TECHNICAL REPORT

LAND USE LAND COVER ASSESSMENT OF BHUTAN 2020

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FOREWARD

The Land Use Land Cover (LULC) 2020 assessment in Bhutan aimed to provide comprehensive information about the distribution of major land use and land cover types in the country. Periodic assessments of land use changes are crucial for strategic planning at national and local levels. The previous mapping exercise was conducted in 2016 using Landsat 8 (OLI) imagery by the Department of Forest and Park Services (DoFPS) under the Ministry of Energy and Natural Resources. Monitoring forest cover is a key responsibility of DoFPS, and remote sensing technologies have played a significant role in deriving land cover information and correlating it with land use statistics.

The current assessment utilized Sentinel-2 satellite imagery, which provides open and free access to high-resolution (10 meters) spatial data. This allowed for the mapping of thirteen major land cover classes, including the forest class. The use of remote sensing data not only facilitates the monitoring of forest cover but also enables the identification of changes in other land cover classes over time across the country. The derived information from this assessment will greatly contribute to spatial planning and the management of limited resources for sustainable development in Bhutan.

The successful completion of the national LULC mapping project was made possible through the funding and support of the Royal Government of Bhutan (RGoB) and the assistance provided by the World Wildlife Fund (WWF). Their contributions were instrumental in carrying out this important assessment, which will serve as a valuable resource for decision-making and conservation efforts in Bhutan.

Secretary

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EXECUTIVE SUMMARY

The Land Use Land Cover Map 2020 assessment was conducted using Sentinel-2 multispectral satellite imagery. Thirteen image tiles from November to December 2020 were selected, ensuring a minimum cloud coverage of 10%. The image classification process was carried out using eCognition software version 9.5. The accuracy of the classified map was evaluated through field validation and comparison with high-resolution Google satellite imagery.

The overall accuracy of the classified map was determined to be 87% with a kappa coefficient of 0.853. The dominant land cover class was forest, which accounted for 69.0% of the total area, showing a decrease compared to the previous land use land cover assessment in 2016 where it was 70.77%. Snow and Glacier covered 4.83% of the land, followed by Shrubs at 4.11%. Alpine Scrubs showed a significant increase from 3.39% in 2016 to 8.89% in 2020. Rocky Outcrops and meadows constituted 4.52% and 4.39% of the land, respectively. Agriculture land increased slightly from 2.76% in 2016 to 2.96% in 2020. The lowest land cover categories were landslides (0.07%) and sandy banks (0.13%), followed by moraines (0.43%) and water bodies (0.61%). Built-up areas accounted for 0.25% of the land, while non-built-up areas constituted 0.03%.

Among the Dzongkhags, Zhemgang had the highest forest coverage with 94.5%, followed by Pemagatshel with 91.2%. Gasa had the lowest forest coverage at 17.3%, and Thimphu had 36.2% forest coverage. In terms of agriculture land, Samtse had the highest percentage with 11.8%, followed by Tsirang and Paro. Gasa had the lowest agriculture land coverage with only 0.12%. These findings provide valuable insights into the distribution of land cover classes across different Dzongkhags in Bhutan.

Director
Department of Surveying and mapping

Acronyms and abbreviations

OLI	Operational Land Imaging
DoFPS	Department of Forest and Parks Services
NLCS	National Land Commission Secretariat
RGOB	Royal Government of Bhutan
WWF	World Wildlife Fund
PHCB	Population and Housing Census of Bhutan
LULC	Land Use Land Cover
ICIMOD	International Centre for Integrated Mountain Development
MoAF	Ministry of Agriculture and Forest
MSI	Multi-Spectral Instrument
ToA	Top of Atmosphere
BoA	Bottom of Atmosphere
NIR	Near-Infra-Red
SWIR	Shortwave Infrared
NDWI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NDSI	Normalized Difference Snow Index
NDBI	Normalized Difference Built-up Index
ESA	European Space Agency
SNAP	Sentinel Application Platform
OA	Overall Accuracy
UA	User's Accuracy
PA	Producer's Accuracy
OBIA	Object Based Image Analysis
RF	Random Forest
DEM	Digital Elevation Model

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1. Introduction

Bhutan, situated in the eastern Himalayas between the neighboring countries of China and India, with most population rely on agriculture for their livelihood. The country's altitude spans from below 100 m to around 7500 m above sea level. According to the Population and Housing Census of Bhutan 2017 (PHCB 2017), approximately 62.2% of the total population resides in rural areas. Notably, Bhutan has experienced significant urbanization and infrastructure development in recent years.

Due to its mountainous terrain and limited availability of usable land, coupled with its fragile ecosystem, there is a pressing need to assess the land use land cover (LULC) in Bhutan. This assessment aims to provide a scientific basis for effective land governance and informed planning. The country faces the challenge of maintaining its vision of preserving 60% forest cover indefinitely, particularly in the face of substantial changes in land use land cover resulting from rapid developmental activities.

Furthermore, the majority of Bhutan's population relies on agriculture and livestock farming for their livelihoods, while only 2.9% of the total land area is dedicated to agricultural use. Consequently, LULC information plays a crucial role in various national interventions concerning vital issues such as climate change, food security, and environmental sustainability. Striking a balance between the needs of the population, infrastructure development, and environmental conservation is of paramount importance.

The demand for information regarding land cover, land use, and their changes has seen a notable increase on a global, regional, and national scale in recent decades. This surge in demand aims to provide crucial support for policy decisions and effective management processes (ICIMOD).

In Bhutan, the first land use land cover mapping was conducted in 1997 as part of the Land Use Planning Project (LUPP), which received funding from the Danish International Development Assistance (DANIDA). This initial mapping utilized spot imageries and aerial photographs. Subsequent assessments were carried out in 2010 and 2016 using ALOS and Landsat imageries, primarily to monitor changes in land cover over time (FRMD, 2017).

The fourth assessment of land use land cover in Bhutan took place in 2020, utilizing the free and open-source Sentinel-2 imagery with a spatial resolution of 10 meters. The mapping process was supported by the Royal Government of Bhutan (RGoB) and received funding from the World Wildlife Fund (WWF).

2. Objectives

Following are the objectives of conducting Land use Land Cover exercise;

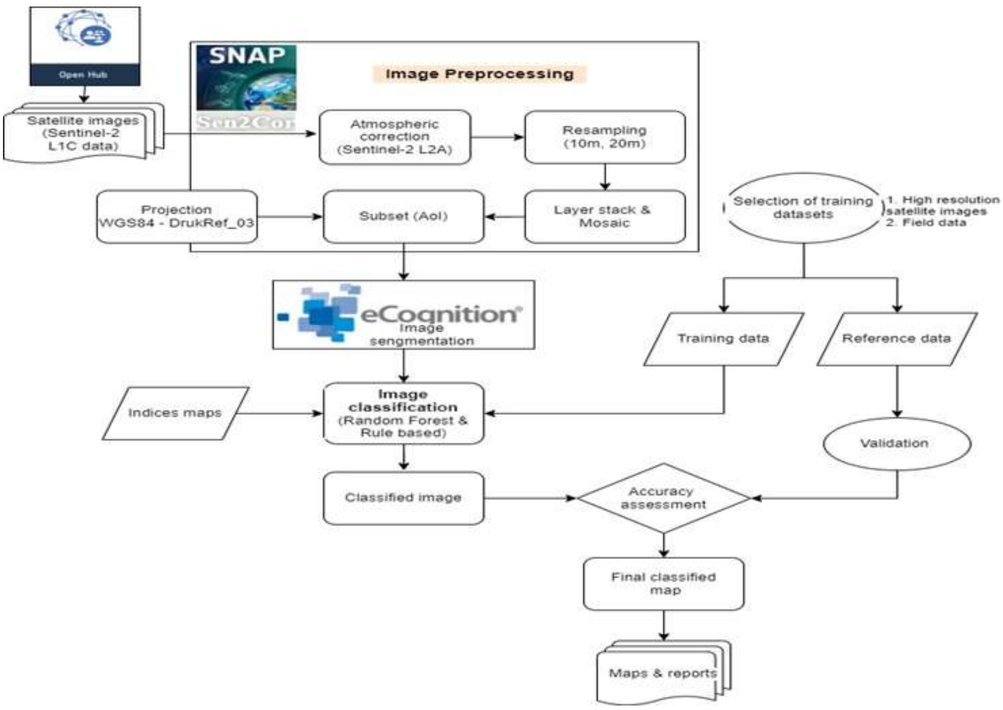
a. The primary objective of this project is to update the existing Land Use Land Cover map (LULC2016) of Bhutan.

b. Another key goal is to derive comprehensive and precise information on land use and land cover.

c. This project aims to contribute to the overall impact of the national land use zoning implementation in Bhutan.

By utilizing the latest data and imagery, we aim to provide an updated and accurate representation of the current land use and land cover patterns in the country. This information will serve as a valuable resource for future planning and developmental purposes in Bhutan. By having an up-to-date understanding of the land use and land cover dynamics, decision-makers can make informed choices and ensure sustainable development practices. Moreover, by providing reliable and detailed data on land use and land cover, the project will support the effective implementation of land use zoning policies and regulations. This, in turn, will help in achieving a balanced and sustainable approach to land management and resource allocation throughout the country.

3. Materials and Methodology



3.1 Satellite Image

The Sentinel-2 Multispectral Instrument (MSI) consists of two satellites, Sentinel-2A and Sentinel-2B, which capture imagery of the Earth's surface at different spatial resolutions. Sentinel-2A was launched on June 23, 2015, followed by Sentinel-2B on March 7, 2017. Both satellites maintain a sun-synchronous orbit at an altitude of 786 km. The imagery is available in various levels of processing, namely Level-1C and Level-2A, each with different correction levels.

The available Sentinel-2 products are categorized into three levels: Level-1B, Level-1C, and Level-2A. The Level-1C products undergo both geometric and radiometric corrections, but they are not atmospherically corrected. These products provide a processed format that is suitable for further analysis and interpretation.

For the LULC mapping, Level-1C products with Top-of-Atmosphere (ToA) reflectance were employed. These products contain imagery from the optical instrument payload of the satellites, which includes 13 spectral bands. The bands are distributed across different spatial resolutions: four bands at 10 m, six bands at 20 m, and three bands at 60 m. To generate the Land Use and Land Cover (LULC) map for 2020, Sentinel-2 satellite images acquired during November to December 2020 were utilized. The following table, Table 1, provides more detailed information about the bands of the Sentinel-2 imagery:

Table 1: Band details of Sentinel-2 imagery

Sentinel-2 Bands	Central Wavelength (micrometer)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.49	10
Band 3 - Green	0.56	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.74	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water Vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.61	20
Band 12 - SWIR	2.19	20

Sentinel-2 satellites have a temporal resolution of 5 days, meaning that they revisit the same location on Earth every 5 days. The imagery is divided into thirteen tiles, which collectively cover the entire country. Each tile represents an ortho-image with a size of 100x100 km2 and is projected in the UTM/WGS84 coordinate system.

The images used in the analysis, as shown in Figure 2, were downloaded from the ESA's Copernicus Open Access Hub (https://scihub.copernicus.eu). This online platform provides access to the Sentinel-2 satellite data, allowing users to acquire the necessary imagery for their analysis and research purposes.

By utilizing the data from the Copernicus Open Access Hub, researchers and analysts can conduct various analyses and studies using the Sentinel-2 imagery to gain insights into land use, land cover, and other environmental variables.

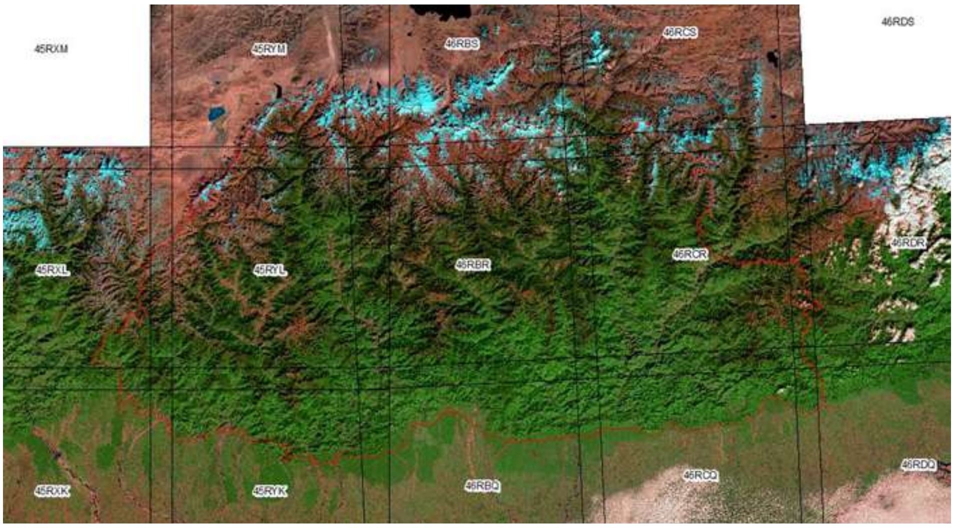


Figure 2: Sentinel-2 image tiles coving the entire country

3.2 Pre-processing

During the pre-processing of the Sentinel imagery, several steps were performed, including atmospheric correction, resampling, and subset. These steps are essential for improving the quality of the data and ensuring consistency among different bands of the imagery.

Atmospheric correction was conducted using the Sen2Core processor provided by the European Space Agency (ESA). This correction process involved converting the Level-1C data, which represents top-of-atmosphere reflectance (ToA), to Level-2A data, which represents bottom-of-atmosphere reflectance (BoA) or surface reflectance. The atmospheric correction removes the influence of the atmosphere on the data, allowing for more accurate analysis of the land surface. The Sen2Core processor preserves the original spatial resolution and spectral band order of the imagery.

After atmospheric correction, the Level-2A data was further processed using the SNAP software. One of the processing steps applied was resampling, which aimed to geometrically correct distorted pixels in the original imagery. Resampling involves adjusting the pixel grid of the imagery to a consistent and uniform spatial resolution. This step ensures that all bands of the imagery have the same spatial resolution, allowing for easier comparison and analysis.

By performing atmospheric correction and resampling, the pre-processed imagery becomes more suitable for subsequent analysis. The resulting data is corrected for atmospheric effects and has consistent spatial resolution, enabling accurate interpretation and extraction of information from the imagery.

3.3 Layer Stacking

To facilitate the analysis, the individual bands of each image tile were stacked using EARDAS IMAGINE software. The bands were grouped into three categories based on their differences in spatial resolution during the pre-processing stage and were stacked separately.

In the first category, Band 2 to Band 4 and Band 8 were combined and stacked as one layer. This grouping allows for the utilization of bands with similar spatial resolutions for further analysis.

In the second category, Band 5 to Band 7, Band 11, and Band 12, including Band 8A, were stacked into a separate layer. These bands also share similar spatial resolutions and were therefore grouped together.

Band 1, 9 and 10 were categorized into one category but those bands are not used in the classification process

This process was repeated for all the image tiles covering the entire country, ensuring that the bands from each tile were appropriately stacked for subsequent analysis and interpretation.

3.4 Projection

The Sentinel-2 imageries were initially in the WGS 1984 UTM Zone 45N and 46N coordinate systems. To ensure consistency and compatibility with the analysis, all the images were re-projected to the DRUKREF 03 Bhutan National Grid coordinate system. This step ensures that all the images are in the same spatial reference system, enabling accurate spatial analysis and integration of the data within the context of Bhutan's national grid.

3.5 Mosaic and subset

To create a seamless image covering the entire area of interest, all thirteen image tiles were mosaicked using the "Mosaic to New Raster" tool in ArcGIS. This tool allows for the combination of multiple raster datasets into a single raster dataset. The resulting mosaic image was then sub set to by using a shape file or boundary layer of Bhutan to extract the desired area of interest.

Figure 3 below illustrates the final mosaic image sub set showing the extent of Bhutan boundary.

Figure 3: Mosaic image (RGB) in 10m resolution

Figure 4: Mosaic image (6, 4, and 3) in 20m resolution

4. Vegetation Indices

Indices play a crucial role in spectral enhancement as they enhance the spectral information and improve the separability of the classes of interest. This enhancement leads to a higher quality land use land cover (LULC) mapping product, as noted by (Ustuner et al., 2014).

In the post-classification refinement process, several vegetation indices are commonly calculated and utilized. These indices provide valuable information about vegetation characteristics and help in further refining the classification results. Some commonly used vegetation indices are reflected in the Table 2 below.

Table 2: Indices calculation

Indices	Formula
Normalized Difference Vegetation Index (NDVI)	(NIR– RED)/(NIR + RED)
Normalized Difference Water Index (NDWI)	(Green – NIR)/(Green + NIR)
Normalized Difference Snow Index (NDSI)	(Green – SWIR)/(Green + SWIR)
Normalized Difference Built-up Index (NDBI)	(SWIR – NIR)/(SWIR + NIR)
Normalized Difference Bareness Index (NDBaI)	(SWIR – VRE)/(SWIR + VRE)

These vegetation indices, among others, are calculated and utilized in the post-classification refinement process to enhance the separation and accuracy of different land cover classes, particularly those related to vegetation.

Normalized Difference Vegetation Index (NDVI) differentiates the vegetation from non-vegetation areas. The NDVI values range from -1 to +1, with positive values indicating the presence of healthy green vegetation. By thresholding NDVI values, it becomes possible to separate vegetation from non-vegetation areas.

The Normalized Difference Water Index (NDWI) ratio helps to discriminate the other land cover classes such as vegetation, built-ups and bare soil from the water bodies which helps to correctly map the water bodies.

Similarly, Normalized Difference Snow Index (NDSI) is specifically designed to detect snow covered areas. Since snow has distinct spectral properties including high reflectance in the visible (green) part of the spectrum and low reflectance in the shortwave infrared, it clearly differentiates from the other land cover classes.

By incorporating these indices, the quality and reliability of the LULC mapping product can be significantly improved.

5. Software

The assessment involved the use of various software applications, each serving specific purposes in the land use land cover (LULC) analysis. The following software programs were utilized:

a. ArcGIS 10.8
b. ERDAS IMAGINE
c. QGIS
d. eCognition version 9.5
e. SNAP

By utilizing these software applications, the assessment could leverage their specific functionalities and tools to process, analyze, and visualize the LULC data, ultimately aiding in the generation of accurate and reliable land use land cover information.

6. Land use Land cover classes (LULC)

The current Land use Land cover (LULC) classes were defined and adopted from the LULC2016 dataset to ensure consistency in class definitions and facilitate future change detection analysis. While the specific details of sub-classes can vary based on project requirements, a total of 13 major classes were considered in this classification system.

Table 3: Land use Land cover classes

Sl. No	Classes
1	Forests
2	Alpine Scrub
3	Shrub
4	Meadows
5	Agriculture Land
6	Built Up Areas
7	Non-Built-Up Areas
8	Water Bodies
9	Snow and Glacier
10	Moraines
11	Landslide
12	Rocky Outcrops
13	Sandy Bank

The 13 major LULC classes serve as broad categories that encompass different land cover types. These classes provide a standardized framework for classifying and organizing the diverse land cover characteristics within the study area. The specific definitions and descriptions of these major classes may be tailored to suit the needs of the analysis.

By maintaining consistency with the previous LULC dataset and adopting a standardized set of major classes, the classification results can be compared and analyzed over time, enabling the assessment of land cover changes and their implications. This approach ensures continuity and allows for efficient monitoring and management of land resources and land use dynamics.

6.1 Class Description

i. Forests: Land with trees spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent. It does not include land that is predominantly under agricultural or urban land use (National Forest Policy of Bhutan, 2011).

ii. Alpine scrub: Alpine scrub is woody plant characterized by stunted growth (height less than 5meter) due to harsh condition. They are found at higher elevation above 3500-meter above sea level close to tree line.

iii. Shrubs: Shrubs are perennial plants with persistent and woody stem without any defined main stem with height less than 5 meter. It also includes abandoned agricultural fields with overgrown bushes and other regeneration in disturbed areas.

iv. Meadows: Meadows include any areas dominated by grasses or any herbaceous plant without or with few scattered trees or shrubs on it. It occurs at all elevations, but is relatively more common at higher elevations.

v. Agriculture Land: Agricultural land includes only those land that are cultivated at the time of land cover assessment. The sub-classes such as Chhuzhing, Kamzhing, and Orchard land type categories are merged together in the class.

vi. Built Up Areas: Built up areas includes artificial constructions covering the land with an impervious (e.g., concrete, CGI sheet, thatch) surface. It includes airport, rural settlements, urban areas, schools & institutes, industrial areas, hospital premises, sewage treatment plant, sports and leisure facilities and roads.

vii. Non Built-Up Areas: This class is defined by absence of the original (semi-) natural cover mainly due to anthropogenic factors. It includes waste dump sites, mines, stone quarries and other extraction sites.

viii. Water Bodies: This class includes both natural and artificially created water bodies (includes rivers and lakes)

ix. Snow and Glaciers: This class includes both perpetual and seasonal snow cover and glaciers.

x. Moraines: Moraines refers to a mass of rocks and sediments carried down and deposited by a glacier typically as ridges at its edges or extremity.

xi. Landslide: This class includes mass movement of soils debris due to gravitational force triggered by other factors such as rainfall and earthquakes.

xii. Rocky Outcrops: Rocky outcrops refer to natural cliffs and rocky areas.

xiii. Sandy bank: This class refers to the sandy area that were deposited along the river banks. In summer this class may be cover under the river. However, during the winter season it gets dried up and deposited as sandy bank along the river.

7. Sampling

Sample data plays a vital role in classification processes, and the majority of machine learning algorithms necessitate a substantial and adequate amount of training data samples (Abdi, 2019). Obtaining and defining reference data from the field can be a challenging endeavor, particularly when dealing with extensive and remote areas. Consequently, it is not uncommon in remote sensing to resort to the utilization of secondary data. Numerous researchers have successfully obtained training data by extracting information from pre-existing land cover maps (Inglada et al., 2017).

In this study, we have used the 2016 land use land cover (LULC) dataset as the primary reference data for sample collection. While utilizing existing maps as training data for LULC classification may introduce errors inherited from the previous classification, it is crucial to ensure the accuracy of the training samples derived from these land cover maps. This is accomplished by comparing them with high-resolution satellite imagery and validating certain points using ground truth data. By doing so, the aim is to minimize misclassification (Hermosilla et al., 2018; Millard & Richardson, 2015; Zhang & Roy, 2017).

The selection of an appropriate sampling design is a crucial aspect of classification tasks, as different sampling techniques can lead to varying classification accuracies. Stratified Random Sampling is a widely utilized technique among researchers, as it ensures that training samples are allocated in proportion to the area of each stratum (Buja & Menza, 2013). In other words, larger strata receive a greater number of points. In this study, we have employed the Stratified Random Sampling method available in the Sampling Design Tool within the ArcGIS software.

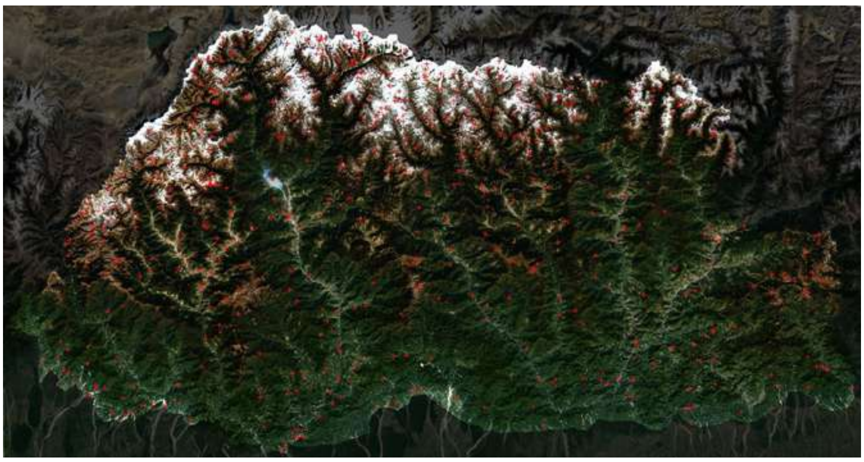


Figure 5: Representation of the sample points

As a general rule of thumb, it is recommended to collect a minimum of 50 samples for each land cover class. However, if the area of interest is larger or if the classification involves a large number of land use classes, it may be advisable to consider a minimum of 100 samples per class (Congalton, 1991).

During this exercise, a total of 1243 sample points were generated including the field validation points to ensure a fair distribution across the entire study area. These samples were subsequently divided into two distinct portions, ensuring statistical independence. The training dataset consisted of 70% of the total samples, while the remaining 30% was reserved for the validation and accuracy assessment of the classified image (Abdi, 2019).

8. Image Segmentation

In the Object Based Image Analysis (OBIA) workflow, the initial step involves segmenting the image into homogeneous objects. This segmentation process considers various factors such as shape, size, color, texture, and context to identify cohesive objects within the image. The segmentation step is critical as it significantly influences the subsequent image classification.

For this exercise, the widely adopted segmentation algorithm called "Multiresolution Segmentation" was applied to generate image objects. This algorithm produces segmentation results by considering different parameters. The accuracy and quality of the segmentation outcome are influenced by the appropriate selection of these parameters.

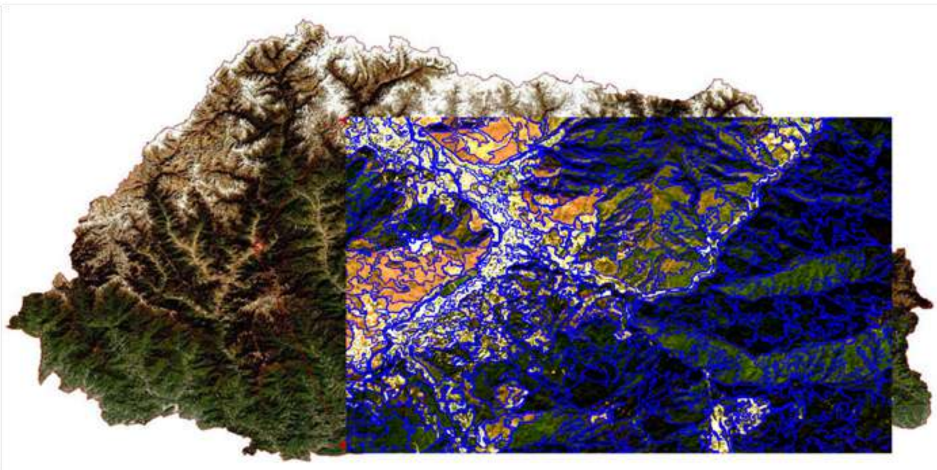


Figure 6: Image segmentation

The segmentation process was applied to the twelve spectral bands of the 10m Sentinel-2 image. Each band was assigned a weight of 1, except for the Near Infrared (NIR) band, which was given a weight of 2. Assigning specific weight to different bands can control the influence during the image segmentation. Moreover, the higher weight to NIR band helps to improve the discrimination between different land cover classes leading to more detailed capture of land cover maps. The scale parameter, which impacts the sizes of the resulting objects, was set to 150. This parameter influences the level of detail captured in the segmentation process. Additionally, the homogeneity criterion, which includes shape and compactness, was set to 0.2 and 0.5, respectively.

These parameter settings were determined through empirical analysis by testing various segmentation configurations. The segmentation results were carefully evaluated to identify clear boundaries for each object, leading to the selection of these specific parameter values.

9. Thematic Datasets

The utilization of vector or thematic layers during image segmentation in Object-Based Image Analysis (OBIA) provides several advantages, as it allows for the creation of more meaningful image objects for classification. Additionally, these layers can be beneficial in the post-classification refinement of the classified image. Here are some examples of vector/thematic layers used in this exercise:

a. Transportation network: The inclusion of transportation network data, such as roads and highways can help in delineating objects related to transportation infrastructure. This information can be valuable in differentiating land cover classes and identifying transportation-related features.

b. River Networks: River network data assists in identifying water bodies, rivers, streams, and their associated features. By incorporating this layer, image objects representing water bodies can be accurately delineated.

c. Cadastral plots: Cadastral plot data provides information about land ownership and property boundaries. By utilizing this layer, it becomes possible to define image objects based on cadastral boundaries, enabling better classification of land cover types related to specific land type.

d. Built-up areas: Incorporating data on built-up areas, such as urban or residential zones, can aid in accurately defining image objects related to human settlements. This layer allows for precise delineation of urban features, assisting in the classification of urban land cover classes.

e. Digital Elevation Model (DEM): The use of a Digital Elevation Model provides information about the topography and elevation of the terrain. By integrating this layer, it becomes possible to create image objects based on elevation or slope thresholds, which can be beneficial in distinguishing land cover classes related to different terrain characteristics.

Overall, the inclusion of various datasets during image segmentation in OBIA enhances the accuracy and meaningfulness of the resulting image objects, thereby improving the classification process and facilitating post-classification refinement efforts.

10. Image Classification

Image classification is a fundamental process in digital image processing that involves extracting valuable information from images. In remote sensing, the spectral characteristics of Earth's surface features serve as the basis for image classification. Various methods have been developed for classifying satellite images, with pixel-based supervised and unsupervised classification being the most commonly used approaches. However, according to (Weih & Riggan, 2010), Object-Based Image Analysis (OBIA) outperforms by utilizing both spectral and contextual information to identify thematic classes in an image.

For the Land Use Land Cover (LULC) classification, OBIA method was used in Trimble eCognition software and a machine learning algorithm known as Random Forest (RF) was applied for the image classification. Random Forest is a supervised learning algorithm used for classification, regression, and other tasks. It constructs multiple decision trees during training and makes decisions through voting. The RF classifier has demonstrated its efficiency and ability to achieve higher accuracy levels compared to other techniques like maximum likelihood and conventional decision trees in land cover classification (Ren et al., 2017). Additionally, the RF model can effectively handle large datasets.

By employing the object-based classification method with the Random Forest algorithm, the LULC classification process aimed to leverage the strengths of both techniques to achieve accurate and reliable classification results.

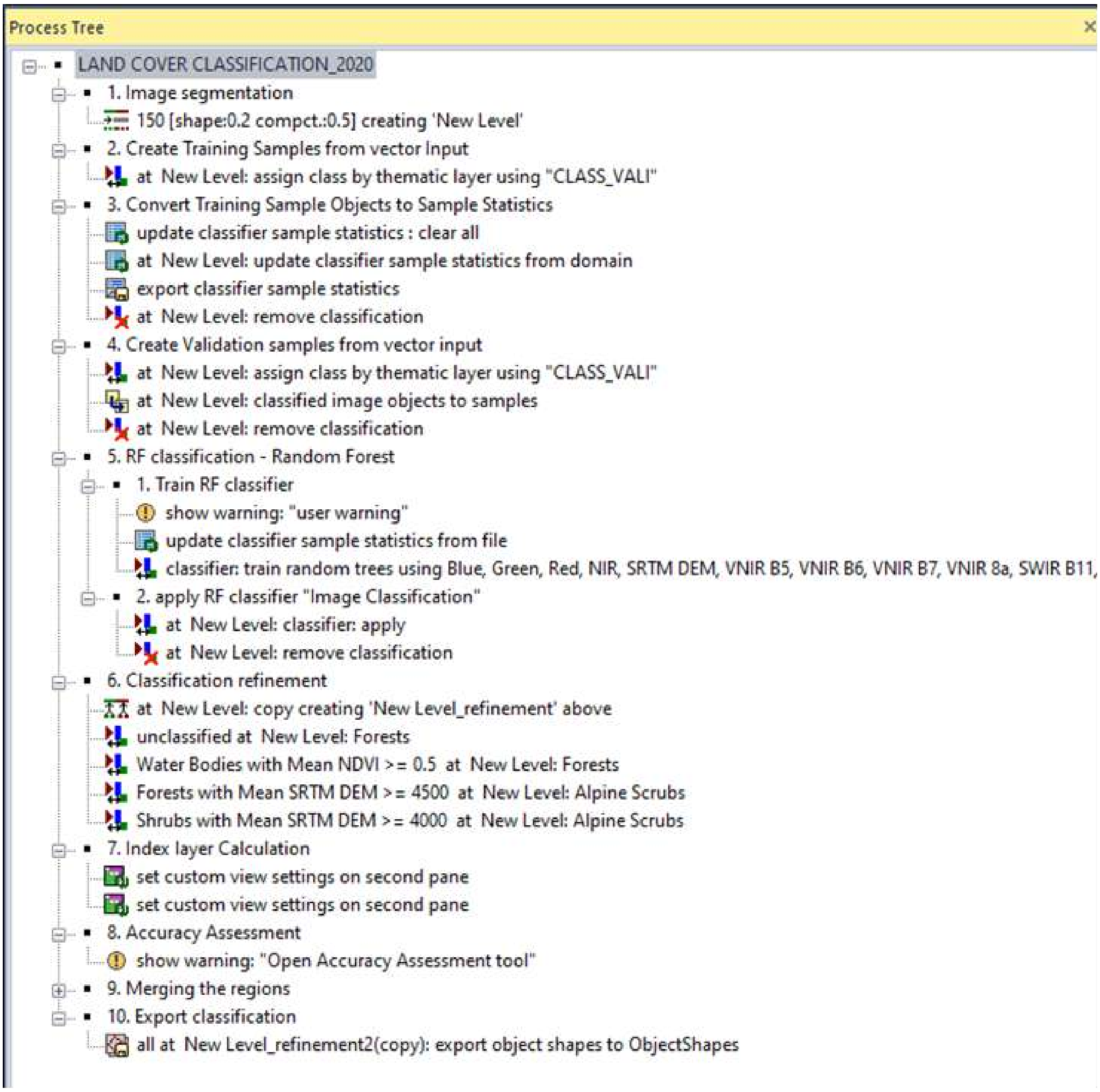


Figure 7: Process for image classification in eCognition software

11. Field Validation

During the validation of the preliminary classification results, it was identified that certain classes had been misclassified, particularly in cases where distinguishing between different types of vegetation cover posed challenges. To ensure the accuracy and reliability of the classification, validation was conducted using high-resolution satellite imagery from Google Earth and other available datasets, such as cadastral data.

The high-resolution satellite imagery from Google Earth provided a detailed view of the land cover, allowing for visual comparison and verification of the classified results. Cadastral data, which provides land type information was also utilized to cross-reference the classified land cover.

In addition to this, random field visits were carried out in select Dzongkhags for further verification and validation. These field visits involved physically inspecting the land cover in specific locations to address any misclassifications or discrepancies that were identified during the classification process.

By incorporating multiple validation methods, including high-resolution satellite imagery, cadastral data, and field visits, the misclassifications in the land cover classification were addressed and the accuracy and reliability of the final classification results were improved.

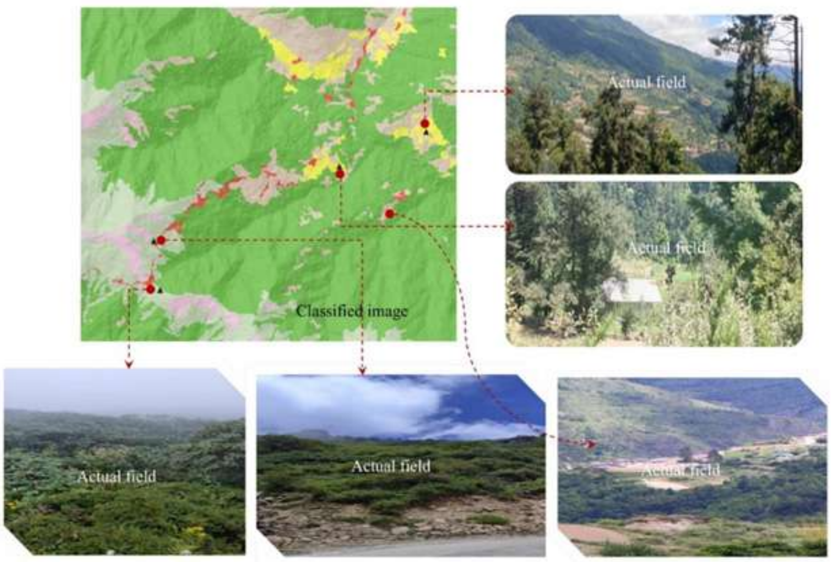


Figure 8: Showing the field validation (Alpine scrubs, Shrubs and Agriculture land)

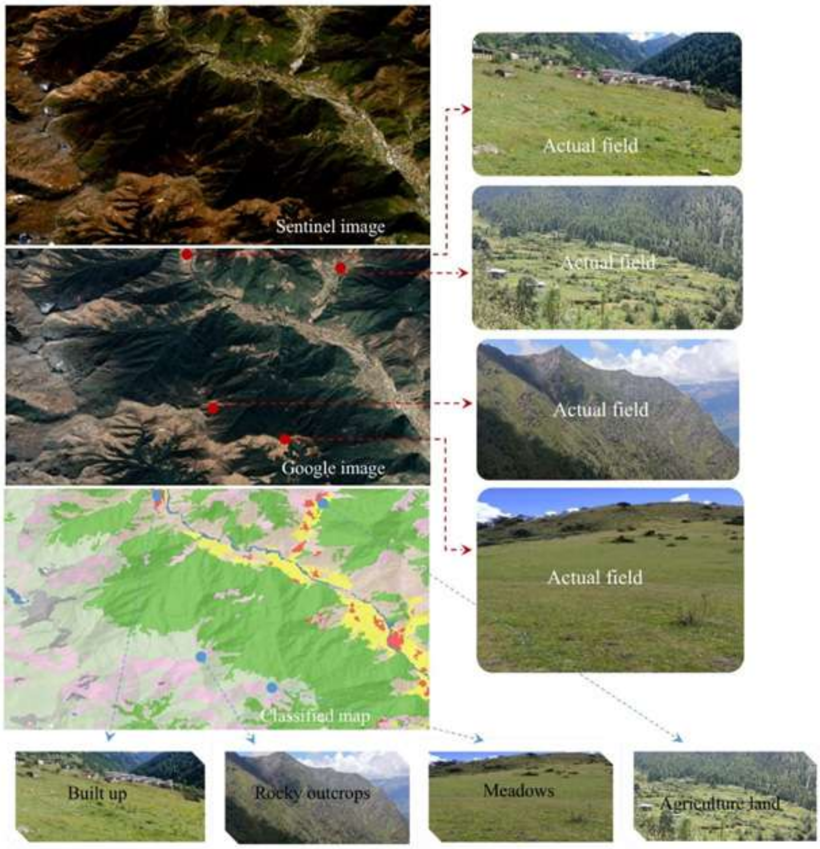


Figure 9: Showing field validation (Built up, Rocky Outcrops and Meadows)

12. Accuracy Assessment

In this exercise, a statistically independent validation dataset was utilized to evaluate the accuracy of the classification results. The validation dataset consisted of 30% of the total samples and served as the reference information for validation purposes.

The validation samples were incorporated into the Random Forest (RF) classifier algorithm. They were converted into sample statistics, which were then used to assess the accuracy of the classification. This process involved constructing an error matrix based on the generated sample statistics.

The accuracy of a land cover classification refers to the level of agreement between the classified land cover and the reference data, as stated by (Zheng et al., 2017). Assessing the accuracy is crucial to validate the results obtained from the image classification process, providing a measure of confidence in the classification outcomes. One widely adopted method for accuracy assessment is the "error matrix" or "confusion matrix" method, as discussed by (Ismail & Jusoff, 2008).

The error matrix method involves comparing the classified land cover with the reference data through a matrix that quantifies the classification results. From the error matrix, several accuracy measures can be computed to evaluate the performance of the classification. These measures include:

i. Overall Accuracy (OA): It represents the percentage of correctly classified pixels in relation to the total number of pixels in the validation dataset. It provides an overall assessment of the classification accuracy.

ii. User's Accuracy (UA): It refers to the probability that a pixel classified as a specific class actually belongs to that class. It measures the accuracy from the user's perspective.

iii. Producer's Accuracy (PA): It denotes the probability that a pixel belonging to a specific class is correctly classified as that class. It measures the accuracy from the producer's perspective.

iv. Kappa Hat statistics (KA): It is a statistical measure that assesses the agreement between the classified land cover and the reference data, considering the possibility of agreement by chance (Congalton, 1991). KA provides a more robust measure of classification accuracy, accounting for random agreement.

By utilizing the error matrix method and computing these accuracy measures, the accuracy of the thematic map, as well as the classification results, can be effectively evaluated, providing valuable insights into the performance and reliability of the land cover classification. According to Anderson et al., (1976), a minimum accuracy of 85 percent should be achieved in the identification of land use and land cover from remotely sensed data. It indicates that the majority of the land cover classes have been correctly identified and labeled, allowing for reliable analysis and decision-making based on the classified data.

$$\text{Overall accuracy (OA)} = \frac{\textit{(Sum Total of diagonals)}}{\textit{(Sum Total of classified image)}}$$

$$\text{Producer's accuracy (PA)} = \frac{\textit{(Classified cell)}}{\textit{(Sum of reference cell)}}$$

$$\text{User's accuracy (UA)} = \frac{\textit{(Classified cell)}}{\textit{(Sum of reference cell)}}$$

Table 4: Showing Producer's and User's accuracy of individual class

Sl. No	Class Name	Producer's Accuracy	User's Accuracy
1	Snow and Glacier	90.91%	89.29%
2	Agriculture Land	91.43%	88.89%
3	Built up	92.31%	85.71%
4	Shrubs	60.00%	75.00%
5	Forests	91.38%	86.89%
6	Water Bodies	92.31%	100.00%
7	Sandy bank	100.00%	85.71%
8	Meadows	87.10%	84.38%
9	Landslides	75.00%	100.00%
10	Non Built up	100.00%	100.00%
11	Moraines	61.00%	100.00%
12	Rocky Outcrops	81.08%	83.33%
13	Alpine Scrubs	98.15%	82.81%

		REFERENCE DATA													
	Land cover Classes	**Snow & Glaciers**	**Agriculture Land**	**Built up**	**Shrubs**	**Forest**	**Water Bodies**	**Sandy Bank**	**Meadows**	**Landslides**	**Non Built up**	**Moraines**	**Rocky Outcrops**	**Alpine Scrubs**	**Total**
CLASSIFIED DATA	**Snow & Glaciers**	**50**	0	0	0	0	0	0	0	0	0	5	1	0	56
	Agriculture Land	0	**32**	0	1	3	0	0	0	0	0	0	0	0	36
	Built up	0	0	**12**	0	0	0	0	0	1	0	0	1	0	14
	Shrubs	0	2	1	**18**	1	0	0	1	1	0	0	0	0	24
	Forest	0	1	0	5	**53**	1	0	1	0	0	0	0	0	61
	Water Bodies	0	0	0	0	0	**24**	0	0	0	0	0	0	0	24
	Sandy Bank	0	0	0	0	0	1	**6**	0	0	0	0	0	0	7
	Meadows	0	0	0	3	1	0	0	**27**	0	0	0	1	0	32
	Landslides	0	0	0	0	0	0	0	0	**6**	0	0	0	0	6
	Non Built up	0	0	0	0	0	0	0	0	0	**3**	0	0	0	3
	Moraines	0	0	0	0	0	0	0	0	0	0	**11**	0	0	11
	Rocky Outcrops	4	0	0	0	0	0	0	1	0	0	0	**30**	1	36
	Alpine Scrubs	1	0	0	3	0	0	0	1	0	0	2	4	**53**	64
	Total	55	35	13	30	58	26	6	31	8	3	18	37	54	**374**

The classified map achieved an overall accuracy of 87%, indicating the proportion of correctly classified samples. The kappa coefficient, a measure of agreement was found to be 0.853, which indicates a substantial level of agreement.

During the validation process, it was observed that out of the total 374 validation samples, approximately 49 sample points were misclassified. In other words, around 325 validation sample points were correctly classified, accounting for approximately 30% of the total sampling data.

13. Results and Analysis

The analysis of the LULC2020 map revealed the dominant land cover type to be forest, covering approximately 69.0% of the total area. Alpine Scrubs accounted for 8.89% of the land cover, followed by Shrubs at 4.11%, Snow and Glacier at 4.83%, Rocky Outcrops at 4.52%, and Meadows at 4.39%. Agricultural land was found to occupy 2.96% of the total area, equivalent to approximately 281,186.290 acres. This land category represents the area utilized for farming and cultivation activities.

The lowest land cover categories were Non-built up at 0.03%, Landslides at 0.07%, Sandy bank at 0.13%, Moraines at 0.43%, and Water bodies at 0.61%. Built-up areas, which include urban and developed regions, constituted 0.26% of the total area.

These findings provide insights into the distribution and composition of land cover classes within the study area based on the LULC2020 map.

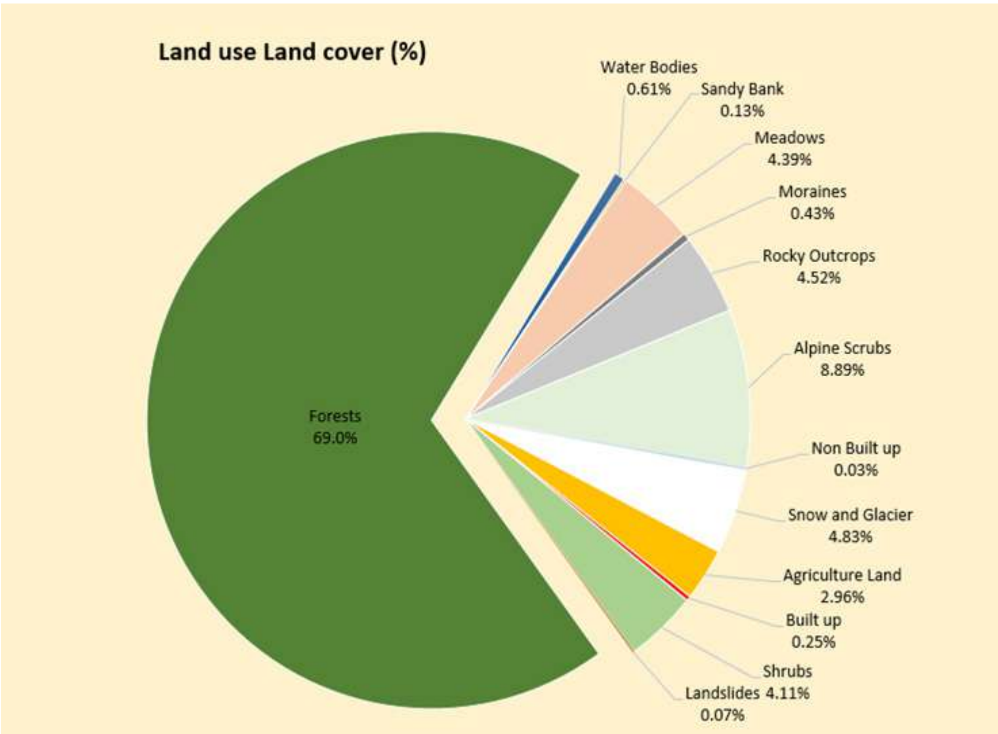


Figure 10: Showing the percentage of land use land cover of the country

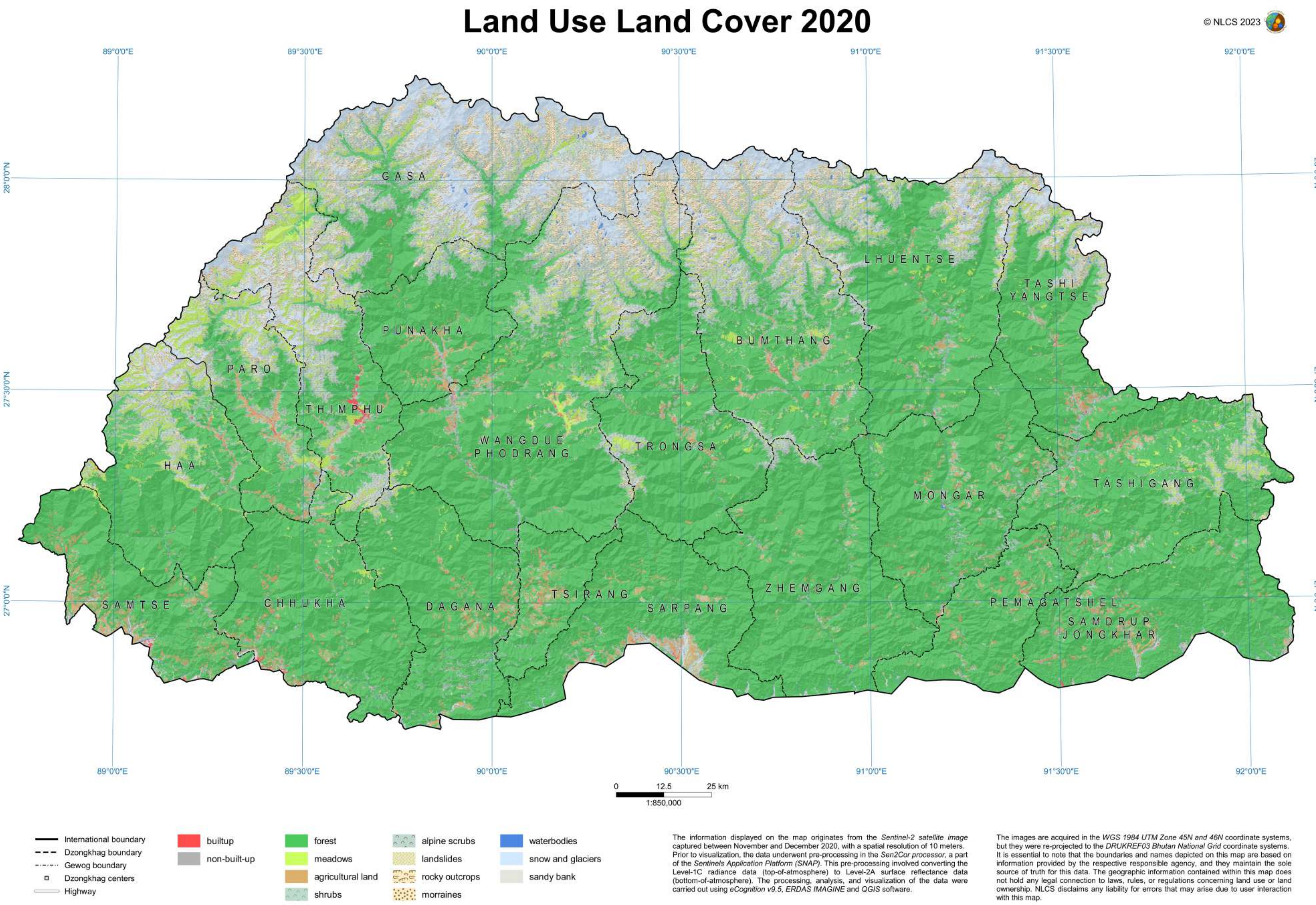


Figure 11: Showing LULC 2020 map

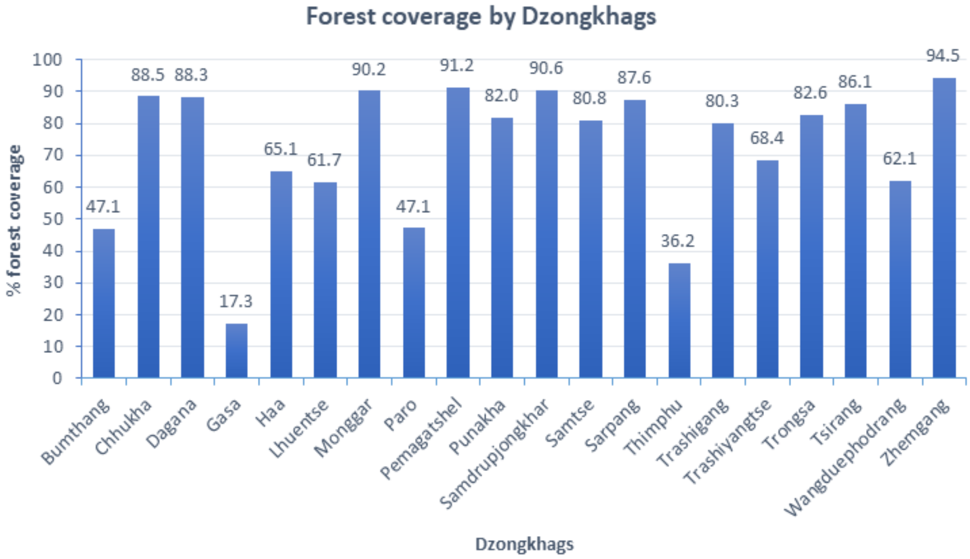


Figure 12: Forest cover by Dzongkhags

Figure 12 provides a visual representation of forest coverage in 20 Dzongkhags. The analysis reveals that Zhemgang Dzongkhag has the highest forest cover, accounting for 94.5% of its total area. On the other hand, Gasa Dzongkhag has the lowest forest cover. Notably, Thimphu Dzongkhag experienced a decrease in forest cover, dropping from 40.0% in the previous 2016 assessment to 36.2%. This reduction can be attributed to developmental activities taking place in the country.

Furthermore, slight decreases in forest cover were observed in five Dzongkhags, namely Mongar, Samtse, Wangdiphodrang, Sarpang, and Samdrupjongkhar. These reductions were primarily a result of infrastructure development activities in the Gyalsung area.

Overall, these findings indicate the changes in forest cover across different Dzongkhags, highlighting the impact of developmental activities on forested areas in Bhutan.

14. Comparative analysis with LULC 2016

The current assessment of land cover in LULC 2020 indicates a decrease of 1.77% in forest coverage compared to LULC 2016. This decrease is followed by decreases in Shrubs and Snow & Glacier land cover categories. However, there has been a significant increase in Alpine Scrubs land cover, rising from 3.39% to 8.89%, and a slight increase in Agriculture land cover compared to the previous assessment.

Table 6: Showing the details of LULC 2020 and LULC 2016

Land cover class	LULC 2020		LULC2016		Diff (%)
	Area (Sq.km)	Total area (%)	Area (Sq.km)	Total area (%)	
Snow and Glacier	1852.95	4.83	2053.40	5.35	-0.52
Agriculture Land	1137.92	2.96	1056.85	2.76	0.20
Built up	96.83	0.25	74.55	0.19	0.06
Shrubs	1576.40	4.11	3740.54	9.74	-5.63
Forests	26414.32	69.00	27171.62	70.77	-1.77
Landslides	26.42	0.07	37.27	0.10	-0.03
Water Bodies	233.54	0.61	251.81	0.65	-0.04
Sandy Bank	48.49	0.13	0.00	0.00	0.13
Meadows	1685.34	4.39	962.56	2.51	1.88
Non Built up	9.68	0.03	5.96	0.02	0.01
Moraines	164.12	0.43	143.94	0.37	0.06
Rocky Outcrops	1736.18	4.52	1594.53	4.15	0.37
Alpine Scrubs	3411.81	8.89	1300.98	3.39	5.50
Total	**38394**	**100**	**38394**	**100**	

These changes in land cover can be attributed to various factors, including vulnerability to climate change and natural disasters, deforestation, and degradation phenomena. Human activities, such as land allotment, hydropower projects, road constructions, timber extraction, and livestock-associated activities, as reported in the Bhutan Forest Note (World, 2019), have also contributed to these changes.

Furthermore, the revival of fallow land by farmers, facilitated by government initiatives like the water flagship program, is another possible reason for the slight increase in agriculture land in the country. Recent data from the National Land Commission Secretariat (NLCS, 2022) indicates that approximately 1276 acres of fallow land have been reverted into cultivation in recent years.

It is important to note that differences in the land covers may also arise from variations in the spatial and temporal resolution of the satellite imagery used, as well as potential misclassification errors in certain classes. These factors can contribute to the slight increases and decreases observed in the overall land cover classification system.

In summary, the changes in land covers are influenced by a combination of factors, including climate change, natural disasters, human activities, and government initiatives aimed at land revitalization.

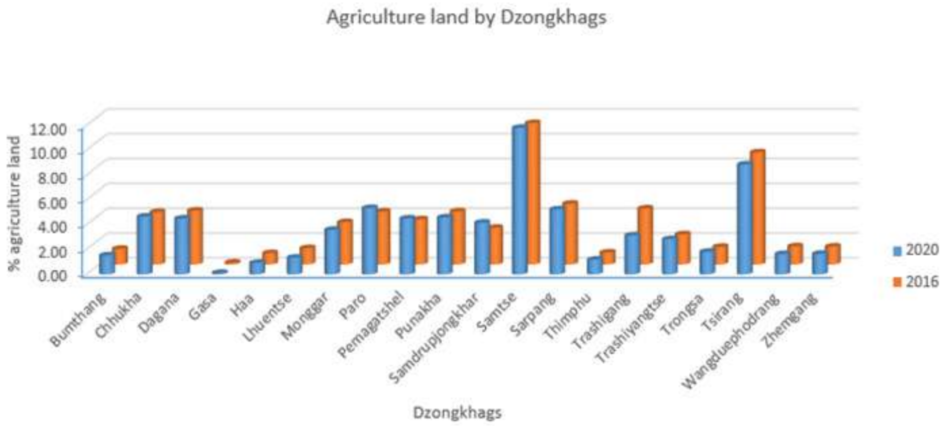


Figure 13: Agriculture land cover by Dzongkhags

The country's agricultural land coverage is illustrated in Figure 13. It was noted that Samtse Dzongkhag has the largest area of agricultural land, followed by Tsirang and Paro Dzongkhags. On the other hand, Gasa and Haa Dzongkhags have the smallest agricultural land compared to other regions. Ne

vertheless, it's important to note that these statistics may not align with the current official figures of agricultural land in the country, as the assessment was based on the image classification using the land type information in the cadastral plot.

15. Constraints and Limitations

The assessment of LULC 2020 has certain constraints and limitations that should be taken into consideration. It is important to consider these constraints and limitations when interpreting and using the results of the LULC 2020 assessment.

1. Spatial resolution: The spatial resolution of Sentinel 2 imagery is 10m, which means that the minimum mapping unit is 100m², equivalent to one pixel. As a result, detailed information on land areas smaller than 100m² may be generalized and not accurately captured in the assessment. This limitation may lead to the omission of small built-up structures that are scattered or isolated.
2. Topography-related challenges: Bhutan's topography presents challenges in differentiating and interpreting correct land cover classes due to image shadows. Shadows can obscure certain land cover features and make it difficult to accurately classify them.
3. Seasonal limitations: The imagery used for the assessment is from the winter season, chosen to minimize cloud coverage. However, this choice may lead to misclassifications in distinguishing certain land cover classes, such as agriculture land, shrubs, and meadows. Differentiating these classes may be more challenging during the winter season.

4. The assessment does not account for temporal changes or long-term trends in land cover. Therefore, the figures obtained from the assessment may not align precisely with the existing national figures that account for a broader time frame.

16. Opportunities

The LULC 2020 assessment plays a crucial role in providing valuable information about the land use and land cover in the country. This information can be utilized for strategic planning and holistic management of Bhutan's limited land resources.

By integrating the assessment results into a spatial decision support system, policymakers and land managers can make informed decisions and implement effective land management strategies. The assessment provides an understanding of the distribution and composition of different land cover classes, highlighting areas of forest cover, agriculture, shrubs, water bodies, built-up areas, and more.

This information is essential for land-use planning, natural resource management, conservation efforts, and sustainable development initiatives. By leveraging the spatial information provided by the assessment, stakeholders can identify areas that require specific interventions, such as reforestation programs, protection of critical ecosystems, or agricultural development plans.

It also enables the identification of areas prone to natural disasters, land degradation, or other environmental challenges. Furthermore, the spatial decision support system can incorporate other relevant data layers, such as demographic data, infrastructure maps, and environmental parameters, to facilitate comprehensive planning and management.

This integrated approach enables stakeholders to assess the potential impacts of land use changes, evaluate alternative scenarios, and make informed decisions that balance economic, social, and environmental factors.

Reference

Abdi, A. M. (2019). Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. GIScience & Remote Sensing, 57(1), 1-20. https://doi.org/10.1080/15481603.2019.1650447

Buja, & Menza. (2013). Sampling Design Tool for ArcGIS Instruction Manual

Congalton, R. G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. Remote Sensing Environment, 37(1), 35-46.

FRMD. (2017). Land Use and Land Cover Assessment of Bhutan2016, Technical Report.

Hermosilla, T., Wulder, M. A., White, J. C., Coops, N. C., & Hobart, G. W. (2018). Disturbance-Informed Annual Land Cover Classification Maps of Canada's Forested Ecosystems for a 29-Year Landsat Time Series. Canadian Journal of Remote Sensing, 44(1), 67-87. https://doi.org/10.1080/07038992.2018.1437719

ICIMOD. Land cover mapping using satellite data_Training Manual.

Inglada, J., Vincent, A., Arias, M., Tardy, B., Morin, D., & Rodes, I. (2017). Operational High Resolution Land Cover Map Production at the Country Scale Using Satellite Image Time Series. Remote Sensing, 9(1), 95. https://doi.org/10.3390/rs9010095

Ismail, M. H., & Jusoff, K. (2008). Satellite Data Classification Accuracy Assessment Based from Reference Dataset. World Academy of Science, Engineering and Technology.

Millard, K., & Richardson, M. (2015). On the Importance of Training Data Sample Selection in Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping. Remote Sensing, 7(7), 8489-8515. https://doi.org/10.3390/rs70708489

NLCS. (2022). About Fallow Land. https://flb.nlcs.gov.bt/index.php/about-flb/

Ren, Q., Cheng, H., & Han, H. (2017). Research on machine learning framework based on random forest algorithm. AIP Conference Proceedings, https://doi.org/10.1063/1.4977376,

Ustuner, M., Sanli, F. B., Abdikan, S., Esetlili, M. T., & Kurucu, Y. (2014). Crop Type Classification Using Vegetation Indices of RapidEye Imagery. ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-7, 195-198. https://doi.org/10.5194/isprsarchives-XL-7-195-2014

Weih, R. C., & Riggan, N. D. (2010). Object-Based Classification Vs. Pixel-Based Classification: Comparitive Importance of Multi-resolution Imagery. XXXVIII-4(C7).

World, B. (2019). Bhutan-Forest-Note-Pathways-for-Sustainable-Forest-Management-and-Socio-equitable-Economic-Development.

Zhang, H. K., & Roy, D. P. (2017). Using the 500 m MODIS land cover product to derive a consistent continental scale 30 m Landsat land cover classification. Remote Sensing of Environment, 197, 15-34. https://doi.org/10.1016/j.rse.2017.05.024

Zheng, H., Du, P., Chen, J., Xia, J., Li, E., Xu, Z., Li, X., & Yokoya, N. (2017). Performance Evaluation of Downscaling Sentinel-2 Imagery for Land Use and Land Cover Classification by Spectral-Spatial Features. Remote Sensing, 9(12), 1274. https://doi.org/10.3390/rs9121274

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