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Review Article

Remote Sensing: An Advanced Technique for Crop Condition Assessment

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Actually, cultivators are increasingly arranging innovative high technical and scientific estimations in the aim to enhance agricultural sustainability, effectiveness, and/or plant health. Innovative farming technologies incorporate biology with smart agriculture: computers and devices exchange with one another autonomously in a structured farm management system. Throughout this structure, smart agriculture can be accomplished; cultivators decrease plantation inputs (pesticides and fertilizers) and increase yields via integrated pest management and/or biological control. The emerging concept of remote sensing may provide a framework to systematically consider these issues of smart farming technology and to embed high-tech agriculture better. The impact(s) may be beneficial depending on how tools, such as data mining, and imagery technologies, such as picture treatment and analysis, are applied. Remote sensing technology is discussed in this review and demonstrates its possibility to create novel opportunities for scientists (and agronomists) to explore aspects of biological phenomena that cannot be accessed through usual mechanisms or processes.

1. Introduction

It is evident that agriculture can be considered as the "vertebral column" of the humanity life and has considerable control on economy. This highlights the process requirement for usual monitoring of the crop state. There are an assortment of features to supervise crop state starting from soil humidity accessibility, plant vigour situation, and stress provided by abiotic causes (for example, humidity, rainfall, and temperature) and also biotic causes (for example, pest and illness). Any delay from the ordinary development parameter influences crop growth in addition to ultimately diminishing the production and productivity, and for this reason it is especially imperative to examine crop state for complete cycle of development.

Appropriate and suitable crop evaluation at better level requires observing wide regions by a powerful system. Remote sensing skill offers this through nondestructive synoptic screening capacities. It is well known that spectral answer of the soil attribute is different for various areas of electromagnetic spectrum. These sensed measures assist distantly in the detection and recognition of the globe surface trait.

The fundamental aim of appliance of remote sensing in cultivation is to conclude vegetation characteristics by examining the data included in the dispersed/returned signal [1]. The initial most important operational implement in the farming uses of remote sensing was that of Large Area Crop Inventory Experiment (LACIE) [2], where an effort was produced to approximate country-wise wheat land and yield via LANDSAT digital information. Landsat is an operation of Earth surveillance satellites expanded under a combined program of the National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS). Evaluations of the consequence of edaphic and meteorological answer aspects to crop have stayed a principal subject; there are a huge number of features as edaphic, climatic, biotic, hydrologic, and agronomic, which control a crop development and production. Furthermore, weather has a considerable position over the development and productivity reaction of crops. Remote sensing method by means of the potential of multispectral, multitemporal,

and synoptic exposure has revealed an excellent potential in giving broad rank of crop situation and production potential at local stage. With remote sensing method, the form of crops developed in an area, crop state, and yield can be considered. Recording crop state by remote sensing can get the crop status in addition to the condition and progress of their development. Obtaining the crop situation data at early steps of crop development is still more significant than acquiring the fixed production after harvest period.

2. Indices of Remote Sensing and Signification

Crop state estimation necessitates an information input, for example, environmental conditions such as air temperature, relative humidity, and rainfalls and surface condition like soil moisture and soil temperature. Remote sensing indices like Normalized Difference Vegetation Index (NDVI), Land Surface Water Index (LSWI), Temperature-Vegetation Dryness Index (TVDI), Soil Adjusted Vegetation Index (SAVI), Water Deficit Index (WDI), etc. obtained from satellite imagery are helpful to derive crop development state and/or soil humidity state. The Normalized Difference Vegetation Index (NDVI) calculates vegetation density through evaluating the variation between near-infrared (which vegetation powerfully returns) and red luminosity (which vegetation attracts). Moreover, the Land Surface Water Index (LSWI) employs the Shortwave Infrared (SWIR) and the Near-Infrared (NIR) zones of the electromagnetic range [3]. There is powerful luminosity assimilation by liquid water in the SWIR, and the LSWI is well recognized to be susceptible to the entire quantity of liquid water in vegetation and its soil [4]. In addition, the Temperature-Vegetation Dryness Index (TVDI) is acquired from spatial Land Surface Temperature-NDVI and can be employed as a marker of soil humidity and therefore the vegetation water pressure [5]. The SAVI (Soil Adjusted Vegetation Index) takes in consideration the visual soil characteristics on the plant cover reflectance [6]. The WDI represents the relative rate of hidden heat change, so it illustrates a rate of "zero" for totally wet surface and a value of "one" concerning dry surfaces where there is no hidden heat change [7]. Remote sensing method aids to create a temporal development profile of plants over its development phase. With the recovery of environmental factors in addition to remote sensing indices, it is simple to recognize the development model of crop and also their connection among each other and consequence of concerned variables on crop development. On the basis of preceding information and test, remote sensing method is especially helpful in estimating the crop development at land level in addition to large level. Assimilation of ecological, surface, and crop state acquired through remote sensing method in addition to soil station aids in improvement of model to calculate the crop state [8].

3. Role of Remote Sensing in Crop State Evaluation

Remote sensing gives immense occasion to obtain a general synoptic vision of the globe organization [9]. Numerous classes of selective information on available resources such as soil humidity, soil use and cover, crop natures and state, and soil type data can be mined since the satellite information [10].

Remote sensing as a device will provide information frequently and at an inexpensive value to permit, in the appropriate time, interference for recovery of crop state. Satellite structures offer spatially and temporally permanent records cover of the globe [11]. Satellite records of visual sensors similar to SPOT (in French: Satellite Pour l'Observation de la Terre), Moderate Resolution Imaging Spectroradiometer (MODIS), Atmospheric Infrared Sounder (AIRS), and LANDSAT, are employed for diverse domains. The Landsat task offers the greatest permanent space-based record of Earth's soil, beginning from 1972 and the Landsat 1 satellite.

Starting through Landsat 4, each of the satellites represented the Earth's surface at a 30-meter resolution about once each five to ten days by means of thermal and multispectral devices. SPOT is an elevated-quality visual imaging globe inspection satellite structure controlling from space. It has been made to develop the understanding and managing of the globe via discovering the globe's reserves, perceiving and predicting phenomena engaging oceanography and also climatology, and supervising human movements as well as innate phenomena. The SPOT structure comprises a chain of satellites and land control reserves for satellite management and training and picture creation and delivery (Table 1) [12].

The Moderate Resolution Imaging Spectroradiometer (MODIS) is known as an imaging device launched into globe orbit by means of NASA [13]. The devices capture records in 36 spectral bands varying in wavelength starting from 0.4×10^{-6}m to 14.4×10^{-6}m and at varying spatial motions. The Atmospheric Infrared Sounder, AIRS, is a service tool whose objective is to help climate study and develop weather prediction.

On the other hand, the Sentinel-2 operation, funded by the European Space Agency (ESA), includes two polar-orbiting satellites: Sentinel-2A and Sentinel-2B. It offers systematic overall treatment of land coverage and surfaces among latitudes 83° North and 56° South [14]. Various functions such as land cover change, agriculture, and mapping of biological parameters (leaf area indicator, leaf chlorophyll amount, and leaf water amount) can be estimated [14].

Sentinel-2A (launched in 2015) furnishes general reporting of the Earth's land every ten days and, when it is connected with Sentinel-2B (launched in 2017), the treatment duration has reduced to five days. The two satellites are similar and transmit a single mixture of general coverage: methodical and organized acquisition of high-resolution pictures, elevated revisit rate of five days, extensive vision field of approximately 290 km, elevated resolution of ten meters and, due to a high-tech Multispectral Imager, thirteen spectral bands [14, 15], of which three are comprised into the 'red edge' fraction of the spectral field.

Because of developed attributes evaluated to preceding operations, Sentinel-2 is able to identify early modifications in plant healthiness, to differentiate between diverse crop

Table 1: Common thermal bands of different sensors and their specifications.

Platform	Sensor	Spatial resolution (m)	Band(s)	Wavelength range (μm)
MTI	MWIR	20	J	3.50-4.10
			K	4.87-5.07
	LWIR		L	8.00-8.40
			M	8.40-8.85
			N	10.2-10.7
Landsat	TM	120	6	10.40-12.50
	ETM+	30	6	10.40-12.50
	OLI	100	TIRS 1	10.60-11.19
			TIRS 2	11.50-12.51
ASTER	TIR	90	11	8.125-8.475
			12	8.475-8.825
			13	8.925-9.275
			14	10.250-10.950
			15	10.950-11.650
MODIS	TIR	1000	20	3.660-3.840
			21	3.929-3.989
			22	3.292-3.989
			23	4.020-4.080
			24	4.433-4.498
			25	4.482-4.549
AVHRR	TIR	1090	1	0.58-0.68
			2	0.725-1.00
			3A	1.58-1.64
			3B	3.55-3.93
			4	10.30-11.30
			5	11.50-12.50

varieties, and distribute appropriate data on diverse biophysical factors. These constituents can facilitate tasks of users and specialists to identify precursors of food deficiencies in countries [16].

Moreover, predictions of crop productions, modelling yield, and crop stress recognition have been determined via remote sensing records. Detection and recognition of plant illness and preparation for efficient manage estimations are important to sustain crop production. One of the possible appliances of remote sensing in farming is the estimation of crop acreage and recognition of crop situation because of either water stress or pest. Vigorous plants provide an elevated reflectance in the near-infrared area and an inferior in the observable area. Illness influenced plants demonstrate an elevated reflectance in the perceptible band and a minor in infrared area. This theory can be employed in discerning vigorous and infected crop.

Once plants are infected with malady, assimilation of incident solar ray transformations in the perceptible and Near-Infrared range [17], this is possibly caused by reduced chlorophyll quantity and modifications in internal organization. The variation of assimilation accordingly affects the reflectance of infected plants. As a result, in evaluating the range difference of infected and vigorous plants, scientists are able to recognize the stress potency of green foliage (Table 2) [12].

While the chlorophyll quantity tends to diminish under illness emphasis, assimilation of incident solar rays by green vegetation declines in the perceptible area. Subsequently, spectral reflectance is important in the red region and declines in the Near-Infrared range depending on the contamination potency. The powerful spectral reflectance of green trees in the Near-Infrared array is principally provoked by its foliar internal constitution. Besides, plants with malady stress show different degrees of morphological internal transformations, which conduct to a decline of spectral reflectance in the Near-Infrared array. These spectral attributes of foliage are the foundation for remote sensing of malady-stressed vegetation [13].

4. Imagery Treatment and Prediction in Mapping

Remotely sensed information has been employed for evaluation of land cover ever since remote sensing initiated.

Table 2: Main spectral vegetation indices used in agriculture.

Index	Equation	Usefulness
NG	G/ (NIR+R+G)	Carotenoids, anthocyanins, xanthophylls
NR	R/ (NIR+R+G)	Chlorophyll
DVI	NIR-R	Soil reflectance
GDVI	NIR-G	Chlorophyll, N status
NDVI	(NIR-R)/ (NIR+R)	Vegetation cover
GNDVI	(NIR-G)/ (NIR+G)	Chlorophyll and photosynthesis, N status

Abbreviation: A=adapted, D=difference, G=green, N=normalized, NIR=near-infrared, R=red, RVI=Ratio Vegetation Index, VI= Vegetation Index.

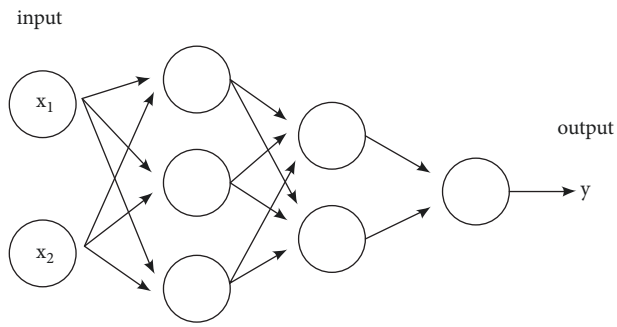

Figure 1: A neural network architecutre.

Land cover estimation via employing remotely sensed records can no longer be identified as entire in the sense of their spatial and spectral determinations, except that land cover categorization of satellite images can be built by image operating and model detection methods [18]. Enhancement of land cover categorization and classification of satellite data can possibly be prepared by means of using techniques like k-nearest neighbor [19, 20], artificial neural nets [21, 22], decision tree analytical technique [23], and finally clustering division and segmentation methods for categorization [24, 25]. Artificial Neural Network designs the function or composition of biological neural networks. The principal objective is to achieve prototype matching for classification and regression problems. Nevertheless, the method imitates the approach employed by biological organisms rather than rigorously relying on an accurate math-based approach. Here are many examples of Artificial Neural Network architecture algorithms: Radial Basis Function Network (RBFN), Perceptron, Hopfield Network, Feed-forward Neural Network, and finally Self-Organizing Map (SOM) [26]. This algorithm is very helpful in finding samples that are in addition difficult for being physically mined and taught to identify to the calculation instrument. In the perspective of this composition, samples are initiated to the Artificial Neural Network via the input layer that has only one neuron for every element present in the input records and is corresponded to one or more hidden layers existing in the system [27]. In fact, the processing happens in the hidden layers through an arrangement of relationships distinguished via weights and biases. The input is collected and the neuron estimates a weighted amount accumulating as well the bias and in accordance with the outcome and a preset activation function, it makes a decision whether it should be discarded or otherwise stimulated. Subsequently, the neuron spreads the record downstream to other joined neurons [28]. At the last part of the process, the final hidden layer is connected to the output layer which has one neuron for each potential wanted output (Figure 1).

Decision tree builds a model of decisions on the basis of real values found in records. The resulting tree configuration permits making comparisons among novel and existing data rapidly. This type of algorithm habitually sees application for regression and categorization problems [29]. Decision trees are machine learning algorithms that gradually separate data sets into less important data sets on the basis of an explanatory attribute, until they achieve sets that are little as much as necessary to be explained via a number of label (Figure 2). They necessitate that data is marked; hence they attempt to validate novel data based on this understanding. Decision tree algorithms are ideal to resolve regression and classification problems.

Regression trees are employed while the dependent value is considered as quantitative or continuous and classification trees are employed while the dependent value is considered as qualitative or categorical. We discern some frequent decision tree algorithms: Chi-squared Automatic Interaction Detection (CHAID), C4.5 and C5.0, Classification and Regression Tree (CART), and Iterative Dichotomiser 3 (ID3) [30].

Clustering method expresses a model for managing data through class or other norms. In general, information points that are in the identical set should have analogous characteristics or else descriptions (Figure 3), although information points in dissimilar sets should have very divergent characteristics or descriptions [31]. The results are frequently hierarchical or else centroid. We obtain data relationships in a way that assists making sense of the data, that is, how

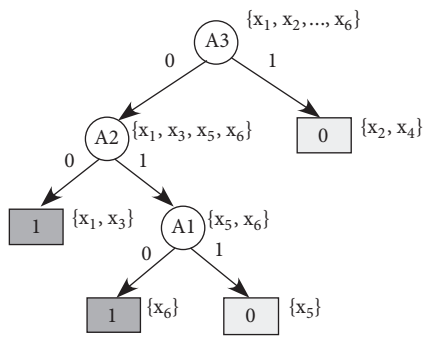

Figure 2: Example of decision tree.

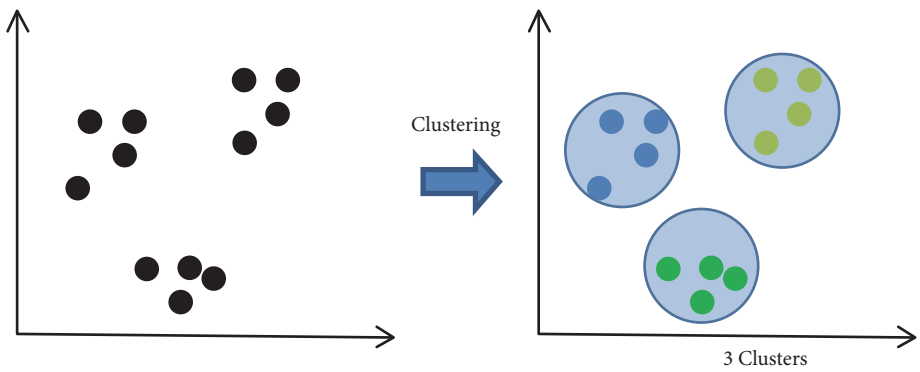

Figure 3: Example of clustering.

the values influence each other. There are many examples of clustering construction algorithms: Hierarchical Clustering, K-medians, Expectation Maximisation (EM), and K-means [32].

The imagery arrangement of remote sensing records either can be prepared in the direction of achieving different spectral groups on the basis of spectral brightness rate or can, besides, be further planned to instinctively concerned soil use categories in regard to the soil-truth plan. The soil-truth plan is made by means of assistance of user interface via imagery treatment method and understanding of categories on the land. Generally, the spectral model existing inside the information for every pixel is utilized as the numeric source for classification. Spectral model identification makes reference to the set of categorization processes that employs the pixel-per-pixel spectral data like the foundation for computerized land cover categorization [33]. Spatial form recognition holds the categorization of illustration pixels on the basis of the spatial connection among pixels neighboring them [34]. These sorts of groups try to repeat the type of spatial fusion done by means of special analysts through ocular analysis operations found on picture quality and texture, pixel nearness, attribute dimension, contour, and duplication, in addition to environment. The objective consists of determining spectral prototypes via spatial liaisons in given remote sensing records instead of exploring by a temporal methodology in which case one would investigate transformations in examples over the specific period of time by means of numerous years of records [35].

Spectral picture categorization is generally separated into two main categorization methods of supervised and unsupervised classifications. The basic distinction among these methods is that supervised classification entails a training stage succeeded by a categorization stage. In the unsupervised theory, the picture data are primarily categorized through combining them into the natural spectral assemblages, otherwise groups, contained in the recorded data. These spectral clusters are in that case categorized by evaluating them to soil reference record. Imagery experts can in addition decide how well a categorization has classified an illustrated subgroup of pixels employed in the training procedure by means of a precision estimate. Model-based clustering has expressed excellent results in imagery examination [36]. One of the most common indications of describing categorization precision is the construction of a classification error table. Obtained findings from the organization and arrangement of remotely sensed records are generally recapitulated as contingency table or else confusion matrix. Error matrices evaluate, on a categorical basis, the possible connection among reference records (symbolizing the soil reality) in addition to the related results of a computerized organization. These particular matrices are called square, through the sum of columns and rows equivalent to the sum of categories whose classification precision is being considered [37]. Picture categorization has frequently been achieved via employing usual numerical and machine learning methods in the earlier periods. Numerical methods such as Bayesian networks are excellent while the data is considered as normalized or noise-free [38], whereas

implicit designs, also known as machine learning algorithms, like Artificial Neural Networks (ANN), are further than a "black box" system, depending on repetitive training in the aim of regulating and adjusting factors by transferring functions to enhance their projecting aptitude concerning training results for which the outputs are acknowledged [39, 40]. The numerical theory achieves more once *a priori* instruction regarding categories is accessible; nevertheless they have restrictions in the case of purpose categorization and when the dispersion of recorded points are not identified, like the case with remote sensing spatial records. Data mining skills have become progressively more important methods to treat information from a large pool of records [41].

The word "data mining" has existed for a few decades, while the majority of the machine learning processes and statistics, for example, Artificial Neural Networks (ANN) and Decision Tree (DT), nowadays attached with data mining were progressed [42].

Nowadays, numerous image classification techniques have been ameliorated and employed to extract significant information from remote sensing descriptions [43]. Assortment of appropriate classification techniques is especially imperative to effectively extract useful results from imagery [43]. Analytical classifiers such as Artificial Neural Networks [44] and Decision Tree [45] do not employ statistical factors to recognize classes. They are better adapted for investigating noisy, multimodal, and/or missing records [18]. In fact, Szuster et al. [46] studied the land cover and land use classification via Artificial Neural Networks. Lakshmi and Vijaya [47] used machine learning methods such as decision tree and Artificial Neural Networks for categorization and classification on the samples. The samples were able to attain good precision, which was elevated for decision trees when evaluating with others. On the other hand, Zanaty [48] applied an evaluation study by using Artificial Neural Networks and Support Vector Machines for data classification and categorization.

Data mining for spatial form recognition is the method of determining interesting information, for instance, configurations, relationships, modifications, irregularities, and major organisations, from big volumes of data stocked in data servers or other data sources [49]. Because of the disposal of colossal quantities of records, data mining has attracted important consideration in the information management business. Generally, data mining assignments can be categorized into two classes: predictive and descriptive data mining [50]. The latter refers to the information set in a brief way and highlights common data characteristics; the first achieves interpretation on the obtainable data set and efforts to forecast the novel data comportment.

A data mining structure could realize at least one of the data mining assignments: (1) arrangement, (2) connection, (3) forecast, and (4) clustering [51]. Between diverse data mining methods and techniques, the Artificial Neural Network (ANN) technique is one of the most extensively employed methodologies in engineering, particularly when data or information is accessible from several sources, in addition to *a priori* understanding of explanatory arrangements or developments which is accessible because of capacity of ANN to study complex configurations rapidly [52]. This method was successfully employed in many fields as biology [53–56], physics [57, 58], chemistry [59, 60], etc. Besides, the decision tree systems of data mining approaches are more directly adapted for classification, from the time when data symbolising a specified individual are classed through the decision tree construction to be classified directly into a preprogrammed group [61, 62]. They not only signify an effective organization technique, but also have the supplementary benefit of simplicity of elucidation of the factors employed to classify data sets to their suitable groups, although concurrently carrying to highlight the relative significance of diverse variables in the concerned system [63, 64]. It is particularly laborious to retrieve clarifications for occurrences when ANN methods are employed because of the "black-box" methodology in ANN [65].

The designs are learnt by ANN via iterative learning successions of illustrative data, hence generating forecasts of spectral ranges by detecting unidentified pixels [66, 67]. Decision trees, conversely, employ dichotomization to route available data to the precise group, as is observed in vegetal basics. Even if the distinction conditions at each stage of the decision tree arrangement are produced by the software, it is probable to examine the conditions in an effort to comprehend what origin distinction has been completed [68, 69].

5. Conclusion

Remote sensing as a device will provide information frequently and at an inexpensive value to permit, in the appropriate time, interference for recovery of crop state. Satellite structures offer spatially and temporally permanent records cover of the globe. Along through the expansion of remote sensing functions, satellite information has become the principal data foundation to supervise high-dimension crop situation. With the aid of satellite and digital imaging methods, it is simple and also price efficient in planning and observing the crop situation.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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