Multi-Season Land Cover Change Modeling of Pantabangan-Carranglan Watershed Using Sentinel-1 and Sentinel-2 Imagery

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Abstract

Understanding land cover change is vital for sustainable management, particularly in diverse and ecologically significant landscapes like the Pantabangan-Carranglan Watershed (PCW) in the Philippines. This study employed multi-seasonal Synthetic Aperture Radar (SAR) and optical imagery from Sentinel satellites to enhance land cover classification and predict future changes in PCW. Data preprocessing and combination were performed using the Sentinel Application Platform (SNAP) software, resulting in multi-season datasets that accounted for the area's distinct climatic patterns. Classification was conducted using the Random Forest algorithm, generating land cover maps for 2017, 2020, and 2023, followed by change detection and prediction using Artificial Neural Network (ANN) for years 2023 and 2026. Results indicated a general increase in forest cover, with notable gains observed from non-forest vegetation and bare soil classes, suggesting ecological succession. Increases in forest cover of about 89 km^2, 34 km^2, and 28 km^2 were observed for 2017-2020, 2020-2023, and 2023-2026 analysis, respectively. Generally, classification accuracy (total accuracy) remained acceptable (77%-85%), and ANN-based predictions showed limitations which were affected by input data misclassifications. In general, the multi-season/combined season model emerged as the most effective for change detection, outperforming the mono-season approach with an average total accuracy of 83.73%. For the predicted future land cover based on the best performing model, the total accuracy for 2023 was at 79%. Despite the challenges, the study underscores the potential of integrating the Sentinel-1 and Sentinel-2 data for land cover monitoring, offering insights into landscape dynamics and conservation strategies. Future work should focus on refining methodologies to improve differentiation between classes particularly bare soil and built-up.

1. Introduction

Understanding land cover change is fundamental to achieve sustainable environmental management, particularly in heterogeneous landscapes that are sensitive to anthropogenic and natural changes. Land cover transitions such as forest to agriculture or agriculture to built-up can significantly affect hydrology, carbon storage, and biodiversity (Foley et al., 2005). These changes are often driven by population growth, infrastructure development, and climate variability, which necessitate detailed and temporally sensitive monitoring systems (Assede et al., 2023; Roy et al., 2022).

Remote sensing developments, such as the availability of Sentinel-1 (radar) and Sentinel-2 (optical) imagery, provide researchers with powerful tools for conducting comprehensive land cover analysis. Sentinel-1 offers cloud-penetrating Synthetic Aperture Radar (SAR) technology. On the other hand, Sentinel-2 satellite provides multispectral data with high temporal and spatial resolution. These platforms offer high-resolution data and complementary spectral and temporal characteristics that make them suitable for detailed monitoring and predictive modeling of land cover changes (Drusch et al., 2012; ESA, 2021).

Sentinel-1 and Sentinel-2 have been widely used in land cover classification. Solórzano et al. (2021) was able to take advantage of Sentinel-1 and Sentinel-2 for land cover classification of select municipalities in Southern Mexico. The combination of multispectral and synthetic-aperture radar data improved the classification and had an overall accuracy of 0.76. Furthermore, satellite-based data fusion where multispectral bands and indices were combined with radar polarization bands were proven effective. Pott et al. (2021) were able to apply satellite-based data fusion in field-scale crop monitoring to monitor agricultural crops in Grande do Sul state, Brazil by combining Sentinel-1, Sentinel-2, and Data Elevation Model (DEM) data from Shuttle Radar Topographic Mission (SRTM). In addition, the data fusion of seasonal images were also studied to provide a more robust classification. In particular, Borges et al. (2020) was able to combine Sentinel-1 SAR and Sentinel-2 optical data from multiple seasons throughout the year to create different land cover models for a savannah ecosystem. They came to the conclusion that the best outcomes were obtained when dry and short dry seasons were combined.

PCW represents a diverse and complex environment characterized by a mix of agricultural, forested, and built-up areas. This heterogeneity poses challenges for accurate land cover classification and change detection using conventional methods and global land cover products (Cai et al., 2019). When applying global models to regional areas, particularly in tropical regions where spectral variability within land cover types is high, misclassification is common (Hansen et al., 2013).

Addressing these issues requires tailored methodologies that integrate the unique capabilities of remote sensing platforms. This study aims to use Sentinel-1 SAR and Sentinel-2 optical data for improved land cover mapping based on the methods proposed by Borges et al (2020) and applied specifically for PCW. By leveraging multi-seasonal imagery, the study seeks to enhance the accuracy and applicability of land cover classification in the study area, contributing valuable insights to environmental monitoring and management. Furthermore, Muhammad et al. (2022) was able to predict future land cover changes using an artificial neural network (ANN) algorithm that could support decision-making for land management and natural resource use.

This paper aims to enhance the accuracy of land cover classification in heterogeneous environments such as the PCW. It also seeks to reduce the error rates typically encountered when applying global land cover products to regional scales. Additionally, the study strives to establish a user-friendly methodology that can support land cover mapping efforts and provide valuable inputs for land management practices in the Philippines.

This study not only seeks to fill critical knowledge gaps regarding land cover classification and analysis in PCW, including the application of regionally tailored methods for heterogeneous environments like the PCW and applicability of remote sensing data integration from multiple sensors and seasons, but also aims to provide practical tools and methodologies for relevant stakeholders involved in watershed management and environmental planning.

2. Study Area

The PCW covers five municipalities across the provinces of Aurora, Nueva Ecija, and Nueva Vizcaya and lies between 15°44’ and 16°88’ north latitude and 120°36’ and 122°00’ east longitude as shown in Figure 1. PCW forms part of the larger Upper Pampanga River Basin, which is essential to the hydroelectric energy and irrigation infrastructure in Central Luzon (Pulhin et al., 2006). Covering approximately 97,318 hectares, the PCW plays a crucial role in water supply, biodiversity conservation, and agricultural productivity in the region.

The PCW is characterized by its diverse land cover types and distinct rainfall pattern (climate type III). This heterogeneity, combined with the land use and topographic variation, presents challenges for land cover mapping and monitoring, highlighting the need for high-resolution, multi-temporal analysis to support sustainable management and planning efforts.

2.1 Geographical and Climatic Features

The PCW falls under Philippine Climatic Type III, which is marked by a relatively short dry season (usually from March to May) and a long wet season (Pulhin et al., 2006). This bimodal precipitation pattern, along with its elevation gradient and proximity to the Sierra Madre mountain range, creates a wide range of microclimates and ecological niches.

The topographic and climatic diversity results in a mosaic of vegetation types that are highly dynamic throughout the year which is ideal for multi-seasonal remote sensing analysis (Lasco et al., 2008).

2.2 Land Use and Vegetation

The PCW landscape includes forested uplands, lowland agricultural fields, grasslands, and patches of built-up or developed areas. Forests in the watershed are mostly composed of secondary growth and mixed broadleaf species, while lowland areas support rice, corn, and vegetable farming. Shifting cultivation and illegal logging have historically threatened the ecological balance of the region (Lasco et al., 2010). The complex mix of land uses and vegetation types within a relatively compact area poses a challenge to conventional land cover classification systems, which often rely on generalized categories or single-season imagery.

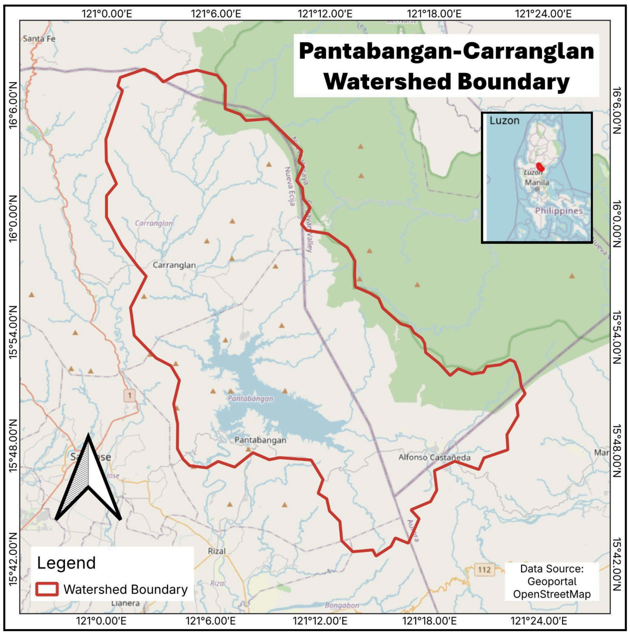

Figure 1. The Pantabangan-Carranglan Watershed.

2.3 Environmental Challenges

The watershed is experiencing significant environmental challenges such as soil erosion, which is exacerbated by deforestation, steep slopes, and intense rainfall events. The RUSLE has been used in several studies to estimate erosion rates in the watershed, showing significant spatial variability depending on land cover and slope (Alejo et al., 2021). Erosion not only degrades agricultural productivity but also leads to sedimentation in the Pantabangan Dam, which threatens water storage capacity and hydropower generation.

Additionally, land conversion for agricultural expansion and infrastructure projects has fragmented forest habitats, affecting biodiversity and increasing vulnerability to extreme weather events. These pressures underline the need for updated, accurate land cover maps that reflect on-the-ground conditions and support better land use policies.

2.4 Reforestation and Conservation Efforts

Efforts to rehabilitate and conserve PCW include reforestation projects aimed at enhancing native species' suitability and improving the success rates of such initiatives. These projects are crucial for preserving ecological balance and ensuring the long-term sustainability of the watershed. (Dolores et al., 2019).

The diverse landscape of PCW, vital role in agriculture, rich biodiversity, and the environmental challenges it faces make it a focal point for studies on land cover change, conservation, and sustainable management practices.

3. Methodology

The study employed Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical data, which were acquired across three distinct seasons—multi-seasonal, short-dry, and wet—to optimize land cover mapping within PCW. Preprocessing of Sentinel-1 data, including radiometric calibration and terrain correction was conducted using the SNAP software, resulting in the extraction of two (2) bands per season (VV and VH bands) and the generation of Grey-Level Co-Occurrence Matrix (GLCM) metrics. For Sentinel-2, ten (10) bands were extracted (B2, B3, B4, B5, B6, B7, B8, B8A, B11, and B12), which were in 10m and 20m resolutions. Normalized Difference Vegetation Index (NDVI) were also generated for each of the Sentinel-2 dataset. The preprocessing for Sentinel-2 included the resampling of 20m bands to 10m, mosaicking, and cloud masking. Using the monthly Sentinel data, averages for short-dry season and wet season were used as datasets for the land cover classification for each season, respectively. For the annual/combined (multi-season) dataset, the datasets for short-dry and wet seasons were taken. The identical bands from each dataset were averaged to form a new set of stacked images for the multi-season dataset, resulting in a similar number of bands across all datasets. This approach accounted for the study area's Type 3 climate, characterized by a short dry season lasting three to four months (March-May) and an extended wet season (June-February). Sentinel-2 data underwent comparable preprocessing in SNAP to ensure compatibility. The images were finalized through the integration of bands (both originally extracted and generated) via layerstacking for the three models (short-dry, wet, and annual/combined). These images were subsequently prepared for land cover classification.

Land cover classification involved the generation of three final composite images by stacking both Sentinel satellite data for years 2017, 2020, and 2023. Training data representing various land cover types—such as bare soil, built-up areas, vegetation, forest, and water—were utilized for classification using the Random Forest algorithm. Initially, 2015 land cover data from Sentinel-2 were considered for comparison with the 2015 and 2020 datasets from the NAMRIA. However, due to the unavailability of Sentinel-2 data prior to 2017, the yearly global land cover data from ESRI, also based on Sentinel-2, were selected as the alternative reference dataset for years 2017, 2020, and 2023.

The land cover data for 2017 and 2020 were subsequently used to predict future land cover for 2023, with validation planned against actual 2023 observations. Projections for 2023 and 2026 were also generated, representing three-year intervals, respectively. Change detection analysis was conducted on all land cover datasets to quantify temporal and spatial transformations.

Future simulations employed the Artificial Neural Network (ANN) multi-layer perception which was implemented via MOLUSCE plugin for QGIS. The ANN model required only the initial and final land cover datasets as inputs. Thus, the 2017 and 2020 generated land covers were used as inputs for 2023 prediction and the 2020 and 2023 generated land covers were used for 2026 prediction. The Data Elevation Model (ASTER) and the slope of the study area were also used as ancillary data for the future simulation. The neural network training was done using the plugin set with the default values, followed by the cellular automata simulation. The methodological framework for the study, including data preprocessing, combination, classification, prediction and simulation, is illustrated in Figure 2.

3.1 Data

3.1.1 Sentinel-2: It comprises two satellites, Sentinel-2A and Sentinel-2B, which were launched in June 2015 and March 2017, respectively (ESA, 2021). Sentinel-2 data, preprocessing steps included downsampling all bands to a spatial resolution of 10 meters, excluding the 60-meter atmospheric correction bands. The visible, near-infrared (NIR), red, and shortwave infrared (SWIR) bands, along with the normalized difference vegetation index (NDVI), were combined to produce 11 bands per season. Data acquisition involved acquiring two tiles for each time period from the Copernicus API hub to comprehensively cover the study area, resulting in the processing of 62 tiles in total.

3.1.2 Sentinel-1: The Sentinel-1, developed under the ESA Copernicus Programme, is an Earth observation mission. Comprising Sentinel-1A and 1B, the mission's satellites were launched in April 2014 and April 2016, respectively (ESA, 2021). Sentinel-1 is equipped with a C-band SAR, which operates independently of cloud cover and weather conditions. This capability has proven effective in mapping land cover characteristics, particularly in complex environments (Schulz et al., 2021). Sentinel-1 imagery is publicly available and accessible via the Copernicus API Hub. Its preprocessing involved the extraction of Grey-Level Co-Occurrence Matrix (GLCM) parameters from the VV and VH polarization bands. These metrics included the 25th, 50th, and 90th percentiles, as well as the standard deviation, resulting in four derived values per band and a total of eight metrics per season.

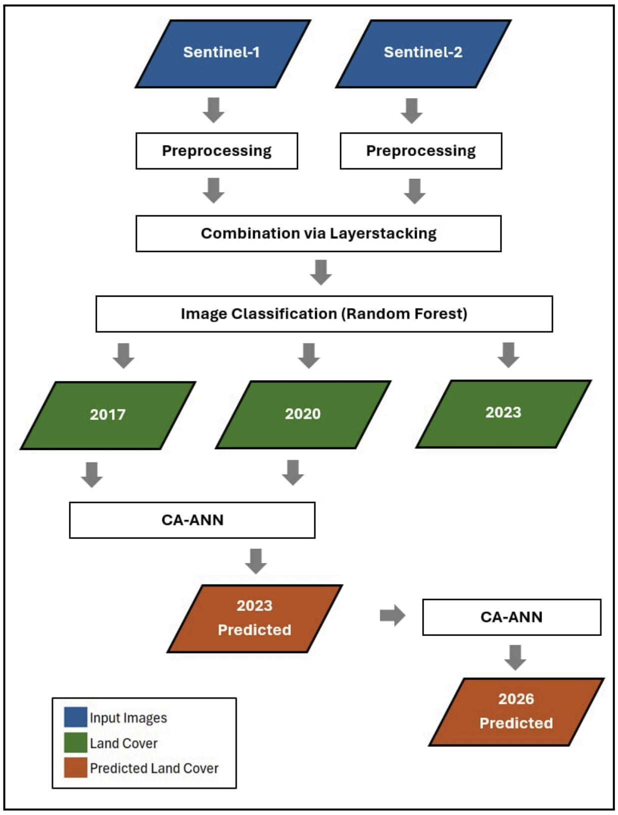

Figure 2. Data processing

3.2 Image Classification

3.2.1 Training Samples and Classification: Training samples were manually for each image composite. The training samples were scattered across the study area to ensure the representation of pixels for the whole area, with a minimum of 10,000 pixels per class. The training samples were used as input for the random forest classifier in Sentinel Application Platform (SNAP). A total of nine (9) classified images were generated (one for each season of the year and the combination). The land cover classification includes five (5) cover types as shown in Table 1.

Land Cover Class	Description
Built-up	Areas covered by man-made structures such as buildings, roads, and other infrastructure.
Bare Soil	Exposed ground with little to no vegetation, including fallow land.
Forest	Dense areas dominated by woody perennials such as trees and undergrowth.
Vegetation	Land covered by grass, shrubs, crops, or other low-lying plant life, excluding dense forests.
Water	Bodies of water such as rivers, lakes, ponds, or reservoirs.

Table 1. Land Cover Classes and Their Descriptions

3.2.3 Result Validation: The study area was sampled using randomly generated validation points. A total of 250 validation points were assigned, with 50 points allocated per class. For the accuracy assessment, 250 validation points were randomly distributed across the study area. This sample size aligns with recommendations in the remote sensing literature, which suggest that approximately 200–300 points (with at least 50 points per class) are sufficient for statistically reliable accuracy estimates while balancing feasibility and computational efficiency (Congalton & Green, 2008; Olofsson et al., 2014). Moreover, Philippines' similar studies on land cover change have employed comparable sample sizes to ensure representativeness without being excessively resource-intensive (Olfato-Parojinog et al., 2023). The accuracy assessment was then performed by manually labelling the correct land cover class of the generated points in reference to Google Earth imagery and Sentinel-2 dataset based on the authors' interpretation and judgement.

4. Results and Discussions

4.1 Accuracy Assessment Results

A total of nine (9) classified images were generated from the Sentinel images (Three for each season model – Short-dry, Wet, and Multi-Season) as shown in Figure 3. The resulting images have null values due to the lack of coverage for cloud-free pixels on Sentinel-2 data. Thus, in the accuracy assessment of the land cover change analysis, these areas were not included. Table 2 summarizes the overall classification accuracy of the images.

Figure 3 shows that the classified images overestimate built-up areas (much of bare soil were classified as built up). Built up areas in the study area are only minimal but are visually evident in the resulting land cover images, which may be caused by the almost similar spectral signature of the bare soil and built up and the differences in brightness within the original image composites.

The total accuracy of the classified images ranges from 78.13% to 83.73%. Generally, the total accuracy of the multi-season model was greater than the short-dry and wet models. Similar to the results of Borges et al. (2020) for savannah, using a multi-season model in a tropical watershed does yield better results. Moreover, the kappa statistics of the classified images only range from 71% to 81% which are better than random chance.

Year	Multi-Season	Short-Dry	Wet
2017	85.20 %	82.80 %	79.55 %
2020	82.00 %	79.20 %	77.20 %
2023	84.00 %	80.80 %	77.64 %
Average	83.73%	80.93%	78.13%

Table 2. Summary of total accuracy.

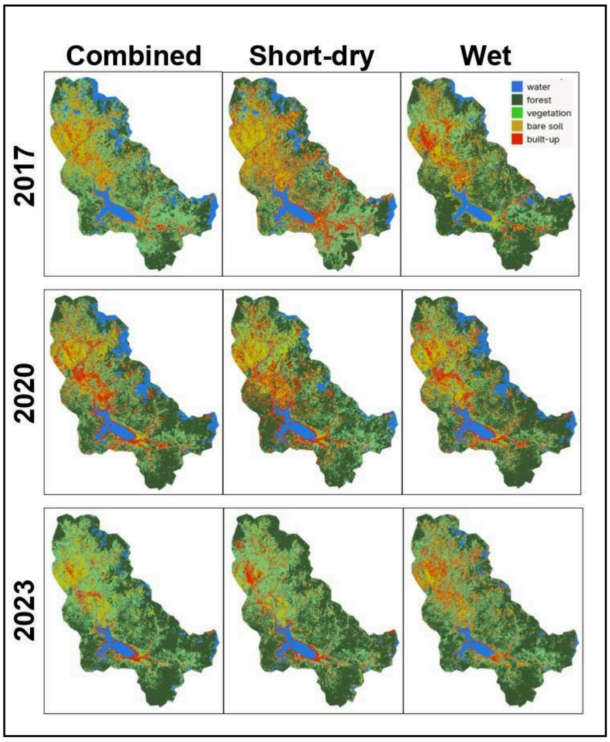

Figure 3. Land Cover Classification

4.2 Land Cover Change Analysis

As the best-performing approach, the multi-season/combined season model was used to examine land cover change, specifically targeting alterations in forest cover. The gains and losses were also analyzed, taking into account the classes that were converted to and from forests. The land cover classes considered for the analysis were mainly bare soil and vegetation, as shown in Table 3. Lastly, forest cover change prediction was made for 2026 using the ANN-generated land cover classification images as shown in Figure 4.

From 2017 to 2023, there was a significant net increase in forest cover within the PCW. Most of the increase comes from the vegetation class, which suggests ecological succession. This can also be attributed to the reforestation efforts in the area (Dolores et al., 2019). The net increase was observed to be about 89 and 34 km^2 for 2017-2020 and 2020-2023 changes, respectively. There is an observed forest cover loss which is mainly converted from forests to vegetation.

4.3 Land Cover Change Prediction

Using the generated images as inputs, predicted land cover for 2023 and 2026 were generated as presented in Figure 4. In comparison to the best performing classified model (short-dry season model), the 2023 predicted land cover has a total accuracy of about 79%. The resulting images especially for 2023 prediction has an overestimation of the built-up areas, which is more than the generated 2023 land cover. This may have been affected by the quality of the input images from the years 2017 and 2020 based on the validation made (Table 2), which have similar inaccuracies. Another simulation was run to generate the LULC map for 2026. Results showed an increase in forest cover of about 28 km^2, which mainly comes from vegetation and bare soil (Table 3).

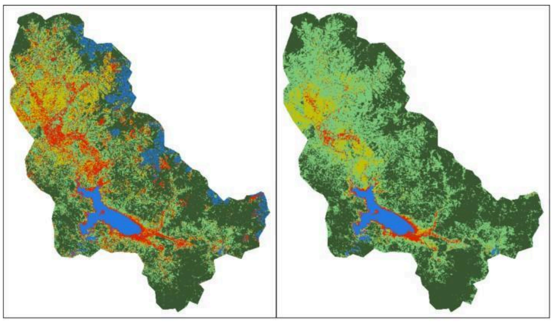

Figure 4. Land Cover Prediction

GAINS	**2017-2020**	**2020-2023**	**2023-2026**
from Bare Soil	3,465,900	3,286,200	8,424,900
from Vegetation	106,419,100	61,213,600	60,724,700
Total	*109,885,000*	*64,499,800*	*69,149,600*
LOSSES	**2017-2020**	**2020-2023**	**2023-2026**
to Bare Soil	1,943,100	1,012,900	1,023,100
to Vegetation	18,875,300	29,091,700	39,258,100
Total	*20,818,400*	*30,104,600*	*40,281,200*
NET	**89,066,600**	**34,395,200**	**28,868,400**

Table 3. Results of forest cover change analysis (in m^2) for the short-dry model

5. Conclusions and Recommendations

This study has conducted a multi-seasonal land cover change analysis and prediction in the PCW using Sentinel-1 and Sentinel-2 imagery. Results revealed important insights and indicated a general increase in forest cover (about 89 km^2, 34 km^2, and 28 km^2 for 2017-2020, 2020-2023, and 2023-2026 analysis, respectively). The use of multi-seasonal satellite imagery has resulted in higher accuracies for land cover classification in PCW, a tropical watershed, in comparison to the monoseasonal models, indicating that the objective of enhancing classification accuracy in such a heterogeneous environment was achieved. However, improvements can still be made. The complexities of the PCW's varied landscapes, which include both forested and non-forested areas, may require more advanced techniques or improved feature extraction to better differentiate land cover classes, especially between bare soil and built-up areas where most misclassifications occurred. In particular, accuracy can be enhanced by integrating additional spectral indices including NDVI for vegetation, NDWI or Normalized Difference Water Index for water bodies, and built-up indices, which have been shown to improve class separability (Tucker, 1979; McFeeters, 1996; Xie et al., 2008). On the other hand, Bare Soil Index (BSI) and Normalized Difference Bare Soil Index (BSI) can improve the classification between bare soil and built-up (Ying et al., 2022). Using multi-temporal imagery can also capture seasonal differences more effectively, while combining Sentinel-1 SAR with Sentinel-2 optical data provides complementary structural and spectral information for improved classification (Torres et al., 2012; Li et al., 2020). On the methodological side, advanced approaches such as Support Vector Machines (SVM) or object-based image analysis (OBIA) have been demonstrated to perform better than pixel-based classifiers in heterogeneous environments (Blaschke, 2010; Mountrakis et al., 2011).

Moreover, the analysis also showed that the land cover models, when applied to regional scales, produced acceptable error rates (77% to 85% total accuracy in comparison to the expected 80%), which demonstrated its ability to generalize global land cover products effectively for local or regional applications. This indicates that while the model encountered some difficulty in adapting global datasets to regional settings, the methods are reliable enough and that can further be improved in future studies. Lastly, although the proposed methodology remains user-friendly, it still needs further refinement to improve its efficiency, particularly in land cover monitoring and management in the Philippines using numerous datasets.

Finally, the objectives of the study were achieved. Additional modifications are required to improve classification between some classes but it provides a solid foundation for using the data of Sentinel-1 and Sentinel-2 for land cover change analysis, especially when focusing on forest cover change. Sentinel-1 has alleviated the negative effects of some thin clouds and other effects of atmosphere present in the Sentinel-2 dataset, while the combination of information from different seasons captures the changing patterns of vegetation (woody and non-woody). Enhanced model accuracy, reduced error rates, and a more robust user-friendly approach will be essential to meet the goals of accurate land cover mapping and supporting effective watershed management in the Pantabangan-Carranglan region.

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