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Remote Sensing and Geographic Information System Applications for Precision Farming and Natural Resource Management

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Abstract: In all types of agriculture practises, RS and GIS are frequently utilised to explain events, anticipate consequences, and plan tactics. The user can examine, evaluate, and comprehend multiple geographically referenced data using such a system. When the two are combined, the user has vast geographic knowledge about any region. Modern geospatial tools such as Remote Sensing (RS), Geographic Information System (GIS), and Global Positioning System (GPS) have provided extremely powerful methods for surveying, identifying, classifying, mapping, monitoring, characterization, and tracking changes in the composition, extent, and distribution of a variety of earth resources, both renewable and non-renewable, living and nonliving in nature. The potential of advanced satellite systems for sustainable agriculture development is investigated, as well as the fusion of GIS and remote sensing knowledge for precision farming, natural resource management, and land management. The capability of RS and GIS for monitoring and managing natural resources at multi-temporal, multi-spectral, and multi-spatial resolution was examined. Remote sensing is quite useful for assessing rates and trends, but GIS is particularly useful for evaluating the causes and implications. However, combining such spatial technologies with other analytical methodologies is frequently useful in order to generate better knowledge about potential implications and improve our understanding of natural resource management. Natural resource managers can better comprehend and interact with remote sensing scientists to create and implement remote sensing science to achieve productive monitoring by utilising such advanced technologies.

Keywords: Remote sensing, Geographic Information System, Global Positioning system, Multi-spatial resolution, Natural Resource Management (NRM)

The world's population continues to rise, with a projected population of 10.0 billion by 2050. In this sense, cost-effective food production is a critical goal, and remote sensing and geographic information systems, which are used to evaluate and visualise agricultural surroundings, have shown to be extremely valuable to the farming community as well as industry. It plays an important role in agriculture around the world, assisting farmers in boosting production, lowering costs, and better managing their property. Geographic information systems (GIS) have been widely used and regarded as a useful and strong tool for detecting changes in land cover and land use (Marshet et al 2019).The remote sensing technique collects geographical data scientifically for large areas at a low cost, and as a result, it has become the standard method for collecting natural and agricultural data surveys in recent decades. The ambiguity of spatial data of agricultural parameters, which is required for crop modelling, is resolved to some extent by remote sensing (Kumari 2020). To estimate agricultural yield locally and internationally, a variety of RS and GIS methodologies were integrated. Using RS and GIS data, studies were conducted to estimate canopy density, biomass, canopy characteristics, and soil parameters, which were then combined with several crop models. Using Geographic Information Systems (GIS) and Remote Sensing (RS) techniques, it is possible to store and interpret complex geo-referenced and themed layers acquired from numerous sources on a computer. This will deliver precise information to decision makers in a short amount of time and at a cheaper cost (Kumari 2020). These methods reduce the use of water, pesticides, and herbicides, maintain soil fertility, and aid in the efficient use of manpower, so increasing productivity and improving quality (Talaviya et al 2020). New technologies that are not only cost-effective but also in line with the country's natural climatic regime; technologies relevant to rain-fed areas specifically; continued genetic improvements for better seeds and yields; data improvements for better research, better results, and sustainable planning; bridging the gap between knowledge and practise; and judicious land use resource surveys, efficient management, and judicious land use resource surveys, efficient management, and judicious land use resource surveys, efficient management, and judicious land use resource.

Sustainable agricultural production is dependent on the wise use of natural resources (soil, water, livestock, plant genetics, fisheries, forest, climate, rainfall, and topography) in accordance with current socioeconomic infrastructure. Technology has a critical role in developing countries' rapid economic growth and social transformation.

GIS and Remote Sensing Application in Various Sector

Horticulture crops assessment: India is the world's second-largest fruit and vegetable grower. Inventory of fruits, vegetables, plantation crops, crop health, disease mapping, yield modelling and year-to-year changes, site suitability, and post-harvest research are all done with Indian satellite sensors such as AWiFS, LISS-III, and IV. Although remote sensing data has been used to measure yield and production for crops such as potato, mango, citrus, and banana, accuracy is still a challenge for other crops due to scattered and tiny fields, mixed cropping, many seasons, and short duration. The utilisation of satellite data and GIS tools, on the other hand, has shown considerable potential for horticulture development, particularly in terms of infrastructure and horticultural extension. The investigations are mostly based on high resolution or hyper spectral remote sensors and time series analysis for crop inventory and production projections.

Table 1. Evolution and advancement in remote sensing sensors

Phases	Time series	Remarks
Airborne remote sensing	During the First and Second World Wars	The use of photographs for surveying, mapping, reconnaissance and military surveillance
Rudimentary spaceborne satellite remote sensing	In the late 1950s	The launch of Sputnik 1 by Russia in 1957 and Explorer 1 by US in 1958
Spy satellite remote sensing	During the Cold War (1947–1991)	Remote sensing for military use spilled over into mapping and environment applications
Meteorological satellite sensor remote sensing	1960˜	The launch of the first meteorological satellite (TIROS-1) by the US in 1960. Since then, data in digital formats and the use of computer hardware and software
Landsat	1972˜	Landsat 1, 2, and 3 carrying a multispectral scanner; Landsat 4 and 5 carried a Thematic Mapper sensor; Landsat 7 carries an Enhanced Thematic Mapper; Landsat 8 carries the Operational Land Imager. Landsat satellites have high resolution and global coverage. Applications were initially local and have become global since then
European Space Agency's first Earth observing satellite program	1991˜	The European Space Agency launched the first satellite ERS-1 in 1991, which carried a variety of earth observation instruments: a radar altimeter, ATSR-1, SAR, wind scatter meter, and microwave radiometer. A successor, ERS-2, was launched in 1995
Earth observing system (EOS)	Since the launch of the Terra satellite in 1999	Terra/Aqua satellites carrying sensors, such as MODIS and taking measurements of pollution in the troposphere (MOPITT). Global coverage, frequent repeat coverage, a high level of processing, easy and mostly free access to data
New millennium	Around the same time as EOS	Next generation of satellites and sensors, such as Earth Observing-1, acquiring the first spaceborne hyperspectral data
Private industry/commercial satellite systems	2000˜	1. Very high-resolution data, such as IKONOS and Quick bird satellites 2. A revolutionary means of data acquisition: daily coverage of any spot on earth at a high resolution, such as Rapid eye 3. Google streaming technology allows rapid data access to very high-resolution images 4. The launch of GeoEye-1 in 2008 for very high-resolution imagery (0.41 m)
Microsatellite era and satellite constellations	2008˜	1. Small satellites and satellite constellation (Rapid Eye and Terra Bella, formerly Skybox): Rapid Eye was launched in August, 2008, with five EOS. These are the first commercial satellites to include the Red-Edge band, which is sensitive to changes in chlorophyll content. On March 8, 2016, Skybox imaging was renamed to Terra Bella. Satellites provided the ability to capture the first-ever commercial high-resolution video of Earth from a satellite and the ability to capture high-resolution colour and near-infrared imagery 2. For the first time, Russia carried out a single mission to launch 37 satellites in June of 2014 3. ESA launched the first satellite of the Sentinel constellation in April of 2014. 4. SpaceX reusable rocket capacity since December of 2015 5. Current satellites in high revisiting period, large coverage, and high spatial resolution, up to 31 cm

Hyper spectral sensors, in particular, allow us to detect the energy reflected from the sun in multiple channels (typically more than 200). It is possible to generate the spectral signature of the targets of interest with great precision and then characterise them radio metrically in this way. It is critical to use the Indian Remote Sensing Satellite (IRS)-ID Linear Imaging Self-Scanning (LISS)-III sensor to estimate the productivity of fruit and vegetable crops cultivated. The optimal method is to use a Supervised Maximum Likelihood Classifier (MLC) plus a visual interpretation of the texture from a PAN (panchromatic) sensor.

For hyper spectral, a portable hyper spectral camera was demonstrated, as well as an object-oriented software framework with models that identified crop, soil, and weed; the study case was sugar beet and green citrus (Talaviya et al 2020). Site-specific crop management (SSCM) is a type of precision agriculture that is commonly used in row crops, although it is rarely used in fruit and nut production. High-resolution satellites, hyper spectral imaging, LIDARS, UAVs, and other technologies; as well as GIS spatial modelling for fruit orchards (Talaviya et al 2020). However, sensors and platforms with higher resolutions, free-access collection imagery (i.e. Sentinel-ESA and Landsat-NASA), aircraft-mounted sensors, UAVs, the power of computational processing, fusion data, the mayor accesses to digital big data, and historical yield information all point to a bright future for GRS in horticulture.Due to the distributed and small field sizes, as well as the comparably short period of vegetable crops and mixed cropping in India, satellite RS technology for horticulture crops has some obstacles. Improved observations from hyperspectral, thermal infrared sensors, and advanced radars or LIDARs on-board forthcoming satellites have a significant potential for application in this industry. Estimating yields, particularly for orchard crops, was difficult.

Crop inventory: Crop discrimination is based on the differential spectral response of distinct crops in a multi-dimensional feature space generated by different spectral bands, time domain, or both, and is influenced by sensor features and pattern recognition techniques. Visual or digital interpretation approaches are used to do crop discrimination/mapping utilising space data. Standard FCC (False Color Composite) created using green, red, and near-IR wavelengths assigned blue, green, and red colours is used in most visual approaches. Over a research site in Imperial Valley, California, it was established that a colour composite formed by the best three bands (TM bands 3, 4 & 5) provided superior discrimination than normal FCC. Digital approaches are recommended for crop discrimination because they apply to each pixel and employ the entire dynamic range of data. When single-date data does not allow for effective crop differentiation, a multi-temporal technique is applied (Kumari 2020). The approach in this case consists of three stages: (a) pre-processing, (b) data compression, and (c) image categorization. Multispectral and multi-temporal data, as well as supervised and unsupervised classification approaches, are employed for crop identification and classification. In supervised classification, training sets are given to categorise pixels of a specific class, and then the image's Information classes (i.e., crop type) are identified. "Training signatures" are what they're called. Unsupervised classification, on the other hand, is a technique that analyses a large number of unknown pixels and separates them into groups based on spectral groupings found in the image data. Analyst-specified training data is not required for unsupervised classification. The so-called "regression estimator," which has been recommended, is one of the practical approaches of using remote sensing in agricultural statistics. The procedure entails pre-processing satellite data to remove radiometric and geometric inaccuracies, as well as classification of the data using supervised methods that include classifier training using sample segments. The area frame sampling and image processing results are statistically connected and used to create an enhanced area estimate per crop in each stratum in this method (Singh 2017).

Assessment of crop condition: The condition of cereal crop seedlings, as well as the status and trend of their growth, can be determined via remote sensing. It also aids in the gathering of crop production data. When large-scale commissariat shortages or surpluses occur, obtaining crop condition information early in the crop growth cycle is even more crucial than obtaining actual production after harvest. Obtaining crop condition as soon as feasible has a significant impact on decisions regarding commissariat price, circulation, and storage. In western industrialised countries, particularly the United States, remote sensing technology is being used to monitor crop conditions. The "Large Area Crop Inventory Experiment (LACIE)" programme was carried out by the United States Department of Agriculture (USDA), the National Oceanic and Atmospheric Administration (NOAA), the National Aeronautics and Space Administration (NASA), and the United States Department of Commerce (USDC) from 1974 to 1977. Wheat is the principal monitoring crop in the programme, with the United States, Former Russia, and Canada as the monitoring areas. The "redirected from Agriculture and Resources Inventory Surveys through Aerospace (AgRISTARS)" initiative, which ran from 1980 to 1986, brought these departments back together. In 1986, a global scale operational crop monitoring system was built as a result of that effort. The system not only assessed crop conditions and predicted production for a variety of crops (including wheat, rice, maize, soybean, and cotton) in the United States, but it also kept track of the world's major food producers, including Former Russia, Canada, Mexico, Argentina, Brazil, China, India, and Australia. The system's operation generates significant economic benefits for the United States. Following that, under the "Monitoring Agriculture with Remote Sensing (MARS)" programme, the European Union's Joint Research Centre (JRC) developed its own crop production estimation method. The system's monitoring results were used in the European Union's common agricultural policy, such as agricultural subsidies and the verification of farmers' declarations. During that time, scientists in the field all over the world focused on crop monitoring methods using NOAA/AVHRR, and significant progress was made.

High-resolution meteorological satellites can collect data on terrestrial processes on a daily basis, allowing for continuous and dynamic crop monitoring. The NDVI profile of crops is created by collating NDVI values along time lines and can indicate the shift in crop NDVI from planting, seedling, tassel, maturation, and harvesting. Varied crops have different NDVI profiles, and even the same crop growing in different conditions has different NDVI profiles. By evaluating the characteristics of the crop's time series NDVI profile, the crop's status and growth trends can be determined. Crop Growing Models allow for the dynamic monitoring of the crop growing process by simulating the crop growing process. The basic concept of a crop growing model is to use a mathematical formula to represent the crop growing process. The interception of solar energy for vegetation canopy and photosynthesis, which produces dry biomass, is the driving force behind all crop growing models. SUCROS (Simple and Universal Crop Growth Simulator), (Modules of all Annual Crop Simulator), CERES (Crop Environment Resource Synthesis), and P-1/2/3 are some of the most prominent crop growing models. Some of these models concentrate on the commonality of all crops, while others concentrate on the specialisation of various crops. Researchers in the field have been working hard in recent years to build new models such as ORYZA, SERES-RICE, and SIMRIW, among others. Crop-growing models can correctly portray the crop-growing process and monitor crop health. The advancement of remote sensing technology, as well as the usage of remote sensing data, has enabled the application of crop-growing models on a broad scale. However, the use of these models necessitates a large number of agro-parameters, and the model must be calibrated using local field data before being used in multiple locations. The lack of local agro-parameters and observable field data, as well as its complexity, limit the use of these models to some extent.

Identification of weeds and its management: Weeds are undesired plants that compete for water, nutrients, light, space, and carbon dioxide, reducing crop yields. Weeds must be controlled to satisfy future food supply demands. Drones, artificial intelligence, and numerous sensors, such as hyper spectral, multi-spectral, and RGB (red-green-blue), all work together to assure a superior outcome in weed management. It is a multidisciplinary science that encompasses spectroscopy, optics, computer science, photography, satellite launch, electronics, communication, and a variety of other disciplines. Future concerns like as food security, sustainability, supply and demand, climate change, and herbicide resistance may be addressed through machine learning-based technology. The integrated weed management (IWM) method, which combines numerous treatments, is a step toward addressing difficulties associated with traditional tactics, such as herbicide resistance (MacLaren et al 2020, Hu et al 2020). In early-season agronomic settings, where crop and weed seedlings have identical spectral signatures, UAV photography aids in better categorising findings (Castro et al 2018). By detecting weeds early in the season as a first and critical stage, precision farming systems can efficiently control weed problems while minimising operating expenses and environmental damage (Chlingaryan et al 2018, Torres et al 2015). Chlingaryanet al (2018) identified multi-spectral remote sensing as a technique for analysing multi-temporal crop diseases employing three high resolutions of remote sensing pictures to undertake a spatio-temporal analysis of the impaction dynamic. The applicability of multi-spectral remote sensing data for disease identification in late occurrences and at high infection rates was demonstrated in this work, showing the suitability of these methods for disease detection in late occurrences and at high infection rates. Establishment of airborne multispectral techniques for analysing tree health problems in a citrus orchard, which can be combined with variable rate technology (VRT) for mandatory pesticide application and environmental modelling for pollutant reduction assessment (Mink et al 2020). Multi-spectral photography was used to detect anomalies, and a spectral linear unmixing-based approach with site-specific agriculture was used to evaluate stress severity and detect past infection, according to the study. The data obtained through airborne multispectral imaging evaluation is more detailed and complete than data obtained visually in field experiments (Mink et al 2020). Image segmentation between crop and weed in a soybean field for weed detection using hyperspectral remote sensing revealed a high degree of accuracy (99.9%) for soil and plant differentiation (Mink et al 2020). This research used a hyperspectral camera with a spectral wavelength range of 360 to 1010 nm and a spectral resolution of 10 nm (ImSpector V10: Specim Ltd., Oulu, Finland). Hyperspectral imaging with wavelet analysis was used to classify plants for weed identification. The authors investigated three alternative plant classification approaches, including Euclidean distance, discriminant analysis, and wavelet coefficient, using hyper spectral pictures with 240 wavebands for spectral information. The wavelet coefficient is more useful for weed detection, and the validation result suggests that the created classification technique will be useful in the future (Li et al, 2021).

The ability of HSI to detect unique spectral signatures of a wide range of weed species, including grasses, broadleaves, annuals, and perennials. In comparison to averaged spectrum data, models constructed with Sp spectral data can deliver superior outcomes for weed classification. When generated with Sp data, MLP is a more robust and reliable method than standard classification systems. The application of HSI in plant identification will be greatly enhanced by this unique approach based on Sp. This is particularly useful in the grazing field, where it is used in mixed swards of a few plant species (Li et al, 2021).

Crop water stress monitoring: The phenological stage of a crop is often referred to when monitoring it. The plant's "internal clock" is defined by a sequence of events that allows us to follow its evolution from emergence to senescence, through various levels of "greenness" that characterise the condition of vegetation and the accumulation of biomass in distinct organs. These stages vary greatly in space, depending on the practise management and climatic interactions. The use of radiometric indices such as the normalised vegetation index (NDVI), the normalised difference water index (NDWI), the global vegetation index (GVI), or the enhanced vegetation index EVI has piqued the interest of many researchers. The NDVI has a number of benefits: it is a stable and trustworthy indicator, and the spectral bands used to calculate it are available on all optical satellites. As a result, it is frequently utilised in science, and its straightforward formulation makes it accessible to non-expert remote sensing users. NDVI maps created from observations made by the FORMOSAT-2 satellite every three days over a small 4 km x 4 km agricultural sector north of Mexico in the Yaqui Valley (27.263°N, 109.892°W). Because of the excellent spatial resolution of the photos, each field can be identified on these maps (8 m). Winter wheat is the most common. Its growth is restricted to the initial stages in November and December (the blue colour represents low NDVI values). The growth of the leaves begins in January–February, increasing the percentage of green colour recorded by the satellite in each pixel of the photos, with the growth peak represented in red (the highest NDVI values) (Seifried 2017).

During the Rabi season, the most common crops grown in the study region are wheat and sugarcane. This study used Landsat data from the 2009-10 and 2013-14 Rabi seasons. Crop discrimination was done using a rule-based classification technique because the study was limited to wheat. Wheat was properly identified from other classes using a rule-based classifier, with individual accuracy of 85 percent and total accuracy of 90 percent (Seifried 2017). Ws LSWI, Ws VWSI, and Ws WSI are three satellite-based water stress indices that were developed separately from optical and thermal datasets. Using multitemporal landsat data, the SEBS model was also utilised to calculate daily ET. Water stress predictions for 2009-10 were compared to ET based on flux towers. The LUE model was used to examine the impact of water stress on productivity. Productivity was calculated using the water scalar, temperature scalar, and maximum light use efficiency. In the LUE model, the two most essential inputs were APAR and LUE. The LUE model was used to analyse the influence of water stress on wheat productivity using the water scalars Ws LSWI and Ws VWSI. Final productivity was validated with yield estimated by crop cutting experiment (CCE) for 2013-14 and crop statistics (BES) for 2009-10. Estimated FAPAR was developed using ground readings taken during field visits and showing a logarithmic relation between FAPAR and NDVI, which was validated and used for productivity calculation (2013-14).The influence of water stress on wheat productivity using two different water scalars, namely Ws LSWI and Ws VWSI. Ws LSWI indices demonstrated to be more accurate in assessing water stress and demonstrating its impact on productivity. Non-imaging chlorophyll fluorescence research has produced some promising results, but it can only provide point data measurements with restricted information on a tiny leaf region sensed rather than the entire leaf or canopy area, which is what advanced chlorophyll imaging wants to solve. The multi-pixel feature of larger-scale fluorescence sensing with imaging provides additional fluorescence fingerprints, allowing for full screening of all points of leaf. This benefit accounts for minor changes in fluorescence emission pattern due to a variety of plant internal variables that would be missed by non-imaging approaches, reducing measurement errors (Buschmann et al 2019).

Thermography, unlike fluorescence imaging, can show stomatal movement without the use of a light source (Vadivambal et al 2018). The thermal signal under investigation is a change in temperature collected in the form of reflected or emitted radiation from the scanned plant. Thermal intensity is determined by the ambient temperature, with infrared radiation intensifying as the temperature rises. The opening and closing of stomata for gas exchange or cooling are common responses to changes in leaf temperature. The cooling process stimulates stomatal opening, which results in a lower temperature and heat loss to the atmosphere. However, nutritional availability in the soil and water flow within the plant determine transpiration and, eventually, stomatal control. Water or nutrient shortage affects the movement of dissolved nutrients and water from the soil to the roots, and then to the entire plant, where nutrient uptake is hindered by greater nutrient concentrations in the soil (Li et al 2017). As a result, the stomata close in order to prevent further moisture loss, and the temperature of the leaf surface rises. This explains why some studies conclude that nutrient deficiency has an impact on stomatal regulation and can lead to an increase in plant temperature. On thermal imaging, a magnesium-deficient bean plant displayed a greater leaf temperature under controlled conditions (Chaerle et al 2017). Under fertilized barley (Hordeum vulgare L.) had a higher temperature than well-fertilized barley (Hordeum vulgare L.) with nitrogen as the reference nutrient (Tilling et al 2016).

Precision farming (PF): Precision agriculture (PA) is an integrated information and agricultural management system that uses a variety of technology instruments such as GPS, GIS, and remote sensing. Precision farming (PF) is intended to boost overall agricultural production efficiency while minimising the negative effects of chemical use on the environment. Precision farming aims to collect and evaluate data about the variability of soil and crop conditions in order to maximise crop input efficiency in tiny areas of the farm field. To achieve this efficiency aim, the field's variability must be controlled. A growing number of scientists, engineers, and large-scale crop growers are using remote sensing technology as part of precision farming (Liaghat et al 2018). In the mid-to-late 1980s, PA research began in the United States, Canada, Australia, and Western Europe. Despite a significant amount of study, only a small percentage of farmers have used any sort of PA technology. PA has primarily been implemented by modifying current field gear with controllers and GPS to enable spatially varied uses. The most common application of PA is still fertiliser application on a site-by-site basis. Most PA trials focused on VRT fertiliser and herbicide applications, several types of PA technologies have been tested around the world (Naiqian et al 2015). A base map or base data layer must be referenced in every GIS database. The database should ideally be linked to a large-scale, highly accurate base map. When attempting to explore the true spatial relationships between features digitised from a small scale map and features whose coordinates were taken with GPS, there may be issues if the base map is smaller scale (quad scale or smaller).This can be a significant issue if a grower decides to use a GIS data layer that was created using small scale base maps as a reference point for any new data generated. Developing an accurate base data layer based on geodetic control and photogrammetric mapping is the best strategy to avoid such mismatch (Hendrickson et al 2020). Another facet of GIS support for precision agriculture is the engineering component, which involves translating research findings into operational systems that can be used on farms. GIS can help with this engineering effort by offering a good platform for storing base data, simple modelling, presenting results, developing a user interface, and controlling farm navigation when used in conjunction with GPS. A decision support system for operationalizing precision farming at the farm level can be constructed using GIS. Crop yield monitors are devices that measure crop yields and are fitted on harvesting machinery. The yield data from the monitor, as well as positional data from the GPS device, are captured and saved at regular intervals of time or distance. They also keep track of distance and bushels every load, as well as the number of loads and fields. Yield maps can be created with the use of GIS software. In recent years, several technologies for quantitatively assessing spatial correlations within and between layers of environmental data have been developed. These tools can be used to determine whether a given variable has a spatial pattern or structure, or if it can be related to other (s), and so explain and/or predict a crop's productive and quality behaviour. Without a doubt, simply visualising data has significant ramifications for our ability to comprehend or visualise possible relationships between, say, environmental variables and yield. However, we can't tell if the connections are meaningful or if they're veiled by other types of inaccuracy or stochasticity. As a result, statistical analysis plays a critical role here, allowing us to quantify and numerically characterise the spatial relationships that exist in the field.

Precision farming necessitates knowledge of the average features of tiny, homogeneous management zones. Soil tests for nutrient availability, yield monitors for crop yield, soil samples for organic matter content, information in soil maps, or ground conductivity metres for soil moisture can all provide these average properties. In most cases, the fields are manually sampled along a regular grid, and the sample results are interpolated using geostatistical techniques. Soil, water, and crop variability geostatistical modelling necessitates the collection of a large number of samples at close intervals over the agricultural area. These kinds of samplings are both expensive and time-consuming. The benefits of using remote sensing technologies to acquire geographically and temporally varied information for precision farming have been demonstrated by a number of researchers. Satellite-based sensors or CIR video digital cameras on board small aircraft can be used to collect remote sensing imagery for PF. Aerial, satellite, and spacecraft observations of the surfaces and atmospheres of the planets in our solar system are included in the science of remote sensing, with the Earth being the most frequently studied. RS is mainly limited to methods for detecting and measuring electromagnetic energy, such as visible and non-visible radiation that interacts with surfaces and the atmosphere. Planners observed RS and GIS technologies to be extremely useful in planning for the efficient use of natural resources at the national, state, and district levels. Due to considerable advancements made in space-borne RS satellites in terms of spatial, temporal, spectral, and radiometric resolutions, application of these technologies in the management of natural resources is quickly growing. Many researchers have debated the benefits of remote sensing technology. Remote sensing imagery can be used for mapping soil parameters, crop species classification, crop water stress detection, weed and crop disease monitoring, and crop yield mapping. The number and width of spectral bands captured by the sensor (multi versus hyperspectral); and spatial (high, medium, and low), temporal (hourly, daily, and weekly), and radiometric (8-, 12-, and 16-bit) resolutions at which sensors collect data are all factors that influence the use of remote sensing in PA.

Through the use of on-board GPS and the Inertial Measurement Unit (IMU) technology, pattern recognition technology, and digital elevation models, efforts have been made in recent years to automate the ortho-rectification process. Although considerable progress has been achieved in automating the ortho-rectification process, it has only been applied to photos captured by UAVs. Images from satellites or piloted planes have not had the same level of success. High overlap (approximately 80% frontal overlap and 60% side overlap) between images acquired by UAVs, as well as GPS on board UAVs that provides detailed metadata describing the camera in terms of position (latitude and longitude) and parameters, have aided the automation of ortho-rectification processes for UAVs images (sensor size, pixel resolution and focal length).

Crop yield and production forecasting: Models that integrate climate, soils, and other environmental variables as response functions to characterise development, photosynthesis, evapotranspiration, and yield for a specific crop are among the traditional techniques of predicting agricultural yields during the growing season. These models are poor predictors when geographical variability in soils, stressors, or management techniques are present (Jensen et al 2016), despite the fact solid physiological and physical ideas. Because of its synoptic coverage and capacity to 'see' in various spectral wavelengths, remote sensing of crop canopies has been suggested as a potentially beneficial tool for agricultural monitoring (Moran et al 2017). Plant development, stress, and yield capacity are all expressed in the spectrum reflectance from crop canopies, which may be evaluated using spectral vegetation indices (Javid et al 2020, Rehman et al 2018). The Normalized Difference Vegetation Index (NDVI) is a vegetation indices (VI) that is a sum, difference, or ratio of two or more spectral wavelengths. They have a strong relationship with photosynthetic activity in non-wilted plant foliage and are excellent predictors of canopy biomass, vigour, and stress. One of the most extensively used indices is vegetation monitoring using the red and near-infrared SPOT VGT channels. Green biomass and the leaf area index are closely correlated with the Normalized Difference Vegetation Index (NDVI). Despite the spatial resolution of 1 km at nadir, several scientific articles have shown the use of SPOT VGT data in monitoring vegetation conditions in near real-time. Crop output is estimated by taking into account crop area estimates and crop yield estimations, which are generally subjective, expensive, and prone to huge errors, resulting in poor crop assessment (Reynolds et al, 2020). Furthermore, the obtained data may become available too late for decision-makers or planners in the country to take necessary action. Remote sensing, on the other hand, can aid in the macroscopical, periodic, and cost-effective acquisition of surface information, and has numerous advantages in agricultural monitoring, with recent success (Narasimhan et al 2018, Dadhwal et al 2018, Bastiaanssen et al 2017, Prasad et al 2016). The Normalized Difference Vegetation Index (NDVI) is a critical indicator of vegetative growth conditions and the degree of vegetative cover in this study (Banair et al 2015). It's worth noting that if a region is covered by vegetation, the NDVI value of that area is positive, and it rises in tandem with the amount of vegetation (Zhao et al 2018). In the last two decades, a few studies have attempted to estimate rice yield using high-resolution remote sensing data (Quick bird; 0.65 m, Worldview; 0.31 m, and IKONOS; NIR 3.2 m, PAN 0.82 m) (Nuarsa et al, 2015), but their technique has run into issues with swath width and expensive prices (Seifried et al 2017). Similarly, due to the temporal resolution of Landsat data, it has been difficult to capture cloud-free images, making it impossible to obtain phenology information throughout the important crop time. MODIS constellations employed to retrieve agricultural crop information, owing to their bigger regional size, smaller dataset, and faster revisiting time (Whitcraft et al 2015). Furthermore, the dynamics of MODIS-derived NDVI products are reflective of crop growth and biomass changes that are directly related to agricultural yield, and they have a direct relationship with LAI, biomass, and plant cover. Several studies have suggested the use of MODIS-derived NDVI data for agricultural yield estimation prediction, crop production, and monitoring (Mahboob et al 2016, Faisal et al 2019).

Rice-SRS (simulation remote sensing) model (Jingfenget al, 2018) was created to approximate rice yield in China using remote sensing data as input. The model receives three types of normalised difference vegetation index (NDVI) inputs: (AVHRR LAC) NDVI, (AVHRR LAC) NDVI, and (AVHRR LAC) NDVI. (AVHRR GAC) NDVI superior extremely high resolution radiometer global area coverage and radiometric measurements NDVI advanced very high promise radiometer limited area coverage To achieve the goal, the leaf area index (LAI) is calculated separately for each input. With AVHRR GAC input, the proposed model produces good results with lower average error. In Haryana, India, Advanced Wide Field Sensor (AWiFS) photos were combined with Monteith's model to assess wheat yield (Patel et al 2016). To estimate wheat yield, a remotely sensed approximation of photo unnaturally active radiation (fAPAR) and every day temperature were used as inputs. The main disadvantage of this model is that as the heterogeneity of field crops increases, the model's accuracy declines. Rice yield is predicted using the Support Vector Regression (SVR) approach. There are three steps in the suggested model (Jaikla et al 2018). To begin, SVR is used to calculate the nitrogen weight of the soil. Second, SVR is used to compute the weight of the rice stem. Third, SVR is used to compute the weight of rice grains.The model's performance is measured in terms of mean absolute error (MAE) and mean absolute percentage error (MAPE), which are compared to their commercial model and reveal that the proposed model's MAPE is higher than the commercial model's but still within acceptable limits, i.e. 5%. To estimate the winter wheat yield in North China, the RS-P-YEC (Remote Sensing – Photosynthesis – Yield Estimation for Crop) model was created (Peijuan et al 2019). To collect the data, the model used remote sensing and meteorological data. The yield of the winter wheat crop was predicted using the harvest index and net primary productivity. The findings of model are compared to meteorological station observations, which provide an R2 of 0.817. At each crop growth stage, a relationship between leaf area index (LAI) and yield is formed (Ren et al 2019). The research area is in North China. To remove the influence of clouds and simulate daily crop LAI to obtain an average for each crop stage, the Savitzky-Golay filter (S-G filter) and Gaussian model are utilised. To predict wheat yield, a link between NDVI computed from remote sensing imagery and LAI is constructed. The biggest disadvantage is that the report does not discuss crop growth stage indicators. (Li et al 2018) discusses various crop growth monitoring indicators used to monitor wheat crop at various stages via remote sensing. Due to the presence of non-vegetation percentage and soil background, NDVI have limitations in vegetation monitoring. The importance of new vegetation indices such as the soil-adjusted vegetation index (SAVI), modified soil-adjusted vegetation index (MSAVI), enhanced vegetation index (EVI), and perpendicular vegetation index (PVI) in achieving accuracy in wheat crop yield prediction is discussed. SAVI with L=0.1 outperforms in heading stage even when crop cover is high, according to the correlation coefficient derived for all variables and LAI. Using Landsat 8 time series pictures, advanced machine learning techniques such as boosted regression tree, random forest regression, support vector regression, and Gaussian process were utilised to estimate silage maize yield (Aghighi et al 2018). To complete the work, the NDVI standards of all fodder maize fields were collected and merged into a two-dimensional dataset for each year. The results suggest that machine learning techniques outperform traditional regression methods because they have the ability to work with high-dimensional composite distribution data.

Water resource management: In the conservation and usage of the country's water resources, remote sensing and GIS play a critical role. Related initiatives and cutting-edge remote sensing techniques must be blended with traditional groundwater measurement and management approaches to provide optimal planning and operation of water resources that will last into the future. Soil moisture patterns in arid settings are a direct indicator of the presence of water. Soil moisture patterns indicate the presence of water in arid environments. Irrigation water distribution or locations with a shallow water table are reflected in moist top soils. Because in-situ sensors make it very hard to obtain soil moisture information at broad spatial scales, soil moisture is rarely included in models. Because it is nearly hard to obtain soil moisture information at wide spatial scales with in-situ sensors, soil moisture is rarely considered in management decisions. Satellites with passive microwave sensors, such as AMSR-E, SMOS, and Feng Yung, give free global scale estimations of daily surface soil moisture. These sensors provide constant estimates of soil moisture that are unaffected by weather conditions. That's also why a new evapotranspiration (ET) method based on soil moisture readings is being used. The brightness temperature collected by satellites is used to predict surface soil moisture using inversion techniques. Because the technique is not error-free, the satellite soil moisture had to be validated before it could be used to estimate other hydrological processes. Classic validation procedures are not technically possible due to the lack of in situ soil moisture measurements in large river basins. As a result, additional validation methods were required in order to increase trust in the use of satellite soil moisture products. To explain soil moisture behaviour, researchers looked at how vegetation reacts to soil moisture and how soil moisture reacts to rainfall. In the land use classes "bare soil," "rainfed," and "very sparse vegetation," there were strong connections between AMSR-E surface soil moisture and TRMM rainfall. In land use classes, AMSR-E surface soil moisture has a strong association with TRMM rainfall occurrences. Furthermore, rather than NDVI and TRMM cumulative rainfall (rs=0.70), there is a substantial link between TRMM accumulated rainfall and the AMSR-E mean soil moisture (Spearman's rank correlation coefficient rs=0.74). In contrast to NDVI and TRMM rainfall (rs=0.70), NDVI and Mean soil moisture have a good connection (rs=0.85) (Muhammad et al, 2017).Groundwater hydrology applications of Geographic information system (GIS) and remote sensing (RS) technology have gotten only a cursory examination. Water management requires a thorough understanding of geographical space and related spatial information such as water sources, watersheds, terrain surfaces, land use, land cover, rainfall, temperature, humidity, soil condition and composition, geology, atmospheric conditions, human activities, environmental data, and so on.The issues, importance, and long-term management of groundwater and freshwater are also described using geographic information system (GIS) and remote sensing (RS) technology (Rani et al, 2018). With careful consideration of source materials and database creation, the integration of geographic information systems and remote sensing techniques has permitted analyses of aquatic vegetation growth, salt marsh quality, and floodplain disturbances throughout time.

CONCLUSIONS

Remote sensing and geographic information systems (GIS) have shown to be useful tools for generating spatial information about natural resources. Soils have been greatly degraded as a result of the planned and indiscriminate exploitation of land. A reliable inventory of soils and other resources is needed, and it must be obtained quickly. Remote sensing data has shown to be an effective technique for mapping soil and other resources. The development of a new generation of high spatial resolution cameras with improved spectral coverage, revisit capabilities, and stereo viewing has opened up new possibilities in a variety of applications. GIS technology is causing rapid changes in natural resource spatial analysis and management. New methods for data gathering, storage, processing, analysis, and modelling are being developed using GIS in conjunction with remote sensing, GPS, and computer technology. Even at small farm holdings, remote sensing is quite effective in analysing various abiotic and biotic stresses in various crops, as well as in recognising and managing various crop concerns. It is necessary to establish a database on diverse crops at the state or district level using remote sensing and GIS techniques in order to effectively use information on crops for policy choices. The implantation of nano-chips in plant and seed tissue, which may be used in near-real time to monitor agriculture, is a novel and non-traditional remote sensing application. Clearly, these and other novel methodologies will emphasise the importance of remote sensing in agricultural science analysis in the future.

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