Importance of Remote Sensing in Site Specific Crop Management

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ABSTRACT

The management of agricultural crops at a spatial scale smaller than the entire field is known as site-specific management (SSM), or precision agriculture. The economic benefits of SSM practices must be considered before they can be widely adopted by farmers. For SSM to be justified, three requirements must be met: (1) there must be significant within-field spatial variability in the factors influencing crop yield; (2) the causes of this variability must be identified and quantified; and (3) the data from these measurements must be utilized to adjust crop management techniques in order to boost revenue or lessen environmental impact. This paper's goal is to examine the situation of SSM at the start of the new millennium and make some predictions about where it might go. The review is structured according to the fundamental elements of SSM mentioned above, which include measuring spatial variability, evaluating the information gathered from these measurements, applying the knowledge gathered to modify management procedures, and assessing whether the benefits generated outweigh the expenses.

INTRODUCTION

Food and fiber, two of humanity's most fundamental requirements, are provided by agriculture, which is a major contributor to economic growth in many countries (Gillespie & Van den Bold, 2017). Agriculture has seen significant changes in the last century due to technological advancements like the Green Revolution (Patel,2013). Crop productivity and food security were increased, particularly in poor countries, by the Green Revolution or third agricultural revolution of the 1960s–1980s, which included improved crop varieties, synthetic fertilizers, pesticides, and irrigation (Pingali, 2012). Therefore, global agriculture has only been able to meet the demands with a 30% growth in the cultivated area, even though the population has doubled and the demand for food has tripled since the 1960s (Wik *et al*., 2008). By 2050, it is anticipated that the demand for food and agricultural goods would have increased by over 70% (World Bank, 2020). Due to the scarcity of arable land, agricultural intensification the greater use of fertilizers, pesticides, water, and other inputs will be used to provide a large portion of this growing demand (Sishodia *et al*., 2020). The art and science of learning about an object or region of the actual world from a distance without making direct physical touch with it is known as remote sensing (Shanmugapriya *et al*.,2019). Additionally, remote sensing can be used for precision farming, weather forecasting, disease and pest infestation monitoring, mapping of water resources and water status in field conditions, crop growth monitoring, land use pattern and land cover changes, weather forecasting, and field observations. Earth's resources are essentially sensed using remote sensing technology. According to Justice *et al*. (2002), remote sensing data can significantly aid in the monitoring of earth's surface features by offering timely, synoptic, cost-effective, and repeatable information on the earth's surface. There are numerous uses for it in the field of agrometeorology as well. For agricultural yield forecasting, remote sensing data in conjunction with crop simulation models is quite beneficial. As ground-based and air-based platforms are time-consuming and have limited applications, space-based satellite technologies are becoming increasingly significant for gathering crop status and spatiotemporal meteorological data to supplement the conventional approaches. Due to the high spatial, spectral, radiometric, and temporal resolutions required for use in PA, remote sensing systems that use information and communication technologies typically produce a considerable volume of spectrum data (Huang *et al*., 2018). Reviews of remote sensing methods and applications in agriculture have previously been published in a number of studies. While some research concentrated on particular application areas, such as evapotranspiration (ET) estimation, disease and pest management, and soil characteristics assessment, others covered many application areas (Atzberger,2013: Mulla,2013: Weiss *et al*., 2020). Numerous of this research demonstrated the current status of remote sensing-based approaches, as well as their drawbacks and potential obstacles for use in agriculture in the future. Complementing these efforts, the primary goal of this review is to offer a thorough history and understanding of the uses of remotely sensed data and technologies in agriculture, with a particular emphasis on precision agriculture. In particular, we present a summary of remote sensing methods, systems, and applications in yield estimation, disease and pest control, nutrient management, irrigation management, and a synthesis table of vegetation indices utilized for various PA applications.

1. Site Specific Crop Management in Agriculture

Since the late 1980s, precision agriculture research has been carried out. However, the 1990s and the first few years of the 21st century saw a sharp increase in the SSCM of agricultural products, particularly row crops (Panda *et al*., 2010). The management of agricultural crops at a scale smaller than the entire field is known as site-specific management, or SSM and Perhaps it is regrettable that SSM is increasingly being referred to by the somewhat deceptive name "precision agriculture" (Plant, 2001). The idea that field-specific crop management is "imprecision agriculture" is generally disputed, because there is much more to agriculture than crop management. SSM is one component of precision agriculture, which is more broadly defined as the application of information technology to all aspects of agriculture. SSM has been made possible by the adoption of current technology, including the geographic information system and remote sensing, as well as the commercialization of new technologies, like the yield monitor, the global positioning system (GPS), and variable rate chemical application (Plant, 2001). In addition to resulting in significant labor savings, the introduction of machinery allowed for the consistent application of inputs by removing the farmer from direct contact with the crop. This consistentpace of application led to decreased input usage efficiency because, in certain areas of the field, inputs were applied at an improper pace. Although the enhanced speed and lower labor costs more than offset this input waste, the environmental impact increased. Uniform input application has become more detrimental to the economy and the environment as input costs have gone up (Plant, 2001 Site-specific information on variables that impact crop development and yields, including nutrient condition, weed pressure, soil moisture status, landscape placement, soil organic matter (SOM) content, soil acidity, and depth to a limiting layer, requires remote sensors (Khanna *et al*., 1999). Applying inputs to crops on a "supply meeting demand" basis is a novel approach to agronomic practice known as site-specific crop management.

2. Remote sensing system in Site Specific Crop Management System

An increasing number of scientists, engineers, and large-scale agricultural growers are using RS technology, which is a crucial part of PA (Liaghat and Balasundaram, 2010). It is now feasible to combine RS technologies with precision crop management systems thanks to advancements in RS data acquisition, data processing, and interpretation of ground-based, aerial, and satellite observations over the past 20 years (Waheed *et al*., 2006). Numerous satellite data sets are currently available, with differences in (i) technology, (ii) spatial resolution, (iii) spectral range, and (iv) viewing geometry. Remote sensing is helpful for tasks like stress mapping, fertilization, and pesticide application, and irrigation management. In addition, RS techniques are crucial for determining crop condition and yield forecasting, estimating the acreage of particular crops, detecting crop pests and diseases, mapping disaster areas, managing wild life, managing water supplies, forecasting weather, managing rangelands, and conducting livestock surveys (Lilaghat and Balasundaram, 2010). Remote sensing technique is also used for disease and pest management. With remote sensing, several crop diseases and insect pests may be tracked. Riedell *et al*. (2004) presented remote sensing technology as a practical and affordable way to detect plants that are ill or infested with pests. To identify particular insect pests and differentiate between insect and disease damage to crops, they employed remote sensing techniques. The terms "precision farming" and "precision agriculture" are used interchangeably and have gained popularity worldwide. A number of advancements have been made in the technologies and instruments utilized in this strategy (Singh, 2006). One of the ten most important breakthroughs that will contribute significantly to the modernization of agriculture is agriculture. In India, there are many research available and discussions regarding precision farming and agriculture are occurring at all levels.

3. Application of Remote Sensing

3.1: Irrigation Water Management: In order to minimize crop water stress and achieve the best possible crop development and production, application timing and irrigation rate are crucial. Farmers employ a range of irrigation management techniques based on a number of variables, such as the availability of water, the farm's current water management infrastructure (such as storage and conveyance systems and irrigation system types), local and regional water regulations, the farmer's economic standing, the size of the farm, and their level of expertise (Upho *et al*., 2018: Boland *et al*., 2006). Based on their past knowledge or experience of farming, soils, and local climate, many farmers use consistent irrigation at regular intervals (Boland *et al*., 2006). Depending on the recorded soil moisture data and crop/plant water requirements, large commercial farmers use soil moisture monitoring systems (wired or wireless moisture sensors) to irrigate (either manually or automatically) (Host *et al*., 2019). Depending on local weather and climate circumstances, local and regional agricultural authorities may offer irrigation consultancy services (Eching *et al*., 2020). Nearly all of these traditional farming methods employ a constant irrigation rate across the field and fail to account for the variations within a field. With widely used irrigation systems like a center pivot, remote sensing data can be used to apply variable rate irrigation and identify field variations. In order to obtain consistently high yields in every area of the field while minimizing water and nutrient losses, variable rate treatment can assist reduce water stress brought on by extremely wet and dry circumstances (McDowell, 2017). A number of indicators of crop water demand, including ET, soil moisture, and crop water stress, are determined using remote sensing photos that are taken several times over a growing season. These metrics are used to precisely schedule irrigation and estimate crop water requirements.

3.2: Field Preparation: By lowering porosity, soil hydraulic conductivity, and nutrient availability, soil compaction has a negative effect on soil health and lowers crop output. Farmers can reduce in-field compaction and associated crop yield losses by having a better grasp of the temporal and spatial extents of soil compaction in a field. Using hyperspectral data taken from the ground in Arkansas, Kulkarni *et al*. investigated how soil compaction affected cotton plant yields and canopy spectral reflectance. The spatial aspect of soil compaction throughout the year and its impact on soil hydraulic properties are still poorly understood, despite the fact that some of these studies have offered a fresh viewpoint on the subject. As of right now, there isn't a well-recognized technique for measuring mechanical characteristics that aids in estimating soil compaction in a field (Alaoui and Diserens, 2018). Given the significance of basic soil properties (such as bulk density, organic matter, texture, and soil moisture) in evaluating soil functions and compaction more research should be done on RS-based evaluations of soil properties.

3.3: Crop Health Monitoring: Throughout the growing season, crops are exposed to biotic (weeds, pests, insects, and pathogens) and abiotic (water, temperature, and nutrients) stresses that can affect the amount and quality of crop grains. Crop scouts and laboratory tests are the mainstays of traditional methods for identifying in-season crop stressors, and they are costly and time-consuming when applied to wider regions. By providing a rapid and non-destructive method for identifying, measuring, and

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mapping crop-related stressors, RS can help inform site-specific management choices regarding the use of pesticides and nutrients as opposed to whole-field treatments (Khanal *et al*.,2020). A crop's chlorophyll content varies when it is under nitrogen stress, which alters the leaves' optical characteristics. In order to overcome some of these constraints, some studies have included additional field condition data (such as soil characteristics, elevation, and management techniques) in their empirical approach. Other studies have suggested integrating RS data with crop models that replicate crop growth and nutrient cycling (Jin *et al*., 2019: Baret *et al*., 2007). Since spatial and temporal resolution RS data is now widely available and may be able to meet the data requirements of crop models, future research should concentrate on combining high-resolution RS with crop modeling to comprehend within-field variability in crop N stress and the possible agronomic advantages of variable-rate N applications (Jin *et al*., 2019).

3.4: Crop disease monitoring: Because infections reduce photosynthetic activity, they usually cause either a reduction in the area of leaves and/or shoots or a change in the color of the leaves. Therefore, using spectral responses in the VIS-NIR range, previous investigations (Lorenzen and Jensen, 1989) have been able to distinguish between healthy and sick plants. However, it can be difficult to identify crop diseases early. Only in the latter stages of infection, when crop damages are significant and obvious to the unaided eye, have some of these investigations been successful (Franke and Menz, 2013). Because crop disease discovery has been delayed, it may be too late to prevent infection for the current growing season. The effectiveness of several machine learning techniques (such as deep neural networks and decision trees) based on high-resolution VIS-NIR data for the detection and identification of plant diseases at their early embryonic stages has also been shown in recent studies (Mohanty *et al*., 2016: Barbedo, 2016). The effectiveness of these techniques, however, is dependent on a sizable library of photos displaying crop leaves with and without illness and A few disadvantages of such a library include limited crop diseases and diseases exclusive to limited crop types. In order to improve the use of potent data-analytic techniques for the identification and categorization of crop diseases, both fresh database construction and database enhancement are required.

3.5: Weed identification and classification: Typically, only a tiny portion of a crop field is covered by weeds (Johnson *et al*., 1995: Rew *et al*., 1996). Out of the 50,000 plant species, weeds are the most common in both agricultural and non-agricultural settings, accounting for about 250 species. Currently, about 30,000 species are classified as weeds worldwide and due to significant losses in the agricultural field, recent research has shown that the weeds mentioned above have a significant impact on the agricultural system. It is therefore necessary to recognize, manage, and lessen their ecological impact (Mishra and Gautam,2021). Mapping weed infestations in annual crops has consequences for site-specific herbicide treatments, creating alternative management techniques, and evaluating weed ecology itself because weed populations exhibit spatial variation among crop types (Smith and Black shaw, 2003). Smith and Blackshaw, 2003 highlighted that the digital reflectance value for each pixel in remote sensing imaging is the result of combining spectral contributions from each scene of the element, i.e., using soil, shadow, and weed and crop species scene components for weed mapping.

CONCLUSION

Over the years, remote sensing technologies have advanced, and the agricultural industry now has a wide range of platforms (such as satellites, manned aircraft, and unmanned aerial systems) and sensors (such as visible, multispectral, hyperspectral, and thermal) to gather various agricultural data. Given the availability of these sensors and platforms, it is critical that the agricultural community gain a deeper comprehension of the potential and constraints of each technology in order to help guarantee that data yields value while lowering the expenses and technical challenges associated with data collection and use. Through the use of RS data, the agricultural community may determine and measure the health of agricultural systems, assisting them in making management choices that can boost farm revenues and reduce environmental issues caused by agriculture. Remote sensing technologies are quite convenient in agriculture, where they could overcome labor shortage issues and reduce human intervention in handling chemical herbicides.

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