Chapter 6
Regional Land Cover Monitoring System for Hindu Kush Himalaya

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6.1 Introduction

The land cover across the HKH region is changing at an accelerated rate due to the rapid economic growth and population pressures that are impacting the long-term sustainability of ecosystems (Fig. 6.1) and their services, including food, water, and energy (Neupane et al. 2013; Wester et al. 2019; Rasul 2016; Song et al. 2018). The vast changes happening in the forested and vegetative areas are leading to changes in environmental and climatic conditions (Hansen et al. 2001). These land cover classes are critical for maintaining the Earth's surface energy balance between the atmosphere, pedosphere, and soil (Duveiller et al. 2018; Schäfer and Dirk 2011).

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Fig. 6.1 Rapid conversion of agriculture land into built-up areas in Kathmandu valley. Photo by Jitendra Raj Bajracharya

Therefore, the accelerated changes in land cover have the potential of causing long-term impacts on many sectors in the HKH region (Xu et al. 2008, 2009).

Land cover mapping is one of the most common applications of EO, which renders meaningful information about the Earth's surface. Changes in land cover are occurring due to both natural and anthropogenic drivers and range from local to global scales. Using a land cover map, policymakers can have a better understanding of a vast landscape and the changes that are taking place in it. To estimate the historical changes over time, past land cover data for different years is critical. This change data provides vital information to land managers so that they can monitor the potential consequences of the ongoing interventions and make decisions that are right in terms of future management. The mapping of land cover and land cover change also helps to get insights into the complex interactions between human activities and global change (Running 2008; Giri 2005; Keenan et al. 2015; Uddin et al. 2015a). Global coverage at regular intervals and a wide range of spatial resolutions offered by EO satellites make them the best source of information for mapping land cover and understanding its dynamics (MacDicken et al. 2016; Estoque 2020; Giri 2012). Land cover data products are also used as a key input for various models of biodiversity, ecology, hydrology, disaster impact, food security, atmosphere, and many more (Chettri et al. 2013; Le Maitre et al. 2014; Karki et al. 2018; Ahmed et al. 2018; Carlson and Arthur 2000; Giri 2012; Uddin et al. 2020). There have been several projects related to land cover classification and change

detection in the HKH region conducted by various organizations (Table 6.1) using medium resolution satellite images. However, a project-based land cover mapping does not always meet the requirements beyond the specific users involved in the mapping. Various agencies and institutions often do not share the necessary reference data which is crucial for systematic land cover mapping efforts. For decision-making purposes, the national agencies (usually the national forest departments) are mostly using single-year, often backdated, national land cover maps with limited capability to monitor in a timely or integrated fashion (Vidal-Macua et al. 2017; Kaim et al. 2016). The land cover data produced through these projects does not always fully meet the requirements of activity data for national and international reporting on the estimation of forest carbon fluxes. As a result, global land cover products are frequently used as the best available alternative when appropriate and timely maps are not available at the regional, national, or subnational levels (Gong et al. 2013). These land cover products also have limitations given they have been created using different sensors and different techniques at varying spatial resolution and classification typologies resulting in inconsistencies on global scales (Verburg et al. 2011; Bajracharya et al. 2009). These inconsistencies often hinder the practical and multiple uses of land cover layers to contribute to planning and policy formulation, as well as overall management (Ziegler et al. 2012; Skole et al. 1997; Coulston et al. 2014).

Recognizing the land cover data gaps inconsistent land cover maps in the HKH countries, ICIMOD initiated the development of regional land cover maps using a harmonized classification schema by adopting the land cover classification system (LCCS) of the FAO. During the first phase of SERVIR-HKH initiative, it developed land cover maps of 1990, 2000, and 2010 based on Landsat images using the object-based image analysis method, for the entire countries of Nepal and Bhutan and the mountain areas of Pakistan, Bangladesh, and Myanmar (Gilani et al. 2015; Qamer et al. 2016; Uddin et al. 2018, 2015). These maps made it possible to analyze changes at a decadal scale since the data for all the three years was prepared using consistent sources, classification schemes, and methodologies. At the beginning of the second phase of SERVIR-HKH, the stakeholders prioritized the need for an annual land cover monitoring mechanism called the regional land cover monitoring system (RLCMS). This was in the wake of the fact that the preparation of land cover maps using object-based segmentation requires substantial time to generate land cover data for each year. The traditional supervised classification system using desktop software also requires large computing and data storage resources. The availability of human and financial resources within these national agencies was also a major obstacle in implementing such operations. The main objective of RLCMS was to develop a system to produce annual land cover maps for the entire HKH region using a robust method and a harmonized classification scheme that could be updated with less human and computing resources. The specific objective was to develop the methodology and workflow, produce annual land cover maps for the years 2000–2018, and develop the capacity of the regional stakeholders to apply the relevant techniques. Co-development, co-learning, and

Table 6.1 Land cover products in the HKH countries

Country	Satellite/sensor	Spatial resolution	Period of data acquisition	No. of classes	References
Afghanistan	SPOT 4, Landsat TM, Aerial photographs, IKONOS, QuickBird	20 m 30 m 1 m 1 m 0.6 m	2009–2011	11	(FAO 2012)
	Landsat TM	30 m	1990, 1993	11	(FAO 2001)
	Aerial photographs	–	1960–1970	10	(FAO 1999)
Bangladesh	Landsat TM	30 m	2005	14	(Altrell et al. 2007)
	Landsat MSS/ETM	30 m	1977, 2000		(Uddin and Guring 2010)
	NOAA AVHRR HRPT	1.1 km	1985–1986; 1992–1993	9	(Giri and Shrestha 1996)
	Landsat imagery	30 m	1981		(FAO 1981)
Bhutan	ALOS	10 m	2006–2009 winter season	11	(MoAF 2011)
	Landsat	30 m	1990, 2000, and 2010 (change detection)	10	(Gilani et al. 2015)
China	Landsat TM	30 m	1995–1996; (updated in 2000, 2005, 2008, and 2010)	25	(Liu and Tian 2010)
					(Chen et al. 2011)
India	Landsat MSS	80 m	1984–1985	14	(Roy et al. 2015)
	Landsat and IRS 1B	30 m and 72 m	1994–1995		
	Landsat and Resourcesat I	30 m and 23.5 m	2004–2005		
	AWiFS	56 m	2005–2006	18	(NRSA 2007)
	Resourcesat-2 LISS III	23.5 m	2011–2012		(NRSC 2012)
Myanmar	Landsat 8	30 m	October 2014–March 2015	11	(MONREC 2006)
Nepal	RapidEye MSS	5 m	February–April 2010/11	3	(DFRS 2015)
	Landsat TM	30 m	November 2010 – February 2011	12	(Uddin et al. 2015)
	Aerial photograph	–	1979	5	(LRMP 1986)
Pakistan	SPOT 5	2.5 m	2007–2008	19	(PFI 2012)

joint validation pathways were also planned to ensure the sustainability of the system. The generated land cover data was then disseminated through a customized application.

6.2 The Approach of RLCMS

As SERVIR HKH initiative transitioned to the second phase, land cover mapping was still one of the priorities. Specifically, the stakeholders, and they were interested in having updated maps at more frequent intervals than those of decades. It was the time when cloud computing was evolving as a strong platform for large-volume image analysis, and the University of Maryland (UMD) and the World Resources Institute (WRI) had set an example by implementing Global Forest Watch using GEE. Around the same time, the newly established SERVIR-Mekong, led by the Asian Disaster Preparedness Center, was conceptualizing and building the RLCMS for Lower Mekong region. The approach and methodology have been published in Saah et al. (2020), and Khanal et al. (2020). The RLCMS adopted a modular architecture built on the GEE computational platform which applied cloud computing and storage frameworks and thus enabled parallel calculations on a large series of data. This made it possible to generate land cover maps at national and regional scales more efficiently and at any desired temporal frequency. Realizing the changing paradigm in land cover mapping technologies and the benefits offered by GEE, SERVIR-HKH and SERVIR-Mekong joined hands to collaborate on expanding the RLCMS to the HKH region. To enable these systems the GEE outreach team provided cloud storage facilities and technical expertise. The basic structure of RLCMS was co-developed through a series of user engagements from 2016 to 2017 in the Mekong region which was later extended to the HKH region in 2018. The details of the RLCMS approach are outlined in Khanal et al. (2020); Saah et al. (2019), while the land cover methods are provided in Saah et al. (2020).

The key highlight of the RLCMS approach is co-development through partnerships and stakeholder engagements which ensure a sense of ownership and trust in developing land cover maps. The joint working environment has enabled a pathway for capacity development in terms of the sustainability of RLCMS (Saah et al. 2019). In the partnership configuration, SERVIR-Mekong and SERVIR-HKH are the regional hubs responsible for implementing the system with regional and country partners in the Lower Mekong and HKH regions, respectively. NASA, the United States Forest Service (USFS), the University of San Francisco (USF), and the GEE outreach team provided the technical assistance for developing the algorithms and implementing them in GEE. NASA also continues to collaborate with the FAO for development of an online reference data collection system called Collect Earth Online (CEO). Collaboration with FAO continues to implement the RLCMS framework in FAO SEPAL (System for Earth Observation Data Access, Processing and Analysis for Land Monitoring) in order to build a user-friendly

interface for the RLCMS. This collaborative process has provided opportunities by leveraging the best practices and the most advanced state-of-the-art technologies on land cover mapping (Saah et al. 2019b). Besides, there were additional collaborations for specific needs, for example, the University of Maryland supported to customize a tree cover algorithm for producing data on tree cover and height.

To address the different needs of the various stakeholders, the RLCMS approach adopted five key principles: exercising flexibility to accommodate the requirements of land cover typologies; maintaining consistency across time and space; regarding remote sensing data as the source; understanding measurable uncertainty; and developing capacities (Saah et al. 2019).

A recent trend on image analysis shows that GEE is growing widely as an analysis platform because it provides publicly available multi-petabyte satellite imagery at planetary scales without any cost. It is also highly efficient in comparison to desktop, server-based image processing, and is capable of processing vast areas immediately (Saah et al. 2020; Duan et al. 2020; Mahdianpari et al. 2019; Uddin et al. 2020). Building upon GEE as its core, RLCMS incorporates the needs of each country and maintains consistency and transparency using contemporary, robust methods, and provides user-friendly analysis tools and products, besides helping build the capacity of the partners (Saah et al. 2019).

6.3 Methods of Land Cover Mapping

The overall methodology of the RLCMS and its eight stages, as outlined in Fig. 6.2, are: defining the land cover classification system and land cover typology; collecting land cover training samples; selection of Landsat imagery, image correction, and preparation of annual composites; selection of additional thematic data, and creation of image indices and covariates to make input layers for machine learning; utilization of supervised machine learning algorithms and creation of land cover primitives, and primitives evaluation and smoothing; evaluation of annual tree canopy and height; preparation of customized land cover maps by modifying the assemblage logic using a decision tree; and validation of the land cover maps and assessment of their accuracy. The steps are described in the following sections.

6.3.1 Defining the RLCMS Classification Schemes and Primitives

Defining an appropriate classification system is the first step in developing RLCMS, as a land cover map with a well-defined legend can provide useful information on the geographical status of a specific area. Classification systems can describe land
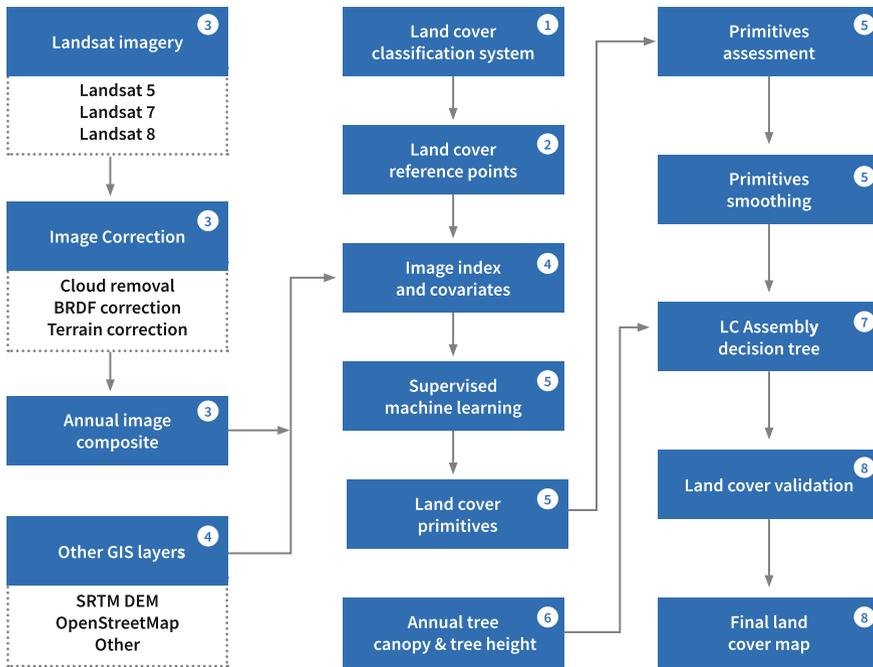
Fig. 6.2 Methodological framework for regional land cover mapping

cover features all over the world at any scale or level of detail. To identify land cover typology and to define the legend for RLCMS, the land cover classification system version 3 (LCCS 3), developed by the FAO (Di Gregorio 2016; Bajracharya et al. 2010; Gregorio 2005), was used. The LCCS provides a framework and assists users in systematically defining land cover categories through specific, observable land cover characteristics or attributes, along with the identification of their spatial and temporal relationships. The LCCS-based classification scheme utilizes the land cover element known as a primitive and employs biophysical entities that can be mapped and assembled into a final land cover map. Primitives are defined as the building blocks or the basis of a land cover class in the RLCMS approach (Saah et al. 2020). There can be one or more primitives for a particular land cover class. The definitions of land cover classes used for RLCMS with the corresponding primitives are given in Table 6.2, which are comparable for international reporting requirements for the countries and recommended by the IPCC (Penman et al. 2003).

For the development of this harmonized land cover classification system for the HKH region, different national and regional consultation workshops (Chap. 3) were conducted across the region involving professionals from key agencies. During the workshops, the stakeholders identified their needs as per land cover typology. At

the regional scale, ten classes were defined (Table 6.2) to develop land cover maps for the whole of the HKH region. When the system was implemented at the national level to develop a National Land Cover Monitoring System (NLCMS), customized schemes were defined in consultation with the national stakeholders.

Table 6.2 Definitions of land cover classes

S/N	Land cover (LCSS)	Description	Comparability to IPCC class	RLCMS Primitives
1	Forest	Land spanning more than 0.5 ha with trees higher than 5 m and a canopy of more than 10%, or trees able to reach these thresholds in situ. It does not include land that is predominantly under crop land or large settlement areas	Forest	Tree height, tree cover Tree
2	Grass land	This class describes the areas covered by herbaceous vegetation with a cover ranging from "closed to open" (15–100%). This category includes rangelands and pasturelands that are not considered as crop land	Grassland	Grassland
3	Crop land	This category includes arable and tillage land and agroforestry systems where vegetation falls below the thresholds for the forest land category, consistent with national definitions	Crop land	Crop land
4	Built-up	Built-up describes artificial structures such as towns, villages, industrial areas, airports, etc.	Settlements	Built-up, NDDBI
5	Water body	A river is a naturally flowing waterbody; typically, it is elongated and has a geomorphologic context. Lakes and ponds of perennial standing are also waterbodies	Wetlands	Open water
6	River bed	Riverbed is a tract of land without vegetation surrounded by the waters of an ocean, lake, or stream; it usually means any accretion in a river course		Riverbeds
7	Bare soil	A soil surface devoid of any plant material	Other	Bare soil
8	Bare rock	Non-vegetated areas with a rock surface		Bare rock
9	Snow	This class describes perennial snow (persistence >9 months per year)		Snow
10	Glacier	Perennial ice in movement		Glacier

6.3.2   Collection of Land Cover Training and Validation Data

The primary reference data was collected for each year from 2000–2020 using various sources. Field campaigns were conducted in collaboration with the national partners using a mobile app. Some data was collected from previous field campaigns by the partner agencies. Additional data was collected for national land cover mapping for each country. High-resolution satellite images were used to collect samples from earlier years using the Collect Earth Desktop or the CEO platform of the FAO. The CEO supports a systematic collection of reference samples using various high- and very high-resolution satellite images as background to meet the requirements of any land cover mapping project for different years (Saah et al. 2019a). The collected 51,002 systematic sampling reference data was divided into two subsets. Randomly, 85% were used for primitives development, while 15% were used for the accuracy assessment of the primitives and the final maps in order to produce a confusion/error matrix.

6.3.3   Satellite Image Processing and Land Cover Mapping

GEE has archived Landsat scenes that have undergone multiple procedures such as computation of the sensor radiance, top-of-atmosphere (TOA) reflectance, surface reflectance (SR), cloud score, and cloud-free composites (Sidhu et al. 2018). The yearly mapping of the HKH land cover from 2000 to 2018 was done using images from Landsat 5 with the Thematic Mapper (TM) sensor, Landsat 7 with the Enhanced Thematic Mapper (ETM+) sensor, and Landsat 8 with the Operational Land Imager (OLI) sensor.

However, a few more important image preprocessing steps still needed to be applied (Saah et al. 2020; Khanal et al. 2020) to these Landsat images to minimize solar illumination, atmospheric noise, and topographic effects. In brief, removing clouds from the images was an obligatory step in Landsat image processing. In this cloud-removal step, the pixel-QA band and a cloud-core algorithm that used the spectral and thermal properties of clouds were used to identify and remove those pixels with cloud cover from the imagery. Besides the cloud area, the cloud shadows were removed in order to avoid misclassification of the areas. For that, the Temporal Dark Outlier Mask (TDOM) algorithm was used (Housman et al. 2018). The pixel quality attributes generated from the CFMASK algorithm (pixel-qa band) were also used for shadow masking (Foga et al. 2017; Scaramuzza et al. 2011; Housman et al. 2018). During the image processing, the correction of the bidirectional reflectance distribution function (BRDF) was also applied following an algorithm developed by Roy et al. (2016). As most of the HKH region has a complex terrain, topographic correction was done to alleviate the illumination effects from the topographic position, aspect, and slope that divert reflectance

values in the case of similar features within different territories (Carrasco et al. 2019; Riaño et al. 2003; Tokola et al. 2001). Once the process of image correction was completed, 80 covariates were generated based on the Landsat annual composites, and SRTM DEM was then used as input to supervise the classification. Thus, the image indices collectively provided a critical parameter for classifying land cover, and this has a noticeable correlation with the particular land cover association (Zhao et al. 2017; da Silva et al. 2019).

6.3.4 Creating Image Indices and Covariates

Image indices and covariates are synthetic image layers usually created by multi-spectral satellite imagery. These indices and covariates often provide a unique distinguished value on a particular land cover that is not found in any of the other individual band. Typically, a wide range of ecological information and plant characteristics is recognized through various indices as it increases the separability of the classes of interest by improving the spectral information. Usually, mapping in the HKH landscape is a challenging task because of topographic variations and heterogenic land cover patterns. The satellite image bands and indices usually emphasize a specific phenomenon that is present in particular land cover classes. Because of that, a set of image bands and covariance matrices is required for accurate classification. In order to effectively classify the land cover map for the HKH, typical Landsat bands—Band 1, Band 2, Band 3, Band 4, Band 5, Band 6, and Band 7—and the multiple indices were used. The indices and covariates were selected from a large number of image matrices through analysis of their importance. The indices used were: normalized difference vegetation index (NDVI); normalized difference moisture index (NDMI); soil adjusted vegetation index (SAVI); atmospherically resistant vegetation index (ARVI); enhanced vegetation index (EVI); green chlorophyll index (GCI); normalized difference water index (NDWI); and bare soil index (BSI) and the SRTM DEM-based slope, aspect were used as input in the regression tree for land cover primitives formation by machine learning. All of these indices and covariates, together with land cover training sets, generated a higher probability of classifying the primitives. The definition of the above indices and corresponding references is available at the index database website (Henrich et al. 2009; Henrich and Brüser 2012).

6.3.5 Primitives Generation by Machine Learning

A supervised machine learning random forest algorithm was applied to produce land cover primitives. For each primitive, the corresponding confidence (0–100) layer was generated. To reduce computational resources, the process of feature importance was performed to identify the covariates and indices with a stronger

influence for each primitive. This gave a list of 15–30 bands for each classification that had the most impact on the results, which was then used as input for the classifier. Finally, generating land cover primitives, a random forest classifier was applied using the imported training sets, the Landsat image, and associated related raster layers.

6.3.6 Annual Tree Canopy Cover and Height

Tree and woody vegetation structure primitives include the annual tree canopy cover and canopy height maps. To improve regional consistency, the vegetation structure product was derived using the same approach as for the Lower Mekong region (Potapov et al. 2019). In order to map the woody vegetation structure, a set of LIDAR-based vegetation structure prediction models was applied regionally using the time series Landsat Analysis Ready Data (Potapov et al. 2019). Tree cover disturbances were detected separately and integrated into the structure's time series (Hansen et al. 2013).

6.3.7 Primitives Assemblage for Land Cover Mapping

Once the primitives were generated, a decision tree classifier was used to run through these primitives and hierarchically classify all the pixels into the final land cover classes (Fig. 6.3). After applying the decision tree, a minimum of 0.5 ha mapping units and continuous pixel counts were calculated for results throughout the study region which helped to remove any stray pixels or patches smaller than the minimum mapping unit. This whole process is referred to as primitive assemblage.

6.3.8 Validation and Accuracy Assessment

In order to ensure the reliability and credibility of the RS-based land cover map for the HKH, an accuracy assessment was considered as a mandatory step. In this regard, the most appropriate method is to validate the land cover map using the ground truth data which is considered to be a more authentic reference. Besides, the spatiotemporal consistency of the land cover data and similar types of products should be evaluated over national and regional representative locations and periods. However, as the HKH region consists of a vast area with rough topography and as there is a problem of inaccessibility, a field-based land cover validation approach was not possible. So, for validation of the land cover, we had to depend on CEO as it has a collection of very high-resolution images. As for the accuracy estimate, it is
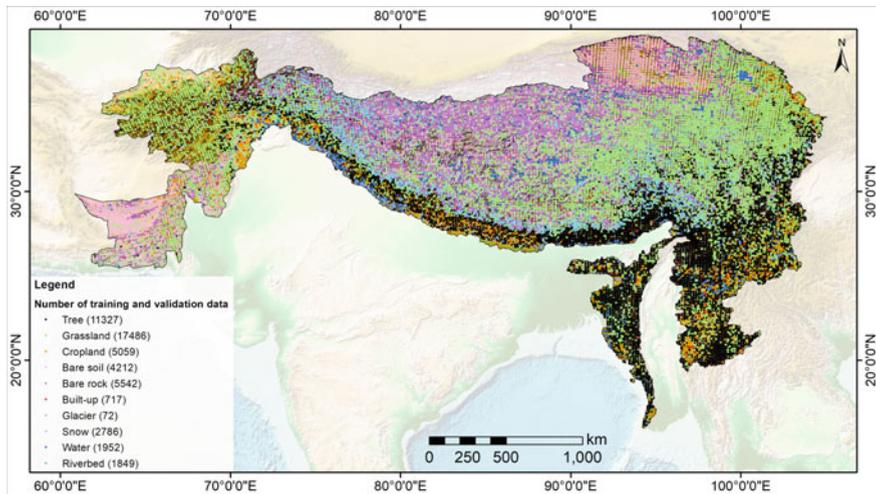
Fig. 6.3 Geographical distribution of reference data collection

derived from the error matrix generated from the validation data with their respective confidence intervals. The overall accuracy of 81.72% and the Kappa statistic values of 0.81 were achieved for the HKH land cover of 2018. These results show that the developed map datasets are reasonably accurate and agree well with high-resolution imagery (Table 6.3).

6.4 Results

The assembled land cover maps between 2000 and 2018 developed by RLCMS are presented in Fig. 6.4. Figure 6.5 shows the distribution of the area covered by different land covers. The results demonstrated that grassland was the most dominant land cover, followed by barren land which include areas with bare soil and bare rock. In the years 2000, 2005, 2010, and 2015, rangeland covered 37.2%, 37.6%, 38.7%, and 38.23%, respectively, of the total HKH region. During the same years, the second dominant land cover was barren areas which include bare soil and bare rock. In 2000, 2005, 2010, and 2015, bare soil and bare rock together covered 32.1, 31.37, 30.35, and 30.69%. The assessed crop land cover in 2000 was about 5.1% and about 5.41% in 2015. As for snow and glacier areas, they covered about 4% of the high-elevation section in 2018, while waterbodies and riverbeds together accounted for 2%. Figure 6.4 shows that topography plays an important role in natural vegetation and crop production. The weather and climatic situations also have some impact on the land cover patterns. In the HKH, forest cover is mostly

Table 6.3 Error matrix for the land cover map of 2018

Land cover	Waterbody	Glacier	Snow	Forest	Riverbed	Built-up	Crop land	Bare soil	Bare rock	Grassland	Total	User's accuracy (%)
Waterbody	36	0	0	0	0	0	6	0	0	1	43	83.72
Glacier	0	71	0	0	0	0	0	0	0	0	71	100.00
Snow	0	0	103	3	0	0	0	1	14	20	141	73.05
Forest	0	0	0	460	0	0	12	0	0	41	513	89.67
Riverbed	0	0	1	0	164	0	16	35	16	27	259	63.32
Built-up	0	0	0	0	0	66	11	1	0	3	81	81.48
Crop land	0	0	0	5	0	0	180	0	0	22	207	86.96
Bare soil	0	0	6	0	5	0	3	911	73	96	1094	83.27
Bare rock	0	0	25	0	0	0	1	72	659	114	871	75.66
Grassland	0	0	36	108	10	2	101	225	233	3366	4081	82.48
Total	36	71	171	576	179	68	330	1245	995	3690	7361	
Producer's Accuracy (%)	100.00	100.00	60.23	79.86	91.62	97.06	54.55	73.17	66.23	91.22		

Fig. 6.4 Land cover maps of the HKH region (2000–2018)

spread in the south and south-eastern areas, where precipitation is higher; the grasslands are mostly distributed in the north and north-western parts while agricultural land is mostly found in the southern part of the region.
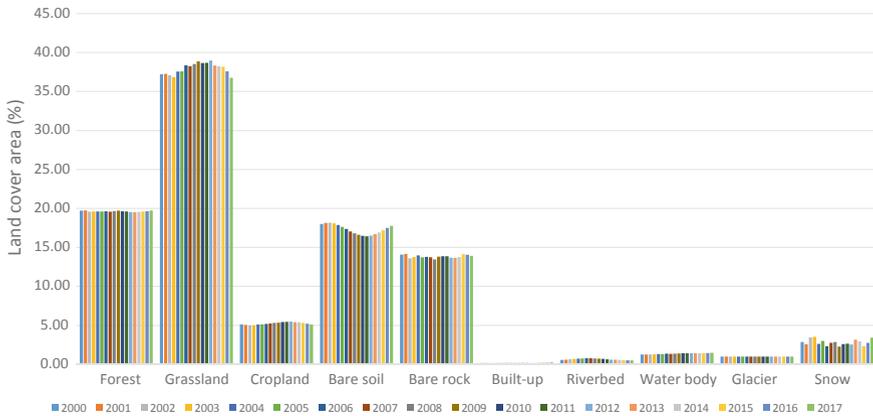
Fig. 6.5 Percentage of different land cover classes (2000–2018)

6.5 Implementation at the Regional and National Levels

The land cover mapping system was implemented at two levels. At the regional level, a spatially seamless and temporally consistent annual land cover maps of the whole HKH region were generated using the broad land use categories recommended by the IPCC; this is also suitable for regional-level change monitoring of carbon stock and GHG emissions (Penman et al. 2003; Li et al. 2017). However, in addition to the IPCC-specified classes, a few additional categories such as snow, bare soil, and bare rock which are important for the region have also been included.

At the national level, the system has been implemented to develop NLCMS in collaboration with the national agencies mandated for land cover mapping and monitoring. In Nepal, the system has been implemented in collaboration with the Forest Research and Training Center (FRTC). To implement RLCMS in Nepal, ICIMOD and FRTC partnered in developing the system. A technical team was formed, comprising of staff from FRTC and ICIMOD, and an advisory team too was set up consisting of senior management of FRTC and the senior leadership of SERVIR, to provide guidance. National workshops, supported by SERVIR and SilvaCarbon, were also organized with participants from most of the agencies using land cover data to get feedback on the classification scheme, data quality, and accuracy. FRTC and ICIMOD worked together for sample collection from images and fields, evaluating classification results and field validation.

In Afghanistan, a land cover map was produced by the FAO for 2010. The Ministry of Agriculture Irrigation and Livestock (MAIL) needed to update this map. Through a workshop attended by high-level officials from MAIL and other key government agencies, the RLCMS methodology and land cover legends for Afghanistan were finalized. A technical team consisting of staff from ICIMOD, MAIL, and the National Statistical Information Authority (NSIA) was formed to co-develop this map.

In Myanmar, NLCMS has been implemented jointly by SERVIR-Mekong, SERVIR-HKH, and the Forest Department. The land cover legends were defined in consultation with the latter.

In the case of Bangladesh, the Bangladesh Forest Department (BFD) carried out a mapping project to develop land cover maps for the years 2000, 2005, 2010, and 2015. The project was implemented by the FAO with funding from USAID. The land cover legend was defined using the FAO LCCS system through country consultations. The mapping was done by interpreting SPOT and Landsat images. Then, in order to update these maps, the BFD requested ICIMOD to implement RLCMS for mapping the 2019 land cover of Bangladesh. Toward this end, field-work and image-based sample collections were conducted jointly by a team consisting of members from the BFD and ICIMOD.

6.6 Challenges and Lessons Learnt

6.6.1 Class Definition

The accuracy of a land cover map depends highly on the clarity and unambiguity of the class definition. Before implementing the RLCMS method for generating land cover maps, priority was accorded to document the class definition so that all the users and developers could agree on it. However, there were some classes where the partners were unsure about how to define them. The following two examples elaborate it:

- A forest is defined as an entity with "more than 20% tree crown cover and average tree height more than 5 m within the minimum mapping unit" (Herold et al. 2009). However, when an area within a forest has very young trees with their height less than 5 meters, there arises a problem in defining that area. While some people argue that since these trees have the potential to grow beyond 5 meters, they should be grouped as a forest, but there are others who do not agree. One issue with RS technology is that it is not capable of determining future growth; it only classifies what is currently on the ground.
- Another confusion is about the classes of "other wooded land" and "open forest." In both cases, the canopy cover is between 20 and 50%.

6.6.2 Reference Data Collection

The accuracy of classification is also dependent on the number and quality of the reference data that are used. While in some cases, high-resolution images provide a good source of reference data, these images are not available for all the previous

years. Besides, the accuracy of the reference data also varies with the operator collecting those data.

6.6.3 Comparison with Legacy Data and Statistics

The accuracy assessment of RS-based classification is usually done with statistically designed validation samples and by calculating various accuracy parameters. But in the HKH region, another issue interrupts the independent assessment of accuracy. Usually, the government agencies have the legacy data on land cover and the corresponding statistics, but they can be reluctant to accept any deviation from those earlier statistics.

6.6.4 Limitation of the GEE Cloud Platform

When processing the whole geographical region of the HKH, the image volumes were too large for a desktop computer to handle. Though GEE provides the opportunity to process these large areas, sometimes processing in GEE could not be done when the number of the reference sample were too many. In such cases, processing needs to be done in batches, focusing on a smaller area at a time. Typically, GEE allows a maximum of 100 million object features and 100,000 vertices for each row's geometry.

The implementation of a few obligatory image-processing algorithms, e.g., atmospheric and topographic corrections, was easy to implement for Landsat images. In a couple of days, GEE could perform all corrections for a country without implementing image tiles options. But that said, in the case of the HKH region, it takes approximately 20 days to create composites. Among the user-defined land cover classes, distinguishing the built-up land cover class was challenging through the random forest algorithm. In this aspect, the newly conceived Normalized Difference and Distance Built-up Index (NDDBI) developed a fusion of OSM and NDVI layers to map built-up accurately (Khanal et al. 2019). Also, NDDBI index takes advantage while negating the limitations on built-up mapping.

6.6.5 Partners' Confidence

It was a challenging task to gain the confidence of the partner agencies to adopt the RLCMS for land cover mapping. It took some time, multiple consultations and training programs to gain their confidence as they had been involved in traditional mapping systems. To ensure that the resultant land cover data would be used by the

partners, SERVIR focused on co-development and partnership. But this took a long time since agreements had to be arrived at through the organizational channels of the partner agencies.

6.6.6   Sustainability and Human Resource

Though the RLCMS relies on an automatic classification method and needs comparatively fewer human resources than the traditional image-interpretation-based land cover map production, the future update of land cover data needs a team with an understanding of the RLCMS algorithm which is based on GEE and JavaScript or Python script. At present, the partner agencies lack sufficient GIS and RS professionals with the appropriate background to update the land cover maps. Sometimes, frequent staff turnover in corresponding agencies makes it difficult for sustainable knowledge transfer on land cover mapping. Sometimes, the trained RS staff get transferred to other departments or field offices. Besides, the technical staff at the respective government agencies is engaged in other administrative work which diverts their time from working on the RLCMS.

6.7   Conclusion and Way Forward

The chapter has presented the SERVIR-HKH efforts in land cover mapping of the HKH region. The currently available land cover datasets in the region are not suitable for analyzing land cover changes over time due to the different classification schemes and methodologies used to generate those maps. SERVIR aimed to address this gap and develop a methodology and system to produce land cover maps on an annual basis using the same classification scheme and processing methodology. While addressing the regional needs, SERVIR also focused on addressing national needs that vary and sought to customize the method for producing land cover maps at the national level. The National Land Cover Monitoring System, or NLCMS, was customized for Afghanistan, Myanmar, and Nepal by addressing the specific needs of the national agencies which were co-developing the system with ICIMOD. The system was built and implemented upon the GEE cloud-based platform using Landsat imagery in combination with other thematic layers. The overall process laid great emphasis on collaboration and co-development with the partners to define the land cover typologies, collect reference samples, and validate the data. This chapter has mainly addressed the process, its methodology, and the primary results of the exercise in land cover mapping. In order to enable the partner agencies to produce and validate land cover maps, extensive training and co-development were conducted for sustainability of

the system. In the future, more validation programs will be conducted in collaboration with the national partners. Further modifications will also be made to increase the number of classes so that additional requirements are met.

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