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Remote Management of Agri-Systems: A review of crop growth monitoring, nutrition management, and yield estimation based on remote sensing data

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Abstract:
The projected increase in global consumption, coupled with erratic weather patterns, unpredictable climate events, and the depletion of agricultural resources, are major pressures on food security systems. An increase in agricultural productivity in a sustainable yet profitable manner by optimization of farm practices is thus critical. Over the years, the use of Precision Agriculture techniques, primarily Remote Sensing (RS) and Geographic Information Systems (GIS), have proven quite effective in optimizing yield potential and ensuring efficient farm resource management. The paper aims to describe the various applications of Remote Sensing & GIS, specifically focused on crop monitoring, nutrition management, and yield prediction which are crucial to ensure high productivity. It aims to provide an overview of the numerous data sources and modes of analysis employed in this context, describing both prevalent as well as novel methodologies. Conceptual aspects for the same have also been illustrated, along with the evaluation of these techniques, both in technical and economic contexts, to determine benefits, limitations, and thus the degree of applicability. It aims to highlight the trends in the usage of the GIS & RS, along with current challenges associated with its implementation and possible future improvements.
***Key Word**: Precision Agriculture, Food Security, Satellite Imagery, Crop Growth.*

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I. Introduction

Currently, the world population is 7.9 billion people, which is expected to rise to 9.8 billion by 2050, with a major increase occurring in developing countries (Calicioglu et al., 2019). A rise of around 70-100% in food production is required given the trends in consumption, diets, and income, along with an increase in area under cultivation to meet the projected hunger demand. This brings major challenges for food security systems as an increase in global demand for agricultural production is adding more pressure on the agroecosystems. The global position on food insecurity is already critical, showing an increasing trend since 2014, with nearly one in three people (around 2.37 billion) not having access to adequate nutrition in the year 2020, thus being "off-track" towards achieving the SDG-2, "Zero Hunger" (FAO, 2021). The major drivers for this trend are the increasing intensity and frequency of natural disasters, pest and disease infections, and degradation of natural resources, with severe impacts, especially in mid-low-income countries. These conditions thus bring in new scenarios for agricultural policies and scientific research. Since agriculture is a major contributor to the economy of most developing countries, there are major incentives for all stakeholders the improvement in agricultural productivity.

Continuous monitoring is required to counter the combined effects of extreme and unpredictable climate events, growing population, soil loss, as well as the natural variability of weather (Food and Agriculture Organization of the United Nations, 2017), to thus minimize their impact on global food production systems (Wheeler & von Braun, 2013), and also to optimize agricultural management practices sustainably (Areal et al., 2018). Due to economic returns, there is high pressure to provide yield prediction at the global, regional, and farmscale, both long-term and short-term. These predictions are also important to anticipate food production shortages and thus ensure food security in the most vulnerable regions of the world (Di Falco et al., 2012). From a long-term perspective, insights from the monitoring and forecasting of particular crops in given locations and climatic conditions can be very instructive to assist the adaptation of farm practices in the same places over different climatic & soil conditions or in other places with such similar environmental conditions. Considering the challenging context for agriculture with regards to both environmental and economic pressures, monitoring and forecasting crop growth and production are important steps in addressing food security problems.

An ideal crop health assessment and growth forecast methodology produces timely, and dependable updates for decision support systems. However, the complexity of production systems, and exorbitant survey costs in terms of both time and resources, often are hurdles in implementation when it comes to traditional crop monitoring and yield prediction processes. Integration of technology in various fields to combat and mitigate challenges due to environmental as well as anthropogenic variables has proven to be quite effective. Precision agriculture, a product of this trend, has grown and established itself as a central tool in agricultural management to forecast yield, monitor plant stress, and optimize fertilization, irrigation, and soil tilling activities for more sustainable management of farming practices and improvements in yield for farmers (Hoogenboom et al., 2004).

Remote Sensing has emerged as one of the major aspects of precision agriculture. It can be in simple terms defined as the science of observing an object without physical interaction. RS data is characterized by objective measurements, systematic, time series, spatially visualized information, and large-scale observation to collect well-known and non-destructive information about earth features (Liang & Qin, 2008). Over the years remote sensing has proven its potential to provide observations of the surface at a range of both spatial and temporal scales. As a non-destructive tool, it helps fulfill most agricultural stakeholder goals. Monitoring agriculture by this approach is a vast topic that has been explored from multiple viewpoints, which are either based on the purpose of data acquisition such as crop monitoring, yield estimation, etc., mode of data acquisition e.g. Unmanned Aerial Vehicles (UAV), proximal sensing or satellite imagery, or any other environmental context. The use of UAVs provides high-resolution imagery with almost no limits to revisit time, while multispectral proximal sensors have sufficient spatial resolution to track the growth of individual plants, however, satellite imagery has proven to be the more easily accessible (Agrophysical Research Institute et al., 2019), resulting in more widespread usage.

Monitoring of agricultural systems, based on satellite data, can support efforts addressing food production and sustainability by providing information with consistent frequency (Klompenburg et al., 2020). Remote sensing techniques and global positioning systems (GPS) have been successfully used to assess spatial variability in crop health and yield. This paper aims to provide a comprehensive review of contemporary methods and processes which involve the use of remote sensing and GIS to tackle current food security problems, focusing on crop monitoring and health assessment, along with associated applications involving nutrient management and yield estimation.

II. Material And Methods

The use of remote sensing in crop monitoring for yield optimization started in the late 1970s and is now commonly used around the globe (Moran et al., 1997). It involves an instrument or a sensor on a platform, which could be either a satellite, an aircraft, or a UAV. The sensor measures the electromagnetic radiation that is either reflected or emitted by the target. The type of information accessible from remote sensing depends on the specific properties of the sensor. In the case of agriculture, the information consists of traits or features of the agricultural systems and their variations in space and time. These traits are morphological, biochemical, physiological, structural, phenological, or behavioral characteristics that influence organism performance or fitness (Nock et al., 2016). The nature of these agronomic traits is often based on crop type, physical aspects such as crop canopy temperature or soil moisture, chemical properties such as leaf nitrogen content, or, phenological or structural features. Traits such as crop productivity, are a result of intertwined biophysical processes during a given period such as the crop growth cycle. However, none of these traits are measured but rather modeled as a relationship and the measured parameter e.g. reflected wavelengths or radiance.

EO (Earth Observation) satellites capture important information about crops that can indicate health and growth across time and space with accuracy. In this regard, it is a unique means to provide information about crop status over large areas with regular revisits and allows deriving spatially explicit and temporally resolved maps of crop conditions and forecasts (Atzberger, 2013). Efforts have included:

- lower-resolution (250–1000 m) maps across country-to-global scales and,
- higher-resolution (<30 m) maps are generally restricted to local scales due to time or computational costs, limited ground data, or imagery limitations (Becker-Reshef et al., 2010).

With recent improvements in imagery accessibility and computational power (Azzari & Lobell, 2017), high resolution, sub-field scale estimates are now increasingly deployed at regional scales across multiple years (Skakun et al., 2019). Most studies using EO satellites are done on optical sensors such as AVHRR or MODIS (coarse spatial resolution), or Landsat (medium-fine spatial resolution) since these are operational satellites that provide open-source data. High-resolution commercial satellites (data with paid access) such as GeoEye-1, Pleiades-1A, Worldview-3, SkySat-2, and Superview-1, collect multispectral images at a higher spatial resolution of less than 2 m with a daily or sub-daily revisit period.

The Copernicus Sentinel 2 mission with its latest launch in 2017, provides improved possibilities for the detection of crop parameters due to its increased spatial, temporal, and spectral resolution (Z. Jin et al., 2019). These are all multispectral (captures multiple ranges of frequencies or wavelengths in the electromagnetic spectrum) and hyperspectral (wide spectrum and narrower spectral bands) sensors, where the spectral value lies mostly in the Visible & Infra-Red bands (Landsat also has a thermal band).

The great majority of studies involve the computation of multispectral information into a value known as vegetation indices (VIs) (Richter et al., 2009). These can be defined as mathematical combinations or ratios of mainly red, green, and infrared spectral bands; they are designed to find functional relationships between crop characteristics and remote sensing observations (Johnson, 2014). Optical vegetation indices have proven to be easy to compute and useful to monitor the quantity, quality, and behavior of the vegetation (Wiegand et al., 1979). Among the most widely used VIs, the Normalized Difference Vegetation Index (NDVI) has been extensively and successfully utilized in agricultural mapping and monitoring (Bolton & Friedl, 2013; Y. Chen et al., 2018; X. Zhang et al., 2003).

Crop canopies provide vital indicators in crop biomass accumulation and stress responses based on their spectral reflectance usually in the red and infrared bands. Thus, NDVI reflects the photosynthetic activity of crops and shows the biomass conditions and stress of photosynthetically active crops (QUARMBY et al., 1993). Another index often used complimentarily with NDVI is EVI or Enhanced Vegetation Index. It alleviates atmospheric effects, values do not saturate unlike NDVI, and is much more sensitive to biomass changes. Several alternative indices have been derived to counter these shortcomings of NDVI (S. Chen et al., 2019; Liu et al., 2010). These include soil adjusted vegetation index (SAVI), atmospherically resistant vegetation index (ARVI), and wide dynamic range vegetation index (WDRVI). Red-edge-based VIs such as red-edge NDVI (RNDVI) and normalized difference red edge (NDRE) have been observed to perform better than NDVI in estimating plant nutrient status biomass in dense vegetation conditions such as those present during the later growth stages (F. Li et al., 2014; Shaver et al., 2017; Sun et al., 2018). In a review of methods of estimating biomass and yield using low-resolution satellite data, three main aspects were highlighted, being that several indices to estimate leaf chlorophyll content exist (Xie et al., 2018). The trade-off on which index to employ is also driven by the type of imagery available for a given study area and period. For instance, Sentinel 2 has the red-edge bands that Landsat 8 does not, yet Landsat 8 is likely to cover more of a particular area (López-Lozano et al., 2015).

A more promising method for crop health assessment is the one that incorporates crop biophysical parameters such as leaf area index (LAI) and a fraction of absorbed photosynthetically active radiation (fPAR), as these are more sensitive to the amount of photosynthetic active vegetation, which depends on the biotic and abiotic conditions that affect crop status and, ultimately, determine final yield (Zhou et al., 2016). LAI and biomass are two essential indicators of crop health and development (Kross et al., 2015). These values can be obtained as special biophysical products (provided by MODIS) or be determined using various relationships between them and the VIs mentioned in the literature.

RS data thus based on multiple parameters enables the monitoring of simple phenological events, such as the start and peak of vegetation growth. To determine the timing of vegetation greenness increase and senescence from a VI time series, various approaches have been developed which can be broadly categorized into two methods (Beck et al., 2006):

- the use of specific NDVI thresholds (LLOYD, 1990; White et al., 1997);
- the detection of the largest NDVI increase between two consecutive observations (Kaduk & Heimann, 1996);
- and backward-looking moving averages.

The first method can have further modes of approach:

- methods estimating the timing of single phenological events (Badeck et al., 2004; Reed et al., 1994; White et al., 1997);
- methods modeling the entire time series using a mathematical function i.e. an empirical model (author & Vidale, 2004; Jonsson & Eklundh, 2002).

Mathematical modeling to track and predict growth can be further enhanced by the incorporation of Machine Learning (ML) techniques. Its ability to capture information about crops, establish and handle simple and complex relations between the agricultural parameters and variables, along with the processing of big data (Biffis & Chavez, 2017) has proven to be quite useful in making crop health insights and growth predictions. Various machine learning techniques using GIS data applied for monitoring and estimation of crop parameters include; Artificial Neural Network (ANN) (C. Chen & Mcnairn, 2006), Support Vector Regression (SVR) (Lee et al., 2020), Random Forest Method (Wang et al., 2016)& Data Mining (Hill et al., 2014). However, the accuracy of these algorithms is heavily dependent on training datasets. Data sampling and filtering can be challenging as it requires heavy computing skills and resources. Although geographically varying parameters can be accounted for using RS data, the complexity of these systems limits the universal application of derived models (Sharma et al., 2021).

Use of optical imagery and data products such as VIs, however, poses challenges such as the presence of cloud cover due to weather changes, which does prevent access to satellite imagery for a particular time frame, thus resulting in systematic errors during analysis as crop parameters at key stages are not recorded. This is often rectified by using an active satellite data source instead of passive sources. Synthetic aperture radar

(SAR) is an effective and important technique in monitoring crops and other agricultural targets because its quality does not depend on weather conditions. It is also sensitive to the dielectric and geometrical characteristics of the plants, and because of its penetrative power can also help gain insights below the canopy cover. A well-known microwave vegetation scattering model, the Michigan Microwave Canopy Scattering (MIMICS) model (MCDONALD & ULABY, 1993; ULABY et al., 1990) was developed based on various scattering mechanisms on vegetation-covered surfaces. This model was successfully run for wheat, maize, and castor after simple model modifications (X. Jin et al., 2015; Toure et al., 1994). Crop height can be measured by generating a digital elevation model (DEM) by interferometry, along with moisture content and dry matter of the crops during nearly the same interval time as the collection of the TerraSAR-X data in the same area and the relationship between measured parameters and SAR data can be further studied. Results confirmed that the X-band SAR data possessed great potential for the development of an operational system for monitoring crop growth (Sonobe et al., 2014). Polarization interferometry techniques combine the characteristics of polarization and interferometry and can fully extract multi-level information about plants (Cloude & Papathanassiou, 2003). Empirical models such as LAI vs Reflectance have been established for particular areas and crops but have a limited application scope (Beauregard et al., 2016). However optical data is preferred in comparison to SAR due to its comparatively finer resolution (i.e., higher resolution or more detail), and the ease of use and interpretation (no intensive preprocessing required), as it provides absorption values instead of RADAR backscatter.

Several data fusion approaches have been proposed to combine high/moderate spatial resolution data with high temporal resolution data (and vice-versa) to generate high spatiotemporal resolution data products (Knipper et al., 2019; Zhu et al., 2018) to take advantage of a wide variety of publicly available satellite data. Satellite data with moderate spatial resolution but high temporal resolution can also be used with reference ground truth data to help develop decision support systems (DSS) (Wolters et al., 2019). A novel approach involving the fusion of optical/hyperspectral and microwave data (SAR) has also been done to fulfill multi-temporal monitoring with a higher spatial resolution, equipped with optical (e.g., Landsat 8 OLI, WorldView-3, and the foreseen Sentinel-2 MSI) and SAR sensors (e.g. COSMO-SkyMed, TerraSARX, RADARSAT-2 and the most recent, Sentinel-1). The integration of SAR and optical sensors data allows us to take advantage of the different sensitivity of both the technologies toward environmental parameters: e.g. soil roughness and moisture, plant water content, and biomass for SAR, and photosynthetically related vegetation features for the optical sensors (McNairn et al., 2009; Stafford, 2000). Moreover, exploiting both optical and SAR images increases the frequency of observation, which, in the case of optical data, can be reduced by cloud cover.

III. Extended Applications of Remote Sensing for Nutrient Management & Yield Estimation

Nutrient Management

Efficient use of resources to boost productivity is required for sustainable yet profitable agricultural practices. For crops to attain optimum growth which will result in high yields, nutrition management which involves agricultural inputs; the right dose at the right time, is very critical. A common practice observed is the application of a uniform dose, although nutrient requirement varies both spatially as well as temporally. Site-specific nutrient management (SSNM) is the dynamic, crop season-specific, field-specific nutrients management to synchronize the supply and demand of nutrients by their disparities in cycling through soil-plant systems (Dobermann & White, 1998). The mapping of soil nutrients is both an arduous and expensive task. Thus models can be developed based on remote sensing data to determine soil properties. Vegetation Indices have been found to strongly correlate with plan health parameters such as photosynthetic activity, productivity, etc.

Nutrient application rates in sensor-mounted tractor systems are determined based on the calculated vegetation indices (e.g., NDVI), which are further communicated to the nutrient applicator/spreader for real-time fertilizer application. Different algorithms are used to convert the measured vegetation indices into recommended application rates. Generally, these are calculated by comparing measured vegetation indices in the target field with a reference vegetation index measured in a well-fertilized plot/strip that is representative of the target field. Several fertilizer rate calculation algorithms (Bushong et al., 2016; Raun et al., 2005) have been developed and successfully implemented in these commercially available sensors to determine vegetation indices based on in-season requirements .based on remote sensing, however, farmer’s adoption remains low in many agricultural enterprises (Higgins (McCormick) et al., 2019). This is often due to a lack of understanding of the technology, efficient implementation mechanisms, and the associated financial aspects. Remote sensing has also been used to determine soil organic matter and phosphorus content to develop spatial maps that can aid in site-specific management (Blasch et al., 2015; Castaldi et al., 2019; Kalambukattu et al., 2018). This data is also an ideal input for crop models in the case of growth simulations.

Yield Estimation

Yield defined as the weight of produce per unit area is the most commonly usedmeasure of farm productivity and profitability (Tonitto & Ricker-Gilbert, 2016). Crop yield estimation from field to global scale is critical, due to its direct economic and social impact on food and commodity prices, agriculture supply chain management, international trade, and public policy and land-use decisions (Lobell & Field, 2007; López-Lozano et al., 2015; Prasad et al., 2006). Although comparatively simpler than other parameters to measure productivity, the computation and prediction of yield is a complex process. Since the initial application of remote sensing, especially satellite data for yield estimation in the 1970s (Macdonald & Hall, 1980), it has proven worthy due to extracted spectral information which gives information that relates statistically to crop yields and mapping of the spatial variability across regions as well as fields (A. Li et al., 2007). Most research on GIS-based yield estimation models includes studies mostly focused on wheat (Rai et al., 2002; Ren et al., 2008; Thenkabail, 2003), rice (Casanova et al., 1998), soybeans (You et al., 2017), maize (Baez-Gonzalez et al., 2005; Báez-González et al., 2002; Lewis et al., 1998; Shanahan et al., 2001), and sugarcane (Rocha & Fernandes, 2011).

EO satellites capture important information about crops that can influence yields across time and space with accuracy. The most common approach is a statistical analysis involving a regression model to relate VIs computed at a particular date with the yield (Doraiswamy et al., 2003), with the index being the independent variable. Other studies used a shape model fitting derived from time series of VIs to detect the phenological stages of crops and determine the dates of the required input data (Sakamoto et al., 2013). The anomalies of VIs during the growing season have also been used to predict changes in crop yield (P. Zhang et al., 2010). The trend observed is that the variables are more likely to be non-linear, with more effective results in the case of multiple independent variables (multiple regression). One common method is the light-use-efficiency approach to Monteith's model (Monteith et al., 1977) in which Biomass is then related to yield by a constant harvest index (HI):

$$Yield = APAR \times RUE \times HI$$

where RUE is the radiation use efficiency inherent to the crop and APAR is absorbed photosynthetically active radiation (Daughtry et al., 1992; Sinclair & Muchow, 1999). The ability of Machine Learning techniques ability to capture information and collect data about a crop and deduce yields with various algorithms has proved to be quite a useful tool in making forecasts. Synthetic Aperture Radar (SAR) data, has been utilized in some recent works (Guan et al., 2017; Mladenova et al., 2017), along with its synergy with optical data for better results (Mateo-Sanchis et al., 2019).

Integration of Crop Growth Models & Remote Sensing Data for Yield Estimation

Crop Simulation Models or Crop Growth Models, are computerized representations of crop growth, development, and yield, simulated through mathematical functions of weather, soil conditions, and management practices (Kasampalis et al., 2018). Models range from simple to complex models where the purpose determines the complexity. Ranging from models carrying out regression analysis between yield and meteorological parameter (statistical models) to complex models providing detailed explanations of the soil-plant-atmosphere system (mechanistic & functional models) and require a large amount of input data. Their applicability is ineffective at the field or regional scales because they are designed to describe the crop growth at the point scale, assuming the field conditions to be uniform (Dorigo et al., 2007). Their performance is also hampered by the variation in calibration and parameterization of various models, as well as the availability of agrometeorological data input (Keita, n.d.).

The lack of spatial information required for the implementation of the crop model beyond point i.e. from field to regional levels can be rectified by the integration of remote sensing data. A major challenge for future research on the response of crops to climate change is the accuracy of the spatial information (Challinor et al., 2009). Due to the parallel development of RS & CGMs, various attempts at the integration of the two have been made. Studies involve the assimilation of remote sensing-derived vegetation indices such as NDVI (Moriondo et al., 2007) and biophysical parameters such as LAI into crop models such as DSSAT-CERES (Z. Li et al., 2015) or EPIC. LAI is the most common parameter used for data assimilation. The availability of biophysical products such as LAI & GPP again aids further in the assimilation of the datasets (Silleos et al., 2014). Although a major disadvantage is that most of these products are often of coarse resolution. With aim of minimizing ground in-situ data to be utilized in the model, Scalable Crop Yield Mapper (SCYM) is used (Lobell et al., 2015), which can effectively allow these point scale models to be implemented at wider spatial scales, allowing multiple parameter analysis and growth simulations, at a higher resolution.

IV. Discussion

Effective management strategies to deal with food insecurities are essential if we are to fulfill the "Zero Hunger" sustainable development goals. For a country like India, where agriculture contributes around 20-25% of the year's GDP, agricultural production must be increased sustainably. The use of remote sensing in agriculture, allows all stakeholders to effectively plan and manage resources to increase productivity since the data sets are available in variable scales from plot to national level. An increasing amount of published literature shows that RS applications for agriculture have now reached a certain level of knowledge or technique, along with exponential growth of interest in the field over the years. It also reflects the major progress in relevant technology, which includes various sensors with numerous combinations of spatial, temporal, and spectral capacities, along with the advent of new platforms such as UAVs, more robust models, and the deployment of cloud computing and machine learning techniques. These technological improvements should allow for meeting the long-term goals for remote sensing-based agriculture applications concerning the relevant stakeholders (Weiss et al., 2019), from individual farmers to food production firms, to policymakers.

Despite advances in the resolution of satellite sensors and ease of accessibility, the use of satellite images is still limited in agriculture, especially in developing countries. Most of these nations often lie in tropical and sub-tropical regions where weather restriction, especially due to the rain-induced cloud cover e.g. the annual monsoon in India, is often a limitation. These countries also lack an adequate framework of established techniques that are accurate, reproducible, and applicable under a wider variety of conditions, along with the infrastructure to process and gain insights from this data. Insufficient agricultural and meteorological data or its unavailability in the public domain renders many stakeholders unable to benefit from this technology, although the latest developments especially in the synergizing of various technologies such as integration of AI/ML with GIS, and data assimilation with crop models, shall, however, mitigate this. Various other issues such as lack of awareness and knowledge of this technology, along with the inadequate technical infrastructure for data access and efficient implementation, persist, especially among cultivators and agricultural entities in developing countries. The commercialization of agriculture-related GIS & RS in these regions has improved the situation in this regard, however, the adaptation of geospatial technology in agriculture remains comparatively low. There is an immense scope for the development of GIS and RS-based use cases applicable to agricultural processes, which when implemented may result in more efficient resource management mechanisms, further alleviating current food security issues. Further research should be carried out and efforts should be taken for automating the modes of data acquisition, ensuring easy availability of processing infrastructure, and provision of knowledge of GIS-based insights for the end-user.

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