subjective validation issues raised by Kim et al. (2021a), which primarily focused on the concept of PCF. However, when using DA, as reported by Kim et al. (2021a), it is constrained by its need for labeled data from the source domain and the impossibility of classifying specific classes for North Korea; examples of such classes include reclaimed forest and unstocked forests, respectively (Kim et al., 2021a). While these instances may be perceived as limitations of DA, it is noteworthy that reclaimed and unstocked forests were primarily classified as agricultural land and grass, respectively. This is attributed to the differences in the target years between this study and the research conducted by Kim et al. (2021a). Therefore, even in the absence of specific classes, using phenological characteristics, elements can still be classified on the basis of using classes that are most relevant. As suggested by Kim et al. (2021a), the classification accuracy and performance improved as data increased during the training of a deep learning model using satellite imageries over multiple periods, (Kim et al., 2021b). Therefore, the characteristics of a deep-learning model can be used effectively. As a result, by employing PCF with DA, we could address the limitations associated with the acquisition time of satellite imagery, resolution, and validation challenges encountered in previous studies, while harnessing the advantages of deep learning algorithms.

PCF enables continuous monitoring using the yearly PSI. If the PSI after 2019 is generated and classified by fine-tuning the model trained in this study, it will be possible to monitor the changes in land-cover and generate a land-cover matrix. The classification criteria used in this study are applicable to the AFOLU sector as specified by the IPCC Guidelines and can be used to estimate emissions of GHGs for land use and land use change (IPCC, 2006; Kathryn Bickel et al., 2006). In the Land-Use, Land-Use Change, and Forestry (LULUCF) section of the National GHGs Inventory Report of South Korea, the need for a land-cover matrix is suggested, and the PCF can be used to respond to this need (The Ministry of Environment, 2021). Through the monitoring of land changes and consequent emissions of GHGs, scientific basis for various policy decisions can be presented, and as a result, it can contribute to land-based carbon neutrality. Furthermore, the use of PCF will serve as a crucial baseline for informing policy development, forest conservation, urban planning, and monitoring of deforestation and agriculture by accurately reflecting the current state of land through monitoring land use and land use changes via satellite imagery, thereby significantly shaping environmental management strategies.

Currently, South Korea generates two types of land-cover maps: macro- and sub-class maps (The Ministry of Environment, 2018). The macro-class map is based on Landsat imageries and has a high spatial resolution of 30 m and a long update cycle of 10 years. In the case of sub-class maps, because they are based on aerial images and visual interpretation, enormous manpower and costs are incurred, and only a part of it is updated by classifying the area. As a result, it is difficult to provide basic data to achieve land-based carbon neutrality using the current land-cover map generation system in Korea. However, because PCF can perform classification when satellite imagery for one year is secured, land-cover maps can be generated every year, and the resolution can be enhanced based on the spatial resolution of the satellite imagery utilized. As Korea plans to operate satellites with a resolution of 5 m through the compact advanced satellite 500 kg (CAS500) development plan, the use of PCF in South Korea is expected (Kwon et al., 2021).

While PCF is designed to perform multi-year land-cover classification, this study only conducted single-year classification for South and North Korea. As a result, the classification performance of the proposed model may deteriorate when used for multi-year classification. In a long-term remote sensing study in an Italian region where the southern and northern ends are distant, such as the Korean Peninsula, ecosystem changes in the southern end do not follow a particular trend (Ghaderpour et al., 2023). Therefore, in the process of performing classification over several years in this study, areas deviate from the overarching ecosystem trends in this region may appear, especially in North Korea. Therefore, further research is needed to confirm multi-year classification performance and improve performance through methods such as fine-tuning, semi-supervised learning and domain generalization. In future studies, it is expected that the multi-year classification performance will be improved by the process of learning classification results and incorporating them into the model. Additionally, using the results, a land-cover matrix that can spatially identify changes between land-cover types can be generated. These are high-level activity data corresponding to Approach 3 of the IPCC Guidelines (Ibnoaf et al., 2006; IPCC, 2006). This enables policymakers, including those in South Korea, to accurately assess land use status and use the resultant outcomes in various environmental policy decision-making processes. In this way, utilizing PCF for ecological information collection would facilitate a rapid acquisition of information on an annual basis, enabling immediate integration of up-to-date environmental trends into decision-making that underlies the creation of environmental policies.

5. Conclusions

Through the PCF proposed in this study, the phenological characteristics of vegetation were trained using a CNN-based U-Net model, and a classification accuracy of 81.31% was achieved by inputting time-series information using PSI without separate time-series data processing. Information on land surface and cover from South Korea was transferred to North Korea and classified using the DA method. The classification accuracy of North Korea was 81.31%, the same as that of South Korea in the source domain. Domain distribution comparison was performed through comparative analysis of phenological spectral characteristics by band with reference data, and similar characteristics were observed in the two regions. Therefore, it was verified that the PCF methodology can effectively reflect climate and phonological characteristics in seasonal climate regions, and classification can be performed using DA even in regions without labeling data. In conclusion, PCF can be used to collected ecological information (i.e., on an annual basis) on various terrestrial ecosystems across the globe.

CRediT authorship contribution statement

Joon Kim: Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Hyun-Woo Jo:** Software, Data curation. **Whijin Kim:** Writing – review & editing. **Yujeong Jeong:** Writing – review & editing. **Eunbeen Park:** Methodology, Conceptualization. **Sujong Lee:** Methodology. **Moonil Kim:** Supervision, Project administration. **Woo-Kyun Lee:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of competing interest

None

Data availability

Data will be made available on request.

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Appendix A. Appendix

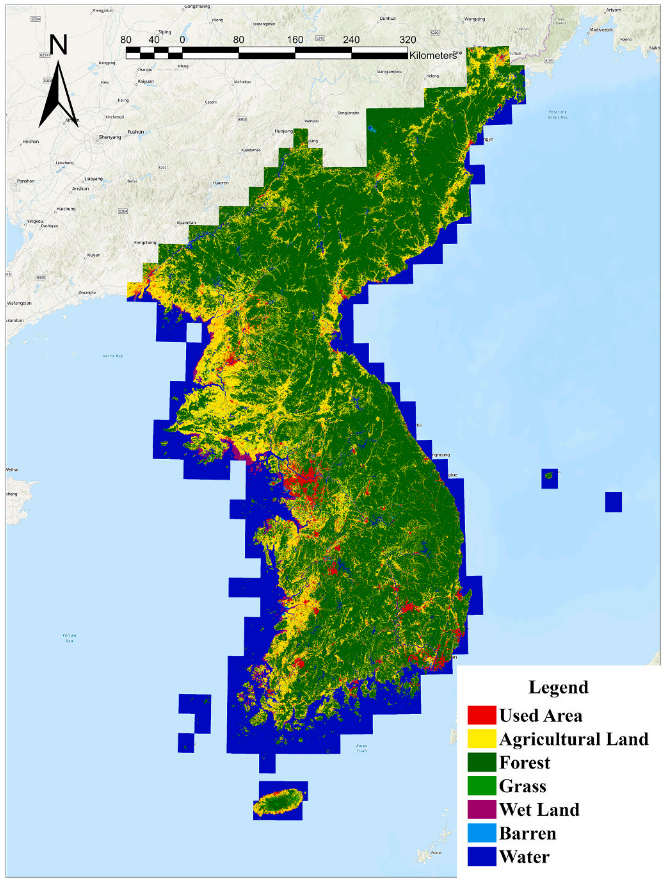

Fig. A1. Macro-class land-cover map of the Korean Peninsula.

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