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A REVIEW : APPLICATIONS OF REMOTE SENSING IN AGRICULTURE

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ABSTRACT

Agriculture plays a central role in safeguarding the region's food supply and achieving the second UN Sustainable Development Goal of zero hunger by 2030. However, the agriculture sector faces challenges from changing consumer demand, demographics, inefficient value chains, climate change and water shortage. Climate change is already impacting significantly on agriculture and food production in developing countries. Agriculture has been able to keep up with the rising demand for food and other agricultural goods because of the development of new farming techniques throughout the previous century. Natural resources will undoubtedly be further stressed as result of rising food demand, population growth, income levels, etc. New methods and approaches should be able to meet future food demands while maintaining or lowering agriculture's environmental imprint as the detrimental effects of agriculture on the environment become more widely acknowledged.

The application of remote sensing in agriculture can aid the evolution of agricultural practices that face different types of challenges by providing information related to crop status at different scales all through the season. Making educated management decisions with the help of emerging technologies including geospatial technology, the Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI). To maximize agricultural inputs, boot agricultural production, and decrease input losses, precision agriculture (PA) uses a variety of such technologies. Over the past few decades, there has been a sharp expansion in the use of remote sensing technology for PA (precision agriculture). It is crucial to investigate and design an easy-to-use yet dependable workflow for the real-time use of remote sensing in PA (precision agriculture) given the complexity of image processing and the quantity of technical knowledge and skill required. Wider usage of remote sensing technologies in commercial and non-commercial PA (precision agriculture) applications is likely to result from the development of accurate yet simple-to-use, user-friendly systems.

Keywords: Agriculture, Remote sensing, Precision Agriculture

INTRODUCTION:

Techniques for remote sensing are frequently employed in agronomy and agriculture. Remote sensing is required because agricultural activity monitoring presents unique challenges not encountered in other economic sectors (FAO) (2011). The first thing to note is that agricultural output adheres to distinct seasonal patterns linked to the biological lifespan of crops. Production is further influenced by climate driving factors, agricultural management techniques, and the physical environment (such as soil type). In both space and time, all variables are highly changeable. Moreover, timely agricultural monitoring systems are necessary since productivity might fluctuate quickly due to unfavourable growing conditions. Consequently, as the Food and Agriculture Organization noted a key element of agricultural statistics and related monitoring systems is the requirement for timeliness; information is of little use if it is made available too late. As it is extremely suitable for gathering information across vast areas with high revisit frequency, remote sensing may greatly contribute to presenting a timely and accurate picture of the agriculture sector.

With the first deployment of the Landsat Multispectral Scanner System (MSS) satellite in 1972, RS technologies were first used in agriculture. Landsat MSS was utilised by Bauer and Cipra to categorise the agricultural landscapes of the US Midwest into corn or soybean farms. However, due to the limited supply of high spatial (>5m) and temporal (daily) resolution satellite data, the use of satellite-based data for PA (precision agriculture) has, until recently, been minimal and restricted only to the large-scale monitoring and mapping of agricultural health. RS technologies can now be applied at a scale considerably smaller than a field thanks to technical improvements in global positioning systems (GPS), machinery, hardware, and software, cloud computing and the Internet of Things (IoT).

Various RS systems, including as handheld, aeroplane, and satellite are currently in use. These platforms can be used to collect data at various spatial, temporal and spectral resolutions. The best PA (precision agriculture) resolutions will rely on a number of variables, such as management goals, crop growth stages, field size and the ability of farm equipment to alter inputs (fertiliser, pesticides, irrigation). For instance, in order to distinguish crop traits (such as leaves and area) at the stand level, better spatial resolution data (0.1m) are crucial for the ability to identify crop emergence (1-3m) (Fernandez-Ordonez et al., 2017). Visible imagery cannot identify some patterns in multispectral imagery that are used to monitor crop health (Yao, X. et al., 2017). Moreover, thermal imaging is effective for identifying pest pressure soil moisture and crop water stress that cannot be seen with the human eye (Calderon et al., 2013). Microwaves, which are less susceptible to air attenuation than visual and infrared-based RS (Park et al., 2017), can assist is determining the biophysical characteristics of crops and soil in both day and night-time environments (Betbeder et al., 2016).

History of remote sensing in Agriculture

Agriculture-related activities have long been observed and analysed using remote sensing. Long before Eveyln Pruitt of the U.S. Office of Naval Research initially used the phrase “remote sensing” in 1958 (Estes and Jensen, 1998). Scientists were conducting soil and crop studies related to agricultural areas in the United States and other countries using aerial photography (Goodman et al., 1959). The U.S. Department of Agriculture’s general crop inventories and the U.S. Soil Conservation Service’s work on soil survey mapping made up the majority of this type of work in the 1930s. During World War II, advances in infrared photography led to the development of remote sensing methods that improved knowledge of crop status, water management and crop-soil conditions.

Robert Colwell at the University of California conducted ground-breaking research on remote sensing in agriculture in the 1950s, and in the 1060s, new labs focused on agricultural applications (Landgrebe et al., 1986), like the one at Purdue, were created. Early goals included crop identification and areal coverage, and (Bauer et al., 1985) details initiatives like the Crop Identification Technology Assessment for Remote Sensing (CITARS) programme and the Corn Blight Watch Experiment.

In an effort to promote the use of remote sensing technologies, NASA started sponsoring a few colleges through its University Affairs Program in the early 1970s. As a result, states where agricultural constituted a significant component of the economy started using remote sensing in that industry. Early contributors to the development of remote sensing science in agriculture included centres and laboratories like those at Purdue and Kansas, and their work was crucial in determining the spectral bands that would eventually be used in sensor systems.

Many different types of sensors have been used in subsequent investigations and remote sensing has shown to be capable of supplying the necessary timely and trustworthy data for a fraction of the price of conventional information gathering techniques.

The Large Area Crop Inventory Experiment (LACIE) was the first U.S. government-sponsored project designed to test the viability of estimating wheat production across wide geographic areas using remotely sensed satellite data, primarily Landsat. The National Research Council first suggested the notion in 1960, and it was only with the launch of the first Landsat sensor configuration in 1972 that the potential of measuring wheat output across large areas became a reality. Under the joint direction of NASA, NOAA and USDA, the LACIE programme was managed.

The focus of the study in 1974-75 was on creating yield-estimation models for the American Great Plains as well as spectral “signatures” for wheat. The Soviet Union and Canada were added to the activities later on. Due to LACIE’s results, a subsequent project named Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing was launched in 1980. (AgRISTARS). Expanding on LACIE, this new programme aimed to monitor various crops, including wheat, barley, corn, cotton, rice, soybeans and cotton. Specifically, semileptonic decays of heavy mesons, while information on the history of remote sensing science historically offers agricultural applications as well (Reeves 1975).

Remote sensing applications in Agriculture

Applications for remote sensing in agriculture rely on the interaction of electromagnetic radiation with plant or soil components. Instead of measuring transmitted or absorbed radiation, remote sensing often measures reflected radiation (Apostol et al., 2003). Non-contact measurements of radiation reflected or emitted from agricultural fields are referred to as "remote sensing".

Satellites, aircraft, tractors and handheld sensors are some of the platforms used to collect this data. Proximal sensing refers to measurements taken with tractors and handheld sensors, particularly if they do not include measurements of reflected radiation. In addition to reflecting, transmitting and absorbing light, plant leaves can also glow or release heat (Cohen et al., 2005).

Historically, crop type mapping, overall crop condition assessment and agricultural acreage estimation have all been accomplished using satellite photography. Due to the low spatial resolution of sensors, these applications were typically applied over wide areas. However, more contemporary satellite sensors with finer resolutions are now making it possible to monitor issues like drought stress, flooding and hail damage on-site.

Stafford (2000) emphasised that changing weather conditions can have an impact on satellite photographs. According to Lamb and Brown (2001), low-resolution satellite pictures are only useful for large-scale studies and might not be suitable for small-scale farms. Furthermore, satellites with higher resolution images, such as QuickBird (2.4 m in VNIR) and ASTER (15 m), have lengthy revisit times (1-3.5 and 16 days, respectively), which limits their usefulness for any application that could need frequent photographs. Satellites are frequently placed in constellations of a new synchronised satellites that cooperate and overlap in ground coverage in order to shorten revisit times.

The amount of radiation reflected from plants varies depending on the wavelength of incident radiation and is inversely related to the amount of radiation absorbed by plant pigments. Chlorophyll is a pigment found in plants that substantially absorbs light in the visible spectrum between 400 and 700 nm (Pinter et al., 2003), especially at wavelengths like 430 (blue or B) and 660 (red or R) for chlorophyll a and 450 (B) and 650 (R) for chlorophyll b.Anthocyanins and carotenoids are two more crucial plant pigments (Blackburn, 2007).

In contrast, leaf density and canopy structure effects cause plants to reflect more light in the near infrared (NIR 700-1300 nm) region. The development of spectral indices that are based on ratios of reflectance values in the visible and NIR regions was motivated by this stark contrast in reflectance behaviour between the red and NIR portions of the spectrum (Sripada et al., 2006). Many different characteristics of plant canopies, including leaf area index (LAI), biomass, chlorophyll content, or N content, are evaluated using these spectral indices.

Based mostly on statistical-empirical connections between yield and vegetation indices, remote sensing has been utilised to anticipate crop yields (Thenkabail et al., 2002; Casa and Jones 2005). For government organisations, commodities dealers and farmers, information on predicted yield is crucial for organising harvest, storage, transportation and marketing activities. Clay minerals, calcium or iron oxides, as well as soil moisture and organic matter content, all have an impact on how much radiation bare soil reflect (Thomasson et al., 2001; Viscarra Rossel et al., 2006).

According to (Ben-Dor et al., 2010), each soil component has a distinct spectral signature and a particular spectral area where reflectance is strongest. In remotely sensed image, bare soil and crop canopies are frequently present, and the combination of the two spectral signatures frequently makes it difficult to interpret reflectance data. When the reflectance is impacted by both sources, spectral unmixing techniques (Demetriades et al., 1990), derivative spectra, or spectral indices that account for soil impacts are frequently employed to separate information about plant properties (Haboudane et al., 2002).

Agricultural remote sensing applications are often categorised based on the platform used to mount the sensor, including satellite, aerial and ground-based platforms. Based on the platform's altitude, the image's spatial resolution, and the minimum return frequency for sequential imaging, these platforms and the imaging systems that go with them can be distinguished from one another. The lowest identifiable pixel's area is impacted by spatial resolution. The smallest pixel's area reduces as spatial resolution rises, while the homogeneity of the soil or crop properties inside that pixel rises. Poor spatial resolution implies large pixels with increased heterogeneity in soil or plant characteristics. Return frequency is important for assessment of temporal patterns in soil or plant characteristics. Cloud cover frequently severely restricts the availability of remote sensing images from satellite and aerial platforms, although ground-based remote sensing is less impacted by this restriction (Moran et al., 1997).

(Dbrowska-Zieliska et al., 2008) used the technique to track the development and yield of wheat in Polish circumstances using AVHRR/NOAA pictures. The authors created a model that used the LAI and evapotranspiration indices derived from AVHRR pictures to estimate wheat yield. (Galvo et al., 2009) investigated the feasibility of estimating soybean production using satellite Hyperion hyperspectral pictures and found a strong connection (r = 0.74) between vegetation indices and weight of harvested seed. The artificial neural network-based model created by Li et al., (2008) allowed for the regional-scale prediction of maize and soybean yields using MODIS sensor data. Results from the model have an accuracy of 85%. Using a calibrated version of the model created by (Doraiswamy et al., 2004) investigated the potential use of MODIS satellite data for yield predictions (2008). Using measurements of ground reflectance, the model was calibrated. Simulated yield figures for maize and soybeans, which differed by 3.12 and 6.62 percent, respectively, were in good agreement with yields reported by the USDA-National Agricultural Statistics Service (NASS).

Farmers are using the GIS (Geographic Information System) as a potent tool to aid in better decision-making. Due to the fact that technology gives farmers precise, timely and spatially explicit information about their land and crops, GIS has become a crucial part of modern agriculture.

Precision Agriculture is one of the most important GIS applications in agriculture. GIS is used in precision agriculture to produce maps that depict the field's variability, including the terrain, vegetation and soil characteristics. Farmer decision about planting, fertilising and irrigation can be improved by the analysis of these maps, leading to increased crop yields and lower input costs (Mishra & Lal, 2017).

By providing spatially explicit information on the land and its potential for agricultural use, GIS is used to enhance land planning. With consideration for elements like soil type, climate and geography, GIS can be used to pinpoint farm regions that are suited for certain crops. With better agricultural planting and location choices made using this information, productivity and profitability are increased (Tishechkin et al., 2016).

Using spatially explicit information about water supply, demand and use GIS is used to support water management in agriculture. GIS may be used to pinpoint the farm's water-scarce zones, choose the best spots for irrigation systems, and keep and eye on water use un real time. Making better judgements about when to irrigate, how much water to apply and when to convert to more drought-tolerant crops is possible with the help of this knowledge (Abde-Hamid et al., 2018).

GIS, which gives farmers and researchers the ability to analyse and interpret spatial data, is becoming more and more significant in the agricultural sector. Although precision agriculture, crop monitoring, land use planning and water management have all been transformed by GIS, there is still a tremendous possibility for new applications.

To estimate future agricultural yields, GIS can be used to assess past crop yields in a specific area coupled with environmental parameters like climate and soil composition. Farmers may make data-driven decisions about which crops to plant, when to plant them, and how to manage them for the best yield by combining these predictions with machine learning algorithms (Kartika et al., 2021). Farmers may automate numerous farming chores by combining GIS with precision agriculture technologies like GPS-guided tractors, drones and sensors. This can lead to increased productivity, lower labour costs, and more accurate crop management (Giasi et al., 2021).

The distribution and make-up of agro-forestry systems, which integrate trees with crops or livestock, can be mapped using GIS. Farmers can maximise their use of land and resources by comprehending the spatial linkages between these systems and their effects on the environment (Stocker et al., 2019). GIS can be used pinpoint regions most at risk from drought, flooding and other climate-related problems as climate change continues to affect crop-growing conditions. Farmers can create plans to modify their methods and lessen the effects of climate change by studying these risks (Folberth et al., 2016).

Along the supply chain, GIS may be used to track the movement of livestock and crops, enhancing traceability and ensuring food safety. Farmers may monitor the conditions under which crops are grown and transported, lowering the danger of contamination, by integrating data from sensors and other sources (Chung et al., 2019). By providing real-time information regarding soil moisture, weather and crop water requirements, GIS can be utilised to optimise irrigation management. Farmers can make data-driven decisions about when and how much to irrigate, minimising water loss and increasing crop output, by combining this information with decision support systems (Yu et al., 2021).

GIS may be used to map the location and density of cattle on a farm as well as other environmental elements like humidity and temperature. Farmers may monitor the health and wellbeing of their animals by combining this data with sensors and other technologies, which minimises the need for antibiotics and other interventions (Berckmans et al., 2019). GIS may be used to map the distribution, composition and physical and chemical characteristics of different types of soil. Farmers may employ fertilisers and other soil amendments to the best of their ability by understanding the spatial correlations between different soil types and environmental elements like water availability and nutrient content (Deb and Shukla, 2017). Rooftop gardens, community gardens and vertical farms are just a few examples of urban agriculture systems whose distribution and attributes can be mapped using GIS. Planners can create plans to increase food security and lessen the environmental impact of metropolitan areas by examining the spatial relationships between these systems and their effects on the environment (Castillo et al., 2018). Using GIS and block-chain technology can result in a secure and transparent system for following agricultural items from the farm to the customer. Customers can track the origin and travel of their food by utilising GIS to generate a digital supply chain map and block-chain technology to produce and unchangeable record of transaction, while farmers can get fair pricing for their goods (De Longueville et al., 2021).

Remote sensing techniques have revolutionized sustainable agriculture and green farming practices by providing valuable information on soil, vegetation and water resources (Huang et al., 2017). Remote sensing can monitor large areas and capture data that is difficult to obtain by conventional ground-based methods (Lu et al., 2019). Remote sensing can be used to manage resources more efficiently, optimize inputs and reduce environmental impacts (Duan et al., 2020). Remote sensing has several applications in sustainable agriculture, such as crop classification, yield estimation and soil moisture mapping (Jiang et al., 2021). Remote sensing can be used to assess crop health and detect stress caused by pests, diseases or environmental factors (Santos et al., 2020). This information can be used to optimize fertilizer and irrigation inputs, leading to more efficient resource use and increased yields (Shao et al., 2019).

Remote sensing techniques can be used to estimate crop yields accurately by analysing the spectral data from crops. Machine learning algorithms such as random forests, artificial neural networks (ANNs), and support vector machines (SVMs) can be used to process this data and generate accurate predictions (Gholizadeh et al., 2020; Khan et al., 2021). Satellite imagery and aerial photographs can be used to classify crops based on their spectral properties. ML (machine learning) techniques such as SVMs, decision trees and object-based image analysis (OBIA) can be used for crop classification. This information can be used for precision agriculture practices such as variable rate application of fertilizers, pesticides and irrigation (Chakraborty et al., 2020; Jiang et al., 2021). Remote sensing and GIS can be used to monitor crop growth and development. This includes monitoring plant health, identifying nutrient deficiencies and detecting pest and disease outbreaks. ML (machine learning) algorithms such as convolutional neural networks (CNNs) and deep learning models can be used to analyse the large amounts of data generated by these technologies (Luo et al., 2020; Lu et al., 2021). Remote sensing and GIS technologies can be used for precision agriculture practices, including variable rate application of fertilizers, pesticides and irrigation. ML (machine learning) algorithms can be used to analyse the data generated by these technologies to optimize agricultural practices (Yang et al., 2020; Zheng et al., 2021). The integration of remote sensing, GIS and AI (artificial intelligence) /ML(machine learning) technologies has greatly improved the efficiency and sustainability of agriculture practices.

Green farming practices aim to reduce the environmental impact of agriculture by minimizing inputs and waste while maximizing productivity (Von Fragstein et al., 2019). Remote sensing can support these practices by providing information on crop growth and health, soil properties and water use efficiency (Kamble et al., 2020). For example, remote sensing can be used to optimize irrigation schedules and detect leaks, leading to water savings and reduced environmental impact (Wang et al., 2019). Despite the benefits of remote sensing, there are several challenges to its implementation, such as the need for specialized training and equipment, limited accessibility in some regions, and data processing and interpretation issues (Liang et al., 2021). Future research should focus on developing user-friendly tools and platforms that can integrate remote sensing data with other sources of information to provide actionable insights for farmers (Yu et al., 2020). Additionally, the development of new remote sensing technologies, such as hyperspectral imaging, can provide more detailed information on crop health and nutrient status, leading to more precise and efficient management practices (Wang et al., 2021).

Remote sensing has great potential for supporting sustainable agriculture and green farming practices. By providing valuable information on soil, vegetation and water resources, remote sensing can help farmers optimize inputs, reduce waste, and increase yields while minimizing environmental impacts. Although there are challenges to its implementation, future research should focus on developing user-friendly tools and platforms and new remote sensing technologies to unlock the full potential of this technique in agriculture.

CONCLUSION

There is unquestionably a need for better management of the world's agricultural resources due to growing population pressure and the requirement for enhanced agricultural production. To accomplish this, it is first important to gather trustworthy information on the types, quality, amount and locations of resources. Aerial or satellite-based RS technologies will be crucial instruments for enhancing the current systems for collecting and producing data on agriculture and natural resources. Currently, surveys on agriculture are carried out all over the world to collect empirical data on crops, rangeland, livestock and other agricultural resources. Remote sensing has revolutionized sustainable agriculture and green farming practices by providing valuable information on soil, vegetation and water resources. It can optimize inputs and reduce environmental impacts. Challenges to its implementation include limited accessibility, the need for specialized training and data processing issues. Future research should focus on developing user-friendly tools and platforms to integrate remote sensing data with other sources to provide actionable insights. Remote sensing holds immense potential in promoting sustainable agriculture and green farming practices.

The use of remote sensing in precision agriculture, which has been increasing quickly in recent years, is often related to the examples given above. This farm management strategy's primary goal is to maximise input returns while promoting environmental stewardship. Precision agriculture uses very modern technologies, which means that it needs ongoing access to information about the environmental factors affecting this production. Such data are essential for the efficient management of finite and diminishing resources. The planning and distribution of scarce resources to various economic sectors can be facilitated by surveys that are based on the PA idea. Based on the biophysical characteristics of crops and/or soils, RS technology has the potential to revolutionise the detection and characterisation of agricultural productivity. The information obtained from RS data is, in essence, more useful when combined with ground data, just like other PA components. Agronomic and economic decision-making can be reliably supported by precise and timely information provided by RS, despite the fact that it cannot collect all sorts of agricultural information.

REFERENCES

1) Abdel-Hamid, M. A., Ahmed, A. E. M., & El-Metwally, M. (2018). GIS-based modeling for sustainable water management in agriculture: A review. Water, 10(3), 277. doi: 10.3390/w10030277
2) Anderson, M. C., Neale, C. M. U., Li, F., Norman, J. M., Kustas, W. P., Jayanthi, H., & Chavez, J. O. S. E. (2004). Upscaling ground observations of vegetation water content, canopy height, and leaf area index during SMEX02 using aircraft and Landsat imagery. Remote sensing of environment, 92(4), 447-464.
3) Apostol, S., Viau, A. A., Tremblay, N., Briantais, J.-M., Prasher, S., Parent, L.-E., et al. (2003). Laser-induced fluorescence signatures as a tool for remote monitoring of water and nitrogen stresses in plants. Canadian Journal of Remote Sensing, 29, 57e65.

4) Ben-Dor, E. (2010). Characterization of soil properties using reflectance spectroscopy. Ch. 22. In P. S. Thenkabail, J. G. Lyon, & A. Huete (Eds.), Hyperspectral remote sensing of vegetation (pp. 705). Boca Raton, FL: CRC Press.
5) Berckmans, D., Vranken, E., &Aerts, J. M. (2019). Precision livestock farming technologies for welfare management in intensive livestock systems. Animal Frontiers, 9(1), 9-15.
6) Betbeder, J.; Fieuzal, R.; Baup, F. Assimilation of LAI and Dry Biomass Data From Optical and SAR Images Into an Agro-Meteorological Model to Estimate Soybean Yield. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2016, 9, 2540–2553
7) Blackburn, G. A. (1998). Quantifying chlorophylls and carotenoids at leaf and canopy scales: an evaluation of some hyperspectral approaches. Remote Sensing of Environment, 66(3), 273e285.
8) Calderón, R.; Navas-Cortés, J.A.; Lucena, C.; Zarco-Tejada, P.J. High-resolution airborne hyperspectral and thermal imagery for early detection of Verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices. Remote Sens. Environ. 2013, 139, 231–245.
9) Casa, R., & Jones, H. G. (2005). LAI retrieval from multiangular image classification and inversion of a ray tracing model. Remote Sensing of Environment, 98(4), 414-428.
10) Castillo, A., Hoover, A., & Joy, A. (2018). Urban agriculture mapping: using GIS technology to quantify and analyze urban agriculture in US cities. Journal of Agriculture, Food Systems, and Community Development, 8(4), 61-76.Chung, E. J., Khan, M. A., & Kim, M. S. (2019). Application of GIS for tracking crop products: a review. Journal of the Korean Society for Applied Biological Chemistry, 62(1), 1-10.
11) Chakraborty, S., Singh, V. K., Dubey, R., & Singh, S. (2020). Crop classification using remote sensing data: A review. International Journal of Applied Earth Observation and Geoinformation, 91, 102149.
12) Cohen, Y., Alchanatis, V., Meron, M., Saranga, Y., &Tsipris, J. (2005). Estimation of leaf water potential by thermal imagery and spatial analysis. Journal of Experimental Botany, 56, 1843e1852.
13) Dąbrowska-Zielińska, K., Ciołkosz, A., Budzyńska, M., &Kowalik, W. (2008). Monitorowaniewzrostuiplonowaniazbóżmetodamiteledetekcji. ProblemyInżynieriiRolniczej, 16(4), 45-54.
14) De Longueville, B., Tardy, A., & Bogaert, P. (2021). Combining GIS and blockchain to improve transparency in the food supply chain. Journal of Cleaner Production, 292, 126023. doi: 10.1016/j.jclepro.2021.126023
15) Deb, S. K., & Shukla, A. K. (2017). Mapping soil health for sustainable agriculture: a review. Environmental Science and Pollution Research, 24(20), 16559-16575.
16) Demetriades-Shah, T. H., Steven, M. D., & Clark, J. A. (1990). High resolution derivative spectra in remote sensing. Remote Sensing of Environment, 33, 55e56.
17) Duan, L., Wang, J., Zhang, W., & Qin, Q. (2020). Application of remote sensing technology in agricultural sustainable development. Journal of Cleaner Production, 270, 122538.
18) Estes, J., & Jensen, J. (1998). Development of remote sensing digital image processing systems and raster GIS. The history of geographic information systems, 163-180.
19) Fernandez-Ordoñez, Y.M.; Soria-Ruiz, J. Maize crop yield estimation with remote sensing and empirical models. In Proceedings of the 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Fort Worth, TX, USA, 23–28 July 2017; pp. 3035–3038
20) Folberth, C., Skalsky, R., Moltchanova, E., Balkovič, J., Azevedo, L. B., Obersteiner, M., ... & Schmid, E. (2016). Uncertainty in soil data can outweigh climate impact signals in global crop yield simulations. Nature Communications, 7, 11872.
21) Food and Agriculture Organization of the United Nations (FAO). Global Strategy to Improve Agricultural and Rural Statistics; Report No. 56719-GB; FAO: Rome, Italy, 2011.
22) Ghiasi, S. E., Alavipanah, S. K., &Saberian, M. (2021). Farm automation and robotics: review, application, and future trends. Computers and Electronics in Agriculture, 183, 106017.
23) Gholizadeh, A., Marofi, S., Khorramdel, S., Gholizadeh, H., &Yari, A. (2020). Crop yield prediction using remote sensing and machine learning techniques: A comprehensive review. Computers and Electronics in Agriculture, 175, 105565.

24) Gnädinger, F.; Schmidhalter, U. Digital counts of maize plants by Unmanned Aerial Vehicles (UAVs). Remote Sens. 2017, 9, 544
25) Goodman, L. A., & Kruskal, W. H. (1959). Measures of association for cross classifications. II: Further discussion and references. Journal of the American Statistical Association, 54(285), 123-163.
26) Haboudane, D., Miller, J. R., Tremblay, N., Zarco-Tejada, P. J., &Dextraze, L. (2002). Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment, 81, 416e426.
27) Hassan-Esfahani, L.; Torres-Rua, A.; Jensen, A.; Mckee, M. Spatial Root Zone Soil Water Content Estimation in Agricultural Lands Using Bayesian-Based Artificial Neural Networks and High- Resolution Visual, NIR, and Thermal Imagery. Irrig. Drain. 2017, 66, 273–288.
28) Huang, W., Yang, Y., Sun, X., Zhang, J., Wang, Z., & Xu, Y. (2017). Remote sensing for crop water management: From ET modeling to practical applications for irrigation scheduling and drought monitoring in agricultural areas. Remote Sensing, 9(9), 888.
29) Huete, A. R., &Escadafal, R. (1991). Assessment of biophysical soil properties through spectral decomposition techniques. Remote Sensing of Environment, 35, 149e159.
30) Jiang, J., Zhou, K., Chen, Y., Ma, L., & Yuan, F. (2021). Remote sensing of crop classification: A review of research progress and perspectives. International Journal of Agricultural and Biological Engineering, 14(2), 1-15.
31) Jiang, Z., Chen, X., Shi, J., Wei, X., & Zhang, J. (2021). Crop classification based on deep learning: A review. Remote Sensing, 13(1), 161.
32) Jin, X.; Liu, S.; Baret, F.; Hemerlé, M.; Comar, A. Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. Remote Sens. Environ. 2017, 198, 105–114
33) Kalayeh, H. M., &Landgrebe, D. A. (1986). Utilizing multitemporal data by a stochastic model. IEEE transactions on geoscience and remote sensing, (5), 792-795.
34) Kamble, A. S., Kamble, S. S., & Sajeev, M. V. (2020). Remote sensing applications in agriculture and allied sectors: A review. Advances in Remote Sensing, 9(1), 1-17.
35) Kartika, D., Ismail, A. H., &Tilaar, H. A. (2021). Predictive analytics for crop yield prediction using geographic information system: a review. IOP Conference Series: Earth and Environmental Science, 791, 012049.
36) Khan, A. H., Jiang, Y., & Al-Yahyai, R. (2021). Application of machine learning techniques for crop yield prediction: A review. Computers and Electronics in Agriculture, 182, 106041.
37) Khanal, S.; Fulton, J.; Shearer, S. An overview of current and potential applications of thermal remote sensing in precision agriculture. Comput. Electron. Agric. 2017, 139, 22–32.
38) Lamb, D. W., & Brown, R. B. (2001). Pa—precision agriculture: Remote-sensing and mapping of weeds in crops. Journal of Agricultural Engineering Research, 78(2), 117-125.
39) Liang, Y., Jiang, L., Wang, J., Gao, P., & Gao, W. (2021). Opportunities and challenges for using remote sensing technology in smart agriculture. Smart Agriculture, 3(1), 68-78.
40) Lu, D., Chen, Q., Wang, G., Liu, L., & Moran, E. (2019). A review of remote sensing applications in natural resource management and conservation. ISPRS Journal of Photogrammetry and Remote Sensing, 157, 57- 65.
41) Lu, W., Zhu, Y., Sun, X., & Zhao, S. (2021). Remote sensing-based crop disease identification and diagnosis using machine learning: A review. Remote Sensing, 13(4), 669.
42) Luo, L., Ma, X., Liu, Y., Xu, X., Chen, Q., & Zhu, X. (2020). Crop growth monitoring and yield estimation based on machine learning techniques: A review. Agricultural and Forest Meteorology, 287, 107948.
43) Mendes, R., Portella, K. F., Godoi, W. C., Galvo, J. C. A., Joukoski, A., Martins, P., ... & de Geus, K. (2009). Determination of crushed stone volume in concrete cores from hydroelectric power plant dams by three-dimensional tomography. Insight-Non-Destructive Testing and Condition Monitoring, 51(12), 654-659.
44) Mishra, S., & Lal, R. (2017). Precision agriculture and soil carbon sequestration: A review. Environmental Development, 23, 77-89. doi: 10.1016/j.envdev.2017.04.002

45) Moran, M. S., Inoue, Y., & Barnes, E. M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sensing of Environment, 61, 319e346
46) Park, S.; Ryu, D.; Fuentes, S.; Chung, H.; Hernández-Montes, E.; O'Connell, M. Adaptive estimation of crop water stress in nectarine and peach orchards using high-resolution imagery from an unmanned aerial vehicle (UAV). RemoBte Sens. 2017, 9, 828.
47) Pinter, P. J., Jr., Hatfield, J. L., Schepers, J. S., Barnes, E. M., Moran, M. S., Daughtry, C. S. T., et al. (2003). Remote sensing for crop management. Photogrammetric Engineering and Remote Sensing, 69, 647e664.
48) Reeves, M., & Miller, E. E. (1975). Estimating infiltration for erratic rainfall. Water Resources Research, 11(1), 102-110.
49) Rundquist, D., & Samson, S. (1983). Application of remote sensing in agricultural analysis. Chapter 15 in B. Richason, Jr., ed. Introduction to Remote Sensing of the Environment, 317-337.
50) Santos, M. A. S., Costa, M. C., & Sousa, J. J. (2020). Satellite-based techniques for detecting crop stress and their applications in precision agriculture. Applied Sciences, 10(18), 6374.
51) Shao, Y., Hu, Q., & Xiao, Q. (2019). Remote sensing applications in irrigation management: A review. Remote Sensing, 11(20), 2362.
52) Sripada, R. P., Schmidt, J. P., Dellinger, A. E., & Beegle, D. B. (2008). Evaluating multiple indices from a canopy reflectance sensor to estimate corn N requirements. Agronomy Journal, 100, 1553e1561.
53) Stafford, J. V. (2000). Implementing precision agriculture in the 21st century. Journal of agricultural engineering research, 76(3), 267-275.
54) Stöcker, F., Albrecht, A., and Mußhoff, O. (2019). "Agroforestry mapping: A review of methods and applications," Land Use Policy, 81, 757-768.
55) Talukder, M. A. I., Masud, M. M., & Islam, M. R. (2019). GIS-based crop monitoring for precision agriculture. International Journal of Agricultural and Environmental Information Systems, 10(2), 1-16. doi: 10.4018/IJAEIS.2019040101
56) Talukder, T., Sathish, S., Garg, V., & Raut, S. (2019). Crop monitoring in precision agriculture using GIS and remote sensing: a review. Journal of Agrometeorology, 21(1), 29-35.
57) Thenkabail, P. S., Smith, R. B., & De Pauw, E. (2002). Evaluation of narrowband and broadband vegetation indices for determining optimal hyperspectral wavebands for agricultural crop characterization. Photogrammetric engineering and remote sensing, 68(6), 607-622.
58) Thomasson, J. A., Sui, R., Cox, M. S., &AleRajehy, A. (2001). Soil reflectance sensing for determining soil properties in precision agriculture. Transactions of the ASAE, 44, 1445e1453
59) Tishechkin, A. K., Han, J., & Alekseev, A. V. (2016). The use of geographic information systems in the development of land use planning for sustainable agriculture. Eurasian Journal of Soil Science, 5(3), 216-224.
60) Tishechkin, A. K., Khabarov, N. V., &Obersteiner, M. (2016). Assessment of land-use change effects on soil organic carbon stocks in the spatially explicit farming system model EPIC using remote sensing data. Journal of Environmental Management, 183, 238-246. doi: 10.1016/j.jenvman.2016.08.057
61) Varela, S.; Dhodda, P.R.; Hsu, W.H.; Prasad, P.V.V.; Assefa, Y.; Peralta, N.R.; Griffin, T.; Sharda, A.; Ferguson, A.; Ciampitti, I.A. Early-season stand count determination in Corn via integration of imagery from unmanned aerial systems (UAS) and supervised learning techniques. Remote Sens. 2018, 10, 343
62) Von Fragstein, P., Li, J., Evers, J., & Kahl, J. (2019). Green farming systems for the future. In Sustainable Agriculture Reviews (pp. 69-87). Springer, Cham.
63) Wang, H., Zhang, Y., Ma, C., Liu, M., & Yao, Y. (2019). The application of remote sensing technology in the monitoring and management of agricultural water resources. Water, 11(7), 1471.
64) Wang, L., Chen, Y., Wei, J., Zhang, C., & Zhang, X. (2021). Hyperspectral imaging technology and its applications in agricultural production. Transactions of the ASABE, 64(1), 267-280.

65) Wirbel, M., Stech, B., & Bauer, M. (1985). Exclusive semileptonic decays of heavy mesons. Zeitschrift für Physik C Particles and Fields, 29(4), 637-642.
66) Yang, Y., Hu, X., Li, J., Huang, C., & Wang, Y. (2020). Precision agriculture based on remote sensing and machine learning: A review. Remote Sensing, 12(8), 1335.
67) Yao, X.; Wang, N.; Liu, Y.; Cheng, T.; Tian, Y.; Chen, Q.; Zhu, Y. Estimation of wheat LAI at middle to high levels using unmanned aerial vehicle narrowband multispectral imagery. Remote Sens. 2017, 9, 1304.
68) Yu, Q., Wu, B., Liu, L., Dong, Y., & Zhang, X. (2020). Review on precision agriculture research based on remote sensing. IEEE Access, 8, 32815-32829.
69) Yu, S., Tang, J., Wang, Y., Huang, H., & Wu, J. (2021). A review of decision support systems for irrigation management based on geographic information system. Journal of Agricultural Science and Technology, 23(3), 1-14.
70) Yu, Z.; Cao, Z.; Wu, X.; Bai, X.; Qin, Y.; Zhuo, W.; Xiao, Y.; Zhang, X.; Xue, H. Automatic image-based detection technology for two critical growth stages of maize: Emergence and three-leaf stage. Agric. For. Meteorol. 2013, 174, 65–84.
71) Zheng, L., Huang, Y., Fang, H., Sun, Z., & Chen, X. (2021). An overview of precision agriculture applications based on machine learning. Computers and Electronics in Agriculture, 181, 105946.