IMPROVING
AGRICULTURAL
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Global Strategy

Handbook on remote sensing for agricultural statistics

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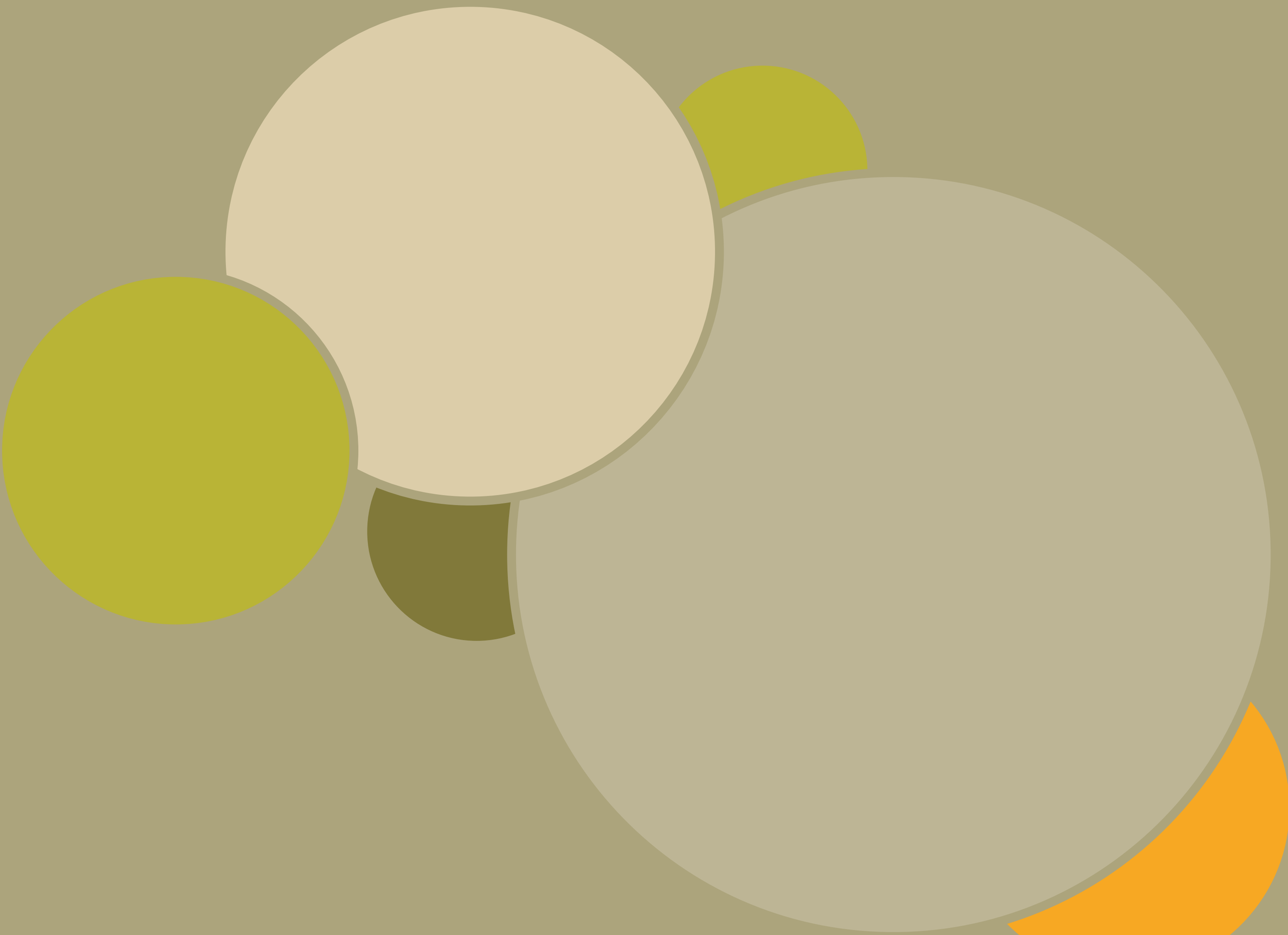

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Acronyms

AAFC	Agriculture and Agri-Food Canada
ACI	Annual Crop Inventory (Canada)
AMIS	Agricultural Market Information System (FAO)
ASF	Area Sampling Frame
ASI	Agroclimatic Information System
ASIA-RiCE	Asian Rice Crop Estimation & Monitoring
ASIS	Agriculture Stress Index System (FAO)
CAPE	Crop Acreage and Production Estimation program (India)
CAS	Chinese Academy of Science (China)
CDL	Crop Data Layer
CHIRPS	Climate Hazards Group Infrared Precipitation with Station data
CLC	CORINE Land Cover
COTS	Commercial-off-the-Shelf Software
CV	Coefficient of Variation
DEM	Digital Elevation Model
DT	Decision Tree Classifier
EA	Enumeration Area
EEA	European Environment Agency
ENSO	El Niño-Southern Oscillation
EO	Earth Observation
ESA	European Space Agency
ETA	Actual EvapoTranspiration
EU	European Union
EWS	Early Warning System
FAO	Food and Agriculture Organization of the United Nations
FAS	Foreign Agriculture Service (USDA)
FASAL	Forecasting Agricultural Output using Space, Agrometeorology and Land-based observations (India)
fPAR	Fraction of Photosynthetic Active Radiation
FRA	Forest Resources Assessment (FAO)
FSA	Farm Service Agency (USDA)
GEE	Google Earth Engine
GEOGLAM	Group on Earth Observations GLobal Agricultural Monitoring
GFW	Global Forest Watch project
GIS	Geographical Information System
GLCN	Global Land Cover Network
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPU	Graphics Processing Unit
GRD	Ground Range Detected level-1 SAR
GSD	Ground Sampling Distance
IIASA	International Institute for Applied Systems Analysis (Vienna)
JECAM	Joint Experiment for Crop Assessment and Monitoring network
JRC	Joint Research Centre (EU)
KML	Keyhole Markup Language file format

LACIE	Large Area Crop Inventory Experiment
LAI	Leaf Area Index
LCCS	Land Cover Classification System
LCML	Land Cover Meta-Language
LSF	List Sampling Frame
MARS	Monitoring Agriculture with Remote Sensing (EU)
ML	Maximum Likelihood classification
MMU	Minimum Mapping Unit
MSF	Master Sampling Frame
NASA	National Aeronautics and Space Administration (USA)
NASS	National Agriculture Statistical Service (USDA)
NCFC	Mahalanobis National Crop Forecast Centre (India)
NDVI	Normalized Difference Vegetation Index
NIR	Near-InfraRed
NOAA	National Oceanic and Atmospheric Administration (USA)
OA	Overall Accuracy (of classification)
OSM	Open Street Map
PA	Producer Accuracy
PPS	Probability Proportional to Size (sampling)
PSU	Primary Sampling Unit
RADI	Institute of Remote Sensing and Digital Earth (China)
REDD+	Reduction of Emissions from Deforestation and forest Degradation
RF	Random Forest Classifier
RMSE	Root Mean Square Error
RWP	Rain Water Productivity
SAE	Small Area Estimation
SAR	Synthetic Aperture Radar
SIGMA	Stimulating Innovation for Global Monitoring of Agriculture activity
S1tbx	Sentinel-1 toolbox
SNAP	Sentinel Application Platform
SRTM	Shuttle Radar Topography Mission
SSU	Secondary Sampling Unit
SVM	Support Vector Machine Classifier
SWIR	Short-Wavelength Infrared
TOA	Top-of-Atmosphere Reflectance
TOC	Top-of-Canopy Reflectance
UA	User Accuracy
UAV	Unmanned Aerial Vehicle
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
USDA	U.S. Department of Agriculture (United States of America)
USGS	U.S. Geological Survey (United States of America)
VHR	Very High Resolution (imagery)
WCA 2020	World Program for the Census of Agriculture 2020
WMS	Web Map Service
XML	Extensible Markup Language

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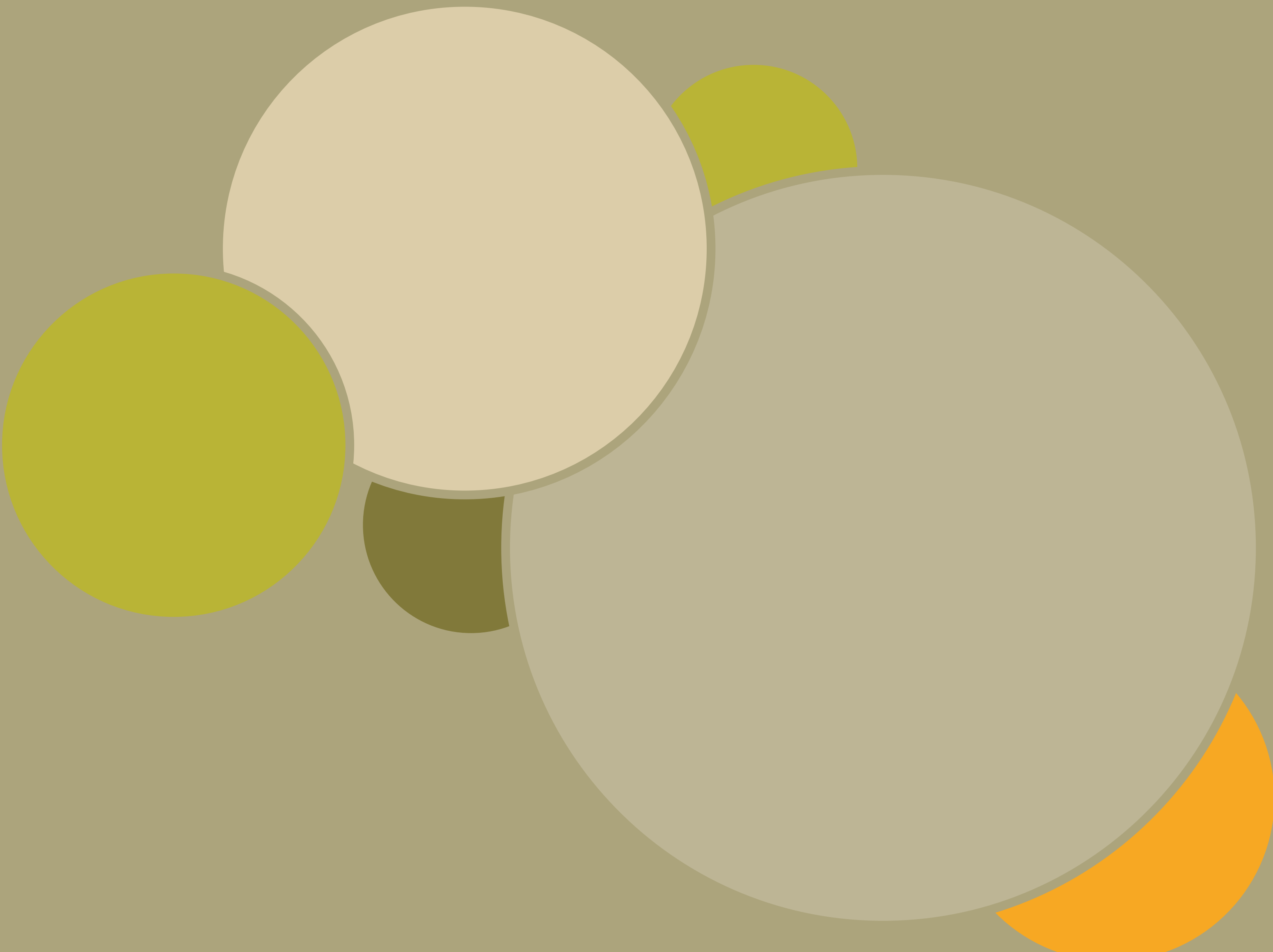

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Overview

Jacques Delincé

The purpose of this handbook on *Remote Sensing for Agricultural Statistics* is to provide guidelines on the use of remote sensing in the context of agricultural statistics. Since the mid-1970s, remote sensing has been considered a promising technique for improving agricultural statistics. Various applications of remote sensing have taken place on all continents and today, several approaches may be considered mature enough to contribute to the sustainability of agricultural statistics. In the context of the Global Strategy to improve Agricultural and Rural Statistics (hereafter, GSARS or Global Strategy; see World Bank, 2011), remote sensing has been identified as a prime contributor to the localization and geocoding of the sampling units, a point of reference for Master Sampling Frames (MSFs), a methodological improvement in design and estimation terms, as a way to achieve sustainability and as a core data set for indicators linked to land uses and covers.

The Research component of the Global Strategy to improve Agricultural and Rural Statistics identified the use of remote sensing as one of its themes of activity. This led to the issue of five publications on remote sensing:

- *Developing More Efficient and Accurate Methods for Using Remote Sensing (2014)*
- *Technical Report on Improving the Use of GPS, GIS and Remote Sensing in Setting Up Master Sampling Frames (2014)*
- *Spatial Disaggregation and Small-Area Estimation Methods for Agricultural Surveys: Solutions and Perspectives (2015)*
- *Technical Report on Cost-Effectiveness of using Remote Sensing for Agricultural Statistics in Developing and Emerging Economies (2015)*
- *Information on Land in the Context of Agricultural Statistics (2016)*

In its 2009 handbook titled *Geospatial Infrastructure in Support of Census Activitie*s, the Statistics Division of the United Nations began to recommend the use of satellite and aerial imagery for the planning, execution and dissemination of census activities. In 2010, the Global Earth Observation System of Systems (GEOSS) Community of Practice published best practices for crop area estimation with remote sensing. Since 2014, on a monthly basis, the Agricultural Market Information System (AMIS) initiative based within the Food and Agriculture Organization of the United Nations (FAO) has been publishing the Group on Earth Observations GLobal Agricultural Monitoring (GEOGLAM) Remote Sensing analyses, aiming to provide real-time monitoring of areas and production for the major traded commodities.

The literature provides various publications dealing with the use of remote sensing in official statistics (FAO, 2015); however, the vast majority of publications focus on specific technical problems without exploring how to start integrating remote sensing into the process of compiling official statistics.

This handbook seeks to enable interested readers to comprehend whether remote sensing can meet their needs, and if its adoption can improve timeliness, coverage, precision and/or costs in a sustainable manner.

In line with the three GSARS pillars (World Bank, 2011), the current priorities of agricultural statistical services should be (1) establishing a master frame to foster the integration of agricultural statistics within the national statistical system; (2) improving the coverage, bias and precision of the estimates of the core indicators; and (3) selecting practices that are sustainable in terms of cost-efficiency, flexibility and accessibility. The technical advances in the digital management of information, global positioning and open access to remote sensing offer important opportunities to meet these priorities and indeed inspired the drafting and publication of this handbook.

The structure of the handbook reflects the diversity and complexity of the domain of agricultural statistics, as well as of the technicalities of remote sensing:

- An agricultural statistical information system is composed of several layers, each corresponding to different core statistical topics and societal needs. Remote sensing can be particularly efficient in improving Global Strategy core items linked to crop areas, yields and productions. Its role is highly versatile, potentially ranging from optimization of sampling design to the facilitation of the the fieldwork of enumerators, quality assurance and even data production. Societal needs can be separated into two components: (1) the production forecasts from early season to pre-harvest time, for food security monitoring and (2) classical agricultural statistics, of which the continuity and consistency over time will allow policy-makers to plan and evaluate agricultural policy and its positive effect on total factor productivity, farmer income and rural development.
- The techniques associated with remote sensing raise issues pertaining to the sensors (optical or radar), image resolution (30 cm to 5 m) and revisiting time (one hour to 16 days); to (non-)open access and the (generally prohibitive) associated prices; and to the software and hardware available for image analysis (open-source or commercial software, local or cloud computing). This aspect will require managers to identify the time, resources and staff competences required to move from experimentation to operational activities.

Chapter 1 describes the data sets relevant to the integration of remote sensing within agricultural statistics. First, the remote sensing data sources themselves will be addressed. The role of reference data and ancillary data layers, and their use in stratification and aggregation, will also be discussed. A key issue arising recently in data access is the general trend towards open access. Thus, while the major commercial remote sensing missions will be listed for reference, attention will be paid to open-access sources for a number of reasons: (1) to create wider awareness on data sets that are available under free and open licenses; (2) to provide a thorough understanding of how these data can be assessed; and (3) to discuss how open data can be used to optimize the acquisition – i.e. minimize the costs – of commercial data. Remote sensing data, from both open and commercial sources, usually requires post-processing for follow-up use in statistical analyses. The use of open-source software for image processing and geospatial analysis is another important development that accelerates the broader adoption of remote sensing data. The use of open-source software is discussed, and a listing of commercial software alternatives is provided. The chapter concludes with a discussion of the more recent trend to move data analytics into cloud computing environments.

Chapter 2 deals with land cover mapping. It first introduces the concept of land cover and then reviews some key elements of land cover mapping. Existing land cover maps are discussed systematically, based on a set of well-defined criteria. While land cover map supporting stratification always refers to previous years, recent experiences of map production throughout the ongoing season will also be explored. Today, land surface can be described in several ways, thanks to the unprecedented development of information technology and observation capabilities, ranging from Unmanned Aerial Vehicles (UAVs) to in-orbit Earth Observation (EO) platforms. Satellite remote sensing is an undisputed source of land information for a vast range of users at all geographical scales. Due to the increasing gap between remote sensing producers and map users, which is very much supported by spatial data infrastructure making a great deal of geographic information widely available, it is important to understand the different concepts and constraints underlying land cover mapping. This becomes even more critical when considering the use of a land cover map to support stratification at the sampling design level in the context of agricultural statistics. Indeed, maps derived from remote sensing that show, for instance, crop intensity classes, may significantly reduce sampling variances or, simply, reduce ground sampling effort and its associated costs. A land cover map can highlight the non-agricultural strata which should not be sampled or those strata which could be sampled differently. The efficiency of stratification is obviously related to the relevance of the land cover map selected for the stratification.

Chapter 3 focuses upon the use of remote sensing at design level in list and area frames. In the context of censuses, surveys or registers, satellite imagery can be of great support when defining or optimizing the design options. The imagery may be of primary importance when reference maps are absent or obsolete, as they enable a clear delimitation of the Enumeration Area (EA), the counting of dwellings and the planning of the workload. With reference to surveys, stratification on classified imagery will lead to a reduced sampling variance and a variation of sampling fraction (or of the probability proportional to size – PPS) that is proportional to agricultural intensity. Particular attention is paid to the creation of list frames, starting with the point area frame. With regard to area frames, if, in stratification, the strata should be as different as possible, in two-stage sampling, the Primary Sampling Units (PSUs) should be as similar as possible. In both scenarios, the imagery is of great help. The chapter reviews practical examples in developing and developed countries, thus illustrating the type of efficiency and homogeneity that can be achieved. Recommendations are given on segment size optimization in function of field pattern complexity.

The overarching goal of **Chapter 4** is to provide an overview of remote-sensing-based approaches for detailed (field-level) annual crop mapping at national scale. First, an overview of the existing approaches based on remote sensing used for cropland mapping is presented. This includes a brief overview of supervised image classification and pixel- versus object-based classification. Second, the various types of satellite data, ground data and secondary data used for detailed crop mapping are discussed. Third, the operational implementation of a national crop mapping program is demonstrated with specific reference to Canada's Annual Crop Inventory. Finally, the main challenges and opportunities for crop type mapping at national scales in the future are outlined. The past decade has borne witness to several attempts to articulate the spatially explicit requirements of remote sensing data to map cropping systems, and, particularly, where, when and how frequently, over which spectral range, and at what spatial resolution, data are needed. Elucidating the best data and methodologies for crop mapping remains a high priority on the international research agenda. Indeed, several international efforts have been made to achieve a convergence of approaches and develop monitoring and reporting protocols and best practices for a variety of global agricultural systems (e.g. the GEOGLAM initiative, which includes the Joint Experiment of Crop Assessment and Monitoring (JECAM), the Asian Rice Crop Estimation and Monitoring initiative (Asia-RiCE), the Stimulating Innovation for Global Monitoring of Agriculture activity (SIGMA), and contributions from the Sentinel-2 for Agriculture system (Sen2-Agri)).

Chapter 5 deals with crop area estimation using remote sensing. The chapter introduces the history of crop area estimation, reviewing the evolution from the use of conventional methods to the use of satellite data, with the attendant challenges and complexities. The major initial crop area estimation programmes using satellite data, such as LACIE and AgRISTARS, are discussed. The various approaches to crop area estimation, such as the Area Sampling Frame (ASF), pixel counting, and regression or calibration estimators are described with examples. Details of current major programmes for use of remote sensing in crop area estimation are provided under three categories: national (USDA-NASS's CDL and India's FASAL); regional (the European Commission's MARS); and global (USDA's FAS, China's CropWatch and GEOGLAM).The concluding section deals with the major issues and limitations in remote-sensing-based estimates and the way forward.

Chapter 6 reviews the fundamental concepts relating to Early Warning Systems (EWSs) and crop yield forecasting, to better address the climatic risks that bear an impact on food security. System-based dissemination of timely alerts and specifications of the probability of hazard occurrence are fundamental components of early warning information; systematic linkages to early action options and possibilities would go a long way towards saving lives and livelihoods. Forecasting crop yields and aggregate production is of significant importance in early warning systems that seek to assess the food supply and demand situation of a given country or region. Accurate analyses of market conditions, and identifications of the surplus and deficit areas in a country or region will contribute greatly to design appropriate policy responses to mitigate food security problems. Robust and accurate agricultural statistics are also crucial to achieve such important objectives. In this context, information derived from remote sensing plays a vital part in improving the production of agricultural statistics because it is capable of introducing independent verifying mechanisms, particularly when area frame or multiple frame sample designs are used. Remotely sensed data and information can be introduced at both design and estimator levels.

Chapter 7 deals with the estimation of forest cover and deforestation from global to national scales using Earth Observation technology. Considering the specificities of forestry statistics (permanence of the stands from year to year, plot sizes far exceeding pixel sizes, long-term management, availability of management registers in non-natural forests), a special chapter is dedicated to forest resources and deforestation. The main approaches to the use of remote sensing for forest cover assessment and evolution are reviewed, with particular focus on specificities and results as shown in the recent literature. After reviewing the background information on the use of remote sensing for monitoring forest cover, the Remote Sensing Survey of FAO's Global Forest Resources Assessment is described, as well as other examples of remote sensing surveys used for forestry statistics. Finally, the complementarity between estimates of changes occurring in forests and agriculture is analysed.

Chapter 8 presents fundamental requirements and criteria for an organization that is beginning to use geospatial analysis and, in particular, remote sensing for producing agricultural statistics. It also elucidates the need for resources and the competences necessary for application of remote sensing systems in the contexts of agricultural data collection and training needs. Furthermore, consideration is given to the human resources required in the multidisciplinary team, its qualifications, size and to the budget required.

Examples of collaboration between statistical services and mapping agencies are also provided, as well as explanations on the importance of close interaction with stakeholders.

The necessary budgets and business plans are presented.

Finally, **Chapter 9** explains how to evaluate the cost-efficiency of remote sensing. Examples are given of past and recent uses, showing why and where clear cases of cost-efficiency exist. Based on the current trend for free and open access to satellite imagery, agricultural complexity may soon be expected to become manageable with the images' increasing information content (spectral, spatial or textural).

5

Chapter 5

Crop area estimation with remote sensing

Shibendu S. Ray & Neetu

5.1. CROP AREA ESTIMATION: INTRODUCTION

Crop production information, which is essential for various economic planning and agricultural market management (Gallego *et al*., 2014), has two components: crop area and crop yield. Among these two, it is always assumed that estimation of the area is comparatively simpler and more straightforward than estimation of the crop yield. However, crop area estimation presents several challenges and complexities, which may not be readily apparent (Craig and Atkinson, 2013).

Factors which determine the complexity of crop area estimation include, but are not limited to, the following: small field size, scattered and diversified cropping patterns, mixed cropping system with phenological differences, extended sowing process (for example, in India, the planting of rice progresses from June to September), changes in cropping pattern, short-duration crops, cropping in homesteads, complex physiography (such as crops grown on hillsides through terrace or contour farming), complex seasonality (sugarcane having a main crop and a ratoon crop; or crops growing in multiple seasons depending upon climate diversity). In addition, there may be changes in the crop sown area due to damage, which may be caused by both biotic (weather) and abiotic (pest and disease) factors. Furthermore, the crop area estimation must take place at multiple stages: before sowing (specifically, the date of intended sowing, which depends upon the profits obtained in the previous year from the crop and weather forecasts); during early sowing; at mid-season and before harvest (Vogel and Bange, 1999).

Craig and Atkinson (2013) have provided a review of the methods used for crop area estimation. Conventionally, crop area is estimated either by complete enumeration of all farms or by samples. The sampling may be Area Frame Sampling (AFS), farm list sampling or a combination of both; the latter case is called multiple frame sampling. In some cases, it also involves the expert opinion of voluntary crop reporters. Other sources of crop area may be administrative surveys, crop processing units (for example, cotton or jute mills) and markets. The final estimate is generated either by direct reference to the survey data or by a panel of experts, which reviews data from different sources and finalizes the estimates.

However, the conventional method of crop area estimation is time-consuming, costly, tedious and subject to human bias. It is also extremely difficult in several land types, such as hilly terrains. To overcome these problems, satellite remote sensing has been used for crop area estimation, either directly or to support the area sampling schemes. Satellite remote sensing provides temporal, synoptic, multispectral and multiresolution images of land use and land cover and offers the ability to classify different crops.

Use of satellite-based remote sensing data for crop area estimation dates back to the early 1970s, when the Corn Blight Watch Experiment was jointly carried out in 1971 by the U.S. Department of Agriculture (USDA), the National Aeronautics and Space Administration (NASA) and a number of universities (Sharples, 1973). In 1972, the ERTS-A was successfully launched and NASA conducted joint experiments with the USDA to establish the feasibility of surveying major crop types from space with multispectral remote sensing technology (Bryan, 1974). Experiments such as the Crop Identification Technology Assessment for Remote Sensing (CITARS) experiment and the Large Area Crop Inventory Experiment (LACIE) were conducted to demonstrate the capabilities of remote sensing in the context of crop inventory (MacDonald, 1984). The CITARS experiment evaluated classification procedures and alternative analysis techniques for corn and soybean crops.

LACIE was the first program sponsored by the Government of the United States of America aimed at examining the feasibility of using remotely sensed satellite data – specifically, Landsat data – to estimate wheat production over large geographic areas (Nellis *et al*., 2009). The LACIE programme was first operated in 1974 in the Great Plains of the United States of America, and was extended to include Canada and the former Soviet Union (MacDonald, 1984). The successes of LACIE led to a follow-on project in 1980 called Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing (AgRISTARS). The goal of this new program was to expand upon LACIE and include monitoring of other crops such as barley, corn, cotton, rice, soybeans and wheat (Holmes *et al*., 1979). The AgRISTARS program was successful in demonstrating the value of timely data and limited ground reference information for identifying crops and predicting yield.

5.1.1. LACIE

The LACIE experiment proved to be a potential model for other programmes designed to globally measure other terrestrial plant communities by remote sensing from satellites (Erickson, 1984; MacDonald and Hall, 1980). The LACIE experiment was a joint programme of NASA, the National Oceanic and Atmospheric Administration (NOAA) and the USDA, and was the first operational agricultural assessment programme to demonstrate the potential uses of Landsat data. LACIE envisaged three phases: Phase I (conducted between 1974 and 1975) developed a methodology in the Great Plains (area estimation was performed in a quasi-operational mode, while yield and production estimation were performed in a feasibility test mode); Phase II (1975-1976) evaluated the methodology in the Great Plains, Canada, and in “indicator regions” in the former USSR (the quasi-operational wheat area estimation was extended to yield and production); Phase III (1976-1977), in which a second-generation technology, developed in Phases I and II, was used to forecast the 1977 Soviet wheat crop at country level. The project also conducted exploratory studies in India, China, Australia, Argentina, and Brazil (MacDonald and Hall, 1980). The area was estimated from selected sample segments using Landsat data, while yield was estimated using weather-based models with data from the World Meteorological Organization (WMO).

LACIE used a performance envelope of 90/90, which means that in 90 percent of the cases, the error was within a 10 percent range. The results from LACIE were more reliable for the former USSR, and also met the 90/90 accuracy criterion for the Great Plains. Although the results for Canada, India, China, Australia, Brazil and Argentina were encouraging, they did not meet the 90/90 accuracy goal (MacDonald and Hall, 1980).

Hanuschak *et al*. (1982) have described how Landsat was successfully used from 1972 to 1982 for the USDA's Statistical Reporting Service (SRS), towards improving (i) the area sampling frame (ASF) and (ii) the regression estimation of crop area.

Subsequently, many methodology development and demonstration programmes were carried out in various countries to explore the use of satellite-based remote sensing data in crop area estimation (Dadhwal *et al*., 2002).

Currently, many countries use remotely sensed satellite data for different aspects of crop area estimations. Table 1 presents a summary of satellite data utilization in various operational national crop area estimation programmes. Countries use different types of satellite data and various approaches, which are described in the subsequent sections. In section 3, two national programmes (USDA/NASS's Cropland Data Layer (CDL) programme and India's Forecasting Agricultural Output using Space, Agrometeorology and Land-based observations (FASAL programme), one regional programme (the European Union's Joint Research Centre's Monitoring Agriculture with Remote Sensing (EU JRC/MARS) Area Estimate) and two global programmes (the USDA's Foreign Agriculture Service (FAS) and China's CropWatch) are discussed in detail to understand various aspects of satellite data use.

5.2. APPROACHES TO CROP AREA ESTIMATION USING REMOTE SENSING

The basic principle guiding the use of remote sensing in the context of crop identification and classification is founded on the fact that crops look different (have different spectral signatures) in multispectral data due to their different structure, physiology, cultural practice and phenology. With the support of selected ground information, called ground truth, crops may be identified. This concept is used in four broad approaches for crop area estimation using remote sensing data: (i) ASF design; (ii) direct estimation or pixel counting; (iii) regression estimator; and (iv) calibration estimator.

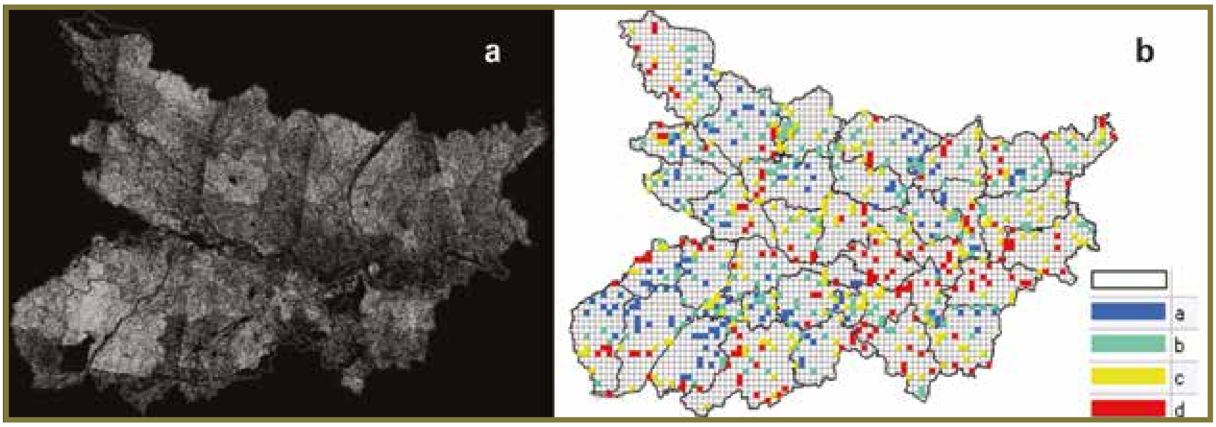
5.2.1. ASF design

Chapter 3 of this handbook addressed the use of remote sensing for sampling frame design. For this purpose, satellite imagery is of the utmost value, as it provides a table of reference when elaborating the population frame; in particular, it may be used to subdivide areas of interest into enumeration areas (EAs) in which list frames of holdings are defined, and it helps with the definition of area frames composed of primary and secondary sampling units (PSUs and SSUs respectively), which are readily identifiable in the digital imagery (Delincé, 2015). The crop proportion derived from remote sensing data, either through visual interpretation or digital classification, is used to characterize spatial variability and, in turn, a parameter of stratification for area frame sample design. There are two types of area frame: (i) an area frame with physical or natural boundaries; and (ii) an area frame having a regular shape (grid sampling).

In figure 1, an example of a regularly shaped (5 x 5 km grid) area frame is shown for India's Bihar State, as assessed under India's FASAL project. The classified crop map (figure 1a) is used to stratify the 5 x 5 km segments into four strata (A type: over 50 percent constituted by crop area; B type: between 30 and 50 percent, C type: between

15 and 30 percent, D type: between 5 and 15 percent). A unique identification number is provided for each 5 x 5 km segment. After stratification, approximately 15 percent of the sample segments (table 2) are selected from each type for final analysis. Approximately 50 percent of these sample segments are visited in the field for ground truth data collection.

FIGURE 1. AFS DESIGN FOR BIHAR STATE, INDIA, UNDER THE FASAL PROGRAMME.



1a) Classified crop map of Bihar State. 1b) 5 x 5 km grids overlaid onto the classified image, with each grid stratified into four classes (A, B, C and D) based on crop proportion. The figure shows selected sample segments (approximately 15 percent) from each type.

Square segments are not the only possible approach for constructing area frames. In FAO's study on rice area estimation in Afghanistan (FAO, 2017), irregular segments, with limits constituted by physical boundaries, were used. Due to a complex local landscape, the ASF was designed at multiple levels: there were PSUs (of 500 to 700 ha), SSUs (from 200 to 300 ha) and Terminal Sampling Units (between 25 and 35 ha). The stratification was based on crop intensity (greater than 75 percent, between 50 and 75 percent, between 25 and 50 percent, and lower than 25 percent). Frame design definition and survey optimization were based on imagery from Pleiades to MODIS.

ASF design using remote sensing data provides a high stratification efficiency. Carfagna (2013) noted that in the pilot areas of the MARS Project, in most cases, efficiency ranged from 1.1 to 1.6 percent. Gallego *et al.* (1999) found the efficiency to lie between 1.7 and 2.2 percent for main crops in Spain. In India, for rice crop estimation using microwave data (Special Aperture Radar, or SAR), the efficiency of stratification ranged from 1.0 to 2.68 percent (table 2).

The Coefficient of Variation (CV) is another parameter that characterizes the usefulness of stratification. In India, for rice areas between 1 million and 3 million ha (at state level), the CVs ranged between 1.15 to 3 percent for sample sizes of 1229 and 450 ha respectively. For rice crops, a significant negative correlation was found between the CV and the crop area at a fixed sampling rate (approximately 15 percent). From the study of ASF design in various countries, Delincé (2015) also found that the CVs increased as crop area decreased.

TABLE 1. USE OF REMOTE SENSING FOR CROP AREA ESTIMATION IN DIFFERENT COUNTRIES

Country	Organization	Name of The Programme	Satellite Data	Scale	Crops	Approach	Ref.
Afghanistan	FAO		ProbaV, Aqua/Terra, Landsat 8, Sentinel 1, Sentinel 2, SPOT 5, 6 &7 and Pleiades 1A & 1B	District, Province	Rice	AFS design, image classification and regression estimator	FAO, 2017
Argentina	*Secretaría de Agricultura, Ganadería, Pesca y Alimentos de la Nación Argentina (SAGPyA)*		Landsat		Wheat, corn, soybean	ASF and classification	Justice and Becker-Reshef, 2007
Asia (6 countries)	International Rice Research Institute (IRRI)	Remote Sensing based Information and Insurance for crops in Emerging economies (RIICE)	X-band SAR from COSMO-SkyMed; TerraSAR-X	Selected sites	Rice	Image classification	Nelson *et al.*, 2014
Australia	University of Queensland		MODIS EVI		Wheat, barley, chickpea	Harmonic analysis, Principal component analysis	Potgieter *et al.*, 2007
Brazil	*Companhia Nacional de Abastecimento* (CONAB)	GeoSafras	Landsat & MODIS		Corn, soybean & wheat	Regression analysis	Fontana *et al.*, 2006
Canada	Statistics Canada	Still at research level	Landsat 8			Classification	Brisbane and Mohl, 2014
China	National Bureau of Statistics (NBS), Ministry of Agriculture	Crop Acreage Estimation by using Remote Sensing and Sample Survey (CAERSS) China Agricultural Remote Sensing Monitoring System (CHARMS)	Province	Corn, rice and soybean	AFS system and regression/ calibration		Pan *et al.*, 2012
Ethiopia	University of California	Research study	Ikonos, Landsat	District	Cropped area	AFS and classification	Husak *et al.*, 2008
European Union (28 countries)	JRC	MARS	Landsat TM & SPOT XS	EU, Member State	Wheat, barley, maize, rice, pulses; rape, sunflower, sugar beet	Stratification and regression estimator	Gallego, 2000 and 2006

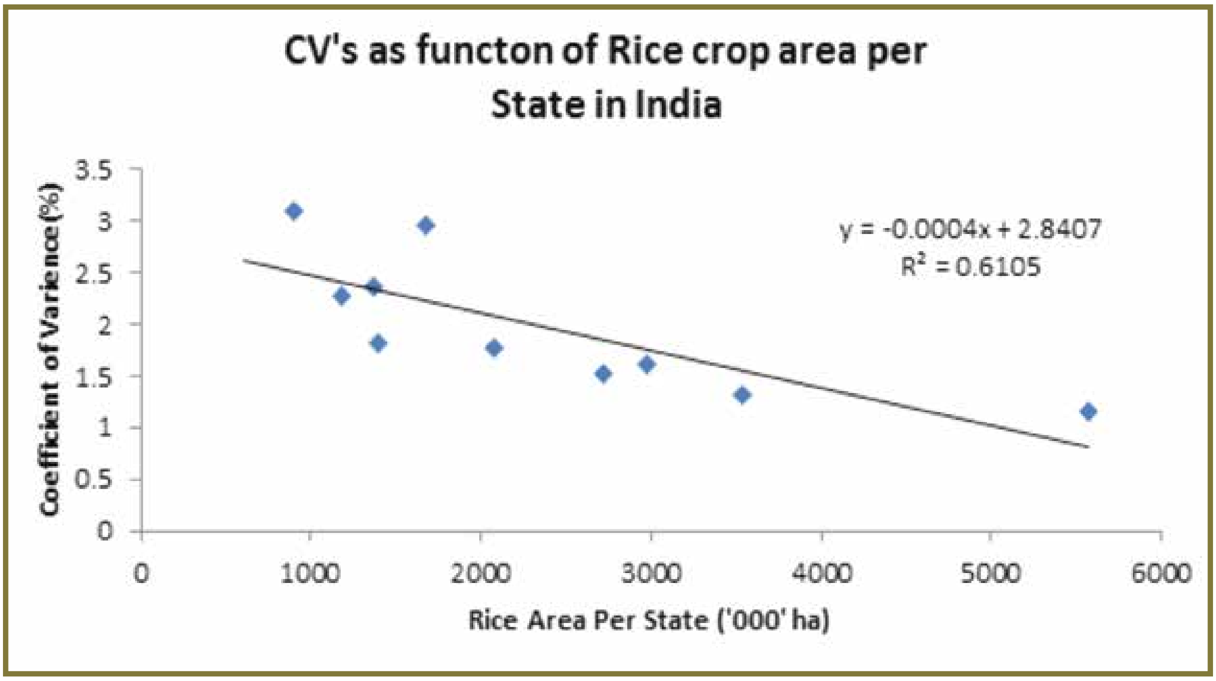
Country	Organization	Name of The Programme	Satellite Data	Scale	Crops	Approach	Ref.
Hungary	FÖMI Remote Sensing Centre	Crop Monitoring and Production Forecast Program (CROPMON)	Landsat and IRS-1C/1D	County	Wheat, maize	Image classification	Csornai et al, 2006
India	Mahalanobis National Crop Forecast Centre (MNCFC), (Department of Agricultural Cooperation & Farmers Welfare, or DAC&FW)	FASAL	Resourcesat 2: AWiFS& LISS III; Landsat & Sentinel 2; RISAT-1 SAR	District, State, National	Rice, wheat, cotton, sugarcane, sorghum, jute, rapeseed and mustard, potato	ASF design and Image classification	Ray *et al.*, 2015
Pakistan	Space and Upper Atmosphere Research Commission (SUPARCO)		SPOT 5	Province	Wheat, rice, cotton, sugarcane, maize, potato	Image classification and AFS system	Ahmad *et al.*, 2015
Russian Federation	Ministry of Agriculture	Agrocosmos	MODIS 16 Day NDVI Product	Oblast/ District	To support agricultural censuses		Temnikov and Sergey, 2007
Spain	Regional Ministry of Agriculture	Castile and León crops and natural land map	Deimos 1 & Landsat 8		CDL	Classification using a machine learning algorithm	Medina and Garcia, 2015
South Africa	National Crop Statistics Consortium	Producer Independent Crop Estimate System (PICES)	Landsat	Province	Sunflower, maize	Image classification	Ferreira *et al.*, 2006
USA	USDA/NASS	CDL	Resourcesat AWiFS, Landsat ETM+	State	Cotton, wheat, sorghum, rice, soybean, etc.	Regression estimator	Bailey and Boryan, 2010

TABLE 2. RICE SAMPLING PLAN, CVS AND STRATIFICATION EFFICIENCY FOR VARIOUS STATES OF INDIA AS USED UNDER THE FASAL PROJECT.

State	Population of 5 x 5 km grids				Samples of 5 x 5 km grids				Population total	Sample total	Sampling fraction	CV (%)	Stratification efficiency
	A	B	C	D	a	b	c	d	N	n	%		
Andhra Pradesh	316	581	736	1201	49	91	111	174	2 834	425	15	2.37	2.68
Assam	524	840	937	681	96	120	125	84	3 000	425	14	1.77	1.46
Bihar	646	989	1091	784	109	145	166	109	3 510	529	15	1.60	1.230
Chhattisgarh	711	979	1042	1 347	111	154	159	203	4 079	642	15	1.31	1.56
Haryana	273	265	339	499	46	53	61	93	1 376	253	18.4	2.28	2.66
Jharkhand	233	552	747	872	47	89	127	141	2 404	404	16.8	1.81	1.234
Karnataka	195	521	741	1 350	41	91	123	203	2 807	458	16.3	3.09	1.22
Madhya Pradesh	273	460	826	848	59	79	130	128	2 407	396	16.4	2.95	1.00
Punjab	462	554	503	387	72	105	93	78	1 906	348	18.2	1.52	1.53
Uttar Pradesh	1 332	2 218	2 154	1 826	227	364	367	318	7 530	1 276	16.9	1.15	1.40

A type: > 50% crop area; B type: 30–50%, C type: 15–30%, D type: 5–15%
Stratification efficiency is the ratio between the variances of Simple Random Sampling (SRS) and stratified sampling.

FIGURE 2. CVS OF ESTIMATES AS A FUNCTION OF RICE CROP AREA IN DIFFERENT STATES OF INDIA.



5.2.1.1 Direct estimation or pixel counting

In this approach, the satellite image is classified using the ground truth collected from sample locations. The number of pixels under each crop within an administrative boundary is multiplied by the pixel size to obtain the area of the crop.

The image analysis is carried out in sample segments or on whole scenes (complete enumeration). In the case of sample segments, the area under each segment is estimated and statistically aggregated to obtain the total area. In complete enumeration, the image is overlaid with the administrative boundary (district/state/county/province), and the total crop pixels are counted and multiplied with the pixel size to obtain the crop area. Additionally, under complete enumeration, a crop map is available, which can be used for several other purposes, such as yield sampling.

The classification can be either supervised (where classes are defined based on the ground truth) or unsupervised (and therefore based on the exploitation of the inherent tendency of different classes to form clusters in the feature space). Minimum-Distance-to-Means, Parallelepiped, and Maximum Likelihood (ML) are the common algorithms used for supervised classification; ISODATA and K-Means are the examples of classifiers used in unsupervised classification. The other newer approaches for crop classification include Hierarchical (Decision Tree) classifiers, Support Vector Machines, Artificial Neural Networks and Fuzzy-set classifiers. Prasad *et al*. (2015) have provided a survey of techniques that may be used for image classification.

Classification is carried out using multitemporal moderate-resolution satellite data (MODIS, Resourcesat AWiFS or SPOT VGT) or single-date high-resolution data (Landsat OLI, Resourcesat LISS III or Sentinel 2 MSI). The costs of the various optical satellite data generally used for crop classification are presented in Table 3.

TABLE 3. EXAMPLES OF THE COSTS OF VARIOUS OPTICAL AND MICROWAVE SATELLITE DATA USED FOR CROP AREA ESTIMATION.

Satellite	Sensor	Product Specification	Price (in euros)*
EO1	MODIS (Terra and Aqua)	250 m/500 m/1 km products	Free
SPOT 5	HRS VEGETATION 2	20 m MS, 60 x 60 km 10 m MS, 60 x 60 km 5 m MS, 60 x 60 km 1 km products	1 900 2 700 5 400 Free
Landsat 8	OLI		Free
Resourcesat-2@	AWiFS LISS III LISS IV	56 m MS, 740 x 740 km 24 m MS, 140 x 140km 5.8 m MS, 70 x 70 km	222 96 147
Sentinel 2	MSI		Free
Rapide Eye	Multispectral	Basic/Ortho, Contiguous 3 500 km2	3 325
RISAT 1@	C-Band SAR	MRS, 18 m, 115 x 115 km2	69
Sentinel 1	C-Band SAR		Free
Radarsat 2	C-Band SAR	Wide 30 m; 150 x 150 km2	2 590
COSMO-SkyMed	X-Band SAR	ScanSAR Wide 30 m; 100 x 100km2	1 650

Source: http://www.e-geos.it/products/ pdf/prices.pdf. Prices are for new acquisitions
N.B. Readers are referred to chapter 1 for the detailed information on sensor characteristics

5.2.1.2. Multidate data analysis

Multidate data analysis is based on the concept of using the differences in the phenology (growing patterns) of different crops grown in the same area. Generally, a moderate spatial resolution with high temporal frequency data is used, such as MODIS (250 m, daily or eight-day products), SPOT VGT (1 km, daily or ten-day products) or Resourcesat 2 AWiFS (56 m, five-day products). Seven to ten dates of coregistered data covering the major part of the crop growing period is used for crop classification. A decision-rule (hierarchical) classification approach is used on multidate Normalized Difference Vegetation Index (NDVI) products to classify different crops based on their growth cycle.

Figure 3 illustrates an example of fortnightly composite NDVI products, derived from Resourcesat 2 AWiFS data, for Uttar Pradesh State, India, during the rabi (winter) season (November/December to March/April). This data set is used to classify its major crops, which are wheat, rapeseed & mustard, potato and pulses. Temporal NDVI profiles for all of these crops are shown in figure 4. For potato, the NDVI increases sharply and peaks in end-December and during the first fortnight of January. For mustard, NDVI increases from end-December and decreases towards end-February. The temporal profile for wheat shows an increase in the NDVI from January which continues throughout the growing period, which goes from December to April. For pulses, the different temporal signatures are comparable to those of other major crops.

5.2.2. Single-date data analysis

Single-date data analysis is based on the criterion that, during the maximum vegetative growth of the target, with a sufficient amount of ground information, it can be discriminated from other crop and land use/land cover classes. In this case, higher-resolution satellite data (such as from Resourcesat 2 LISS III, Landsat 8 OLI, or Sentinel 2 MSI) are used. Ground truth information is used for crop signature generation. Supervised classification (such as the ML Classifier) approach is followed for classifying the pixels under a particular crop. The pixel area is multiplied with the number of pixels to obtain the crop area under an administrative boundary. Figure 5 shows an example of mustard and wheat classification using Landsat data.

FIGURE 3. WEEKLY/FORTNIGHTLY COMPOSITE NDVI IMAGES FOR UTTAR PRADESH STATE, INDIA.

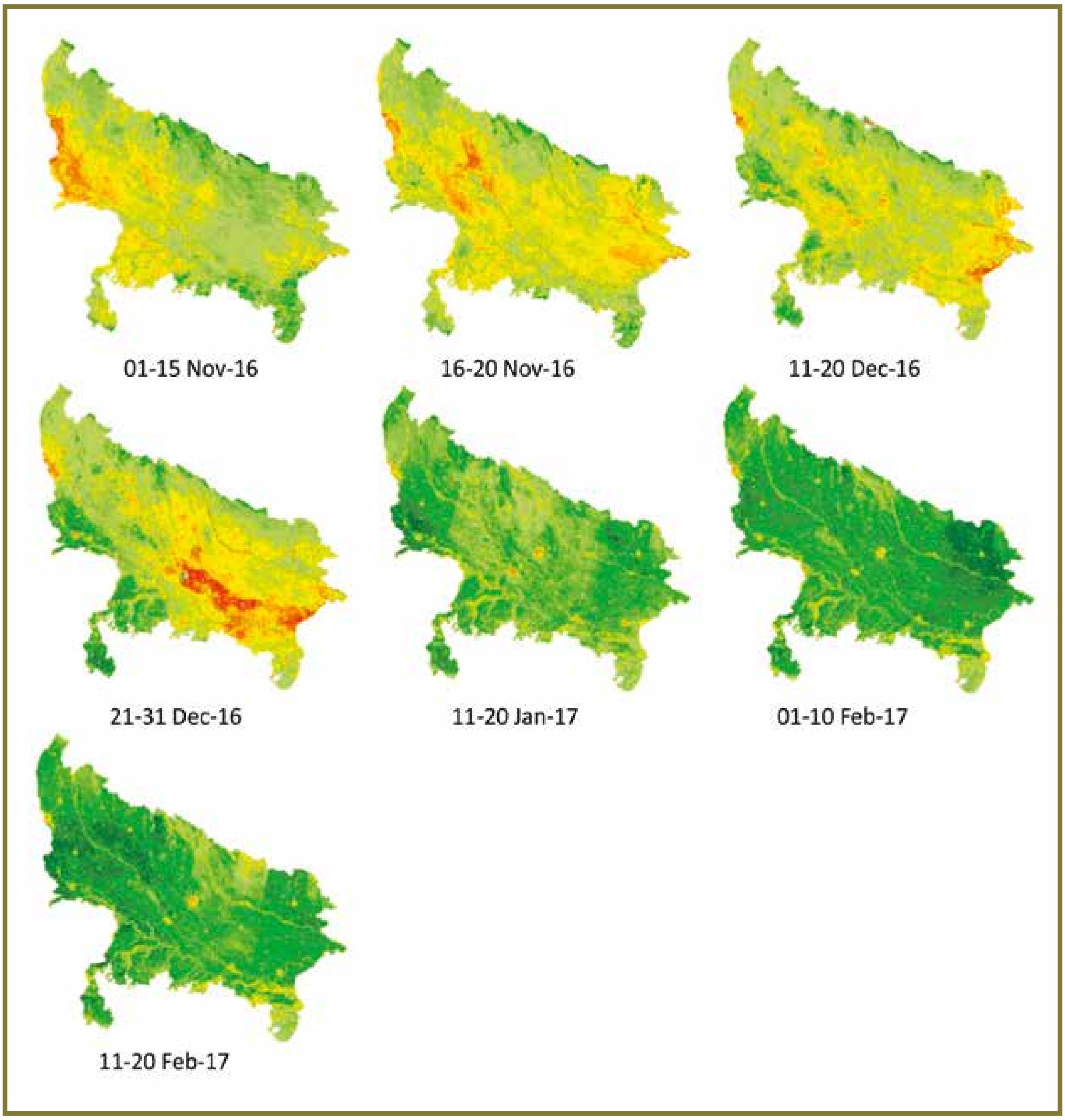


FIGURE 4. TEMPORAL NDVI (SCALED) PROFILE OF VARIOUS CROP CLASSES FOR UTTAR PRADESH STATE, INDIA.

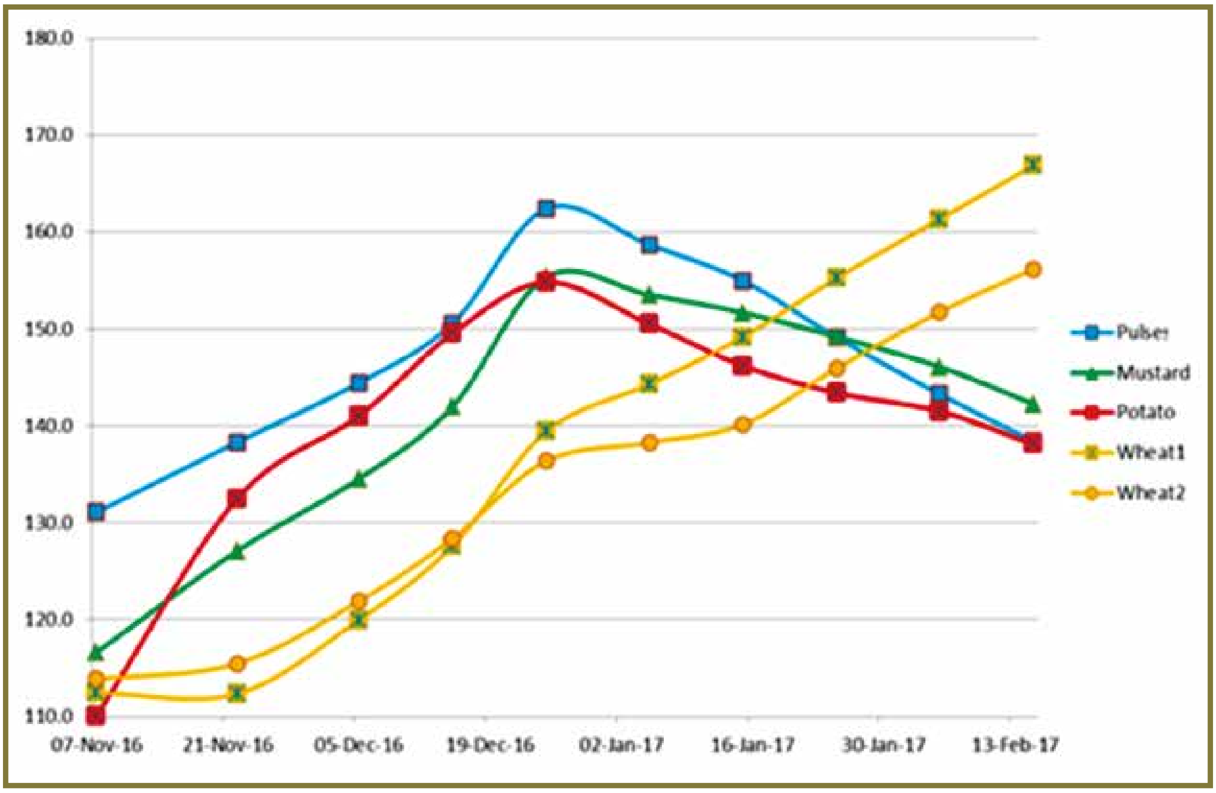
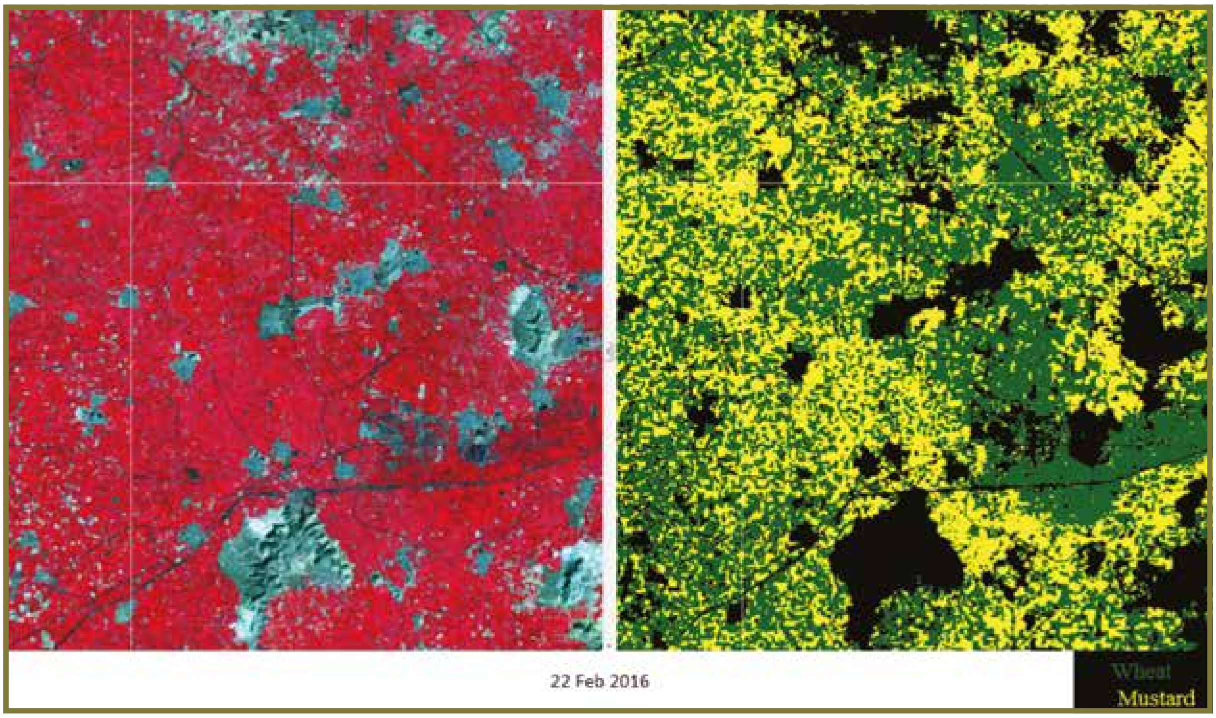


FIGURE 5. LANDSAT FCC (LEFT) AND CLASSIFIED (WHEAT AND MUSTARD, RIGHT) IMAGES FOR BHIWANI DISTRICT, HARYANA STATE, INDIA.PRADESH STATE, INDIA.



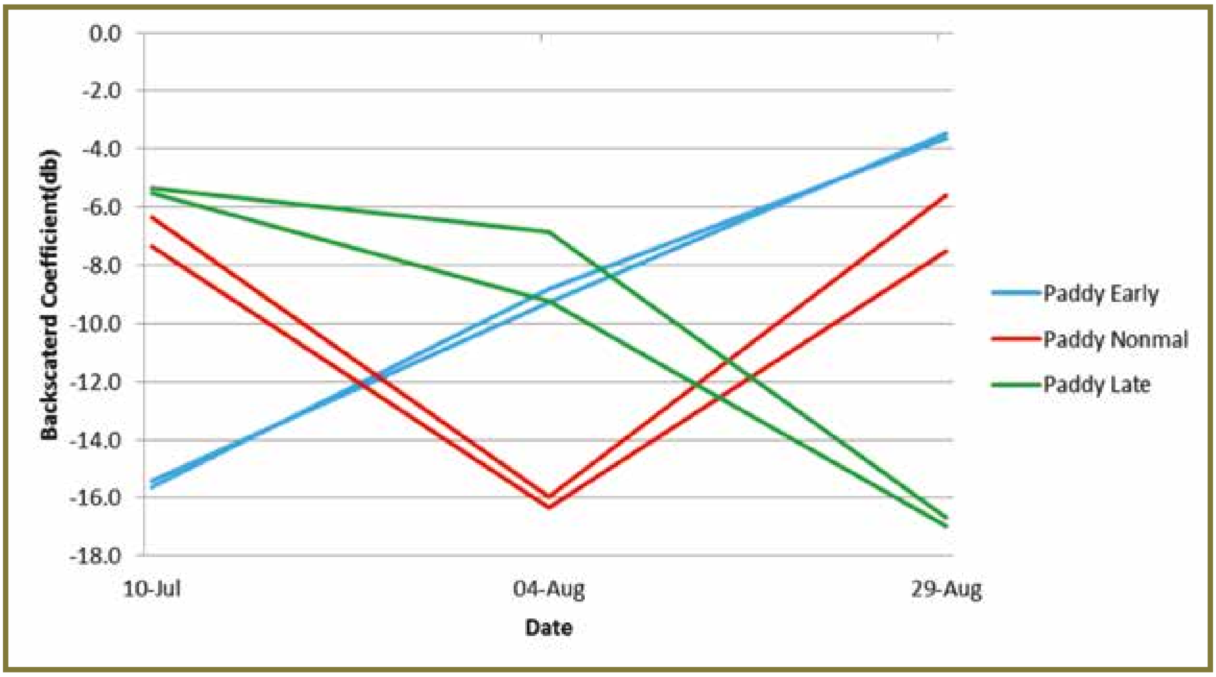
5.2.3. Use of SAR data for crop area estimation

In most South Asian and Southeast Asian countries where paddy rice is grown, it is difficult to obtain optical data during the rainy season (the major rice-growing season) due to persistent cloud cover. The issue of cloud cover can be addressed by using microwave SAR data. SARs are sensitive to surface roughness. Rice is generally grown through transplanting in flooded fields. Freshly transplanted rice plants provide a very low backscatter value due to specular reflection from standing water in the field (Choudhury and Chakraborty, 2006; Suga and Konishi, 2008). As the plant grows and develops tillers, the radar backscatter increases until the plant reaches the reproductive stage. This is due to volume scattering from the vegetation and multiple reflections between the plants and water surface (Chakraborty *et al*., 2006; Nelson *et al*., 2014). Beyond this stage, the radar backscatter remains nearly constant (Chkraborty *et al*., 1997). Therefore, typically, for rice area estimation using SAR data, data from at least three different dates is required: before planting, during planting and after planting, with a gap of approximately 20–25 days between each date.

The general steps for processing SAR data for rice crops are the following:

- Image georeferencing;
- Image calibration and speckle removal using a predefined adaptive low-pass filter;
- Multidate (three dates) image coregistration and data set preparation;
- Conversion of pixel digital numbers to backscatter values;
- Overlaying of ground truth sites and identification of rice sites;
- Development of a decision rule based on the temporal profile of backscatter values for the rice crop (figure 6); and
- Rice crop classification and area estimation.

FIGURE 6. TEMPORAL PROFILE OF VARIOUS RICE CLASSES FOR MIRZAPUR DISTRICT, UTTAR PRADESH STATE, INDIA.



The typical example of decision rule for rice classification is given in the box below.

BOX 2.

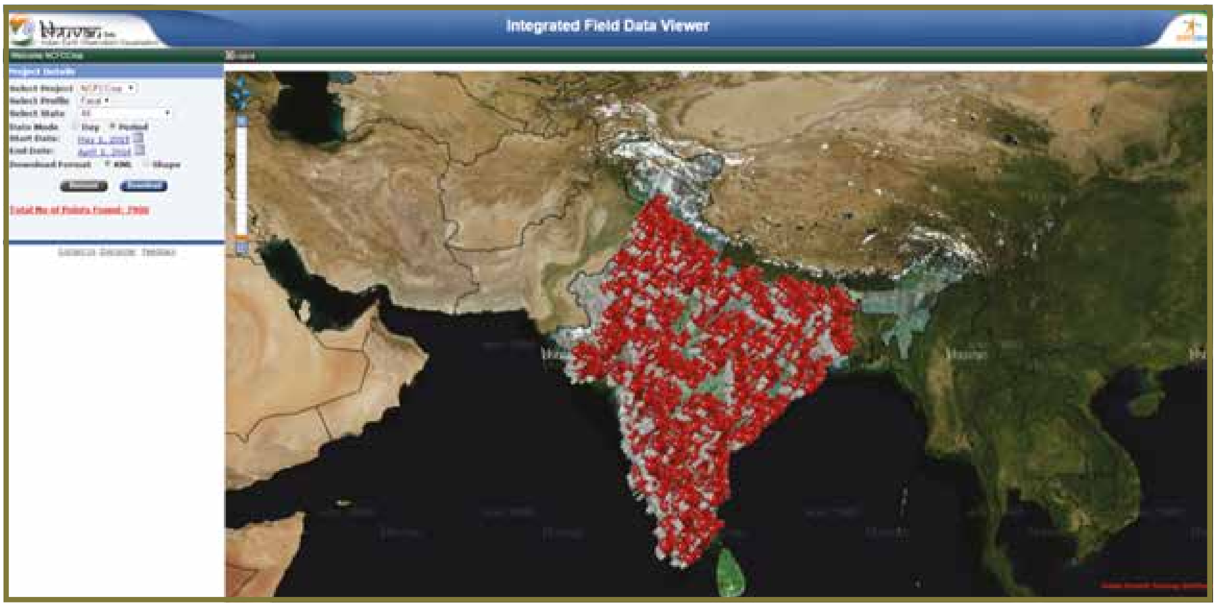
- Urban: L1 > -6.0 AND L2 > -6.0 AND L3 > -6.0
- Water: L1 < -17.0 AND L2 < -17.0 AND L3 < -17.0
- Early transplanted rice: (-18.0 <= L1<=-14.0) AND (-12.0 < L2 <=-8.0) AND (-6.0 < L3 <= -2.0) AND (L2>L1+1.0) AND (L3>L2+1.0)
- Normal transplanted rice: (-10.0 <= L1<=-4.0) AND (-18.0 < L2 <-12.0) AND (-10.0 < L3 <=-3.0) AND (L1>L2+1.0) AND (L3>L2+1.0)
- Late transplanted rice: (-8.0 <= L1 <=-3.0) AND (-11.0 < L2 <-5.0) AND (-18.0 < L3 <=-14.0) AND (L2>L3+1.0)

Where
L1 = Backscatter Coefficient (dB) at first date
L2 = Backscatter Coefficient (dB) at second date
L3= Back scatter Coefficient (dB) at third date.

5.2.4. Ground truth data

Ground truth is an essential component for crop classification, either as an input for building a classification algorithm or as validation of the classification. The ground truth is collected with respect to land use and land cover. Typically, ground truth for crop classification includes geographical location, the village, district or state, the name of the crop, the coverage, the condition, the stage, whether it is irrigated or rainfed, the expected yield, the sowing and harvesting dates, etc., along with two photographs (close view and wide view) of the field. The ground truth is collected from selected sample locations spread over the entire study region, covering all types of diversity. Various Android apps for smartphones have been developed for field data collection. The data collected through smartphones can be uploaded in real time to a central server for use by the analysts working on image analysis. In India, ground truth is collected by officials of the agriculture department of the individual state governments, and is then uploaded to the Bhuvan server (a geoportal of the Indian Space Research Organisation, or ISRO; see figure 7).

FIGURE 7. GROUND TRUTH DATA COLLECTED USING SMARTPHONES, AVAILABLE ON THE BHUVAN GEOPORTAL.



5.2.5. Accuracy estimation: confusion matrix and relative deviation

The confusion matrix, which is also known as the error matrix, represents the visualization of the performance of a classification. In table 4, the two dimensions show the actual or reference class and the predicted or classified pixels in columns and rows respectively. The confusion matrix summarizes the results and enables further inspection of the classification.

Examples of confusion matrices for two classification scenarios (total area of crops and individual crops) are presented in tables 4 and 5 below. In the pilot study conducted in Kazakhstan, Gallego showed that the total area of crops (cereals and fallow) can be estimated by pixel counting with a subjectivity margin of approximately 5 percent, while in India, the individual crop classification accuracy ranged between 70 and 90 percent, with an overall accuracy of 81.09 percent and Kappa statistics of 0.7606. Clauss *et al*. (2016), when mapping paddy rice in China using MODIS time series data, found an overall accuracy of 0.90 and a user accuracy of 0.90 for the no_rice and 0.89 for the rice class.

TABLE 4. EXAMPLE OF CONFUSION MATRIX FOR A PILOT STUDY IN KAZAKHASTAN.

		Reference			
Classification		Cereals + fallow	Grass + abandon	Total	Producer Accuracy
	Crop	1 470 + 152	57	1 679	96.6%
	Grass + abandon	39 + 68	353	460	76.7%
	Total	1 729	410	2 139	
	User Accuracy	93.8%	86.1%		

Source: Gallego, J. 2008. Crop Area Estimation with Remote Sensing: Some considerations and experiences for the application to general agricultural statistics, presentation prepared for the Workshop on measurement of cultivation and production of coca leaves, 25–27 November 2008, Bogotá. Available at: https://www.unodc.org/documents/crop-monitoring/Workshop_coca_leaves/Javier_Gallego1.pdf
Satellite data used: MODIS (250 m resolution)

TABLE 5. EXAMPLE OF CONFUSION MATRIX FOR MADHYA PRADESH STATE, INDIA.

	Reference data									
Classified data	**Gram**	**Wheat**	**Mustard**	**Potato**	**Pea**	**Fallow**	**Settle**	**Lentil**	**Row Total**	**User accuracy**
Gram	153	28	0	3	6	5	2	0	197	78%
Wheat	1	474	62	4	43	2	1	0	587	81%
Mustard	0	56	525	6	27	1	4	2	621	85%
Potato	0	25	28	334	48	0	0	0	435	77%
Pea	0	30	23	11	323	2	2	0	391	83%
Fallow	0	0	3	12	9	102	3	2	131	78%
Settle	3	2	0	1	6	4	112	5	133	84%
Lentil	0	12	9	0	1	0	1	99	122	81%
Column Total	157	627	650	371	463	116	125	108	2 617	
Producer Accuracy	97%	76%	81%	90%	70%	88%	90%	92%	81.09	

Overall classification accuracy = 81.09 %
Kappa statistics =0.7606
Satellite data used: Resourcesat 2 LISS III (23.5 m resolution)

While confusion matrices show the internal accuracy of classification, the accuracy with respect to a standard estimate (such as a ministry of agriculture's estimates) is evaluated using various parameters such as relative deviation, the Root Means Square Error (RMSE) and the correlation coefficient.

In India, the correlation coefficient between remote-sensing-based estimates and Ministry estimates for the state-level area of four crops ranged between 0.986 and 0.999. When mapping paddy rice in China using MODIS time series data, Clauss *et al*. (2016) found a coefficient of determination between 0.91 and 0.93 with the Government's estimates.

5.3. REGRESSION ESTIMATOR

Methods such as regression, calibration and small area estimators combine exhaustive but inaccurate information from satellite images with accurate information on a sample, most often from ground surveys (Gallego, 2006).

Regression estimators are described in standard statistical texts (see for example Cochran, 1963).

The estimator at regional level is (Sud *et al*., 2015):

$$\hat{Y}_R = \sum_{i=1}^{L} N_h \, \bar{y}_{h(Reg)}$$

where $\bar{y}_{h(Reg)} = \bar{y}_h + \hat{b}_h \, (\bar{X}_h - \bar{x}_h)$

$\bar{y}_h$ = average ground-reported crop area per sample segment of stratum *h*, that is

$$\bar{y}_h = \frac{1}{n_h} \sum_{j=1}^{n_h} y_{hj}$$

$\hat{b}_h$ = regression coefficient of ground-reported area on remote sensing-derived area based on $n_h$segments for stratum *h*

$\bar{X}_h$= average remote-sensing-based area for all frame units of stratum *h* (thus, the entire area must be classified to obtain this mean of the population, namely,

$$\bar{X}_h = \frac{1}{N_h} \sum_{j=1}^{N_h} X_{hj})$$

$\bar{x}_h$= average remote-sensing-based crop area per sample segment of stratum *h*,

$$\bar{x}_h = \frac{1}{n_h} \sum_{j=1}^{n_h} x_{hj}$$

Many countries, such as the United States of America, Brazil and China, use a regression estimator for crop area estimation from remote sensing data. FAO (2017) followed a hybrid approach based on the integration of the area frame with image classification to enhance the accuracy of crop statistics. This approach was followed for rice area estimation in Afghanistan. The area frame was developed using satellite imagery from Sentinel-2 and SPOT-5 (having a spatial resolution of 10 m). The agricultural land within the pilot project area was stratified and systematic random segments were visually interpreted together with the ground information to estimation the crop statistics based on the area frame. Visual interpretation of the satellite imagery was used as a training sample in the supervised image classification algorithm to extract the pixel based crop estimates. The R2 in the linear regression in the variables of rice pixels and rice area in segments was 0.96. This showed a very high accuracy between these two systems.

In China, under the CAERSS project, crop area is estimated using a similar approach. First, by using multisource and multitemporal remote sensing, an area frame is constructed and updated for crop sample design. Second, a strategy for sample selection is developed to conduct a reasonable stratification and to select samples to be surveyed as ground truth. Finally, combining the ground survey data with the classified grain acreage from remote sensing imagery as auxiliary data, a linear model is adopted to produce the crop acreage estimation with satisfactory precision. The planted acreage estimation for major crops at provincial and county levels are thus generated. More details on the methodology and procedure are given by Zhou (2013). The CV of estimates by linear regression for three major crops (corn, rice and soybean) ranged between 4.2 percent and 7.0 percent.

5.4. CALIBRATION ESTIMATOR

Calibration estimators incorporate auxiliary information, represented by remotely sensed data, into the estimation process (Benedetti *et al*., 2015). The commission and the omission errors of a confusion matrix can be used to correct the bias. Stehman (2009) indicated that the reference information from a sample used to construct the confusion matrix can also be used to infer the area of the target, directly or via model-assisted inference. The direct estimator and inverse estimator are two approaches that utilize the confusion matrix to adjust the pixel count area. The difference between these two estimators is that the former employs the user's accuracy, and the latter employs the producer's accuracy. The main note of caution is that the confusion matrix must be computed using ground information on a statistical sample of points or segments (area elements) and that the extrapolation is correctly made, taking into account the sampling plan (Gallego *et al*., 2008).

To improve the accuracy of area estimation from classification, Zhu *et al*. (2014) explored the performance and stability of several model-assisted estimators. They used the confusion matrix calibration direct estimator, the confusion matrix calibration inverse estimator, the ratio estimator and the simple regression estimator to infer the areas of several land cover classes, using simple random sampling without replacement. Their comparison showed that confusion matrix calibration estimators, ratio estimators and simple regression estimators were capable of providing more accurate and stable estimates than the simple random sampling estimator.

5.5. SMALL AREA ESTIMATOR

Small area estimation is important in survey analysis when domain (subpopulation) sample sizes are too small to provide adequate precision for direct domain estimators. In remote-sensing-based estimates, the accuracy may be good for large areas (country and states or provinces), because of the higher sample size; however, this may not be the case for smaller areas (districts or counties). To improve the accuracy of estimation for smaller areas, the Small Area Estimation (SAE) technique is followed. Various alternative methodologies have emerged to carry out the SAE; these can be grouped broadly into statistical approaches and spatial microsimulation approaches, each with multiple differing approaches within them (Whitworth, 2013). The statistical approach is based on the regression model that enables the relationship between a characteristic of interest and explanatory variable(s) to be formally assessed. Zhou (2016) used a combination of crop classification from satellite images with field survey data and SAE techniques to generate county- and town-level estimations of rice and corn.

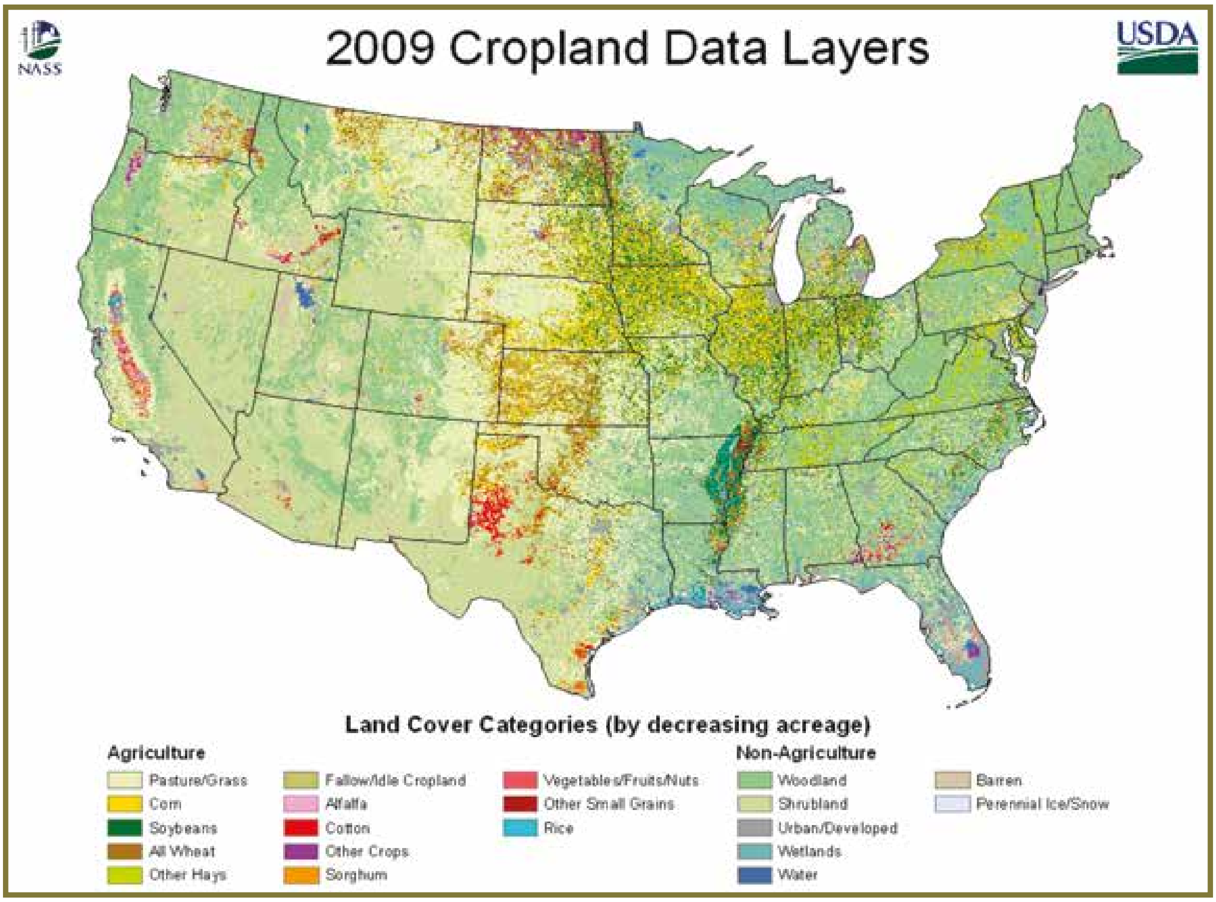
5.6. EXAMPLES OF NATIONAL, REGIONAL AND GLOBAL CROP AREA ESTIMATION PROGRAMMES

5.6.1. National-level programmes

5.6.1.1. USDA/NASS's CDL

The USDA/NASS provides timely, accurate and useful statistics for agriculture in the United States of America. The NASS conducts a large number of surveys to collect information about various aspects of agricultural activity. In 2010, the NASS CDL Program played an important role towards fulfilling this mission, using remote sensing techniques to provide operational in-season acreage estimates to the NASS Agricultural Statistics Board (ASB) and Field Offices (FOs) for 27 states and 16 crops (Baily and Boryan, 2010). The NASS has experimented with many pioneering programmes, including LACIE and AgRISTARS, to show the use of remote sensing data for crop acreage estimation. The NASS started the CDL programme in1997, with in-house software and Landsat data. In 2006, the CDL underwent a major change, with the introduction of the use of commercial software and Resourcesat 1 AWiFS data. The CDL product is a raster-formatted, georeferenced, crop-specific, land cover map (Boryan *et al*., 2011). In 2009, the CDL program played an important role towards providing operational in-season acreage estimates for 15 crops in 27 states. Boryan *et al*. (2001) provide an overview of the CDL program, describing various input data, processing procedures, classification and validation, accuracy assessment, CDL product specifications, dissemination venues and the crop acreage estimation methodology. Using the CDL as the foundation, NASS runs a regression estimator to produce crop acreage estimates.

FIGURE 8. 2009 CROPLAND DATA LAYERS.



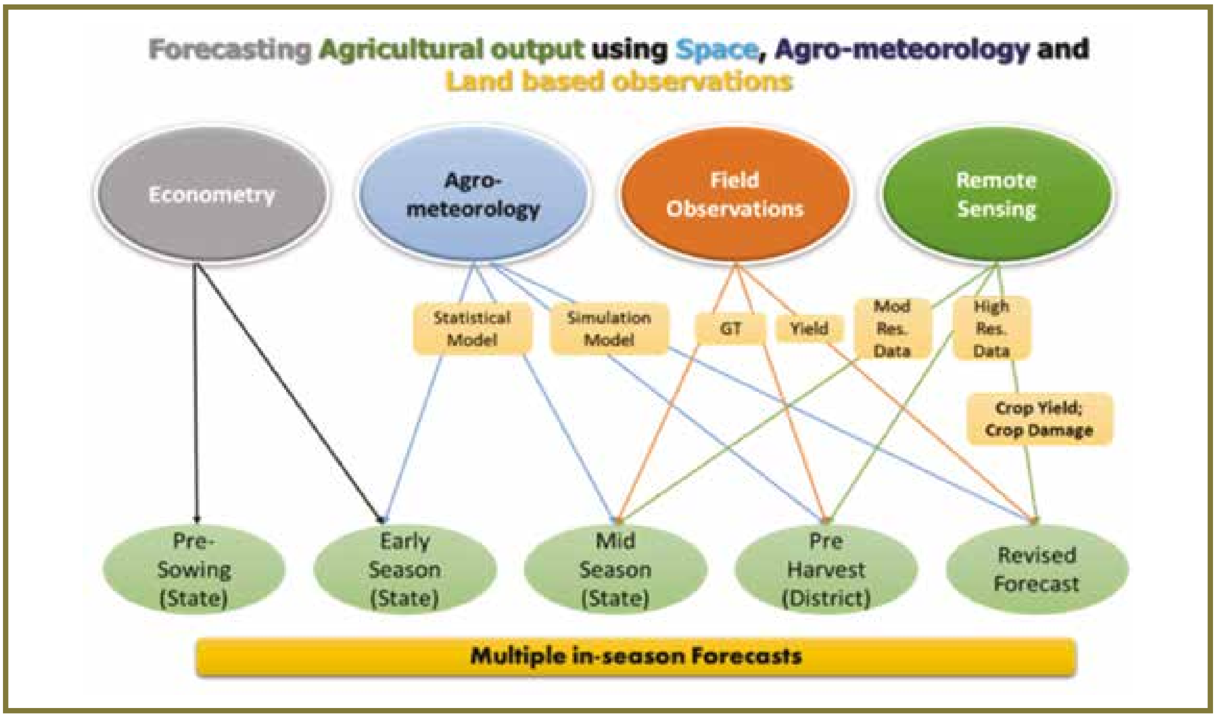
Source: USDA/NASS. (https://nassgeodata.gmu.edu/CropScape/)

5.6.1.2. India's FASAL programme

In India, crop estimation using remote sensing data started in the late 1970s, with a systematic study on crop inventory using Colour Infrared (CIR) aerial data carried out jointly by the ISRO and the Indian Council of Agricultural Research (ICAR) under the Agricultural Resource Inventory and Survey Experiment (ARISE) project (Sahai *et al*., 1977). Subsequently, many experimental studies were conducted using airborne data and, later, Landsat-1 data. These early studies using aerial and Landsat data are documented in Bhavsar (1980), Navalgund and Sahai (1985) and Sahai and Dadhwal (1990). With the launch of IRS 1A, a major national-level programme was launched for Crop Acreage Production Estimation (CAPE), under which the area and production estimation of major crops in district and state level was carried out. The research studies carried out under the CAPE programme helped to develop an optimum sampling plan, sensor specifications, accuracy figures, an optimum analysis procedure and in-house software for crop assessment (Dadhwal *et al*., 2002). Simultaneously, methodologies were developed for using SAR (initially from ENVISAT and later from Radarsat) data for rice area estimation, to overcome the problem of cloud cover during kharif (rainy season) (Patel *et al*., 1995; Panigrahy *et al*., 2000). Based on the experience gained under the CAPE project and various other pilot studies carried out, and on the requirements of the Indian Ministry of Agriculture, a comprehensive crop inventory project was developed – the FASAL programme.

The FASAL programme, which was officially launched in 2007, aimed at providing multiple pre-harvest district-, state- and national-level production forecasts using multiple approaches (econometric, remote sensing and agrometeorological), multiple satellite data (optical and microwave) for 11 major crops of the country (Parihar and Oza, 2006). After the methodologies were developed and optimized for crop production forecasting at the ISRO's Space Applications Centre, the programme was operationalized at the MNCFC, which was established under the Ministry of Agriculture (Ray *et al*., 2015). The approaches followed in FASAL for crop production forecasting are illustrated in figure 9.

FIGURE 9. APPROACHES FOLLOWED FOR CROP PRODUCTION FORECASTING UNDER THE FASAL PROJECT.



The methodology adopted by FASAL for area estimation uses remote sensing data to: (i) design the sampling plan and (ii) to generate estimates through image classification, using single-date high-resolution data or multidate medium-resolution data. For rice and jute, RISAT-1 SAR data is used, while for other crops (wheat, rapeseed and mustard, sorghum, cotton, and sugarcane) Resourcesat-2 AWiFS, LISS III, Landsat OLI or Sentinel 2 MSI data are used. The rice and jute crops are analysed using a sample segment approach with a 5 x 5 km sample size and a 15 percent sampling fraction with four strata (the stratification is based on crop coverage in each segment). For other crops, a complete enumeration approach is followed. The ground truth data is collected using smartphone-based Android apps. The yield is estimated using agrometeorological models (empirical and crop simulation), remote-sensing-based models and sample crop cutting experiment (CCE) data, where the CCE is done using a remote-sensing-based sampling plan. The estimates generated under the FASAL programme form one of the inputs for generating the final estimates of the MA&FW. A detailed discussion on the approach, results and accuracy of estimates of the FASAL programme is available in Ray *et al*. (2016). Based on the success of remote-sensing-based crop production, the MA&FW has launched a new programme for the Coordinated Horticulture Assessment and Management using geoinformatics (CHAMAN), for the inventorying of horticultural crops (mango, banana, citrus, potato, tomato, chilli and onion) and horticultural developmental planning (Ray *et al*., 2015).

5.6.2. Regional programmes

5.6.2.1. The EU/JRC's MARS Programme

The MARS project was conceived to develop large-scale operational tools in the field of agricultural information for satellite image analysis and related fields, such as area frame sampling and agrometeorological models (Gallego, 2000). In the first period of the MARS project (1988–97), crop area estimation played a central role and envisaged two major components: (1) regional crop inventories and (2) rapid estimates of crop area change at EU level. Gallego (2000) summarizes the progress made during this period. The regional crop inventories combined high-resolution satellite images and ground surveys in a classical statistical scheme based on area frame sampling and ground visits, providing the main estimation variable through a regression estimator. The rapid estimates of crop area change attempted to provide an early estimate of crop area change at EU level on the basis of a sample of 60 sites of 40 x 40 km each, without ground information. Both programmes were later abandoned, the first because it had almost reached the cost-efficiency threshold and the second due to its wide margin of subjectivity.

Currently, the MARS's AGRI4CAST sampling programme focuses on the Land Use/Cover Area-frame Survey (LUCAS) (Gallego and Delincé, 2010). Estimates of the area occupied by different land use or land cover types are computed on the basis of observations taken at approximately 2,70,000 points sample points throughout the EU, rather than mapping the entire area under investigation. By repeating the survey every few years, changes to land use can be identified[1]. LUCAS is a two-phase systematic stratified sampling process: in the first phase, the sample is photointerpreted; in the second phase, field data is collected from the samples. The latest LUCAS survey was carried out in 2012 in 27 EU countries, where total crop land constitutes 24.7 percent of the total area.

1 http://esdac.jrc.ec.europa.eu/projects/lucas.

5.6.3. Global programmes

5.6.3.1. CropWatch (China)

CropWatch was developed by the Institute of Remote Sensing and Digital Earth (RADI) of the Chinese Academy of Sciences (CAS). CropWatch has four assessment levels: global (65 homogeneous crop Monitoring and Reporting Units MRU); regional (seven Major Production Zones or MPZs); national (31 key countries); and subnational (subdivisions of nine large countries) (Wu *et al*., 2015). Different indicators are selected at different levels to best characterize the environmental and agricultural information at the corresponding scale. The various indicators used at different levels of assessment include rainfall, air temperature, photosynthetically active radiation, agroclimatic biomass production potential, cropping intensity, cropped arable land fraction, vegetation health index, maximum vegetation condition index and crop type proportion. CropWatch adopts different crop area estimation methods for different countries. For China, remotely sensed estimates of arable land area and Cropped Arable Land Fraction (CALF) are combined with field-survey-based estimates of crop type proportion (Wu and Li, 2012).

For other 30 key countries and provinces or states of nine large countries, CALF is used to estimate individual crop area using the following equation:

$$Crop\ area = a \times b \times CALF$$

where *a* and *b* are linear regression coefficients between the cropped area from FAOSTAT or, preferably, subnational data when available from the website of China's Ministry of Agriculture or National Bureau of Statistics.

5.6.3.2. USDA FAS (United States of America)

The USDA FAS provides monthly crop condition assessments, monitoring and crop estimates for 17 global commodities; 159 countries; 1 020 country-crop pairs (for example, Australia-Wheat); and three attributes: area, yield and production (Hoffman, 2016). FAS uses various information, such as satellite imagery, attaché reports, crop travel, official data and news reports to conduct global crop assessment and monitoring. The USDA FAS uses data from eight of 18 of NASA's Earth Observing fleet. FAS uses additional satellites from the European Space Agency (ESA), ISRO and private organizations. The FAS Crop Explorer Web Portal displays numerous weather and vegetation condition data sets over major crop regions every ten days.

5.6.3.3. GEOGLAM

Following the global food price hikes in 2007–2008 and 2010, as part of the Action Plan on Food Price Volatility and Agriculture, the heads of state of the G20 countries endorsed, in their 2011 Declaration, both the GEOGLAM and the Agricultural Market Information System (AMIS) initiatives. GEOGLAM provides a framework that strengthens the international community's capacity to produce and disseminate relevant, timely and accurate forecasts of agricultural production at national, regional and global scales through the use of Earth Observations (EO), including satellite and ground-based observations . Within this framework, GEOGLAM developed the Crop Monitor reports, which provide global crop condition assessments in support of the AMIS market monitoring activities[2]. Asia-Rice is the work of an ad hoc team of stakeholders with an interest in the development of an Asian Rice Crop Estimation & Monitoring (Asia-RiCE) component for the GEOGLAM initiative. In Phase 1 (2013–2015), Asia-Rice developed Technical Demonstration Sites (TDSs) in Chinese Taipei, Indonesia, Japan, Malaysia, Thailand and Viet Nam. Phase 2 of Asia-RiCE is intended to prepare rice growth outlooks for Indonesia, the Philippines, Thailand and Viet Nam, and provide them to AMIS (Asia-Rice, 2016).

2 https://cropmonitor.org/.

5.7. COST-EFFECTIVENESS OF REMOTE-SENSING-BASED AREA ASSESSMENT

Analysing the cost-effectiveness of a system requires its comparison with the cost that would be required pursuant to the use of alternative systems (such as traditional agricultural data collection systems) to achieve the same end result (Radhakrishnan *et al*., 1991). For remote-sensing-based area estimation, the costs include satellite data cost, ground truth collection cost and analysis cost. The benefits may consist not only in direct cost savings (achieving the same estimate in the reduced cost), but also in the improving the timeliness and accuracy of estimates. The accuracy can be assessed in terms of reduction in variance and increases in efficiency (for sampling designs using remote sensing). According to Carfagna (2001), the cost-effectiveness of remote sensing for agricultural statistics has long been debated and depends on several parameters, such as the level of fragmentation of the landscape, the weather conditions, the level of optimization and automation of the project, and the cost structure. Thus, different results have been obtained in different experiences.

Delincé (2015) has studied in detail the cost-effectiveness of the remote-sensing-based agricultural statistics of four national systems. These include Haiti (point area frame sampling), Morocco (area frame sampling), China (area frame sampling and regression analysis) and India (area frame sampling and pixel counting). His findings may be summarized as follows:

- For Haiti, the CNIGS's point frame survey was analysed. The cost of stratification reflected the increased field survey costs of 3 percent; however, decreases in the variances of as much as 50 percent at regional level were obtained.
- In Morocco, the stratification based on land-cover maps of 66 000 km2 derived from expensive SPOT imagery increased annual survey costs by 30 percent. However, in view of the efficiencies obtained, the investment is worthwhile.
- In China, remotely sensed stratification covered 1.65 million km2. The cost increase was only 3 percent, but in Anhui province, relative stratification efficiencies of 2.8 for rice and 1.4 for corn were obtained.
- In India, radar and optical imagery is used to monitor 90 percent of the production of the eight major crops. A stratification efficiency for rice between 1.2 and 3.3 was achieved, and bias induced by pixel counting could be evaluated.

For USDA/NASS, which runs most important operational applications based on area frame surveys and remote sensing for agricultural statistics, the cost-efficiency analysis has yielded positive conclusions (Carfagna, 2013). According to Carfagna (2013), "remote sensing applications to agricultural statistics can be sustainable if their total cost fits in the budget without endangering the feasibility of surveys that cannot be substituted by satellite technology".

However, considering the availability of a great volume of free satellite data (from Landsat, Sentinel, etc.) and the significant reduction in the prices of Indian satellite data, the cost-effectiveness of remote sensing for crop statistics dramatically improves.

5.8. ISSUES AND LIMITATIONS

MacDonald and Hall (1980), while providing a summary of LACIE, wrote that "[a]gricultural information should have the qualities of objectivity, reliability, timeliness, adequacy of coverage, efficiency and effectiveness. Production statistics in many important agricultural countries do not meet any of these standards". This may remain true in many countries today. Although – as seen in the examples shown above – remote sensing data from various satellites have been successfully used for different components (area sampling plan design, estimation by classification or regression) of agricultural statistics collection, there are still many issues which limit the use of remote sensing data for operational crop area assessment. These include:

- Small field size, especially in many countries in Asia and Africa (table 6), which requires high-resolution remote sensing data for crop identification.
- Persistent cloud cover during rainy season. Clouds strongly limit the usefulness of optical imagery for agricultural applications (Eberhardt *et al*., 2016). SAR data is required to overcome the cloud problem. However, the usefulness of SAR data for estimation of crops other than rice is yet to be established.
- Diverse cropping and agronomic practices.
- Mixed and intercropping systems.
- Large varieties of crops grown in a small area, which occurs especially in the context of horticultural crops.

Other technical issues arising in the analysis and use of remote sensing data include the availability of sufficient amount of quality ground truth data describing the variability existing in the field; the computing power, sophisticated software and data storage facilities required to analyse multitemporal high-resolution data; and the availability of satellite data with a low turnaround time.

Despite these issues, several studies have demonstrated the cost-efficiency of using remote sensing data for area estimation (Delincé, 2015; Gallego *et al*., 2014).

With the current and proposed availability of many high-resolution remote sensing satellite constellations, the temporal frequency of satellite data and classification accuracy are expected to increase. There is a need to develop methodologies for the use of SAR data in the area estimation of crops other than rice.

Various opinions have been expressed as to the methods to be used for area estimation, that is, the regression estimator or pixel counting. Carfagna and Gallego (2005) maintain that at the estimator level, classified satellite images should be used as auxiliary variables in a regression estimator or for estimators based on confusion matrices. They also mention that in general, classified or photointerpreted images should not be directly used to estimate crop areas because the proportion of pixels classified into specific crops is often strongly biased.

However, for many applications, in addition to crop area, classified crop maps are also essential, such as for planning CCEs for crop yield. Furthermore, qualified staff are required if better execution for regression-based estimation needs is to be assured; however, such staff are not necessarily available, even in many official organizations (Gallego, 2006). Craig and Atkinson (2013) opined that pixel counting estimates consistently underestimate the actual area under crop, a problem that can be remedied through regression. Therefore, it is necessary to adopt an integrated approach, which is a combination of sampling frame design, pixel counting and regression.

TABLE 6. AVERAGE SIZE AND FRAGMENTATION OF AGRICULTURAL HOLDING, 1995–2005.

Countries by continent (Number of reporting countries is given in parenthesis)	Average area per holding (hectare)	Average number of parcels per holding
World Total (114)	5.5	3.5
Africa (25)	11.5	3.0
America, North & Central (14)	117.8	1.2
America, South (8)	74.4	1.2
Europe (29)	12.4	5.9
Asia (29)	1.0	3.2

Source: FAO, 2010.

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