**Remote Sensing for crop area estimation**

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**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**

**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. Timely and consistent information on crop area and production for tactical and strategic decision making is the need of the hour by all stakeholders in agriculture and horticulture, *viz.,* producers, processors, resource managers, marketing, finance and the government.

**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.

i) With the global shift in the market economies, reliable information on crop areas has gained more importance than ever before.

ii) Crop area estimation helps estimate a particular crop cultivated in an area to support the crop forecasting system at a regional level.

iii) 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

**III. SATELLITE DATA FOR CROP AREA ESTIMATION**

Remote sensing has the scope for cost-effective precise estimates 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 estimation. It can provide a timely, accurate, synoptic, and objective measure of crop identification, crop observance, and area estimation. Owing to the benefits of high temporal resolution, wide-coverage and low cost, remote sensing has been utilized in many earth observation activities and provides an excellent tool for crop recognition and planting area observance at an outsized scale

**A. 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 challenges viz., cloud cover during cropping season, wide range of environments, small land holdings, and diverse and mixed cropping systems limits the use of optical remote sensing as a tool 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.

**B. SAR Data**

Synthetic Aperture Radar (SAR) imagery is a promising option 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 simultaneousl**y.**

For the past twenty years, tremendous development in SAR application for crop identification has been reported. Scientists have tried combinations of SAR bands with different polarization to identify and estimate crop and 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.

**C. Data Integration**

To extend the accuracy of crop identification and spatial estimation, we need to possess a much better understanding of the crop and the underlying soil characteristics that influence the measuring instrument to break up throughout the season and establish acceptable methodologies to extract crop data [6].

Owing to the distinction in imaging and knowledge content, information from optical and SAR-based measuring device systems are unit complementary. Many studies have shown that desegregation information from the two sources improves classification accuracies 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].

**IV. 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 status, plant height, and crop stage. Following the random stratified sampling procedures, the details on land cover information are collected.

**V. 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.

**A. Unsupervised classification**

As the name suggests, unsupervised classification involves classification of image based on spectral properties 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*).

**B. 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 entire 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 to associate with each class by selecting representative sample sites of a known cover type called training sites. The computer algorithm uses spectral signatures from these training areas to classify the whole image. Preferably, the classes should not overlap or should overlap negligibly with other classes.

Maximum Likelihood Classification (MLC) algorithm quantitatively evaluates the variance and covariance of the category by discriminating reflectance response pattern while classifying an unknown pixel value. The distribution of a training class can be described by the mean vector and covariance matrix based on an assumption that the distribution of the training set is Gaussian. By these parameters, we may compute the statistical probability of a given pixel being a member of a particular class [10].

Maximum likelihood classification assumes that the statistics for each class are normally distributed and calculates the probability of a given pixel that belongs to a specific class. Each pixel is assigned to the class that has the highest probability. If the highest probability is smaller than a threshold to specify, the pixel remains unclassified

**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 performance of a parametric classifier depends largely on how well the data matches the pre-defined models and on the accuracy 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.

**VI. ACCURACY AND VALIDATION**

The Error matrix and Kappa statistics were used for evaluating the accuracy of the estimated area. The class allocation of each pixel in the classified image was compared with the corresponding class allocation on reference data (ground truth data) to determine the classification accuracy. The pixels of agreement and disagreement were compiled in the form of an error matrix, where the rows and columns represent the number of all classes and elements of the matrix represent the number of pixels in the testing dataset [4]. The accuracy measures, such as overall accuracy, producer's accuracy, and user's accuracy, were estimated from the error matrix [1]. The overall accuracy of correctly classified cases lying along the diagonal was determined as follows:

$$Overall Accuracy=\frac{Ʃ(Correctly classified classes along diagonal)}{Ʃ(Row Total or Column Total)}$$

The producer's accuracy (errors of omission) of each class was computed by dividing the number of samples that were classified correctly by its total number of reference samples as follows:

$$Producer^{'}s Accuracy=\frac{Number of correctly classified class in a column}{Total number of items verified in that column}$$

The user's accuracy (errors of commission) of each class was computed by dividing the number of correctly classified samples of that class by the total number of samples that were verified as belonging to the class as follows:

$$User^{'}s Accuracy=\frac{Number of correctly classified item in a row}{Total number of items verified in that row}$$

**VII. KAPPA COEFFICIENT**

Another measure of classification accuracy is the kappa coefficient, which is a measure of the proportional (or *percent*age) improvement by the classifier over a purely random assignment to classes [9]. The kappa coefficient is estimated from the formula for an error matrix with r rows and hence the same number of columns.

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

where,

A = the sum of r diagonal elements, which is the numerator in the computation of overall accuracy

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

N = the number of pixels in the error matrix (the sum of all r individual cell values)

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