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10. Remote Sensing and GIS in Crop Production

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Abstract:

Remote Sensing (RS) constitutes the scientific discipline dedicated to the detection of distant observations through the analysis of different wavelengths of light. Simultaneously, Geographic Information System (GIS) serves as a spatial technique, functioning as a comprehensive database system for the organization of spatial observations. The exponential growth in data storage capabilities and computational resources has led to the widespread utilization of these tools across various scientific domains. RS relies on the principles of electromagnetic radiation, where the intensity of such radiation aids in delineating the characteristics of observed objects. Presently, both RS and GIS have found remarkable success in the realm of agricultural research, offering versatile applications such as floodplain mapping, hydrological modeling, analysis of surface energy flux, monitoring urban development, assessing land-use changes, and detecting stress in crops. Furthermore, they play a pivotal role in crop growth monitoring, crop condition assessment, and the creation of contour maps for elevation and fertility. These sophisticated tools have streamlined the process of analysis and interpretation, providing an efficient and accessible means for researchers to delve into the complexities of agricultural landscapes. This chapter expounds upon these diverse applications, presenting a seamless exploration of the manifold ways in which RS and GIS contribute to advancing our understanding of agricultural phenomena.

10.1 Introduction:

In the world there is increasing demand to minimize the human intervention in technology generation and dissemination by means of mechanization. Modern science has given two useful technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) to acquire data and manage them remotely. RS is a science of obtaining observation without its direct contact with the object.

GIS is database system consists of spatial information i.e. the position of the object with respect to the earth. This book chapter has been dedicated to application of RS and GIS in crop production. Section 2 and 3 will describe the RS and GIS in brief followed by its application in crop production.

Remote Sensing:

It is the science of studying a distant object or area without coming in it's direct contact. This involves an instrument, or a sensor mounted on a platform, such as a satellite, an aircraft, anUAV/UGV, or a probe. The sensor typically measures the electromagnetic radiation that is either reflected or emitted by the target.RS is a tool to monitor the earth's resources using space technologies in addition to ground observations for higher precision and accuracy. Lillesandet al. (2015) defined RS as, "The science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation".

In RSa physical carrier is required for collection of information on distant object. The electromagnetic radiation is generally used as an information carrier in RS. Various sensors are used for recording information about an object by measuring the radiating and reflecting energy from that object. The typical responses of the targets to these wavelength regions are different, so that they are used for distinguishing the vegetation, bare soil, water and other similar features (Figure 10.1).

The sensors receive images of the earth surface by measuring the intensity of electromagnetic radiation coming from the distantly placed object.

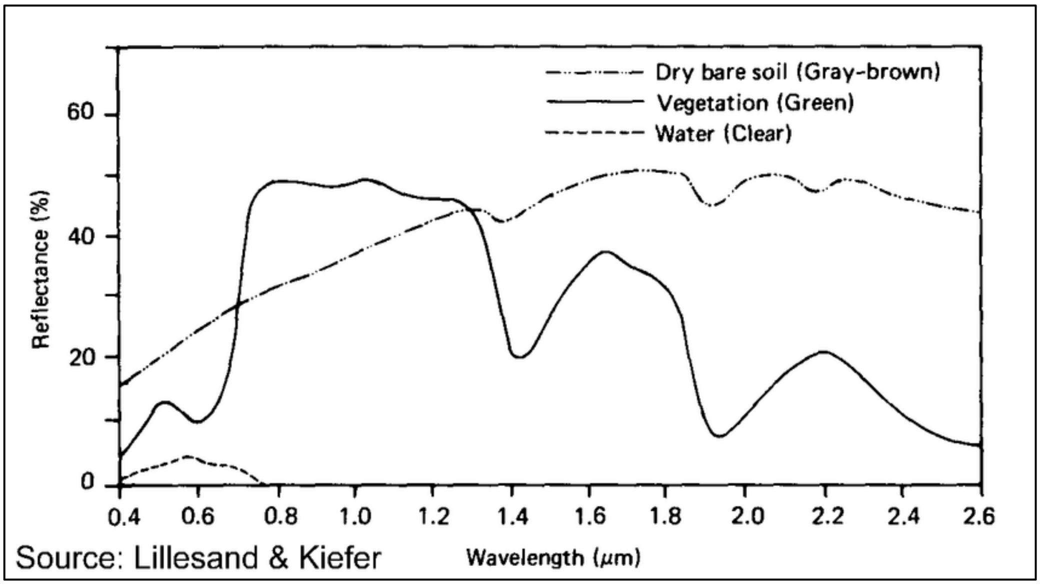

Figure 10.1. Typical Spectral Reflectance curves for vegetation, dry bare soil and water

B Geographical Information Systems:

Geographic Information Systems (GIS) are powerful tools integrating spatial data, mapping, and analysis for enhanced decision-making. These systems organize layers of information, such as topography, land use, and demographics, to reveal patterns and relationships.

GIS finds applications in urban planning, environmental management, and disaster response. It enables professionals to map phenomena, identify trends, and solve complex problems. From tracking disease spread to optimizing logistics, GIS is a versatile technology, fostering a deeper understanding of our world. As technology advances, GIS continues to evolve, playing a pivotal role in creating smarter, more sustainable communities and addressing global challenges through spatial intelligence.

10.2 Application in Agricultural Crops:

During the early stages of the satellite RS, most researchers are focused on the use of data for classification of land cover types with crop types being a major focus among those interested in agricultural applications. In recent years, the work in agricultural RS has focused more on characterization of plant biophysical properties. RS has long been used in monitoring and analyzing of agricultural activities. RS of agricultural canopies has provided valuable insights into various agronomic parameters. The advantage of RS is its ability to provide repeated information without destructive sampling of the crop, which can be used for providing valuable information for precision agricultural applications. RS provides a cheap alternative for data acquisition over large geographical areas (Debeurs and Townsend, 2008).RS along with GIS is highly beneficial for creating spatio-temporal basic informative layers which can be successfully applied to diverse fields including flood plain mapping, hydrological modelling, surface energy flux, urban development, land use changes, crop growth monitoring and stress detection (Kingra *et al.*, 2016).The advances in the use of RS methods are dueto the introduction of narrow band or hyperspectral sensors and increased spatial resolution of aircraft or satellite mounted sensors. Hyperspectral RS has also helped to enhance more detailed analysis of crop classification. Then kabail *et al.*, (2004) performed rigorous analysis of hyperspectral sensors (from 400 to 2500 nm) for crop classification based on data mining techniques consisting of principal components analysis, lambda–lambda models, stepwise discriminant analysis and derivative greenness vegetation indices. Many investigations have included different types of sensors which are capable of providing the reliable data on a timely basis on a fraction of the cost of traditional method of data gathering.

RS applications in farming vary from crop classification, crop acreage estimation, crop growth monitoring, soil moisture estimation, soil fertility evaluation, crop stress detection, detection of diseases and pest infestation, drought and flood condition monitoring, yield estimation, weather forecasting and precision agriculture. The monitoring of agricultural production system follows strong seasonal patterns in relation to the biological life cycle of crops. All these factors are highly variable in space and time dimensions. Moreover, the agricultural productivity can change within short time periods, due to unfavorable growing conditions. Monitoring of agricultural systems should be followed in timely manner. It serves as a crucial instrument for consistently monitoring and providing a precise overview of the agricultural industry, boasting both frequent revisits and heightened accuracy. It also functions in the sustainable management of agricultural foundations, requiring the analysis of all factors influencing the agricultural sector in both spatial and temporal dimensions. The RS along with the other advanced techniques such as Global Positioning Systems (GPS) and Geographical Information Systems (GIS) are playing a major rolein the assessment and management of the agricultural activities. Therefore, it is a crucial factor overall in agricultural systems, contributing to the enhancement of the economic growth of the nation.

10.3 Crop Classification and Acreage Estimation:

Using RS, we can prepare a land use and land cover map by classifying a satellite data. There are mainly two types of classification techniques available for crop classification, one is supervised, and another is unsupervised. In the supervised classification technique, it is the responsibility of the user to specify the number of classes to be created following the image classification process.

The supervise learning refers to the action where labelled training data is used for inferring a function. The training data will include examples with two main parts – Object (vector, etc.) and desired output result (known as a supervisory signal). The algorithm will analyze training data before producing an inferred function that is useful in designing new examples.

Some examples of supervise classification techniques are Maximum Likelihood Classification (MLC), Bayes classifier, Support Vector Machine (SVM) and Artificial Neural Network (ANN).

The unsupervised learning refers to the action where the function is inferred to give details about a hidden structure within non-categorized data. The key difference between unsupervised learning and supervised learning is that as the latter is given examples that are unlabeled, there is no signal for reward or error, for evaluating the potential solution. The examples of unsupervised classification techniques are K means classifier, Optics classifier and Mini shift classifier etc.

Civco (1993) studied the application of ANN for land-cover classification using Landsat satellite Thematic Mapper (TM) digital imagery for Coventry, Connecticut region of USA. The image analysis work was done by ERDAS^{TM} (Earth Resources Data Analysis Systems).

Reddy *et al.* (1994) studied land use land cover classification in Hyderabad. Indian RS Satellite (IRS) data was used in their study. There are four spectral bands present in IRS data. MLC method was applied for satellite image classification with various band combinations. These band combinations were used as variable to determine the best one. The band combination of 1-2-3 gave best results with overall accuracy of 84.62%.

Singh and Goyal (2000) have given an estimation of wheat crop yield for district Rohtak, Haryana using crop cutting experiments data for the year 1995-96 and satellite spectral data from the Indian Remote Sensing Satellite IRS-1B LISS II data for February 17, 1996. Post stratified estimator of crop yield using spectral data in the form of vegetation indices NDVI and RVI for stratification have been obtained for the district.

Misra (2001) tried to improve the conventional survey methodology for agricultural surveys with the help of spatial sampling procedures using the potential of GIS and Remote Sensing. An improved spatial sampling technique known as *Contiguous Unit Based Spatial Sampling (CUBSS)* for regular area units and *Distance Unit Based Spatial Sampling (DUBSS)* for irregular area units was developed and its efficiency was compared with the traditional sampling techniques and the proposed technique was found to be better than the existing techniques.

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Yadav *et al.* (2002) studied acreage estimation of mango using satellite data by boundary mask method and sample segment approach. Satellite data of Indian RS Satellite (IRS) Linear Imaging Self Scanning-II (LISS) and LISS III for Krishna district of Andhra Pradesh was used in the study. LISS III gave better result as compared with LISS II due to high spatial resolution.

They found that mango acreage estimation using satellite data leads to deviation of 6.32% (LISS-II) and 12.71% (LISS-III) from the actual data of Department of Horticulture (DoH). Rao *et al.* (2004) studied estimation of production of fruits (Coconut and Mango), vegetables (Potato and Tomato) and other crops (Rice and Mulberry). They used LISS-II and LISS-III data. LISS III gave better result as compared with LISS II due to high spatial resolution. They found that mango acreage estimation using satellite data leads to deviation of 6.32% (LISS-II) and 12.71% (LISS-III) from the actual data of Department of Horticulture (DoH). Study was conducted in Kolar district of Karnataka using MLC method.

Melgani and Bruzzone (2004) used SVM classification technique for classification of hyperspectral satellite data. They applied binary SVM classifier for multiclass classification of hyperspectral data. They made comparison between four algorithms such as one-against-one, one-against-all and two hierarchical tree-based strategies.

Rai *et al.* (2004) estimated area under nine-fold classification using Remote Sensing data and compared it with usual nine-fold classified land use classes in Lalitpur district of UP. They found that these statistics of land use classes obtained through RS could be used as auxiliary information in spatial /non-spatial models to get reliable statistics of different classes. They also developed spatial models for prediction of area under different land use categories covered under nine-fold classification based on satellite data which were found to be quite satisfactory.

Pal and Mather (2005) made comparison among multi-class SVM, MLC and ANN methods for land cover classification. The accuracy was assessed on the basis of confusion matrix. They used multispectral (Landsat-7 ETM+) data in eastern region of England and central region of Spain. The results showed that overall accuracy for SVM, MLC and ANN were 87.9%, 82.9% and 85.1% respectively.

Sahoo *et al*. (2005) developed methodology based on integrated approach using Remote Sensing, GIS and ground survey for estimating area under paddy crop for Northeastern Hilly Region since there is no objective methodology for estimation of area under different crops in North-Eastern states due to the typical problems existing in these regions.

Dixon and Candade (2008) studied multispectral image classification using SVM and ANN techniques. They used Landsat TM 5data for land use classification in Southwest Florida. They also made comparison of both the techniques with traditional MLC method. They found that SVM and ANN performs better than MLC method. Final result showed that SVM is the best classifier with overall accuracy 79.2% in comparison to MLC and ANN with overall accuracy 50.6% and 78.4% respectively.

Pal (2008) discussed finite and infinite ensembling approaches of SVM to improve the accuracy of land cover classification using support vector machines. Finite ensemble approach composed of boosting and bagging techniques and infinite ensembling created by embedding the infinite hypothesis in the kernel of support vector machines. Littleport area of United Kingdom (UK) was taken as study area. ETM+ data was used for land cover classification. He found Radial Basis Function (RBF) kernel-based support vector machines superior than infinite ensemble approach.

Sahoo *et al.* (2010) developed an integrated methodology based on remote sensing, GIS and ground survey for multi crop in Meghalaya state at district level. New idea of spatial stratification based on elevation and extent of cultivation was developed under this study.

The estimates of area under major crops of the state like paddy, maize, potato, ginger, pineapple, cashew nut and vegetables were given. The developed methodology was found to be effective, efficient and feasible for adoption by Department of Economics and Statistics (DES) in future for acreage estimation of major crops in Northeastern part of the country and is now being extended to other NEH states.

Yang *et al.* (2011) used Satellite Pour I' Observation dela Terre (SPOT) imagery for identification of crops. In a SPOT image four spectral bands are present namely green, red, near infrared and short-wave infrared.

SPOT image of south Texas was used in this study. Five supervised classification techniques, namely Minimum distance, Mahala Nobis distance, MLC, Spectral Angle Mapper (SAM) and SVM were applied in this study. Results has shown that MLC and SVM performs better than the other three classifiers.

Devadas *et al.* (2012) compared traditional pixel-based image classification with object-based classification using SVM for crop mapping study in southern Queensland. Landsat TM images, 2010-11 were used in this study. The results shows that object-based SVM performs better with overall classification accuracy (95%) as compared to traditional pixel-based MLC method (89%).

Nitze *et al.* (2012) explored classification of agricultural crop types using SVM, ANN, Random Forest (RF) and MLC method. Multi-spectral Rapid Eye images from 2009 growing season were used in this study.

Support Vector Machine classifiers using radial basis function or polynomial kernels gives better result in comparison to ANN and RF in terms of overall accuracy. MLC results in inferior accuracy among all the methods.

Soliman *et al.* (2012) used SVM and Particle Swarm Optimization (PSO) algorithm for ASTER satellite imagery classification in North-Eastern part of Egypt. The results showed that Polynomial kernel function is the best classification technique with classification accuracy (95.2%) as comparison with Radial Basis Function kernel function (94.9%) and sigmoid kernel function (80%).

Yekkehkany*et al.* (2014) developed a framework for crop classification using polarimetric features from multi-temporal Synthetic Aperture Radar (SAR) imageries using SVM in Winnipeg of Canada. Kernel such as linear, polynomials and RBF were used in this study. The result showed that SVM classifier RBF kernel increases the Overall Accuracy (OA) to up to 3% and 1% in comparison to linear kernel and 3rd degree polynomial kernel respectively.

Goswami *et al.* (2014) described use of ANN to select waterbody object from satellite data. Two types of datasets namely training and testing dataset were used to train the neural network using Error Back Propagation (EBP) learning algorithm. Accuracy assessment was done on the basis of Confusion matrix and Kappa coefficient.

Surase*et al.* (2015) studied crop discrimination and area estimation in Aurangabad region of Maharashtra using Remote Sensing (RS) data. They compared several kernel functions associated with SVM technique such as linear, sigmoid, polynomial and Radial Basis Function (RBF). They used IRS-Resourcesat-1 LISS-III data in their study. The result showed that both Polynomial kernel function and Radial Basis Function have same overall accuracy of 94.82%. RBF and polynomial kernel function obtains almost 5.17% and 3.45% better overall accuracy in comparison to linear and sigmoid kernels respectively.

Ahmad *et al.* (2015) developed a methodology for acreage estimation under agro-forestry using LISS-IV (Spatial resolution- 5.8 m) data in Ludhiana district of Punjab State was taken as area of study. In this study supervised classification, MLC was applied and overall accuracy of 94.28% was achieved. Area under agroforestry at district level was again classified into different classes such as area under *Populous trichocarpa*, *Eucalyptus globus* and *Melia azedarach*.

Paul (2016) studied acreage estimation of mango using EO-1 Hyperion sensor based hyper spectral data. Statistical techniques like Analysis of Variance (ANOVA), Classification and Regression Tree (CART), Jafrries Matusita (J-M) distance and Linear Discriminant Analysis (LDA) were used for identifying most suitable bands for discriminating fruit crops. The study has been conducted in Sabour district of Bihar, Meerut in Uttar Pradesh to estimate area under mango. They have used ENVI and ARC GIS software to analyze the remote sensing data.

Udgata et al. (2020) tried to prepare a land-use and landcover map using three supervised classification techniques Support Vector Machine (SVM), Artificial Neural Network (ANN), Maximum Likelihood Classifier (MLC) in West Godavari district of Andhra Pradesh. SVM with Radial Basis Function (RBF) outperformed all the supervised classification techniques. They have used Sentinel 2 satellite data to conduct the study. Various software such as ERDAS, ARCGIS and SNAP has been used to implement the study. With the advent of RS, it is possible to cover a large field with non-invasive and productive techniques (Romero et al. 2018) to detect the spatial variability in plant water status with high temporal resolution. RS methods based on spectral vegetation indices and infrared thermometry (Ihuoma and Madramootoo 2017) are widely used forcrop water stress detection because they are non-destructive and not labour- or time-intensive. The RS method is extensively used in vegetation studies that make use of the spectral reflectance of crops. The RS method is extensively used in vegetation studies that make use of the spectral reflectance of crops. Spectral reflectance is a measure of the wavelength of the electromagnetic energy collected from objects on Earth. The biochemical and biophysical properties of plants, such as biomass, crop evapotranspiration and canopy water content, are related to spectral properties that are used for spectral reflectance. Mathematical combinations of two or more spectral bands are referred to as spectral indices that are applied to detect water stress in crops. Infrared thermometry is an effective method to assess plant water stress at a local scale and is used to schedule irrigation in various crops. This method focuses on measuring the canopy temperature, which was originally suggested by Jackson et al. (1977). The variability in canopy temperature (Gonzalez-Dugo et al. 2006) and spectral indices derived using canopy temperature (Osroosh et al. 2015) have been used to indicate water stress.

10.3.1 Breeding/Phenotyping:

Selecting the best cultivars to improve the crop production has been practiced for thousands of years by farmers. Plant varieties are indeed adopted by the farmers because they improve yield, they are more resistant to specific diseases or pest infestation, and they are adapted to a given environment characterized by an ensemble of conditions including climate, soil, and farmer practices. For their selection, crop breeders must therefore cross a maximum of phenotypic and genomic information in given environmental conditions by quantitatively measuring the plant anatomical, ontogenetical, physiological, and biochemical properties (Walter et al., 2015). Phenotyping experiments were first conducted in controlled conditions with plants in pots in greenhouses or gas chambers.

However, several studies have shown some limitations of these experiments such as the reduced soil volume or depth or the plant microclimate that do not reproduce actual field conditions (Mittler and Blum Wald, 2010; Fiorani and Schurr, 2013;

Araus and Cairns,2014). Conversely, high-throughput field phenotyping allows to characterize genotypes of a given species within given environmental requisites and agricultural practices, by monitoring thousands of plots composed of varieties sowed along few rows. While the genotyping efficiency increased significantly this past 30 years thanks to DNA sequencing, the field phenotyping capabilities progressed more slowly due to the need for developing means to carry out repeated measurements over a huge number of plots throughout the crop cycle (White etal., 2012). Non-destructive and automatic measurements are indeed mandatory to monitor a phenotyping platform, making proximal and UAV remote sensing essential for these experiments. This requires the design of robots that automatically acquire the data (Deery et al., 2014), the design of sensors mounted on these robots (Li et al., 2014), and new methods to process, analyze, and interpret the data (Kamilaris and Prenafeta-Boldú, 2018). Finally, the high throughput nature of field phenotyping raises the questions of data storage and computing facilities (White et al., 2012). If precision farming allowed making progress in understanding and exploiting the signal at the canopy level to detect intra-field heterogeneities, high-throughput field phenotyping opens new ways to investigate remote sensing issues at the plant, and even at the vegetation element scale.

10.3.2 Monitoring of Vegetation Cover:

Vegetation cover of a particular area can be done by using RS in a cost-effective manner. Many research experiments were done using aerial photographs and digital image processing techniques. But the field of RS helps in reducing the amount of field data to be collected and improves the higher precision of estimates (Kingra*et al.,* 2016). The ability of hyper spectral data to significantly improve the characterization, discrimination, modeling, and mapping of crops and vegetation, when compared with broadband multispectral RS, is well known (Thenkabail*etal.,* 2011).This was helpful in establishing the33 optimal HNBs and an equal number of specific two-band normalized difference HVIsare used to characterize, classify, model and map and also to study specific biophysical and biochemical quantities of major agricultural crops of the world (Thenkabail*et al.,* 2013).In relative to the crop condition, some RS techniques are more focused on physical parameters of the crop system such as nutrient stress and water availability in assessing the crop health and yield. And other researchers are focused more on synoptic perspectives of regional crop condition using RS indices.

10.3.3 Crop Condition Assessment:

RS can play an important role in agriculture by providing timely spectral information which can be used for assessing the Bio-physical indicators of plant health. The physiological changes that occur in a plant due to stress may change the spectral reflectance/ emission characteristics resulting in the detection of stress amenable to RS techniques (Menon, 2012). Crop monitoring at regular intervals of crop grow this necessary to take appropriate measures and also to know the probable loss of production due to any stress factor. The crop growth stages and its development are influenced by a variety of factors such as available soil moisture, date of planting, air temperature, day length, and soil condition. These factors are responsible for the plant conditions and their productivity. For example, corn crop yields can be negatively impacted if temperatures are too high at the time of pollination. For this reason, knowing the temperature at the time of corn pollination could help forecasters better predict corn yields (Nellis *et al.,* 2009).

10.3.4 Soil Fertility Evaluation:

The most important fields where we can opt for application of RS and GI through the application of precision farming are nutrient and water stress management. Detecting nutrient stresses by using RS and GIS helps us in site specific nutrient management through which we can reduce the cost of cultivation as well as increase the fertilizer use efficiency for the crops. In semi-arid and arid regions judicious use of water can be made possible through the application of precision farming technologies. For example, drip irrigation coupled within formation from remotely sensed data such as canopy air temperature difference can be used to increase the water use efficiency by reducing the runoff and percolation losses (Das and Singh, 1989). The spectral reflectance in the visible region was higher in water stressed crop than the non-stressed. The vegetation indices like NDVI, RVI, PVI and GI were found lower for stressed and higher for non-stressed crop. The advent of microwave RS has made possible for estimating the soil moisture availability in the field. Information on crop water demand, water use, soil moisture condition, related crop growth at different stages can be obtained through the use of RS data. Bandara (2003), for example, used NOA satellite data to assess the performance of three large irrigation projects in Sri Lanka. Within this analysis, estimates using RS of crop-water utilization were compared to actual water availability to determine irrigation efficiency.

10.3.5 Crop Evapo-Transpiration:

The decline in the productivity of crops is due to irregularities in rainfall, increase in the temperature rate etc., which causes a decrease in the soil moisture. Drought is a situation which can be defined as a long-term average condition of the balance between precipitation and evapo-transpiration in a particular area, which also depends on the timely onset of monsoon as well as its potency Wilhite and Glantz, (1985).

Estimation of evapo-transpiration is essential for assessing the irrigation scheduling, water and energy balance computations, determining crop water stress index (CWSI), climatological and meteorological purposes. The energy emitted from cropped area has been useful in assessing the crop water stress as the temperature of the lants are mediated by the soil water availability and crop evapo-transpiration. Batra *et al.*, (2006) estimated evaporative fraction (EF), defined as the ratio of ET and available radiant energy, by successfully using AVHRR and MODIS data. Neale*et al.*, (2005) provide an historical perspective on high resolution airborne RS of crop coefficients for obtaining actual crop evapo-transpiration. Most of the approaches use simple direct correlations between remote sensed digital data and evapo-transpiration, but some combine various forms of remotely sensed data types. RS is playing a major role in the water management for agricultural system. And this can be further enhanced by the development of hyperspectral sensors and linking the RS data with other spatial data through GIS and GPS technologies.

10.3.6 Weed Identification and Management:

Precision weed management technique helps in carrying out the better weed management practices. RS coupled with precision agriculture is a promising technology in nowadays. Though, ground surveying methods for mapping site–specific information about weeds is very time–consuming and labor–intensive.

However, image–based RS has potential applications in weed detection for site–specific weed management (Lamb et al. 1999). Kaur *et al.*, (2014) by using radiance ratio and NDVI, pure wheat can be distinguished from pure populations of *Malva neglect* after 30 DAS and remain distinguished up to 120 DAS and different levels of weed population can be discriminated amongst themselves from 60DAS onwards. Weed prescription maps can be prepared with Geographic Information System (GIS), on the basis of which farmers can be advised to take the preventive control measures.

10.3.7 Pest and Disease Infestation:

RS has become an essential tool for monitoring and quantifying crop stress due to biotic and abiotic factors. RS methodologies need to be perfected for identification of insect breeding grounds for developing strategies to prevent their spread and taking effective control measures. TheRS approach in assessing and monitoring insect defoliation has been used to relate differences in spectral responses to chlorosis, yellowing of leaves and foliage reduction over a given time period assuming that these differences can be correlated, classified and interpreted (Franklin, 2001). Mirik*et al.,* (2012) reported that the Landas at 5 TM image can be used to accurately detect and quantify disease for site-specific Wheat Streak Mosaic disease management in the wheat crop.

10.3.8 Crop Stress Detection:

With the advent of RS, it is possible to detect the spatial variability in plant water status with high temporal resolution. RS methods based on spectral vegetation indices and infrared thermometry (Ihuoma and Madramootoo 2017) are widely used for crop water stress detection because they are non-destructive and not labour- or time-intensive. The RS method is extensively used in vegetation studies that make use of the spectral reflectance of crops. Spectral reflectance is a measure of the wavelength of the electromagnetic energy collected from objects on Earth. The biochemical and biophysical properties of plants, such as biomass, crop evapotranspiration and canopy water content, are related to spectral properties that are used for spectral reflectance. Mathematical combinations of two or more spectral bands are referred to as spectral indices that are applied to detect water stress in crops. Infrared thermometry is an effective method to assess plant water stress at a local scale and is used to schedule irrigation in various crops. This method focuses on measuring the canopy temperature, which was originally suggested by Jackson et al. (1977). The variability in canopy temperature and spectral indices derived using canopy temperature (Osroosh et al. 2015) have been used to indicate water stress. The crop water stress index (CWSI), one of the most adopted indicators of plant water stress, is computed from canopy temperature. Canopy temperature is inversely related to leaf stomatal closure and transpiration. Stomatal closure is a consequence of water stress in crops, which, in turn, diminishes the transpiration rate in plants. A low transpiration rate decreases the cooling of plants; hence, canopy temperature increases, which is treated as an indicator of water stress. This concept forms the basis to develop the CWSI, which was first introduced by Jackson et al. (1977). The empirical CWSI is given in equation 1.

$$CWSI = \left(\frac{dT - dT_{ll}}{dT_{ul} - dT_{ll}}\right) \tag{1}$$

where dT =Difference between canopy temperature (T_c) and air temperature (T_a)

dT_{ll} =Lower baseline of fully watered crops

dT_{ul} = Upper baseline of water-stressed crops

dT_{ll} and dT_{ul} are computed from the atmospeheric Vapour Pressure Differential (VPD) and Vapour Pressure Gradient (VPG). The upper baselineprovides the difference between air and canopy temperature, which is much less in waterstressedcrops, concluding that the crop lacks water. Relative humidity in air inverselyaffects transpiration in non-water-stressed crops. The lower baseline describes the situationfor non-water-stressed crops where more transpiration takes place that lowers the canopytemperature. The lower baseline depends on the VPD, whereas the upper baseline does not.

Assessing crop water stress involves measuring evapotranspiration (ET), which quantifies the water lost to the atmosphere through both soil evaporation and plant transpiration. The measurement of ET is crucial for understanding its impact on water resources, managing water rights, and influencing the hydrological cycle at both local and regional levels. The most frequently used method for estimating ET at present is the Penman–Monteith equation. The point-based approach makes this technique limited to the local scale and therefore is not suitable for large heterogeneous areas. There was a need to introduce the RS technique to evaluate ET at local and regional scales. Large area coverage with high-resolution imagery in an instantaneous view is possible through RS and the data can be utilized to retrieve parameters such as radiometric surface temperature, VI and albedo (Choudhury 1989). The energy balances concept and net radiation are used as the principal parameters in most remote sensing methods used to estimate ET. There are two widely used satellite-based models for ETi.e. SEBAL and METRIC. SEBAL is based on visible and thermal infrared spectral radiances of dry and wetland surfaces (Bastiaanssen et al. 1998). The mapping evapotranspiration at high resolution with internalized calibration (METRIC) is based on short wave and long wave thermal images that provide better accuracy and consistency in results. However, the predictive accuracy of these methods depends on the retrieval of vegetation indices and meteorological variables obtained from remote sensing techniques (Glenn et al. 2010). In summary, applications of machine learning algorithms to RS data, i.e., spectral bands, parameters retrieved through LST, VI and albedo, can greatly contribute to the determination of plant water stress.

10.3.9 Precision Agriculture:

RS technology is a key component of precision farming and is being used by an increasing number of scientists, engineers and large-scale crop growers (Liaghat and Balasundram, 2010). The main aim of precision farming is reduced cost of cultivation, improved control and improved resource use efficiency with the help of information received by the sensors fitted in the farm machineries. Variable rate technology (VRT) is the most advanced component of precision farming. Sensors are mounted on the moving farm machineries containing a computer which provides input recommendation maps and thereby controls the application of inputs based on the information received from GPS receiver (NRC, 1997).

The advantage of precision farming is the acquisition of information on crops at temporal frequency and spatial resolution required for making management decisions. RS is a no doubt valuable tool for providing such information's. Bagheri *et al.,* (2013) used multispectral lRS for site- specific nitrogen fertilizer management. Satellite imagery from the advanced spaceborne thermal emission and reflection radiometer (Aster) was acquired in a 23-ha corn- planted area in Iran.

10.4 Conclusions:

In conclusion, the synergy between remote sensing and GIS holds immense potential for revolutionizing the agricultural sector. Their complementary roles contribute significantly to enhancing the quality of data in crop production. The integration of these technologies not only facilitates the mechanization of data collection and analysis but also ensures the acquisition of high-quality data. As we navigate the ever-evolving landscape of agricultural technology, it is evident that further research in this field is essential. By delving deeper into the applications of remote sensing and GIS in agriculture, we can unlock new avenues for innovation, leading to more efficient and sustainable practices. Embracing these advancements will not only propel the agricultural industry forward but also empower stakeholders with the tools they need to make informed decisions, ultimately contributing to global food security and sustainable resource management.

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