Chapter 5
In-Season Crop-Area Mapping for Wheat and Rice in Afghanistan and Bangladesh

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5.1 Introduction

Cereal grains are the most commonly grown crops in the world. Wheat and rice are important commodities which contribute to 50% of the world's food-calorie intake (McKevith 2004). These two cereals are critical to food security in the developing regions. In this context, crop-mapping services can be used for detailed monitoring of the cultivated areas; it can also provide the area statistics of specific crops and the data on their intensity across the landscape. This mapping process is also valuable for government agencies since it provides them with critical information that can be used to manage their stocks (for imports and exports). This chapter dwells on a crop-mapping service developed under the SERVIR-HKH program. In this regard, the needs assessment was carried out with the assistance of the governments of Bangladesh and Afghanistan through a consultation workshop. Wheat mapping in Afghanistan and rice mapping in Bangladesh were the top priorities for the respective governments. Here, we discuss two particular mapping exercises that were undertaken in these two countries: wheat mapping in Afghanistan at a national level and the mapping of Boro rice in selected districts of Bangladesh.

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5.1.1 Cereal Crop Production and Food Insecurity

In-season mapping of major crops is important for early assessment of production and to know about any potential threats to food security. As all of us know, South Asia is the most populated part of the world, wherein recent years, both industrialization and urbanization have grown by leaps and bounds. This has created an imbalance in food supply and demand in the region. While it is true that more land came under agricultural activity from the 1960s to 2000s, resulting in an increase in food production (Ramankutty et al. 2018). In recent times, it has been observed that the production levels have gone down because, increasingly, agricultural land is housing urban infrastructure. Another reason for the dip in food production is that conventional methods are still being used for agricultural land management. Then there is the factor of monsoonal variability due to changing climatic conditions which has also affected crop production. The other factors are poor quality of seeds, small farms that have limited or no access to technology, and natural disasters in the form of floods and even earthquakes.

The decrease in domestic crop production and the yearly fluctuations in the same pose serious threats to the food security situation in the HKH region. Thus, swift and accurate estimation of crop production becomes vital in providing a baseline for formulation and implementation of policy related to agriculture management at the national level. This also plays a significant role in the planning and decision-making processes related to food and social security (Demeke et al. 2016).

5.1.2 Crop Dynamics in Afghanistan and Bangladesh

Figure 5.1a,b shows the bioclimatic zones—a proxy for agro-ecological zones (AEZs)—of Afghanistan and Bangladesh (Balasubramanian 2011). AEZs are areas with similar climates, vegetation, and soils. Some examples are deserts, savannas, tropical forests, steppes, temperate forests, and cold regions. These zones are developed utilizing different parameters such as elevation, climatic conditions, and soil and vegetation types. Agricultural activity is closely related to the conditions of these zones. The sowing, growing, and harvest time of crops are dependent on the conditions and varies from one AEZ to another. Broadly, there are five AEZs in Afghanistan and two in Bangladesh. This is mainly because of the diverse topography and climatology in Afghanistan as compared to those in Bangladesh. However, at the micro-level, there may be many AEZs because of diverse geography, with thousands of microclimates and micro-watersheds, as conditions frequently change from one valley to the next, within a fairly short distance.

The phenology of a crop is referred to as the periodic life cycle events of plant growth and how these are influenced by seasonal and inter-annual variations in climate (Martínez and Gilabert 2009). Crop phenology plays an important role in understanding the dynamic vegetation-growth patterns in a crop (Fisher and
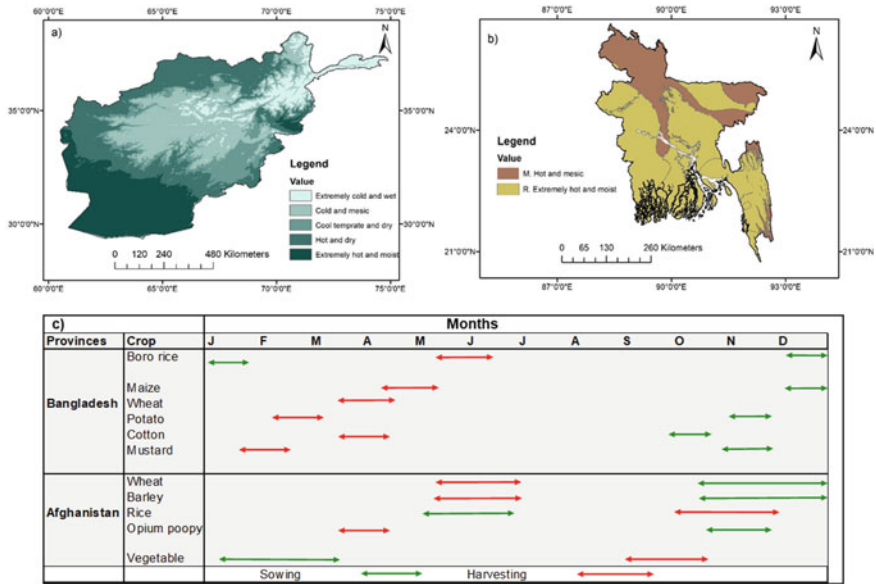
Fig. 5.1 a AEZ of Afghanistan; **b** AEZ of Bangladesh; **c** Crop calendar

Mustard 2007; Myneni et al. 1997). The vegetation indices derived using satellite images help in studying the phenology of a crop at different stages (Ahl et al. 2006); these indices are normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and a two-band enhanced vegetation index (Zhang et al. 2014; Piao et al. 2006; White et al. 1997; Zhang et al. 2003). For crop mapping using EO technology, information on the growing season of crops is critically important as this enables the construction of a phenological profile for the crops.

Information on the growing season of a crop can be derived using a crop calendar. A crop calendar for an AEZ or province provides information on the planting, sowing, and harvesting periods of the crops in that zone. Figure 5.1c depicts generalized crop calendars for Afghanistan and Bangladesh. While such generalized calendars provide useful information, RS-based crop mapping requires a crop calendar at the AEZ or province level. For this study, the crop calendars—of provinces or districts—were provided by the Afghanistan Ministry of Agriculture, Irrigation and Livestock (MAIL) and by the Bangladesh Agriculture Research Council (BARC). These calendars were utilized as a starting point to determine the timing of the phenological stages of wheat (in the case of Afghanistan) and Boro rice (in the case of Bangladesh), and then satellite images were used for a more comprehensive study.

5.1.3 Wheat Crop in Afghanistan and Recent Efforts in Mapping

The agricultural sector plays a significant role in Afghanistan, providing revenue for nearly three-quarter of the country's population. It contributes nearly 28% to the country's GDP (United Nations 2013). Wheat is the primary crop and food of Afghanistan and is grown in every province of the country; and mostly, it is grown for self-consumption. That said, its production has not yet been able to meet the internal demand. Figure 5.2 depicts the import of wheat to Afghanistan during 1960–2019. It can be observed that wheat imports have consistently increased in the past few years. In recent times, about 1 million ton (equivalent to 25% of the internal demand) of wheat have been imported annually to meet the internal requirement (Martínez and Gilabert 2009), making Afghanistan one of the leading importers of wheat in the world (Persaud 2013).

The government utilizes the statistics on wheat—about the areas where it is grown and how much is produced—to assess the current demand and also for procurement in case of shortages. However, limited work has been done till now in the case of wheat-area estimation in Afghanistan. While MAIL carries out yearly qualitative assessments of wheat-sown areas using ground sample data and with the help of some conventional RS techniques based on interpretation of satellite images
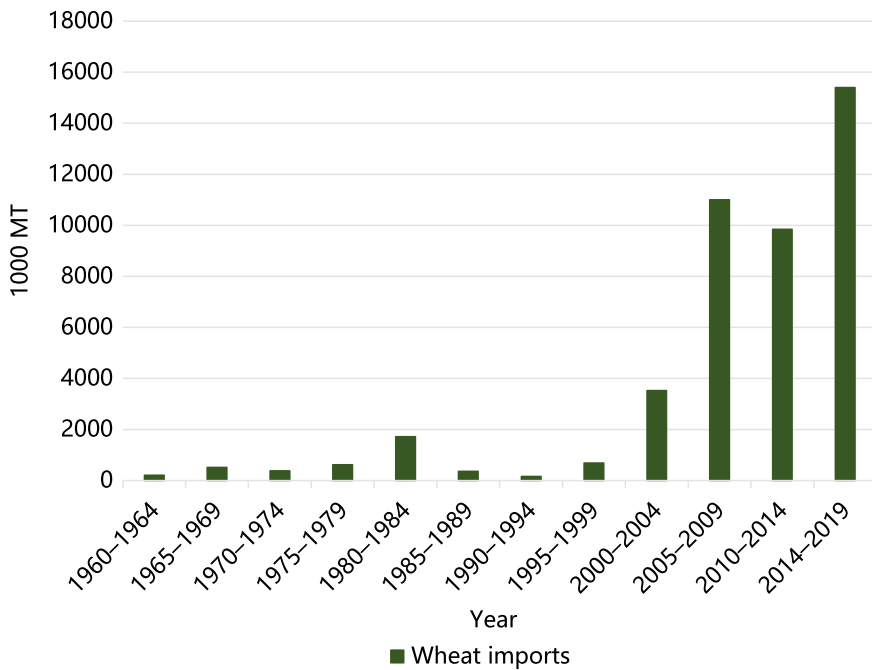

Fig. 5.2 Wheat import data of Afghanistan. *Source* USDA

(FAO 2016), United States Department of Agriculture (USDA) has made some qualitative assessments using NDVI anomalies (Baker 2015; Pervez et al. 2014).

Recently, donor agencies such as United States Agency for International Development (USAID) have shown interest in food security management in Afghanistan. They have started projects like grain research and innovation (GRAIN) which primarily supports wheat-related research in order to boost production; the project also works on resilience building and diversification. Then, there is the Kandahar food zone (KFZ) project which focuses on strengthening rural livelihoods (USAID 2017). However, currently, there is no operational framework in Afghanistan that can provide a rapid assessment of wheat-sown areas essential in terms of food security management.

5.1.4 Rice Crop in Bangladesh and Recent Efforts in Mapping

The economic growth of Bangladesh depends highly on agriculture. Two-third of the labor forces in the country are either directly or indirectly employed in the agricultural sector (Raihan 2011). Moreover, nearly 80% of the population belong to rural areas which directly rely on the agricultural sector for their livelihood. And, agricultural production accounts for one-third of the country's GDP and 32% of its value of exports (Rahman and Hossain 2014).

Rice is the most valuable commodity in the economy of Bangladesh. It is the most dominating cereal crop, making Bangladesh the world's sixth-largest producer of rice. This also makes Bangladesh one of the top exporters of rice in the world. However, it is becoming increasingly evident that the production of rice can be extremely vulnerable to the impacts of climate change (Aryal et al. 2019). Rice production has been adversely influenced by unpredictable rainfall, temperature extremes, increased salinity, droughts, floods, river erosion, and tropical storms. Moreover, the prediction is that these events would be highly repetitive and intensify in the future (Sivakumar and Stefanski 2010), which could lead to a decrease in crop yields by up to 30%, thereby posing a very high risk to food security. Figure 5.3 shows the uneven trends in rice exports which strongly explains the variability in the production of rice. Therefore, there is a strong need for an in-season assessment of the rice-crop area and yields for the formulation and implementation of policy-related rice exports and food security management.

Numerous works have been carried out for rice-area estimation, using both RS as well as the conventional field-based sampling approaches. The Bangladesh bureau of statistics (BBS) is the agency that is in charge of rice-area mapping. It utilizes conventional methods such as crop-cut surveys and statistical approaches ("Yearbook of Agricultural Statistics-2017" 2018). This approach is cumbersome and inefficient as it requires manual field data collection, rich sampling, and significant post processing before releasing any reliable statistics on crop area. But that
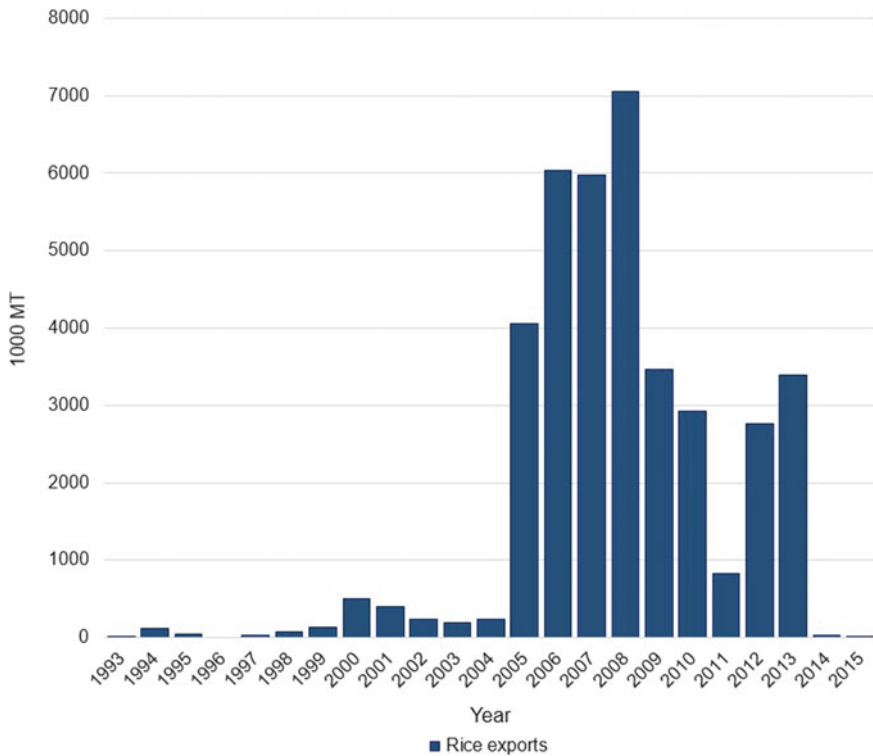
Fig. 5.3 Rice export of Bangladesh. Source: BARC

is slowly changing—in recent times, the BSS, in collaboration with various research institutes and NGOs, has been working on rice-area estimation using RS techniques which have several advantages over the conventional approaches.

In the meantime, researchers have been using both optical and SAR data with spatial extents for crop mapping (mainly rice). Some of their approaches have been: unsupervised and supervised (Cheema and Bastiaanssen 2010; Konishi et al. 2007; Lin 2012; Turner and Congalton 1998), rule-based (Boschetti et al. 2017), phenology-based (Dong et al. 2015, 2016), and time-series classification algorithms (Dong et al. 2016; Shew and Ghosh 2019). Besides, MODIS too has been effectively used for rice mapping and monitoring application scales (Burchfield et al. 2016; Nelson et al. 2014; Shapla et al. 2015). This is mainly due to high repetitiveness, the relatively small data size, and the high spectral resolution, and available bands which are particularly pertinent to agriculture (Whitcraft et al. 2015; Zhang et al. 2017). Further, MODIS time-series images have been integrated with data from the ENVISAT in rice mapping (Nelson et al. 2014). However, due to its coarser resolution (250 m), using MODIS for crop-type mapping has its limitations in Bangladesh due to small field sizes.

Bangladesh's SPARRSO has also attempted to use RS for rice monitoring using MODIS data and the AI-based semi-automatic approach (Shew and Ghosh 2019; Rahman and Hossain 2014; Begum and Nessa 2013). Besides, the time-series seasonal maximum value NDVI composites from MODIS data were used for classifying the rice fields in Bangladesh (Gumma 2011). In 2014, Nelson et al. attempted to integrate SAR and optical data for rice-crop mapping. They used MODIS and ENVISAT, as also phenology, to map the rice fields in Bangladesh. However, they have not yet reported on the achieved accuracy. Earlier, in 2013, multi-date SPOT images and ISODATA image-classification techniques had been used for rice mapping (More and Manjunath (2013)). Change detection techniques too have been used in Bangladesh—to assess the surplus or deficiency in rice cultivation—based on a phenological analysis of MODIS data (More and Manjunath 2013; Shapla et al. 2015).

Some of the studies have also taken advantage of the high-resolution SAR and optical data, along with cloud-computing techniques like GEE, for mapping different crops. Recently, Singha et al. (2019) used the high-resolution SAR Sentinel-1 and MODIS data on the GEE platform for mapping rice in Bangladesh, and they reported more than 90% accuracy. Similarly, Shew and Ghosh (2019) utilized EVI and the normalized difference fraction index (NDFI) derived from the landsat archive on the GEE platform for mapping rice in the country. These approaches focus more on commission error—i.e., if a pixel in an image is classified as rice, but it is not—and less on omission error, i.e., if a pixel in an image is non-rice, but is classified as rice.

5.1.5 Global RS-Based Crop-Mapping Techniques

Globally, several researchers have developed methods for crop-type mapping using different RS techniques. These techniques can be classified as those based on: sensors—optical or SAR (Inglada et al. 2015), the resolution of satellite data (Wardlow and Egbert 2010), and threshold and classification.

The remote sensing data sets, both optical and SAR, utilized time-series NDVI profiles for identification of seasonal thresholds, which is utilized for classifying different crop types. The acquisition time of the image plays a major role in identification and classification of different crop types. The information on life cycle, i.e., sowing, growing, and harvesting time of any crop is obtained by consulting the crop calendar. Although time-series NDVI thresholding approaches require fewer number of samples from the ground, they enable high accuracy even though they are unable to classify crops with similar phenological characteristics (with the same sowing, peak, and harvest time).

Alternatively, machine-learning classification algorithms, such as random forest (RF), support vector machine (SVM), and artificial neural network (ANN) require a systematic sampling approach and an ample amount of accurate ground samples for training the classification model (Tatsumi et al. 2015; Camps-Valls et al. 2003;

Murmu and Biswas 2015; Tamiminia et al. 2015; Gao et al. 2018; Sonobe et al. 2014). Here, it has to be noted that poorly sampled and inaccurate sample data from the field results in under fitting and overfitting of the classification model and therefore may result in overestimation or underestimation of the classification results (Liakos et al. 2018). The study of Tiwari et al. (2020) provides detailed insights into well-known crop-type mapping methods using different sensors and resolutions.

5.1.6 Challenges and Needs

Despite several approaches available for crop-type mapping, developing a systematic framework for crop-area assessment in the two countries is rather challenging. The key challenges are field inaccessibility because of tough topography, security concerns, the phenomena of cloud cover which restricts the use of optical imagery, low Internet bandwidth to download the satellite data, and limited computing infrastructure for data processing and analysis. The challenges in both the countries are depicted in Table 5.1.

The system was developed harnessing the power of multisensory remote sensing (RS) imagery (optical and SAR) and cloud-computing (GEE) techniques (Gorelick et al. 2017; Dong et al. 2016). The system has been designed keeping in mind the challenges in the region and provides the capacity for operationalization. It can provide independent and evidence-based information on the status of annual crops at the province level. And by ingesting field data at regular intervals for different seasons, the system would achieve higher accuracy in crop area estimates at the subnational level too.

Table 5.1 Challenges for Afghanistan and Bangladesh in crop mapping

Country	Internet bandwidth	Computing infrastructure	Field accessibility	Security concerns	Cloud cover
Afghanistan	Limited, high-speed Internet only available in the cities	Limited	Limited field accessibility because of the topography	Not safe to carry out fieldwork	Availability of optical data is limited during the wheat-growing period due to heavy cloud cover in the winter season
Bangladesh	Limited, not available everywhere in the country, especially in remote villages	Limited	Limited field accessibility, especially during monsoon because of floods	No safety issues	Availability of optical data is limited during the summer-rice and Boro-rice harvest seasons due to cloud cover in the monsoon season

5.2 Setting up Crop Interpretation Applications and Operation

The workflow for in-season crop mapping that is being implemented by SERVIR is shown in Fig. 5.4. Broadly, the methodology has six major components. The first step is reference data preparation. This involves the collection of ground sample points and quality check, after which the reference data is prepared for training and validation. In the second step, the agriculture mask (representation of agriculture area) is delineated which is used in the further stages. After obtaining the
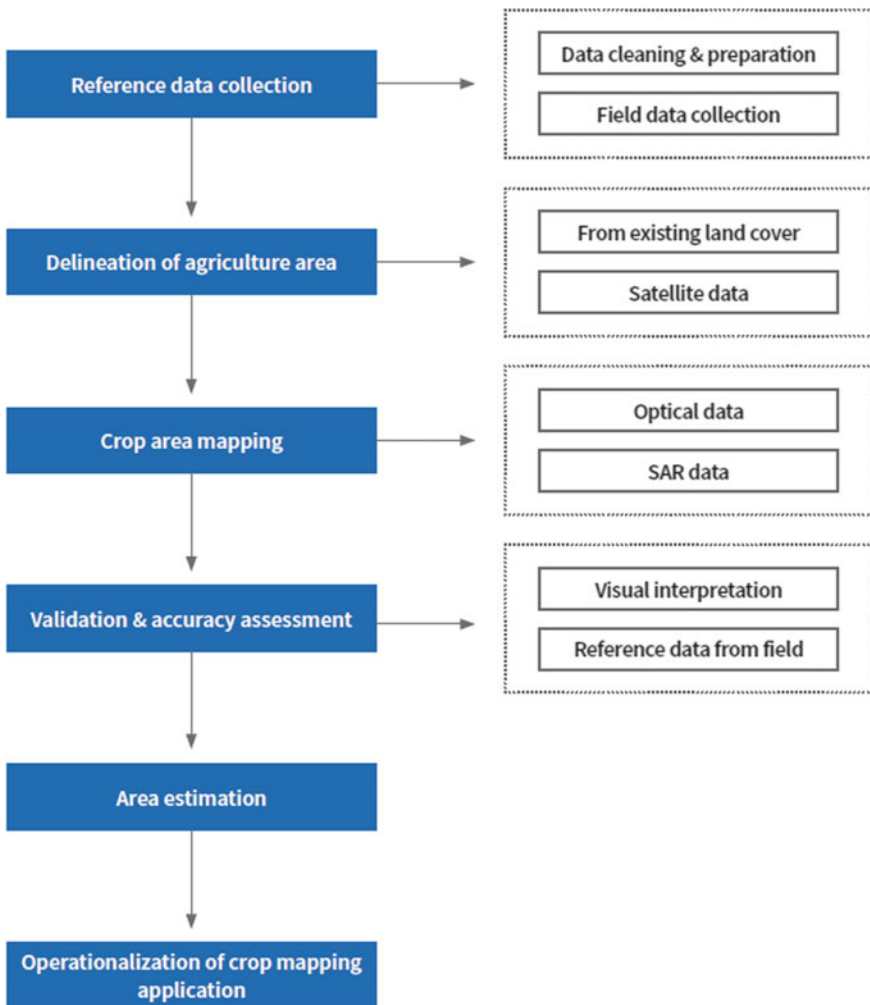

Fig. 5.4 Methodology of crop mapping

agriculture mask, the crop mapping is done in the third step using optical and SAR data to obtain a crop map. This crop map is then validated at the fourth stage using validation samples. In the fifth step, the crop area is calculated using the resolution of the images and pixel counts. In the final step, the application is customized for operationalization and to disseminate the results.

Each of these components is described in detail from Sects. 5.2.1–5.2.3.

5.2.1 Reference Data Preparation

5.2.1.1 Field Data Collection

Crop mapping based on RS techniques requires reference data from the ground. The reference data preparation is a process of collecting data from the different sources described in Fig. 5.5. The collected reference data from the various sources are then utilized for training and validation of the crop classification model. These data sets are broadly categorized as qualitative (based on social surveys and field forms) and quantitative data (based on GPS location and the geo-tagged photographs of crops). Qualitative data provide information on the crop cycle, crop rotation, crop conditions, production, and on the irrigation network. This information is utilized in developing crop calendars or for refining the existing crop calendars, and for deciding about the period of the satellite images which should be used for the crop assessment.
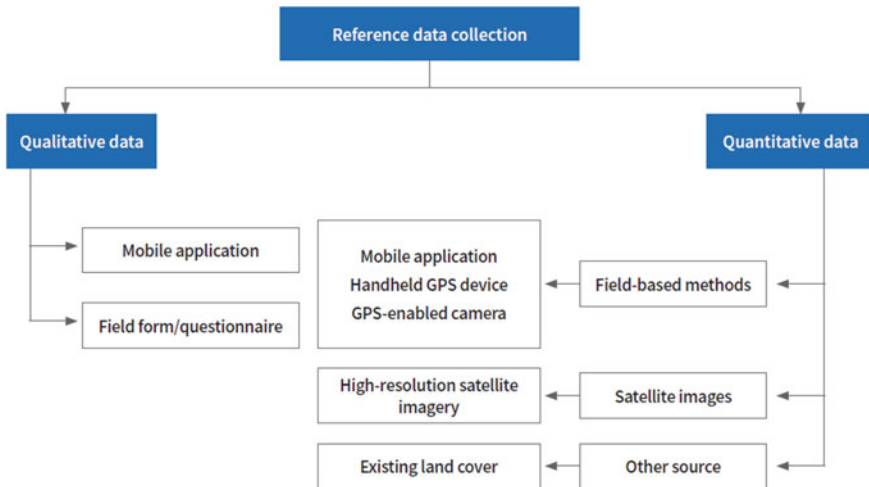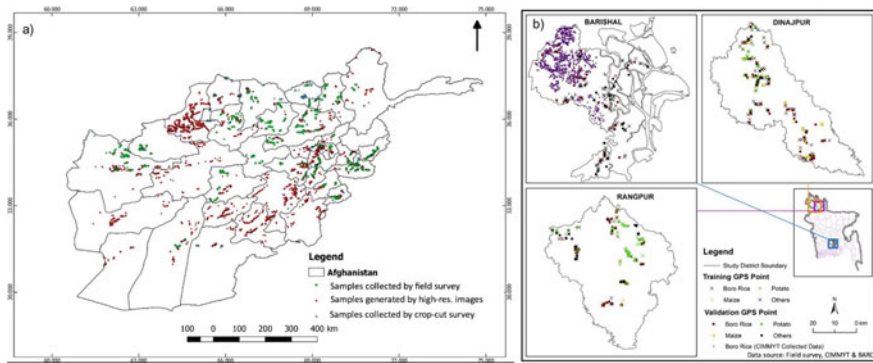

Fig. 5.5 Data collection workflow

Fig. 5.6 Field data collection—**a** Afghanistan. **b** Bangladesh

In quantitative data collection, the GPS locations and multidirectional photographs of the crops are captured which are then utilized in understanding the crop dynamics and in training and validating the classification model for crop mapping. Depending on the type of the data, these data sets are collected using the different data collection platforms described in Fig. 5.5, such as mobile applications, handheld GPS, GPS-enabled camera, high-resolution satellite images, and existing land-cover maps.

Figure 5.6a,b shows the reference data collected from different sources in Afghanistan and Bangladesh using a random sampling approach. In Afghanistan, the quantitative reference data were collected using a field-based method (GPS-enabled camera), high-resolution satellite images (Pleiades and Google Earth images), and the existing food and agriculture organization (FAO) land-cover data (FAO 2010). The qualitative data were collected using field forms/questionnaires prepared by professionals from MAIL. In Bangladesh, both quantitative and quantitative reference data were collected using a mobile application (Geo-ODK) by professionals from the International Maize and Wheat Improvement Center (CIMMYT), BARC, and ICIMOD.

5.2.1.2 Data Cleaning and Preparation

The collected field data were then subjected to a quality check. This was because some of the samples were not taken from the middle of the crop field due to inaccessibility. So, the reference points collected from the corner of the crop field were then adjusted and moved inside the fields to make them useful for the training and validation of the models. The judgment was made on three criteria: the direction and orientation of the field photographs, the phenological characteristics of the crop, and the visual interpretations through high-resolution Google Earth

images. The cleaned reference points were then merged and divided randomly into two categories—for training and validation; while 70% of the samples were used for training, the remaining 30% were utilized in the validation process.

5.2.2 Delineation of Agriculture Mask

For crop-area mapping, the delineation of agriculture areas is important, so as to confine the identification of specific crops within an agriculture mask. There are two ways of delineating an agriculture mask: by the existing land cover and by deriving it using optical time-series images. In the case of Afghanistan, the agriculture area was delineated using the existing FAO land-cover data (FAO 2010) and by extracting the area of agricultural land from it. Whereas, in the case of Bangladesh, the agricultural land extent was delineated by performing the random forest (RF) classification using ground reference points on time-series NDVI images derived from optical (Sentinel-2) images (from January 2017 to December 2018). The agriculture mask was delineated for two years (2017 and 2018) and combined to obtain the maximum agriculture mask.

5.2.3 Crop-Area Mapping

In RS-based crop mapping, two things are important and must be considered before proceeding to mapping: knowledge of the crop-growing season and selection of the data set (optical or SAR). The knowledge of the growing season of the target crop helps in deciding the time period for acquisition of satellite data which eventually helps in reconstructing the crop phenology through time-series NDVI (refer to Sect. 1.2). Phenology is measured commonly by the onset of greening, peak development during the growing period, the onset of senescence, and the length of the growing season (Hudson and Keatley 2010). The selection of the data set completely relies on cloud cover. Sometimes, despite using high-temporal optical satellite data sets (e.g., Sentinel-2), the crops cannot be separated using the optical data sets. This is because the intermixing/overlapping of NDVI (crop phenology) values with the limited cloud-free images makes it difficult to select the appropriate seasonal thresholds (sowing, peak, harvest).

Alternatively, SAR sensors have the unique capability to penetrate clouds and collect during all weather and are also sensitive to plant structure. However, SAR-based classification alone would require much more sample data on all the crops. Also, SAR is incapable of capturing the chlorophyll content present in the crops which is directly proportional to the growing stage of the crops. Therefore, SAR cannot alone be used for crop identification in case of limited availability of sample points. However, a crop map (developed from optical data) can be refined using SAR data under the following conditions:

- SAR data should have consistent time series in terms of incidence angle and should have a wide swath in mapping different crops (Inglada et al. 2016)
- The data should be preprocessed which entail: orbital file correction; thermal noise removal; terrain correction; and removal of speckle noise

5.2.3.1   Wheat-Area Mapping in Afghanistan

Wheat mapping (both for irrigated and rainfed crops) in Afghanistan was carried out at the district/provincial level in order to capture the phenological response of the crop. For this, time-series Sentinel-1&2 images were used. The mapping was done in two steps. At first, NDVI thresholds were determined by analyzing the field data for each province to separate the wheat area from other crops using Sentinel-2 (optical) imagery. Once the wheat areas were separated, Sentinel-1 (SAR) imagery was used to refine the estimated wheat area through an RF classifier. Then, after consulting a crop calendar, the time-series Sentinel-2A Level 1-C (top-of-atmosphere) satellite images with less than 30% cloud cover (from November 2016 to July 2017) were fetched. These images were preprocessed and masked with the agriculture mask (Sect. 5.2.2). Due to the cloud cover during the wheat-growing cycle, the seasonal NDVI median composites were generated for the sowing, peak, and harvest seasons of the wheat crop. Figure 5.7a,b shows the growth pattern of wheat and other crops for the Laghman and Helmand provinces of Afghanistan. After examining the growth pattern of different crops, it was found that the spatio-temporal (time-series NDVI) signal and growth pattern of vineyards are completely different from the wheat crop cycle. The NDVI values of orchards were found to be higher when compared to wheat in peak and harvest times. The NDVI response from vegetables varied a lot, but the values were generally lower than those of wheat during the peak and harvest seasons. A high degree of overlap between the NDVI values of opium poppy and wheat was also observed during the sowing period. As opium poppy has a shorter cropping season, a separation of the
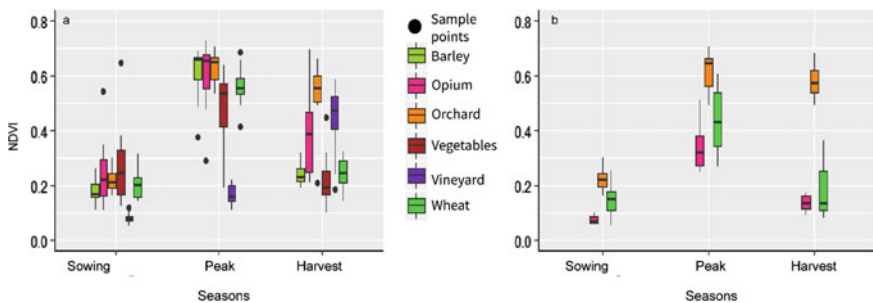

Fig. 5.7 Phonological characteristics of crops in the provinces of **a** Laghman. **b** Helmand in Afghanistan

former with barley would have been possible if cloud-free monthly images could
have been obtained. Figure 5.7b shows the NDVI characteristics of opium poppy in
Helmand which shows higher separability from wheat during the sowing and peak
seasons.

The rule for defining the threshold for separating wheat from other crops is given
in Eqs. 5.1–5.3.

$$\text{Minimum of NDVI}_{\text{wheat samples}} < \text{Wheat}_{\text{sowing}} \leq \text{Maximum of NDVI}_{\text{wheat samples}}$$
$$(5.1)$$

$$\text{Wheat}_{\text{peak}} \geq \left(\text{Minimum of NDVI}_{\text{wheat samples}}\right) \tag{5.2}$$

$$\text{Minimum of NDVI}_{\text{wheat samples}} < \text{Wheat}_{\text{harvest}} \leq \text{Maximum of NDVI}_{\text{wheat samples}}$$
$$(5.3)$$

In general, the NDVI seasonal composites were useful to distinguish wheat from
orchards, vineyards, and some vegetables. It was also observed that much more
separation between these crops could be achieved when combining data sets from
the sowing, peak, and harvest times rather than using the sowing or peak times
alone. However, a significant overlap in NDVI was still observed between wheat,
opium poppy, and barley while using the optical image composites.

Therefore, in the second step, these crops (opium poppy and barley) were
separated from wheat using Sentinel-1 (SAR) time-series data. These time-series
Sentinel-1 data sets had been preprocessed by orbital file correction, thermal, and
speckle noise removal, as well as terrain correction. Monthly median composites
were also developed for the entire wheat-crop cycle (i.e., from sowing till har-
vesting). After performing analysis on Sentinel-1 SAR data, it was observed that
different crops had different and unique response patterns across the different
growth phases of wheat. However, the variability of responses showed overlaps and
made it difficult for threshold-based separation (Fig. 5.8a,b). Therefore, an RF
classification technique was performed on time-series Sentinel-1 data using training
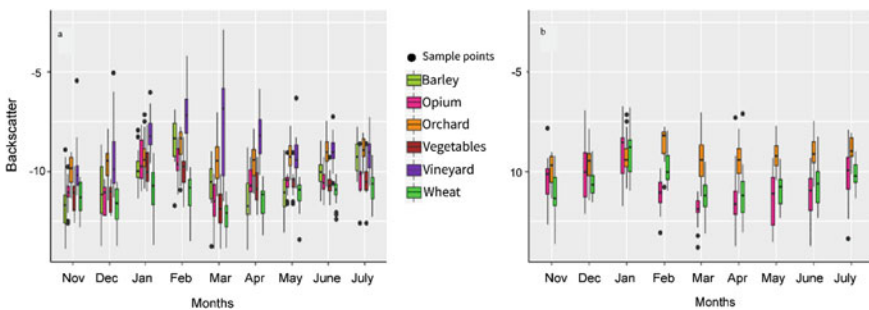

Fig. 5.8 Phenological characteristics observed using Sentinel-1 SAR data in **a** Laghman.
b Helmand provinces in Afghanistan

sample points to separate the wheat from the other crops. The RF classification was applied within the classified mask generated from the optical image analysis. This step was applied only after the harvest season.

5.2.3.2 Boro-Rice Mapping in Bangladesh

Bangladesh has a different crop calendar for Boro rice (Islam and Hossain 2012) since it demonstrates wide variability in its growing seasons across the entire landscape. Therefore, the mapping of Boro rice was done at the district level to capture the unique phenological responses, region-wise. Time-series Sentinel-1 and -2 (optical and SAR) images were used for mapping Boro rice in three districts—Rangpur, Dinajpur, and Barisal. Because of the availability of an adequate number of randomly collected samples from the field, time-series Sentinel-1 images were utilized in the first step followed by time-series Sentinel-2 data in the second step for refinement of the Boro-rice map. Firstly, the time-series Sentinel-1 images from November 2018 to May 2019 were collected. After that, the images were masked using a delineated agriculture mask (Sect. 5.2.2). Sentinel-1 has two bands (VV and VH); therefore, to test the most suitable band for Boro-rice mapping, Sentinel-1 images were classified using training samples from different crops. Three combinations were tested (VV, VH, and VV + VH) for the classification using RF classifiers for mapping Boro rice and other crops. The highest accuracy was observed while using cross-polarization data sets (VH)—an accuracy of 92.10%; this was followed by VV + VH (86.48%) and VV (71.05%). The backscattered response from VH band was also examined (Fig. 5.9a). Different backscattered patterns were observed for different crops because of the sensitivity of the backscatter toward the crop structure. Since the highest accuracy was achieved using VH, the classification was performed using Sentinel-1 (VH) band to classify Boro rice and other crops.
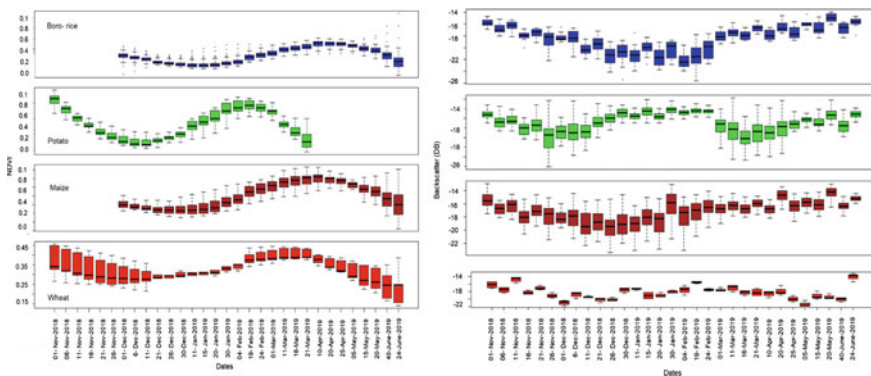

Fig. 5.9 Phenological characteristic of crops determined by using **a** Sentinel-2 (Optical) data. **b** Sentinel-1 (SAR) data

In step two, the Sentinel-2 (optical) data were used to refine the results obtained in step one. Figure 5.9b shows phenological characteristics of different crops, i.e., Boro rice, maize, wheat, and potato using Sentinel-2 data. By examining the phenological characteristics of these major crops, it can be interpreted that potato's sowing, peak, and harvest seasons differ completely from other crops, while Boro rice, wheat, and maize have different length of the season and slightly different sowing and harvest times. Also, the cropping cycle of these crops (maize, Boro rice, and wheat) can vary because of late sowing or early harvest and sowing. The classification results obtained using Sentinel-1 data may have high accuracy, but it may have overestimation in terms of area. This is mainly because of the dependence of the RF classifier on an ideal number of ground sample points (of different crops) for training. This might result in overfitting or underfitting of the classifier and ambiguity in the estimated area. Therefore, to further refine the results, Sentinel-2 time-series images were utilized using the phenological and threshold-based approach discussed in Sect. 5.2.3.1. Sentinel-2 images with less than 20% cloud cover (from November 2018 to June 2019) were utilized. The NDVI thresholds were derived using Eqs. 5.1–5.3 and were applied on the Boro-rice map derived from the Sentinel-1 images for further refinement of the result.

5.3 Validation and Area Assessment

The validation and area assessment of the maps were done using the standard RS-based accuracy assessment technique. The accuracy assessment was conducted in three ways: the results were checked by comparing with various ancillary data to identify gross errors, by visual interpretation, and by quantitative accuracy assessment. A confusion matrix/error matrix was also generated, and statistical accuracy assessment primitives such as the producer's and user's accuracy, including the Kappa coefficient, were utilized in understanding the distribution of errors. The confusion matrix for Afghanistan and Bangladesh for wheat and Boro rice, respectively, is depicted in Tables 5.2 and 5.3.

In RS-based classification, the area for the class can be calculated by counting the number of pixels in a particular class and resolution of the classified map. Equation 5.4 (below) is generally used for estimating the crop area.

$$\textbf{Crop area (ha)} = \frac{(\text{Pixel count}) * (\text{resolution of the image}) * (\text{resolution of the image})}{10,000}$$

$$(5.4)$$

Figure 5.10a,b shows the distribution of wheat (in Afghanistan) and Boro rice (in Bangladesh), whereas Fig. 5.10c,d depicts the areas of wheat and rice, respectively.

Table 5.2 Accuracy assessment of Afghanistan

Class	Non-wheat	Irrigated wheat	Total	User's accuracy (%)
Irrigated wheat				
Non-wheat	1839	282	2121	86
Irrigated wheat	341	1388	1729	80
Total	2180	1670	3850	
Producer's accuracy (%)	84	83		
	Overall	83.8 (%)		
	AC	0.50		
	Kappa	0.67		
Rainfed wheat				
Non-wheat	710	59	769	92
Rainfed wheat	58	238	296	80
Total	768	297	1065	
Producer's accuracy (%)	92	80		
	Overall accuracy	89 (%)		
	AC	0.59		
	Kappa	0.77		

Table 5.3 Accuracy assessment for Bangladesh

Class	Boro rice	Other crops	Total	User's accuracy (%)
Boro Rice	609	18	627	97
Other crops	3	95	98	97
Total	612	113	725	
Producer's accuracy (%)	99	84		
	Overall	97 (%)		
	AC	0.75		
	K	0.88		

5.4 Service Delivery

5.4.1 Operationalization/Application Development

The dissemination of the final results for Afghanistan was done through the development of a web-based visualization system as depicted in Fig. 5.12. Such a web-based visualization system is also planned for Bangladesh. The Afghanistan portal can be accessed via the following URL: http://geoapps.icimod.org/afwheat/. The wheat and Boro-rice mapping workflow was implemented in GEE using a customized interface. The modules (https://code.earthengine.google.com/?accept_
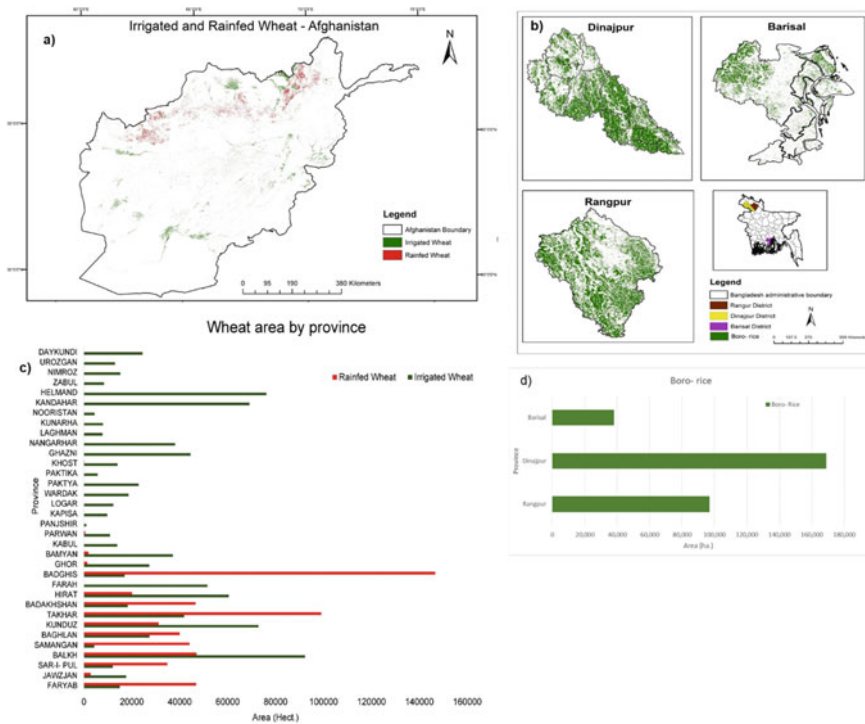
Fig. 5.10 **a** Distribution of wheat in Afghanistan. **b** Distribution of Boro rice in selected districts of Bangladesh. **c** Wheat area in Afghanistan. **d** Boro-rice area in selected districts of Bangladesh

repo=users/varunkt91/Wheatmapping) depicted in Fig. 5.11 shows how crop mapping is performed. A total of four modules were developed for: phenological profile assessment, reference data preparation, crop mapping using optical data, and for crop mapping using SAR data.

5.4.2 Technology Transfer (Capacity Building)

Capacity building is a key element in the sustainability of any project. The details on the framework of capacity building are described in Chap. 14. A number of training events (on-the-job training) were organized in crop mapping for building the capacity of the relevant professionals from MAIL and BARC. On-the-job training focused on agriculture mapping using optical and SAR data, and on wheat and rice mapping using GEE-based applications (described in Sect. 4.1). In addition, training on RS and GIS, a basic introduction on GEE, and field data collection application Geo-ODK were also organized. The OJTs were conducted mainly in Kathmandu, Kabul, and Dhaka.
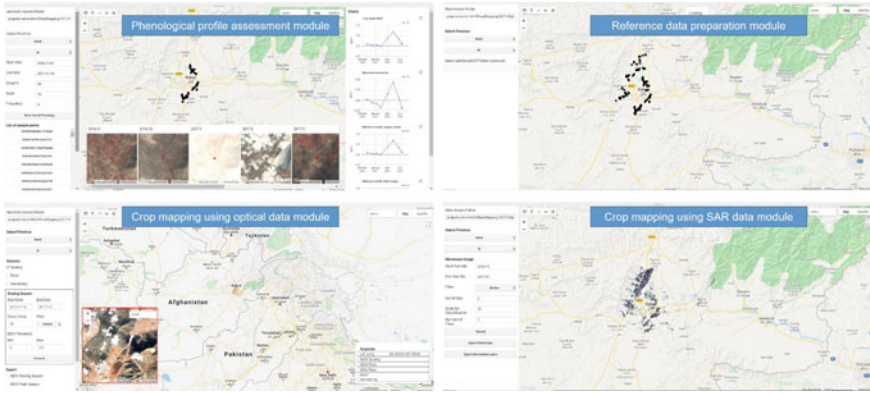
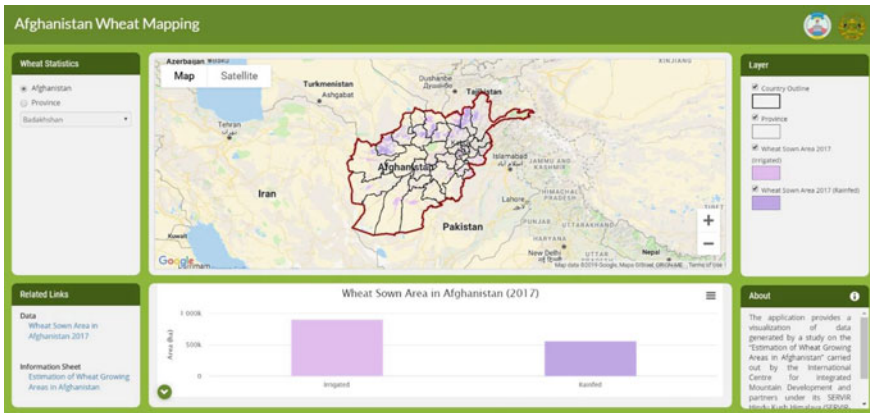**Fig. 5.11** Customized GEE-based application for crop-area mapping

Fig. 5.12 A web-based visualization system for wheat in Afghanistan

5.5 Conclusions and Way Forward

In this chapter, a systematic and robust framework for mapping wheat (in Afghanistan) and Boro rice (in Bangladesh) has been explained. This framework has good potential for operationalization to strengthen the food security management of both the countries. The overall framework was designed keeping in mind challenges such as limited Internet bandwidth, scarcity of ground samples, and cloud-free optical images.

The system uses a multistep approach to provide area estimation as the wheat and Boro-rice season progresses in Afghanistan and Bangladesh, respectively. However, the methodology can also be utilized to map other varieties of rice such

as Aman (spring rice) in Bangladesh if sample points are available for the spring season. In the first stage, time-series Sentinel-2 was used to map different crops using a phenology-based approach in different seasons. While in the second stage, time-series Sentinel-1 (SAR) data sets, along with the RF machine-learning classification technique, were utilized to refine the result. The first estimation was provided during the peak season to give an early indication about the cultivated areas of wheat and Boro rice. A more accurate estimation was provided immediately after the harvest season. The entire workflow was automated in GEE considering the low capacity and the need for timely estimation of the crop area. Meanwhile, capacity building activities—mainly in the area of crop mapping and monitoring using GEE—in order to enhance the skills of the local staff in government agencies are under way through the SERVIR initiative.

These two case studies from Afghanistan and Bangladesh are primarily about RS-based crop-area assessment. A standard RS-based method was utilized for accuracy assessment which provided statistical exactitude based on the Kappa coefficient and primitives such as user and producer accuracy (Sect. 5.3). However, in remote sensing-based crop-area estimates can be adjusted by performing bias adjustment using ground-based area measurement. This can only be achieved by incorporating more robustly sampled ground truth data for different crop samples. Such a bias-adjusted area provides for a more robust insight into the mapped area of any class of crop. The logistics and feasibility of acquisition of adequate sample data required for this method have to be ensured before deciding the use of such method.

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