RECENT TRENDS IN CROP IDENTIFICATION AND ANALYSIS BY USING REMOTE SENSING AND GIS

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ABSTRACT
Precision agriculture (PA) is a farming technique that utilizes information technology to determine the specific needs of crops and soil for optimal health and productivity. With the recent advancement in high resolution satellite imagery, remote sensing has been implemented in various PA applications, such as monitoring crop yields, mapping soil, monitoring crop health, managing diseases and pests, assessing water stress, and controlling fertility rates. This paper investigates the advantages of employing various crop identification and analysis strategies. The identified strategy involves pre-processing captured data using a variety of methods and collecting crop data from a wide variety of satellite platforms. Various crop identification strategies have been identified and analysed using various techniques.
Keywords: Precision agriculture, Remote Sensing and GIS, Satellite Sensors

Introduction

Agriculture is crucial for producing essential items such as food, textiles, fuel, and raw materials necessary for human survival. As the population grows, it is important to ensure that agricultural activities can provide for both basic needs and sustenance. while also being sustainable and addressing issues such as climate change. According to the World Summit on Food Security, the projected number of people in the world by the year 2050 is estimated to reach 10 billion, which will increase agricultural demand by about 50% compared to 2013, assuming moderate economic growth. (Weiss, Jacob, & Duveiller, 2020)

Precision agriculture enables sustainable farming practices, which are crucial for increasing food production. Precision agriculture (PA) is a farming management approach that employs information technology to evaluate the precise needs of crops and soil in order to achieve maximum health and yield. Despite its recognized importance, PA is currently only practical on large farms. It employs a comprehensive systems approach that combines advanced technologies such as remote sensing, geographic information systems, and global positioning systems to manage crops in-season and between seasons (Praveen & Sharma, 2019).

Geospatial technology includes RS (Remote Sensing), GIS (Geographic Information System), and GPS (Global Positioning System) as shown in the following figure (1). Farmers are now able to use global navigation satellite system technology to track agricultural machinery and enhance the quality and availability of geographic information in digital form. This allows them to evaluate the spatial and temporal variations in soil, terrain, and vegetation. Additionally, farmers who use mobile technology can save their field notes and farm records on the device, which makes it easy for them to input and access data locally. GIS and GPS technology are used to create maps that are linked to geographic coordinates, which can be used to visualize different crop and soil parameters, giving farmers new tools for management and communication (Sabtu, Idris, & Ishak, 2018)

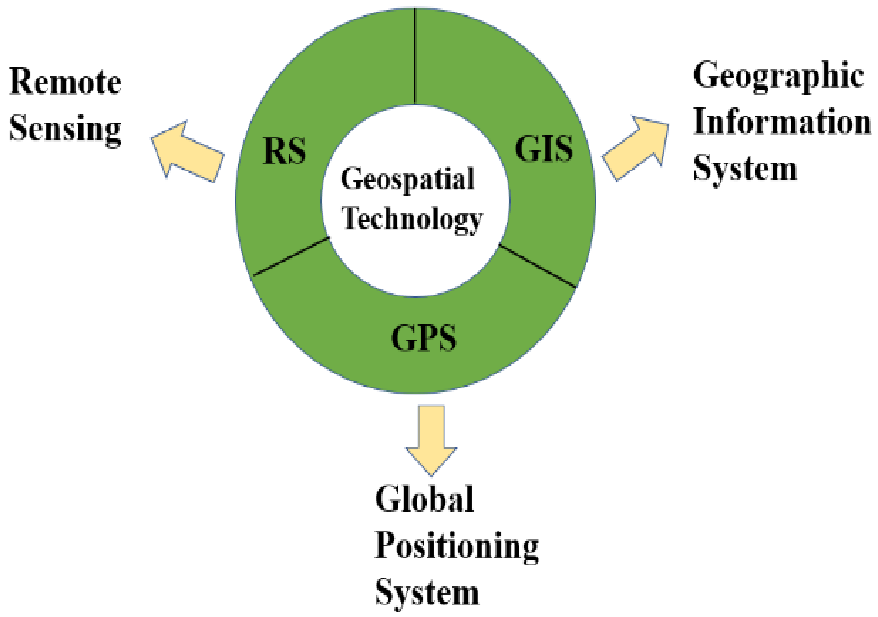

Figure 1: Components of Geospatial Technology

Precision agriculture (PA) is the use of advanced technologies to optimize inputs in farming to increase output and reduce waste. In recent years, the use of remote sensing technology in PA has grown rapidly. This is because remote sensing offers high-resolution satellite images that can be used for various PA applications such as crop monitoring, irrigation management, nutrient application, disease and pest management, and yield prediction. (Sishodia, Ray, & Singh, 2020).

Related Work

Several agricultural applications have successfully employed satellite imagery. Since 1970, satellite-based remote sensing has been used in agriculture for various purposes, including determining land use, identifying crop types, measuring leaf area, determining plant height, identifying weeds, managing diseases, forecasting crop yields, tracking crop growth and development, managing nutrient, assessing flood damage and other precision agriculture applications. The author shows that techniques for evaluating plant characteristics using satellites can be used to evaluate plant characteristics like how proximal and unmanned aircraft system-based phenotyping systems currently evaluate similar qualities. (Zhang, Marzougui & Sankaran, 2020).

Different authors use different dataset and techniques with a good result. Following table 1 describes datasets and techniques for Soybean, Maize, Sugarcane, Cotton and Wheat crops.

Crop	Dataset	Technique	Result	Ref
Soybean	MODIS	Binomial Areal Kriging Model, Gaussian Areal Kriging Model, Block Kriging Model	Global accuracy 92.1% Kappa index 0.84%	(Eustáquio Dantas Chaves , De Carvalho Alves , Silva De Oliveira , & Sáfadi , 2018)
Soybean	Google Earth Engine	Artificial neural networks (ANN), Radial basis function network (RBF), Decision tree algorithms J48 (DT) and Reduced error pruning tree (REP), Random forest (RF), and Support vector machine (SVM)	ANN was the most accurate model	(Gava, et al., 2022)
Soybean and Corn	VENµS, Sentinel-2	WISE approach	Result is compared with three data products which is consistent	(Gao, et al., 2020)
Maize	Sentinel-2 and GaoFen-1 (GF-1)	K-nearest neighbor (KNN), support vector classification (SVC), random forest (RF), and long short-term memory (LSTM)	Accuracy : RF and LSTM 88%, LSTM 90%, KNN 82% and SVC 86%	(Ren , et al., 2020)
Maize	Landsat 8 and GaoFen-1 (GF-1), Gaofen 2 satellite (GF-2) panchromatic data	Random forest (RF)	overall accuracy 95.90%, Kappa coefficient 0.92, and producer accuracy 93.91%. overall accuracy 97.79%, Kappa coefficient 0.95, and producer accuracy 97.65%.	(Zhang, et al., 2020)
Sugercane	LISS-IV	ISODATA, MLC, and vegetation indices based decision tree approaches	Vegetation indices based decision tree method , user's accuracy 88.17, producer's accuracy 86.59, overall accuracy 87.93%, and kappa coefficient 0.86	(Verma, Garg, & Hari Prasad, 2017)
Sugercane	LISS-III and LISS-IV of Resourcesat-2A	object-based classification, multi-date supervised classification and knowledge-based classification methods	overall accuracy 86.15% with kappa coefficient of 0.73	(Singh, Patel, & Danodia, 2020)
Cotton	AVIRIS sensor's Indian Pines standard dataset , EO-1 Hyperion sensor	Deep learning convolutional neural network (CNN)	For Indian Pines dataset 97.58% accuracy, while 79.43% accuracy for study area dataset	(Bhosle & Musande, 2019)
Cotton	Sentinel-1 synthetic aperture radar (SAR) and Sentinel-2 Multispectral Instrument (MSI)	Cotton Mapping Index (CMI), k-nearest neighbors, support vector machine and random forest	overall accuracy 81.20%	(Xun, Zhanga, Cao, Yang, & Yao, 2021)

Table 1: Summary of Crop Identification and Analysis

Methodology
Several strategies help with crop identification and analysis in the literature review. Therefore, the potential methodology is determined in accordance with it, as illustrated in the provided Figure (2). The first step in the data collection process is the collection of imagery data from various satellites, followed by the necessary pre-processing. Prerequisite features are retrieved after pre-processing, and the data is then categorised using several classifiers. Finally, accuracy evaluation is carried out.

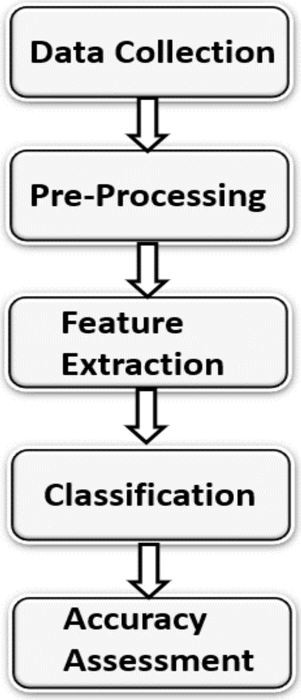

Figure 2: Methodology for processing

Data Collection
There are several satellite systems in use today that capture imagery and then deliver it to users. Each form of satellite data has its own set of features that make it suitable for a certain crop. In general, spatial resolution and spectral resolution are two features that may aid in the selection of satellite data.

The author employed MODIS, Sentinel-2 and Landsat 8 images in a recent study on the soybean crop. The author suggests that using MODIS images and the Google Earth Engine platform is a practical and effective way to automatically estimate the area of soybean fields on a large scale (Antonio da Silva Junior, 2020).

Another author examined many crops, including wheat, maize, barley, potatoes, and sugar beet, using a variety of satellite data. The study used a variety of remote sensing systems, including RapidEye, ASTER, Landsat-5-8, IRS-P6, and SPOT 6/7, to gather geographical and temporal data of the study area at low cost every year. The author found that when data was resampled for the study, the spatial resolution of the ASTER data was a good balance between the high resolution of RapidEye (5 m), the resolution of ASTER (15 m), and the lower resolution of Landsat (30 m). For the satellite images, the author has employed high-resolution images in several research projects to phenotype plant characteristics. The research demonstrates that the satellite-based phenotyping techniques can be used to evaluate plant attributes in a way that is like current methods that use UAS-based and proximal phenotyping systems (Zhang, Marzougui & Sankaran, 2020) (Waldhoff, Lussem, & Bareth, 2017).

Pre-processing
Before images are used again, errors and artefacts are fixed during pre-processing. The purpose of pre-processing functions is to enhance the capacity to understand image components both qualitatively and quantitatively. These functions include operations like geometry correction, radiometric correction, and atmospheric corrections. By accounting for sensor anomalies and eliminating superfluous sensor distortion and air noise, these techniques purge the data.

The author employed Landsat images and the time series of Sentinel-2A/B (S2) in a recent study on maize crops. For S2 time series data, the author used Framework for Operational Radiometric Correction for Environmental Monitoring (FORCE). Additionally, the pre-processing comprises picture co-registration based on Landsat data, cloud masking, topography correction, atmospheric correction, and tiling. According to the author, the accuracy of farmland identification was 84% overall, while the accuracy of the crop type map was 72% on average for the five key crop classes (Ibrahim, 2021) . The author used HLS filtering for preparing the SAR imagery data. Linear spatial and High pass filter (HPF) are combined to create the HLS filter (LSF) (Natteshan & Suresh Kumar, 2020).

Feature Extraction

Any image-based classification process must begin with the feature extraction step, in which the image is turned into meaningful information by means of a number of mathematical operations. This information is commonly referred to as features. It is envisaged that a variety of spectral and textural properties would be useful for crop classification. Vegetation Indices (VIs) are a combination of reflectance from multiple wavelengths of the Earth's surface, used to assess the vigour and cover of vegetation, as well as its growth dynamics. Table 2 contains different formulas for a variety of vegetation indices that are derived from remote sensing-based canopies. These algorithms are advantageous in providing quantitative and qualitative evaluations of vegetation (Xue & Su, 2017 & Vibhute, 2017).

Basic Vegetation Indices	**Formulas**
Ratio Vegetation Index (RVI)	$\mathrm{RVI} = \frac{R}{\mathrm{NIR}}$,
The Difference Vegetation Index (DVI)	$\mathrm{DVI} = \mathrm{NIR} - R.$
The Perpendicular Vegetation Index (PVI)	$\mathrm{PVI} = \sqrt{(\rho_{\mathrm{soil}} - \rho_{\mathrm{veg}})_R^2 - (\rho_{\mathrm{soil}} - \rho_{\mathrm{veg}})_{\mathrm{NIR}}^2}$,
Normalized Difference Vegetation Index (NDVI)	$\mathrm{NDVI} = \frac{(\rho_{\mathrm{NIR}} - \rho_R)}{\rho_{\mathrm{NIR}}} + \rho_R.$
Vegetation Indices considering Atmospheric Effects	**Formulas**
Atmospherically Resistant Vegetation Index (ARVI)	$\mathrm{ARVI} = \frac{(\mathrm{NIR} - RB)}{(\mathrm{NIR} + RB)}$, $\rho_{rb}^* = \rho_r^* - \gamma(\rho_b^* - \rho_r^*)$,
Adjusted-Soil Vegetation Index	**Formulas**
Soil-Adjusted Vegetation Index (SAVI)	$\mathrm{SAVI} = \frac{(\rho_n - \rho_r)(1+L)}{(\rho_n + \rho_r + L)}.$
Modified Soil-Adjusted Vegetation Index (MSAVI)	$\mathrm{MSAVI} = 0.5 * \{2R_{800} + 1 - \mathrm{SQRT}[(2R_{800}+1)^2 - 8(R_{800} - R_{670})]\}.$
Optimized Soil-Adjusted Vegetation Index (OSAVI)	$\mathrm{OSAVI} = \frac{(\mathrm{NIR} - R)}{(\mathrm{NIR} + R + X)}$,
Tasseled Cap Transformation of Greenness Vegetation Index	**Formulas**
Green Vegetation Index (GVI), Yellow Vegetation Index (YVI), Soil Brightness Index (SBI)	$\mathrm{GVI} = -0.290\mathrm{MSS}_4 - 0.562\mathrm{MSS}_5 + 0.600\mathrm{MSS}_6 + 0.491\mathrm{MSS}_7$, $\mathrm{YVI} = -0.829\mathrm{MSS}_4 - 0.522\mathrm{MSS}_5 + 0.039\mathrm{MSS}_6 + 0.149\mathrm{MSS}_7$, $\mathrm{SBI} = +0.433\mathrm{MSS}_4 - 0.632\mathrm{MSS}_5 + 0.586\mathrm{MSS}_6 + 0.264\mathrm{MSS}_7.$

Table 2: Vegetation Indices for different crops

Classification

Organizing data into categories is referred to as classification. It provides a structured approach to data, making it simpler to use, and helps ensure that it is utilized in the most efficient manner. Classification grants data a uniformed analytical and productive form. It is the process of categorising statistical data into a variety of easily comprehensible homogeneous groupings for easy interpretation. The foundation criterion for classification is attribute uniformity, and data is grouped according to similarity. When the data collected is diverse, classification is required for effective presentation and analysis. Following figure 3 shows different types of classifiers available for further processing.

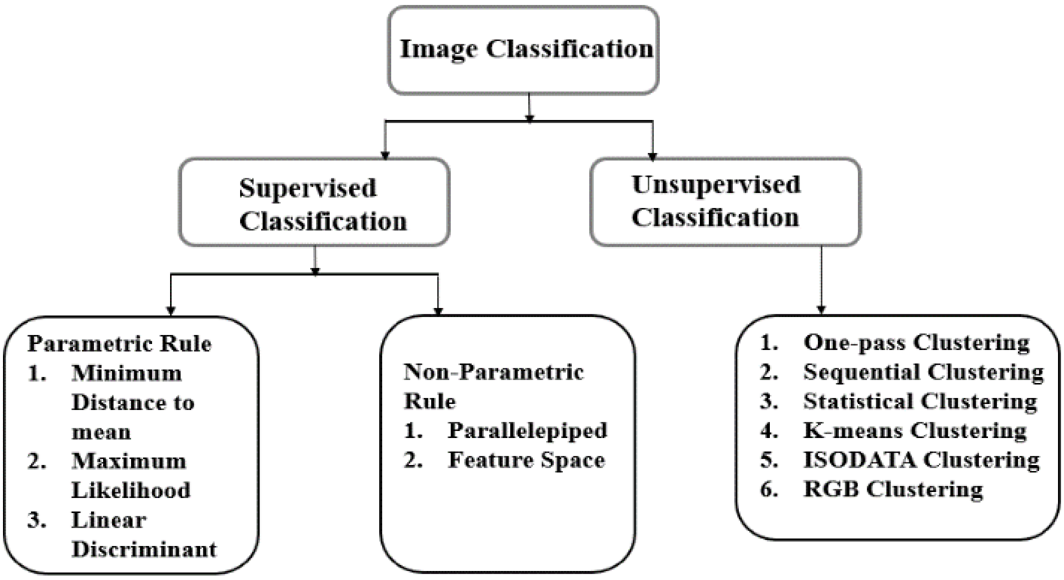

Figure 3: Types of Image Classifiers

The maximum likelihood classifier is a commonly utilized method of remote sensing classification, wherein a pixel with the highest probability of being in a specific class is assigned that class. (Ratnaparkhi, Nagne, & Gawali, 2016) This approach is both efficient and accurate. The likelihood that a single pixel falls into a certain category is assessed using maximum likelihood classification, which supposes that the data for each class in each band is normally distributed (Shivkumar & Rajashekararadhya, 2018). Linear Discriminant Analysis is a supervised technique used to reduce the number of dimensions in a dataset. It is effective in distinguishing binary outcomes, however its limitations become more evident when trying to classify multiple, distinct groups (Ducinskas & Dreiziene, 2021). Parallelepiped classification is a straightforward decision-making technique that is used to organize multispectral data. It is relatively simple to use and understand, yet highly effective. The decision boundaries create an n-dimensional parallelepiped, in the image data space allowing for the classification of data. (El Rahman, 2016). K-means clustering falls into the category of unsupervised algorithm which partitions an unlabelled dataset into distinct subsets or clusters. (Yuan & Yang, 2019) With clustering, we can group unlabelled data into distinct categories, without the need for any prior training. It offers a straightforward way to determine which group a data point belongs to (Shedthi, Shetty, & Siddappa, 2017). Hybrid Classifier is a fusion of supervised and unsupervised classifiers. Although this classification provided more correct classifications than the supervised classification, it did not considerably increase the accuracy in contrast to the unsupervised classification (Nagne, 2018). The objective of the support vector machine (SVM) algorithm is to discover a hyperplane in an N-dimensional space that can accurately separate data points (in this case N is the number of features) (Dhumal, 2018) . A random forest is constructed of multiple decision trees which are linked to the same data but with various resamples. The trees are grown by randomly selecting data points and attributes to form each tree. (Gibson, Danaher, Hehir, & Collins, 2020) All the decision trees then come together to vote on the outcome of a given test, with the result being an average of all the decisions. The Gini index can be used to segment a subset of the characteristics. Bootstrapping allows for the formation of subsets from the original dataset that have the same size as the original dataset (Mfuka, Zhang, & Byamukama, 2019).

Accuracy Assessment

We acquire the final analysis, which is the final outcome of our research effort, from which we may make strong statements about our work, once all of the previous phases are effectively finished. This is the conclusion of our work and the start of new work. Using producer accuracy, any classification scheme can be verified for accuracy. It indicates the proportion of ground classes correctly classified. How accurate the classification results are is actual representation of User Accuracy. The measure of the overall behaviour of the classifier is the overall accuracy. For a complete image, it combines user and producer accuracy. Accuracy or agreement is measured by the kappa coefficient. It indicates the degree of image classification accuracy (Jog & Dixit, 2016).

Result and Discussion

For Soyabean crop by utilizing MODIS dataset, binomial aerial kringing model, gaussian aerial kringing model shows most elevated exactness which 92.1%. For maize crop utilizing landsat information creator utilizes arbitrary woodland calculation which gives most elevated precision 97.65% and kappa coefficient 0.95. The author claims 88.17 % user accuracy, 86.59% producer accuracy, 87.93% overall accuracy, and 0.86 kappa coefficient for sugarcane using LISS-IV data. Using a deep learning convolutional neural network, the author claims an accuracy of 97.58% for cotton using data from the AVIRIS sensor. Using lansat-8 and sentinel-1A data, the author achieves an accuracy of 85% for wheat and all major crops. The author employed three methods for it: convolution neural networks (CNNs), random forest (RF), and multilayer perceptron (MLP).

Conclusion

Earth perception symbolisms have seen outstanding development as of late and turned into a well-known use instance of geospatial innovation. The primary aim of this paper is to explore the benefits of using different crop identification and analysis techniques. The identified strategy involves pre-processing captured data using a variety of methods and collecting crop data from a variety of satellite platforms. Prominent work was done to extract useful features for crop analysis from vegetation indices. Additionally extricated highlights are grouped with various classifiers like supervised, unsupervised and machine learning classifiers. Finally, overall, users and producer's accuracy assessment can be conducted to guarantee results. We intend to employ the prescribed method in the future for crop analysis and the identification of additional significant crops. In addition, to further evaluate the method's efficacy, we are thinking about incorporating the proposed model into an additional dataset for the identification of imbalanced crops.

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