

# REMOTE SENSING FOR CROP AREA ESTIMATION

## Abstract

Remote sensing satellites aid in area estimation of agricultural and horticultural crops through various classification methods with the help of ground observed data. The estimated area can be verified with ground observations collected earlier.

**Keywords:** Crop area estimation, Classification methods, Accuracy and validation

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## **I. INTRODUCTION**

Sustainable resources management and planning requires crop monitoring and area estimation. The need for real-time and reliable, accurate information is much needed for the present developmental condition in our country. Diligent and robust details on crop acreage and performance for conceptual and operational verdict is the need of the hour by all contributors in agriculture and horticulture,

## **II. NEED FOR CROP AREA STATISTICS**

Precise crop statistics are necessary for policy-makers, economy assessment of farming community, evaluation and planning of agricultural investments for improvement of production, thereby increasing profit for all scales of farmers. The challenge in area estimation includes diverse cropping conditions in small-scale farming region. Out of various methods, area estimation through remote sensing techniques is likely suitable for entire farm and village scale with no sampling error and bias in conversion units.

The role of agricultural / horticultural crops in the Indian economy, employment, self-reliability, food security, and general well-being has undoubtedly been vital and always has taken centre stage.

Identifying and mapping crops is essential for several reasons.

1. With the universal shift in the market financial prudence, reliable information on crop areas has added reputation than ever before.
2. Crop area estimation helps estimate a particular crop cultivated in an area to support the crop forecasting system at a regional level.
3. Agricultural / horticultural crops usually face fluctuation in production and consumption. Hence, genuine statistics concerning the area and production are necessary for market planning and export.

Such data are inevitable for private and government sector firms, policy-making agencies for monitoring trends in data and assessment of deterministic factors in crop production [7]. Minor magnitude of errors results in biased output, and miscalculation of agricultural productivity.

## **III. CONVENTIONAL METHOD VS REMOTE SENSING APPROACH FOR AREA ESTIMATION**

The conventional method of estimating crop acreage by traditional ground truth survey is costly, labour-expensive and time-consuming. The introduction of remote sensing technology into crop acreage estimation using satellite data has proven reliable and efficient in collecting necessary information. In addition, remote sensing based acreage estimation provides detailed structural information in real-time crop health status with higher accuracy. National and multinational crop agencies, insurance agencies and regional boards involve in creating maps of specific crops to prepare an index of crop area with temporal and spatial variability.

The conventional statistical methods of collecting data cannot always meet the requirements as it involves human resources, high cost and sometimes biased

#### IV. SATELLITE DATA FOR CROP AREA ESTIMATION

Remote sensing has the room for cost-effective accurate guesstimates of the crop area. The launch and continuous convenience of multi-spectral (visible, near-infrared) sensors on polar-orbiting earth observation satellites (LANDSAT, SPOT, IRS, etc..) make Remote Sensing informative. Remote Sensing (RS) information has become a vital tool for space and yield assessment. It can provide a timely, accurate, synoptic, and objective measure of crop identification, crop observance, and area estimation. Owing to the benefits of high periodic resolution, wide-coverage and low cost, remote sensing has been utilized in many earth observation tasks and supplements as an excellent tool for crop identifying and planting area observance at an outsized scale

**1. Optical data:** The Optical remote sensing systems use reflectance of the objects in the electromagnetic spectrum of visible and infrared regions. Optical images have been used for crop mapping studies as the bio-physical characteristics remain varying in vegetative stages [2]. In semi-arid conditions, irrigated land has been successfully monitored by the optical data as there was no hindrance to the sun's energy during the entire crop growth stages [5]. Hence, the cloud-free optical data required during the crop growing season is indispensable [11]. But the technical encounters viz., cloud cover all through the cropping time of year, wide range of milieus, small land affluences, and sundry and mixed cropping systems restricts the use of optical remote sensing as a device for crop monitoring.

Among various forms of satellite data, optical remote sensing data with higher resolution are preferred for crop delineation and acreage estimation due to the capability of interacting directly with the object under investigation. The surface reflectance of object under the visible and infrared region of the electromagnetic spectrum is resultant from the characters of the object, thereby exhibiting different reflectance patterns during different growth stages pertinent to their bio-physical characters like moisture, canopy cover, leaf area, chlorophyll content [2]. The information embedded within the spectral reflectance of an object can be extracted using different classification methods.

**2. SAR Data:** Synthetic Aperture Radar (SAR) imagery is a hopeful choice to overcome cloud cover and potential in delivering data in all situations. European Remote Sensing Satellites (ERS) 1&2, RISAT from ISRO, COSMO-SkyMed from the Italian space agency and Sentinel-1 from the European Space Agency are some of the Space-borne SAR systems which have the potential for diverse applications in agriculture with unrestricted observation capability. SAR data acquires both single and cross-polarization in the same swath, which has the latent to retrieve different crop information simultaneously.

For the former two decades, incredible progress in SAR application for crop mapping has been reported. Experts worked with combination of different SAR bands with different polarization to recognize crop and estimate acreage. Agricultural targets have complex scattering mechanisms which will be either a direct backscattering from the

plant components or direct from soil/underlying ground or double-bounce backscattering from soil and plant components or the multiple backscattering from the ground, vegetation, and ground.

- 3. Data Integration:** To extend the accuracy of crop recognition and spatial approximation, we need to possess a much recovering knowledge of the crop and primary soil features that impact the measuring instrument to break up throughout the season and establish acceptable methodologies to extract crop data [6].

Due to the distinction in imaging and knowledge gratified, information from optical and SAR-based measuring device systems are unit complementary. Many revisions have shown that desegregation information from the two bases, expands classification exactitudes over the employment of either one. The combination of two SAR images and one optical image can be integrated for crop mapping while the absence of periodical optical images [8].

## V. GROUND DATA FOR SATELLITE DATA

Ground truth surveys aids in assembling land cover information to validate crop area estimates derived from satellite data. Date of ground observations should match the image acquisition date, and it includes latitude and longitude from handheld GPS receivers, descriptions of the area and object, photos of the field's grade, plant height, and crop stage. Following the random stratified sampling procedures, the details on land cover information are collected.

## VI. CROP-BASED STRATEGY FOR IMAGE CLASSIFICATION

Classification is most followed strategy for extracting information from Remote sensing imagery. The information from the classified image is depicted thematically for better and easy visual interpretation. The classification process is not limited to area estimation. Several other properties of classes can be interpreted based on user's interest.

Classification approaches were developed like Unsupervised classification, Supervised classification based on several factors like dataset, interest, etc.

- 1. Unsupervised classification:** As the name suggests, unsupervised classification involves classification of image based on spectral belongings of the image (pixel). The algorithm itself classifies the image based on spectral properties, provided the number of classes the image to be classified is predefined by the user. The analyst then assigns the classified data into each class based on prior knowledge or ground data whichever is familiar. Frequently used algorithms are K-means algorithm, ISODATA clustering (Iterative Self-Organizing Data Analysis Techniques).
- 2. Supervised classification:** Here, the image is classified based on the analyst's point of view. An entire image is classified based on fewer training sites developed using ground observation data. The algorithm then uses spectral characters from these training sites for classification of the entire image.

For example, in an image of 100,000 pixels (250x400), training sites are developed using 600 pixels of the same image. The algorithm then uses the pixel characters from these 600 pixels to classify the complete image.

Few supervised classification techniques which can be used for area estimation studies are discussed below.

- **Maximum-likelihood classification:** Maximum-likelihood classification is the most commonly used classification methodology for remote sensing imagery. In Supervised classification, various pixel values or spectral signatures will be specified as each class with the help of training sites. These training sites are the representative sample sites of the known land cover type. The computer algorithm uses spectral characters from these training sites to classify the image. Preferably, the classes should not intersect or should intersect negligibly with supplementary classes.

Maximum Likelihood Classification (MLC) algorithm quantitatively assesses the variance and covariance of the class by discriminating reflectance pattern while categorizing an unfamiliar pixel value. The distribution of a training class can be described by the mean vector and covariance matrix based on an assumption that the dispersal of the training set is Gaussian. By these boundaries, we may figure out the statistical possibility of a given pixel being associated to a particular class [10].

Maximum likelihood classification considers that the statistics for each class are normally distributed and calculates the possibility of a given pixel that belongs to a specific class. Individual pixel is assigned to the class with maximum possibility. If the maximum possibility is smaller than a threshold to specify, the pixel is assigned as uncategorized.

- **Parametric classification:** Parametric classification is where there is an assumption that the data set is normally distributed, thus prior knowledge of class density function is considered known. The act of a parametric classifier rests largely on how well the data matches the pre-defined models and on the exactness of the estimated model parameters. The method may not sufficiently integrate ancillary data as in fuzzy classification or non-parametric classification [3].
- **Object-based classification:** Per-pixel classification is less preferred for high-resolution imageries, due to large information content. The increased variability in more detailed satellite images will reduce the classification accuracy. Unlike maximum-likelihood classification, Object-based classification does not use single pixel for statistical analysis. Out of several segmentation techniques, multi-resolution technique is extensively used to delineate clusters of homogeneous segments of the image is known as objects. The objects result from spatial segmentation of images based on their geometrical extents like shape, texture, geographic context and spectral properties.

The homogeneous characterized objects are used as training areas with the ground truth points. The machine-learning algorithm of Random Forest increases the accuracy of the regression analysis and overcomes the limitations of decision trees and classifies with less configuration of classification parameters.

## VII. ACCURACY AND VALIDATION

The Error matrix and Kappa statistics were used for exactness and validation purpose of the predicted area. The class of each pixel in the classified image was equated with matching class on reference data (ground truth data) to estimate the precision measures. The pixels that match and does not match with reference data were assembled in the form of an error matrix, where the rows and columns characterize the number of all classes and elements of the matrix represent the number of pixels in the testing dataset (combination of true positive (TP), false positive (FP), true negative (TN), and false negative (FN)) [4]. Various accuracy measures, such as overall accuracy, producer's accuracy, and user's accuracy, were estimated from the error matrix [1].

The overall accuracy of the classification methodology can be calculated from perfectly categorized cases in crosswise as follows:

$$\text{Overall Accuracy} = \frac{\Sigma(\text{Positively categorized elements in crosswise})}{\text{Total number of elements}}$$

The producer's accuracy (omission error) of individual class can be calculated by dividing the number of elements that are positively categorized by its total number of reference samples as follows:

$$\text{Omission Error} = \frac{\text{Total number of positively categorized elements in a column}}{\text{Total number of reference elements in that column}}$$

The user's accuracy (commission error) of each class can be calculated by dividing the number of elements that are positively categorized by the total number of samples that were verified as belonging to the class as follows:

$$\text{Commission Error} = \frac{\text{Total number of positively categorized elements in a row}}{\text{Total number of reference elements in that row}}$$

## VIII. KAPPA COEFFICIENT

Kappa coefficient is the degree of proportional (or *percentage*) enhancement by the classifier over a purely arbitrary assignment to categories. This directly describes the classification accuracy level [9].

The kappa coefficient is valued from the following formula for an error matrix with r number of rows and columns.

$$\hat{K} = \frac{NA - B}{N^2 - B}$$

**where,**

A = the sum of positively categorized elements

B = sum of the r products (row total x column total)

N = total number of pixels in the confusion matrix (the sum of all individual cell values)

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