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Performance of chickpea (*Cicer arietinum* L.) in soil assessing spectral reflectance under different nutrient gradient levels

Sunil Kumar Upadhyay, PS Kulhare, Sanjay Singh Jatav, Rishikesh Tiwari, Sangya Singh, Vishakha Rai and Devid Sahu

Abstract
Chickpea is a critical crop known for its high protein, fiber, and mineral content, providing essential nutrition to millions worldwide. To enhance chickpea agriculture and address food security challenges, researchers are increasingly utilizing remote sensing technology. The research focuses on understanding the relationship between nutrient availability, spectral reflectance, and crop parameters to develop effective nutrient management strategies. Remote sensing, including satellite imagery and aerial surveys, along with geospatial tools, play an important role in achieving these goals. Land cover changes, specifically the expansion of chickpea areas over the last decade, are analyzed to gain valuable insights into crop dynamics and their impact on agricultural landscapes. Hyperspectral data analysis is highlighted as a valuable tool for soil property determination, outperforming traditional methods. This enables precision nutrient management tailored to the crop's specific needs and reduces yield losses through early detection of nutrient stress. The findings have practical implications for farmers, as data-driven precision nutrient management optimizes fertilizer application based on specific nutrient requirements in different field areas. This improves crop health while minimizing environmental impacts. Agronomists and policymakers benefit from the (IRS) with (GIS), enabling accurate soil mapping and promoting sustainable land management practices. Informed decisions can be made to support environmentally friendly agricultural practices and enhance overall food security.

Keywords: Chickpea, spectral reflectance, nutrient gradient, remote sensing, hyper spectral data, nutrient management

Introduction
Chickpea (*Cicer arietinum* L.) is a widely cultivated legume crop known for its nutritional value, contribution and adaptability, to sustainable agricultural systems. The successful growth and yield of chickpea are closely tied to the availability of essential nutrients in the soil. Understanding the relationship between nutrient levels and chickpea performance is crucial for optimizing crop productivity and ensuring food security. Chickpea is the third-largest grown pulse crop across the globe, with a harvested area of 137.2 lakh hectares and production of 142.5 lakh tons in 2019 (FAOSTAT, 2019) [18]. In India, chickpea has played a significant role in the 'Pulse Revolution', making the country near self-sufficient in pulses. From a level of seven 75.9 lakh tonnes in 2014-15, chickpea production rose to an all-time high of 126.1 lakh tones during 2020-21. Vertisols offer the advantage of good water-holding capacity, making them suitable for dry land farming. Nonetheless, their high clay content can also lead to poor nutrient availability and hinder root development, impacting crop performance. Efficient nutrient management is critical in such soils to maximize crop productivity and achieve sustainable agricultural practices. Similarly, an increase of >26% was also observed in its productivity during the period (Dixit, 2021) [17]. In recent years, remote sensing technologies and spectral reflectance analysis have emerged as powerful tools in monitoring plant health and nutrient status in real-time. Spectral reflectance involves measuring the light reflected by plants at multiple wavelengths, which provides valuable information about their physiological condition and nutrient content. This non-destructive and rapid assessment method can help researchers and farmers make informed decisions regarding nutrient management. Understanding the relationships between nutrient availability, spectral reflectance, and crop parameters is vital for developing effective nutrient management strategies. By enhancing our understanding of how chickpea plants respond to different nutrient levels in Vertisols, we can work towards optimizing their performance, improving yields, and promoting sustainable

agricultural practices. These findings can benefit farmers, agronomists, and policymakers in making informed decisions to ensure food security and economic prosperity in regions reliant on chickpea cultivation. Remote-sensing imagery analysis is a valuable tool for documenting and studying significant changes in cropping patterns across large areas (Mundia and Aniya 2005) [47]. It provides an efficient and independent approach to estimate cropping intensity, area, and changes in land use, assisting in the analysis of vast amounts of data (Badhwar 1984; Lobell *et al*. 2003; Thiruvengadachari and Sakthi vadivel 1997; Thenkabail 2010) [6, 39, 63, 61]. Various studies have successfully utilized multispectral and multi-temporal data to map irrigated areas, land use, land cover, and crop types in diverse locations (Velpuri *et al*. 2009; Goetz *et al*. 2004; Thenkabail *et al*. 2005; Knight *et al*. Varlyguin *et al*. 2001; 2006) [66, 25, 62, 35, 65]. Additionally, the Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) time-series satellite data has been widely employed to map agricultural areas and monitor seasonal changes in crop area (Gaur *et al*. 2008; Gumma *et al*. 2011, Biggs *et al*. 2006;) [23, 33, 9]. Monitoring land-use change is of utmost importance to understand shifting cropping patterns, crop types, and promote sustainable agricultural development (Coppin *et al*. 2004; Lu *et al*. 2004; Singh 1989) [15, 40, 59]. While several earlier studies have focused on major crops like rice, sugarcane, and maize, there is a notable lack of research specifically targeting chickpea, a significant leguminous crop in the semi-arid tropics (SAT) of India. To address this gap, our study aims to map the land use/land cover and expansion of chickpea cultivation over the past decade, utilizing 16-day NDVI time-series imagery obtained from the MODIS instrument on board the Terra satellite. To enhance the validity of the findings, remote-sensing results will be validated through ground and secondary data. Furthermore, we will conduct household surveys to identify the primary drivers behind the rapid expansion of chickpea cultivation in the study region. This research will provide valuable insights into agricultural dynamics in the SAT region and contribute to sustainable agricultural planning. Soil is an important natural resource that provides many ecosystem services. Traditional soil sampling and laboratory analysis cannot efficiently provide the required information, as these analyzes are generally time-consuming, costly and limited in spatial variability and capturing temporal. In this remote sensing (RS), context is now in a strong position to provide meaningful spatial data to study soil properties at different spatial scales using different parts of the electromagnetic spectrum. Data sources provided by remote and proximal sensors (RS and PS), global positioning systems (GPS), and digital elevation models (DEMs) have increased the potential for soil mapping over vast areas.

Vertisols, abundant in India, are primarily concentrated in the peninsular region, covering the area between 80° 45' and 26° 0' N latitude and 66° 0' and 83° 41' E longitude. The Deccan plateau alone encompasses approximately 0.42 million km2 of these vertisols (Sharma *et al*., 2011) [55]. In order to manage these unique soils effectively, a soil management approach has been adopted, focusing on the integration of Global Positioning System (GPS) and Geographic Information Systems (GIS), and remote sensing techniques (Schepers and Mulla, 1997) [46]. Remote sensing has gained considerable recognition due to its advantages, such as cost-effectiveness, rapid data acquisition, and relatively high precision compared to traditional methods like the drying combustion method for soil organic carbon concentration. As a result, remote sensing imaging is progressively being acknowledged as an essential tool in precision farming practices for soil property assessment. However, the success of a remote sensing approach relies on the establishment of robust relationships between the targeted soil properties and the corresponding reflectance spectra accessibility (Lagachere *et. al*, 2008) [36]. Remote-sensing imagery studies have revolutionized the analysis of vast datasets, offering a quick and independent approach to estimate area and cropping intensity, changes in land use (Lobell *et al*. 2003; Sakthivadivel and Thiruvengadachari 1997; Thenkabail 2010) [39, 63, 61]. The efficiency of using multispectral and multi-temporal data to map irrigated areas, land use, land cover, and crop types across diverse locations has been widely demonstrated in various research studies (Goetz *et al*. 2004; Thenkabail, Turral 2005 and Schull, Velpuri *et al*. 2009; Knight *et al*. 2006, Varlyguin *et al*. 2001;) [25, 62, 66, 35, 65]. Researchers have harnessed the power of the Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) time-series satellite data to accurately map agricultural areas (Gaur *et al*. 2008; Gumma *et al*. 2011 and Biggs *et al*. 2006;) [23, 33, 9] and monitor seasonal changes in crop area (Sakamoto *et al*. 2005) [54]. The ability to monitor land-use changes is of utmost importance as it provides critical insights into shifts in cropping patterns, crop types, and fosters sustainable agricultural development (Lu *et al*. 2004; Coppin *et al*. 2004; Singh 1989) [40, 15, 59].

In the 1930s, when black & white aerial photos were prepared as the base plots for soil surveys, the early attempt to use remote sensing for soil studies occurred in the US (Stoner *et al*., 1980) [59-60]. Hyperspectral data analyses are superior to traditional broadband analysis in spectral information. In the field of remote sensing, hyperspectral image analysis is one of the most influential and fastest-growing technologies. It can reduce methods of collecting labour-intensive soil data. It is accepted in digital soil mapping workshop that, poor soil dataset has been an issue that can rigorously limit the progress of digital soil mapping. Hence it is significant to include the soil sensors that can provide precise estimates of soil property over large areas (Bottinger *et al*., 2010) [11]. Imagery was used to map the spatial extent of land use years 2000–2001, 2005–2006, and 2012–2013. The process begins with rescaling 16 day NDVI images and later stacking into a single data composite for each cropping year (Dheeravath *et al.* 2010; Gumma *et al*. 2015, 2011a) [33]; Reflected light in the visible region of the electromagnetic spectrum is affected by the presence of chlorophyll pigments in leaf tissues, and these pigments have been found to be closely related to the concentration of leaf nitrogen (Thomas and Gausman 1977; Wessman 1990) [64, 68]. Chlorophyll a and b, the two main leaf pigments, contribute to about 65% of the total concentration of pigments in higher plants. As much as 75% of the plant's total nitrogen is contained within the chloroplasts, predominantly in proteins such as Rubisco and chlorophyll binding proteins (Lawlor 1993) [37]. Therefore, the remote sensing of chlorophyll content offers the potential for rapidly estimating the nitrogen status of crops (Blackmer *et al*. 1986) [10]. To accurately estimate chlorophyll content through remote sensing, researchers have developed empirical models based on reflectance measurements taken far from the pigment absorption maxima, for instance, in the 550 or 700 nm regions. The reason for this is that even small amounts of chlorophyll can saturate absorption in the 660–680 nm region, reducing the sensitivity of spectral indices. However, to achieve maximum sensitivity in estimating pigment concentration, wavelengths should be chosen as close as possible to the absorption bands. The spectral region of particular interest is between the strong red light absorption by chlorophyll (around 680 nm) and the highly reflective near-infrared wavelengths (approximately 780 nm) (Barnes *et al*. 2000) [7]. This region has been termed the 'red edge,' and researchers have proposed several red edge indices for pigment estimation (Vogelmann *et al*. 1993; Filella and Pen˜uelas 1994; Barnes *et al*. 2000) [67, 20, 50, 7]. In summary, remote sensing of chlorophyll content plays a crucial role in rapidly assessing the nitrogen status of crops. While empirical models often use wavelengths away from the pigment absorption maxima for practical reasons, the red edge region (between 680 nm and 780 nm) offers significant potential for maximizing sensitivity in estimating chlorophyll concentration.

Importance of remote sensing tools

Remote sensing and geographical information systems (GIS) help develop an erosion map, which is necessary for predicting excessive soil loss. The map is also practical in the implementation of erosion management strategies. Many factors affect the efficiency of irrigation water use. The evaluation of the spatial variability of micronutrients and their mapping is essential to understand soil behaviour variations (Denton *et al*., 2017) [16]. Several other studies have also utilized vegetation indices derived from Landsat 8 OLI data for reliable and rapid yield estimates at the farm level. For example, Liaqat *et al*. (2017) [73], and Lai *et al*. (2018) [74] used the Soil Adjusted Vegetation Index (SAVI) to obtain yield estimates. Over the course of several decades, the Earth's surface has experienced significant alterations in land use and land cover. These changes are projected to persist, driven by demographic pressures and the consequences of climate change. As an integral part of the Earth's spheres, the pedosphere, encompassing the soil layer, is both influenced by and contributing to these environmental transformations (Macías and Arbestain, 2010) [41]. Notably, the observed shifts in the functioning of the pedosphere have renewed the acknowledgment of the essential role played by soil resources in providing critical ecosystem services and ensuring food security (Global Soil Partnership, 2011; Grunwald, 2011; Mulder, 2013) [24, 32, 44]. Consequently, there is an urgent need for monitoring tools to promote sustainable ecological practices and enhance soil conservation. Achieving sustainable agricultural, hydrological, and environmental management demands a more comprehensive comprehension of soil properties at progressively finer resolutions. Accurate data on spatial and temporal variations in soil properties are indispensable for conservation efforts, climate and ecosystem modeling, as well as applications in engineering, agriculture, forestry, and erosion and runoff simulations (King *et al*., 2005) [34]. Traditional soil sampling and laboratory analyses often fall short in efficiently providing the requisite information. These methods are typically time-consuming, costly, and limited in their capacity to capture the full extent of temporal and spatial variability. To address these challenges, remote sensing (RS) has emerged as a potent tool for collecting meaningful spatial data on soil properties across varying spatial scales, employing diverse segments of the electromagnetic spectrum. RS techniques offer invaluable insights into soil characteristics, empowering researchers to monitor and analyze soil properties over extensive geographical areas with remarkable efficiency. It's essential to note that vegetation indices should be regarded as measures of composite fertility performance rather than just indications of single variable effects. They can reflect various soil characteristics and different plant biophysical variables. Studies by Govaerts *et al*. (2007) [29], Gaso *et al*. (2019) [22], and Maimaitiyiming *et al*. (2017) [22] have explored how vegetation indices capture diverse soil properties and plant characteristics. Similarly, Zhao *et al*. (2020) [72] employed vegetation indices such as OSAVI, CI, and SI derived from Sentinel 2 images for wheat yield predictions. Their research yielded promising results with a validation R2 value of 0.74–0.93, further supporting the use of vegetation indices for crop yield estimation. In summary, various studies have demonstrated the usefulness of vegetation indices, derived from different satellite data sources like Landsat 8 OLI and Sentinel 2, for predicting winter wheat yield and obtaining reliable estimates at the farm level. These indices offer valuable insights into both composite fertility performance and various plant biophysical variables, contributing to our understanding of crop growth and productivity.

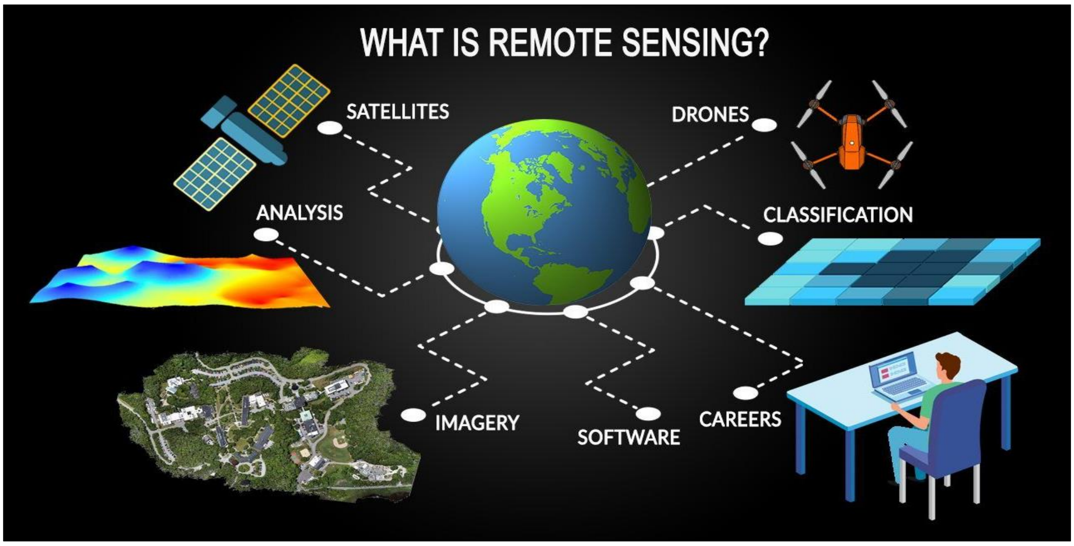
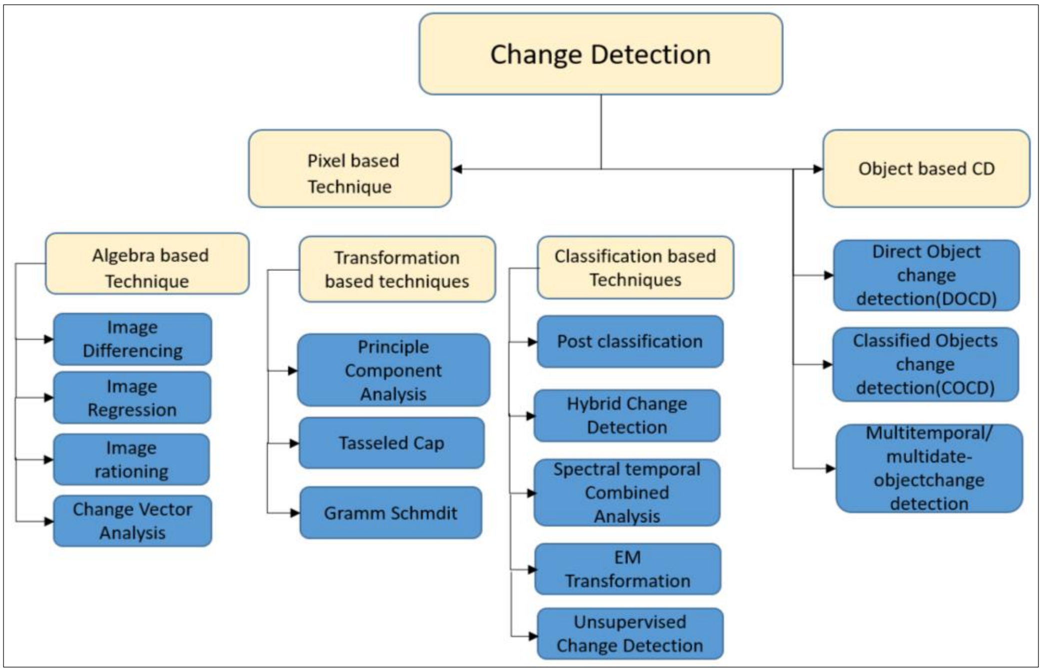


Fig 1: What is remote sensing?

Sensing techniques and analysis

Data analysis and sensing techniques play a crucial role in extracting valuable information from soil spectra. The spectral resolution of the sensor heavily influences the richness of information that can be derived for soil property determination. Higher spectral resolution enables more detailed insights to be extracted. Remote sensing (RS) imagery of bare soil, obtained from space platforms, typically exhibits lower spectral resolution (multispectral), making it suitable for qualitative determinations. Qualitative methods, such as color composites, band ratios, and discriminate analysis, are effective in discriminating and mapping soil surface units. While these methods do not provide precise soil property information, they serve as useful tools for premier soil classification and surface characterization. RS images of bare soil have long been utilized as baseline maps for soil survey and classification, especially with the advent of commercially available RS technology. In the past, when satellite-sensor capabilities were predominantly multispectral rather than hyperspectral, RS was not regularly employed for precise soil property characterization. Soil reflectance properties were often confounded by variations in factors like soil moisture and surface roughness, making quantitative assessments challenging (Moraan *et al*., 1997) [45]. However, in recent years, there has been a promising shift towards using hyperspectral data and more sophisticated quantitative methods for RS-based soil property analysis. Researchers like Mustard and Sunshine (2003) [48] have contributed to this trend, exploring advanced techniques to extract more accurate and quantitative information about soil properties from hyperspectral RS data. The cornerstone of successful soil studies using remote sensing lies in the ability to establish robust relationships between soil properties of interest and their corresponding reflectance spectra (Lagacherie *et al*., 2008) [36]. Early attempts to utilize remote sensing for soil investigations date back to the 1930s in the US, when black & white aerial photos served as the base plots for soil surveys (Stoner *et al*., 1980) [59-60]. The field of soil studies has significantly progressed with the advent of satellite remote sensing technology and geographic information systems. Earth-observing optical remote sensing satellites equipped with sensors capturing broad bands in the visible and near-infrared spectral regions, such as Landsat multispectral scanner, Thematic Mapper(TM), Enhanced TM, and Advanced Space borne Thermal Emission and Reflection Radiometer, have played a pivotal role by offering varying spatial resolutions to cater to diverse research needs. In recent times, the introduction of hyperspectral sensors has propelled remote sensing analyses for soil studies to new heights. Hyperspectral data analysis outperforms traditional broadband analysis by providing rich spectral information. This technology has rapidly become one of the most influential and transformative methods in the field of remote sensing. A key advantage is its ability to significantly reduce the need for labor-intensive soil data collection, thereby enabling more efficient and extensive coverage of large areas. One of the significant challenges in digital soil mapping has been the availability of poor soil datasets, hindering progress in this field. Addressing this issue is important,, and the integration of soil sensors capable of providing precise estimates of soil properties over large areas has emerged as a promising solution (Bottinger *et al.* 2010) [11]. In conclusion, the combination of satellite remote sensing systems with geographic information systems has revolutionized soil studies. The introduction of hyperspectral sensors has further amplified the capabilities of remote sensing for soil property analysis. By establishing strong relationships between soil properties and reflectance spectra, remote sensing methods offer invaluable insights into soil characteristics over vast territories, reducing the reliance on laborious and time-consuming field surveys. As technology continues to advance, remote sensing techniques are expected to play an increasingly vital role in and sustainable land management practices, soil mapping and monitoring.



Remote sensing in vertisols

The cornerstone of successful soil science studies using remote sensing lies in the ability to establish robust relationships between soil properties of interest and their corresponding spectral reflectance (Lagachere *et al*., 2008) [36]. Early attempts to utilize remote sensing for soil investigations date back to the 1930s in the US, when black & white aerial photos served as the base plots for soil surveys (Stoner *et al*., 1980) [59-60]. The field of soil studies has significantly progressed with the advent of satellite remote sensing technology and geographic information systems. Earth-observing optical remote sensing satellites equipped with sensors capturing broad bands in the visible and near-infrared spectral regions, such as Landsat multispectral scanner, Thematic Mapper (TM), Enhanced TM, and Advanced Space borne Thermal Emission and Reflection Radiometer, have played a pivotal role by offering varying spatial resolutions to cater to diverse research needs. In recent times, the introduction of hyperspectral sensors has propelled remote sensing analyses for soil studies to new heights. Hyperspectral data analysis outperforms traditional broadband analysis by providing rich spectral information. This technology has fast become one of the most influential and transformative methods in the field of remote sensing. A key advantage is its ability to significantly reduce the need for labor-intensive soil data collection, thereby enabling more efficient and extensive coverage of large areas. One of the significant challenges in digital soil mapping has been the availability of poor soil datasets, hindering progress in this field.

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Variability's of Soil nutrients

The primary objective of soil is to explore the cause and effect relationships between soil nutrients. Geostatistics (Yost *et al*., 1982) [69] is frequently employed to analyze the spatial distribution of soil nutrients. It proves particularly valuable in soil science for mapping soil properties and estimating in unsampled areas through interpolation (Goovaerts, 1997) [28]. Precise assessment of the spatial variability of soil nutrients is crucial for effective soil management practices (Zhang *et al*., 2014) [71]. India's agricultural landscape is divided into fifteen Agro-climatic zones, taking into account factors such as soil pattern, climate, physiography, and cropping patterns (Venkateswarulu *et al*., 1996) [1]. A prominent feature of agriculture in India is the prevalence of small farmlands, especially in the Deccan plateau. Around 80% of farmers own plots of land approximately 2 hectares in size, contributing to over 50% of the country's agricultural production. Over time, the average size of agricultural land ownership has decreased from 2.3 hectares in 1970 to 1.3 hectares in 2000, with only 0.32 hectares per capita in 2001 (Goedecke, 2016 and Mythili) [49]. This trend has imposed significant financial pressures on farmers. Due to constraints in labor, land, and capital resources, small-scale farmers in India often encounter limitations in adopting green fertilizers or investing in soil conservation facilities (Bhattacharyya *et al*., 2015) [8]. The limited access to resources can hinder the implementation of advanced soil management practices, potentially impacting agricultural productivity and sustainability.

Digital soil mapping (DSM)

Digital soil mapping (DSM) is defined as the process of creating and populating spatial soil information through the integration of field and laboratory observational methods with spatial and non-spatial soil inference systems (McBratney *et al*., 2003 Lagacherie *et al*., 2007;) [43, 36] This approach relies on quantitative methods to combine diverse soil observations obtained from field surveys, laboratory analyses, and data collected through remote sensing and proximal sensing techniques (Carré *et al*., 2007) [14]. (Grunwald, 2010) [31]. In essence, DSM harnesses advanced digital technologies and data analysis methods to generate detailed soil maps and information across a given geographic area. By collecting data from various sources and applying quantitative analysis, DSM aims to produce accurate and comprehensive soil maps, providing valuable insights into the spatial distribution of soil properties and variations across the landscape.

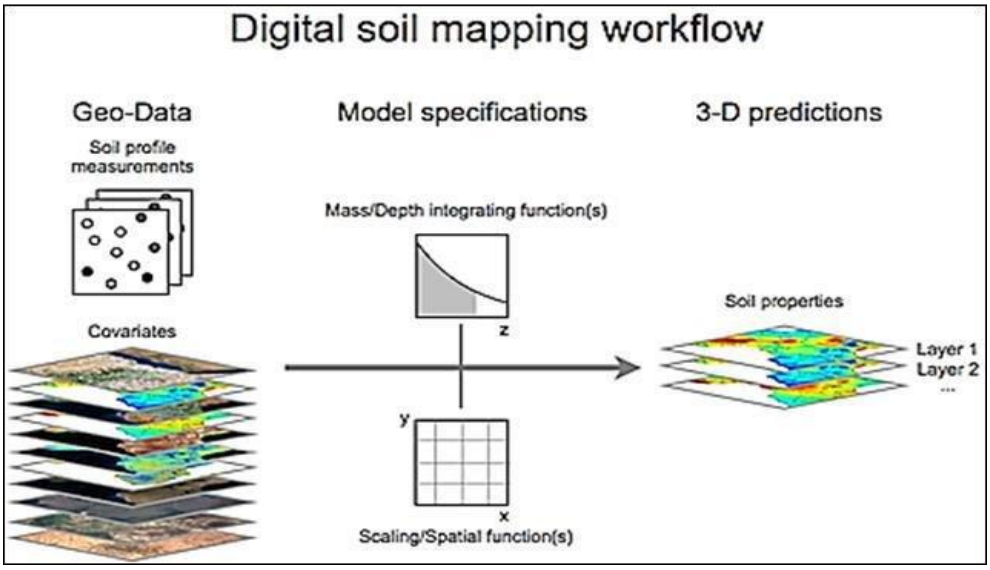


Fig 2: Digital soil mapping workflow

Enhancing Chickpea Agriculture through Remote Sensing

Remote sensing, particularly using satellite imagery and aerial surveys, enables the mapping and characterization of soil properties over large areas. Different soil types and variations in soil characteristics can be identified, helping farmers and researchers understand the spatial distribution of nutrients and other soil parameters [1]. Remote sensing allows for the estimation of soil fertility by analyzing the spectral responses of vegetation. Vegetation indices derived from satellite data can provide insights into soil nutrient levels, especially for essential elements like nitrogen, phosphorus, and potassium [2]. Remote sensing helps in identifying nutrient deficiencies in chickpea crops. Nutrient stress often manifests in specific spectral responses of plants, enabling early detection of nutrient deficiencies and targeted remedial actions [3]. By integrating remote sensing data with geographic information systems (GIS), farmers can implement precision nutrient management. This involves applying fertilizers in optimal amounts to match the specific nutrient needs of different areas within a field, thus reducing waste and enhancing nutrient use efficiency [4]. Remote sensing data can be used to estimate chickpea crop yields. Monitoring crop health, canopy development, and growth patterns from satellite images provide valuable information for yield prediction models, helping farmers plan their harvest and post-harvest activities effectively [5]. Remote sensing allows for real-time monitoring of crop health and stress factors. This includes detecting diseases, pest infestations, water stress, and nutrient deficiencies, enabling timely interventions to mitigate potential yield losses [6]. Remote sensing data, when integrated into decision support systems, can provide actionable information to farmers and stakeholders. It aids in making informed decisions related to crop management, resource allocation, and sustainable agricultural practices [7]. Remote sensing data helps in evaluating the impact of agricultural practices on the environment. By monitoring nutrient runoff, soil erosion, and land use changes, policymakers can develop sustainable land management strategies [8]. Remote sensing provides valuable data for evaluating the performance of chickpea crops grown under varying nutrient levels. Researchers can assess the impact of different nutrient gradients on crop growth, development, and yield. This knowledge contributes to the development of better crop management practices and breeding programs. Chickpea holds a crucial position as the most significant pulse crop in India, both in terms of cultivated area and production. conducted a study to explore the connection between chickpea's spectral reflectance in the red and near-infrared bands and various biophysical parameters such as leaf area index (LAI), biomass, and chlorophyll content. Their findings revealed a substantial correlation between spectral and biophysical parameters, indicating that spectral variables can effectively describe the impact of water stress on chickpea crops. However, up until now, no research has been reported on the applicability of remotely sensed canopy temperature for estimating evapotranspiration, crop yield, or describing the water status of chickpea plants. The primary objective of this study was to investigate the potential use of remotely sensed canopy temperature-based indices, specifically Stress Degree Day (SDD) and Crop Water Stress Index (CWSI), to assess water stress levels. Furthermore, the study aimed to evaluate the empirical relationships between canopy-air temperature difference, Vapor Pressure Deficit (VPD), and evapotranspiration (ET) in chickpea crops subjected to varying levels of irrigation.

Remote Sensing: Advancing Science & Environment

Different nutrients have distinct spectral signatures, and by analyzing the reflectance patterns of chickpea crops in specific spectral bands, researchers can infer nutrient levels in the soil and plant tissues [1]. Vegetation indices, derived from remote sensing data, are widely used to assess plant health and nutrient status. Indices like the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI) can provide valuable insights into the overall health and vigor of chickpea crops, indicating nutrient sufficiency or deficiencies [2]. Remote sensing allows for the detection of nutrient stress in chickpea crops. Nutrient-deficient plants often exhibit specific spectral responses that can be identified through remote sensing imagery. Such stress detection aids in early intervention and targeted nutrient application [3]. Remote sensing data, when combined with Geographic Information Systems (GIS), enables precision agriculture practices. Farmers can create prescription maps for variable rate nutrient application based on the specific nutrient levels and requirements in different areas of their fields [4]. Remote sensing provides time-series data, allowing researchers to monitor nutrient dynamics and chickpea crop growth over time. This longitudinal analysis helps identify trends and changes in nutrient levels, supporting decision-making for nutrient management strategies [5]. By analyzing remote sensing data, researchers can create soil fertility maps, indicating the spatial distribution of various nutrients across the landscape. These maps can guide soil management practices and help identify areas with nutrient deficiencies or excesses [6]. Remote sensing data can be integrated with crop models to estimate chickpea yields based on vegetation health, growth patterns, and environmental conditions. Yield estimation helps in crop forecasting and planning for the harvest [7]. Remote sensing allows for the early detection of nutrient disorders in chickpea crops, enabling timely corrective actions to improve crop health and maximize yield potential [8].

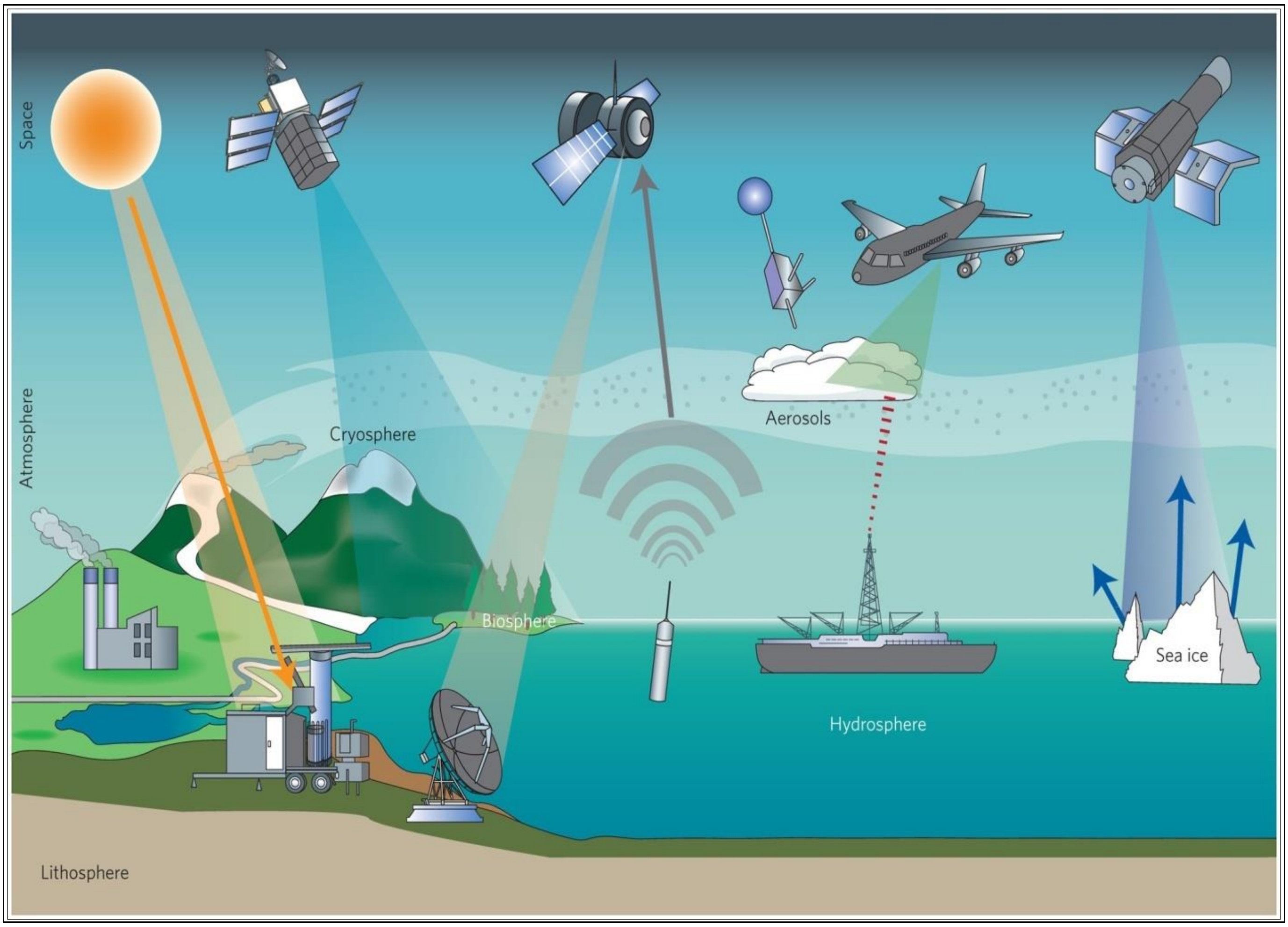
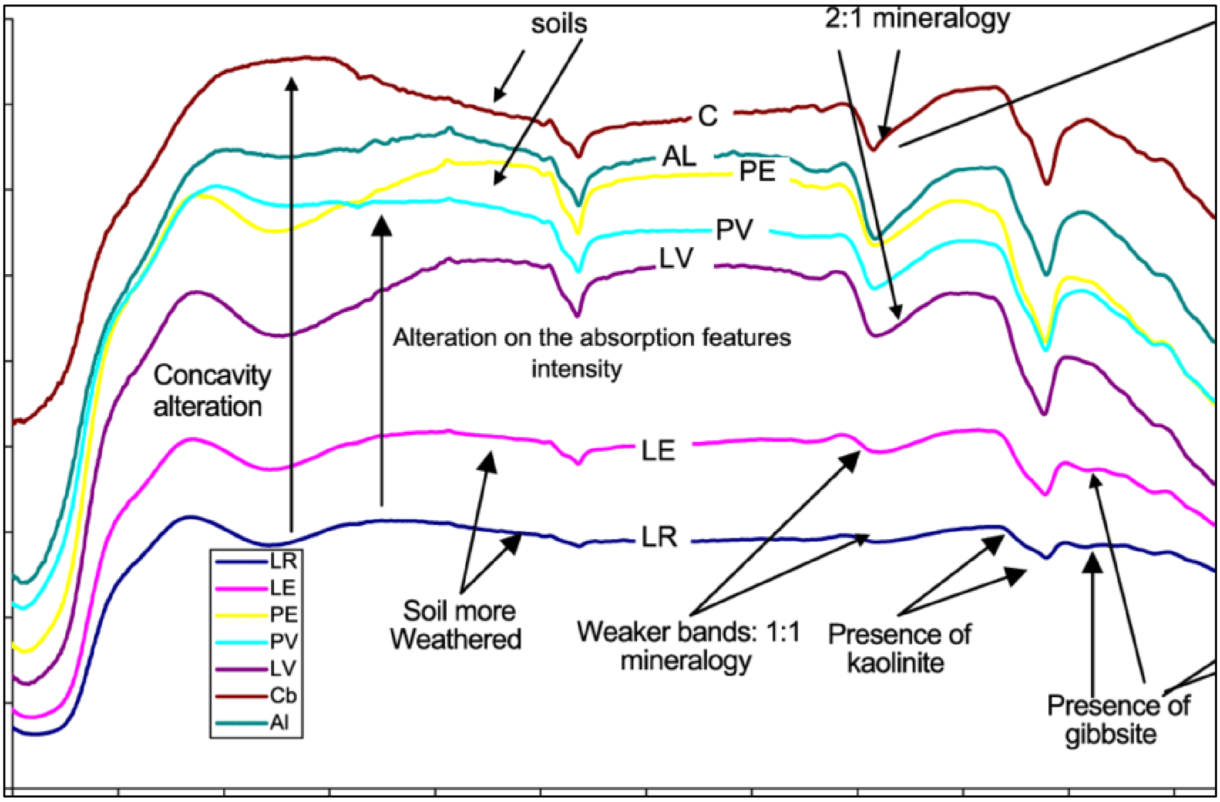


Fig 3: Remote Sensing: Advancing Science & Environment

Spectral Reflectance for Soil Nutrient Assessment

Set up a well-designed experiment with multiple plots or experimental units. Each plot represents a specific nutrient gradient level, ranging from low to high nutrient availability. Ensure that other environmental factors, such as water availability and sunlight, are kept relatively constant to minimize their influence on the results [1]. Apply different levels of nutrients (e.g., nitrogen, phosphorus, potassium, and other essential elements) to the respective plots based on the desired nutrient gradient. Keep some plots as control with no additional nutrient application [2]. Plant chickpea seeds in each plot according to standard agricultural practices. Ensure that the planting density and other cultivation practices are consistent across all plots [3]. Throughout the growing season, use a spectroradiometer or a multispectral/hyperspectral remote sensing device to measure the spectral reflectance of the chickpea plants in each plot. Conduct multiple measurements at different stages of plant growth to capture changes in reflectance over time [4]. Collect data on plant growth parameters such as plant height, leaf area, number of pods, and yield at the end of the growing season. Also, collect soil samples from each plot to analyze their nutrient content [5]. Correlate the spectral reflectance data of chickpea plants with the soil nutrient analysis and plant growth parameters. Analyze how different nutrient levels affect the reflectance patterns of the plants [6]. Identify specific wavelengths or spectral bands that are most sensitive to different nutrient levels in the soil. Certain nutrients may show distinctive spectral signatures, which can be detected through the analysis [7]. Interpret the findings to understand how chickpea plants respond to varying nutrient levels. Assess whether certain spectral features correspond to improved plant growth and yield [8]. Discuss the implications of the results and draw conclusions about the performance of chickpea under different nutrient gradient levels. Highlight the importance of using spectral reflectance as a non-destructive and efficient method for assessing nutrient levels in both soil and plants [9]. Based on the findings, provide recommendations for optimizing nutrient management practices for chickpea cultivation. This information can be valuable for farmers and agronomists to improve crop yields and sustainability [10]. Validate the results by repeating the experiment in subsequent growing seasons or at different locations. Replication is essential to ensure the reliability and generalizability of the findings.



Conclusion

Remote sensing technology offers valuable tools for enhancing chickpea agriculture by providing critical information about soil nutrient levels and crop performance. The ability to analyze spectral reflectance patterns of chickpea crops allows for the estimation of nutrient status, early detection of nutrient deficiencies, and precise nutrient management strategies. Geostatistical analysis using remote sensing data helps understand the spatial distribution of soil nutrients, allowing for effective soil management practices. This knowledge is vital for maximizing crop productivity and promoting sustainable agriculture. By integrating remote sensing data with geographic information systems (GIS), farmers can implement precision nutrient management, applying fertilizers at optimal rates to match the specific nutrient needs of different areas within a field. This approach reduces waste and enhances nutrient use efficiency. Nutrient stress and other crop-related issues can be detected early through remote sensing imagery, enabling timely interventions to mitigate potential yield losses. This real-time monitoring supports informed decision-making for crop management. Monitoring nutrient runoff, soil erosion, and land use changes through remote sensing allows policymakers to develop sustainable land management strategies, promoting environmental conservation. Well-designed experiments using remote sensing devices help establish robust relationships between spectral reflectance patterns and soil nutrient levels. Specific wavelengths or spectral bands can indicate nutrient concentrations in the soil and plants. Based on the remote sensing findings, tailored recommendations can be provided to farmers and agronomists for optimizing nutrient management practices, ultimately improving chickpea crop yields and sustainability. As remote sensing technology continues to advance, further research and validation of results in different settings and growing seasons are essential to ensure the reliability and generalizability of the findings. In summary, the integration of remote sensing technology with agricultural practices offers tremendous potential for revolutionizing chickpea agriculture. By harnessing the power of remote sensing, we can achieve more efficient and sustainable soil nutrient management, leading to increased crop productivity, food security, and economic prosperity in regions reliant on chickpea cultivation.

Reference

1. Venkateswarulu J, Ramakrishna YS, Rao AS. Agro-climatic Zones of India. Ann. Arid Zone. 1996;35(1):1-7.
2. Academic Databases: Access academic databases like PubMed, Google Scholar, or Web of Science to search for scientific papers related to chickpea performance, soil assessment, and spectral reflectance under nutrient gradients.
3. Agricultural and Forest Meteorology Temporal Monitoring: Remote sensing provides time-series data, allowing researchers to monitor nutrient dynamics and chickpea crop growth over time.
4. Agricultural Research Institutions: Websites of agricultural research institutions or universities often publish research findings related to crop performance and soil nutrient assessment. Check the websites of institutions that focus on agronomy and crop research.
5. Agronomy Journals. Soil Fertility Mapping: By analyzing remote sensing data, researchers can create soil fertility maps, indicating the spatial distribution of various nutrients across the landscape.
6. Badhwar GD. Automatic Corn-Soybean Classification Using Landsat MSS Data. I. NearHarvest Crop Proportion Estimation. Remote Sensing of Environment. 1984;14(1-3):15-29. DOI: 10.1016/0034-4257(84)90004-x
7. Barnes EM, Clarke TR, Richards SE, Colaizzi PD, Haberland J, Kostrzewski M, *et al.* Coincident detection

of crop water stress, nitrogen status and canopy density using ground-based multispectral data. In 'Proceedings of the 5th International Conference on Precision Agriculture'. (Eds PC Robert, RH Rust, WE Larson) (American Society of Agronomy: Madison, WI); c2000.
8. Bhattacharyya R, Ghosh B, Mishra P, Mandal B, Rao C, Sarkar D, *et al.* Soil Degradation in India: Challenges and Potential Solutions. Sustainability. 2015;7(4):3528–3570.
9. Biggs TW, Thenkabail PS, Gumma MK, Scott CA, Parthasaradhi GR, Turral HN. Irrigated Area Mapping in Heterogeneous Landscapes with MODIS Time Series, Ground Truth and Census Data, Krishna Basin, India. International Journal of Remote Sensing. 2006;27(19):4245-4266. DOI: 10.1080/01431160600851801
10. Blackmer TM, Schepers JS, Varvel GE. Light reflectance compared with other nitrogen stress measurements in corn leaves. Agronomy Journal. 1986;86:934-938.
11. Boettinger JL, Howell DW, Moore AC, Hartemink AE, Kienast-Brown S. Digital Soil Mapping. (J. L. Boettinger, D. W. Howell, A. C. Moore, A. E. Hartemink, and S. Kienast-Brown, eds.), Dordrecht: Springer Netherlands; c2010.
12. Books and Monographs. Some books and monographs focus on crop nutrient management and remote sensing applications in agriculture. Look for books authored by experts in these fields.
13. Books and Reports: Look for books and reports focused on crop physiology, remote sensing in agriculture, and soil nutrient management. These can provide valuable insights into the topic.
14. Carré F, McBratney AB, Mayr T, Montanarella L. Digital soil assessments: Beyond DSM, Geoderma. 2007;142(1-2):69-79
15. Coppin P, Jonckheere I, Nackaerts K, Muys B, Lambin E. Digital Change Detection Methods in Ecosystem Monitoring: A Review. International Journal of Remote Sensing. 2004;25(9):1565-1596. DOI: 10.1080/0143116031000101675\
16. Denton OA, Aduramigba-Modupe VO, Ojo AO, Adeoyolanu OD, Are KS, Adelana AO, *et al.* Assessment of spatial variability and mapping of soil properties for sustainable agricultural production using geographic information system techniques (GIS). Cogent Food Agric., (M. Tejada Moral, ed.). 2017;3(1):1-12.
17. Dixit GP. Sustaining Chickpea growth in India: Breeder's Perspective. Journal of Food Legumes. 2021;34(2):73-75.
18. FAO-STAT Statistical Database. Food and Agriculture Organization of the United Nations [FAO]; c2019. Retrieved from http://www.fao. org/faostat/en/
19. Field Crops Research Yield Estimation: Remote sensing data can be integrated with crop models to estimate chickpea yields based on vegetation health, growth patterns.
20. Filella I, Penuelas J1. The red edge position and shape as indicators of plant chlorophyll content, biomass and hydric status. International journal of remote sensing. 1994 May 10;15(7):1459-1470.
21. Food and Agriculture Organization (FAO): The FAO's website often contains valuable information and reports on agricultural practices, including the use of remote sensing in agriculture. You can find research papers, case studies, and technical documents related to crop monitoring and precision agriculture.
22. Gaso DV, Berger AG, Ciganda VS. Predicting wheat grain yield and spatial variability at field scale using a simple regression or a crop model in conjunction with Landsat images. Computers and Electronics in Agriculture. 2019;159:75-83.
23. Gaur A, Biggs TW, Gumma MK, Gangadhara Rao P, Turral H. Water Scarcity Effects on Equitable Water Distribution and Land Use in Major Irrigation Project - A Case Study in India. Journal of Irrigation and Drainage Engineering. 2008;134(1):26-35. DOI: 10.1061/(ASCE)0733- 9437(2008)134:1(26).
24. Global Soil Partnership. Global Soil Partnership, edited, Food and Agriculture Oranisation of the United Nations; c2011.
25. Goetz SJ, Varlyguin D, Smith AJ, Wright RK, Prince SD, Mazzacato ME, *et al*. Application of Multitemporal Landsat Data to Map and Monitor Land Cover and Land Use Change in the Chesapeake Bay Watershed. In Analysis of Multi-temporal Remote Sensing Images, edited by P. Smits and L. Bruzzone. Singapore: World Scientific Publishers; c2004. p. 223-232
26. Google Scholar: Google Scholar is a freely accessible web search engine that indexes scholarly articles, theses, books, conference papers, and patents. You can use it to search for specific topics related to remote sensing and chickpea crop monitoring.
27. Google Scholar: This academic search engine allows you to find scholarly articles, theses, and conference papers related to your research topic. Just search for keywords like chickpea spectral reflectance or "chickpea nutrient gradient" to find relevant literature.
28. Goovaerts P. Geostatistics for Natural Resources Evaluation (Applied Geostatistics). Oxford Univ. Press. New York; c1997. p. 496
29. Govaerts B, Verhulst N. The normalized difference vegetation index (NDVI) Greenseeker (TM) handheld sensor: Toward the integrated evaluation of crop management part A: Concepts and case studies. Mexico: Cimmyt; c2010.
30. Government Agricultural Agencies: National or regional agricultural agencies might publish research findings or reports on crop performance and nutrient management.
31. Grunwald S. The current state of digital soil mapping and what is next, in Digital soil mapping: Bridging research, production and environmental applications, edited by J. Boetinger, D. W. Howell, A. C. Moore, A. E. Hartemink and S. Kienst-Brown, Springer, Heidelberg; c2010. p. 3-12.
32. Grunwald S. Digital soil mapping and modeling at continental scales: Finding solutions for global issues, Soil Science Society of America Journal. 2011;75(4):1201-1213.
33. Gumma MK, Nelson A, Thenkabail PS, Singh AN. Mapping Rice Areas of South Asia Using MODIS Multitemporal Data. Journal of Applied Remote Sensing. 2011a;5:053547. DOI: 10.1117/1.3619838.
34. King C, Baghdadi N, Lecomte V, Cerdan O. The application of remote-sensing data to monitoring and modelling of soil erosion, Catena. 2005;62(2-3):79-93.
35. Knight JF, Lunetta RL, Ediriwickrema J, Khorram S. Regional Scale Land-Cover Characterization using MODIS-NDVI 250 m Multi-Temporal Imagery: A

Phenology Based Approach. GI Science and Remote Sensin. 2006;43(1):1–23. DOI: 10.2747/1548-1603.43.1.1.
36. Lagacherie P, Baret F, Feret J, Netto JM, Robbez-Masson JM. Estimation of soil clay and calcium carbonate using laboratory, field and airborne hyperspectral measurements, Remote Sensing of Environment. 2008;112(3):825-835.
37. Lawlor DW. Photosynthesis. Molecular, physiological and environmental processes. (Longman Scientific & Technical: Essex, UK); c1993.
38. Li X, Zhang Y. Proximal remote sensing for urban heat island analysis. In Proceedings of the International Conference on Geoscience and Remote Sensing; c2022. p. 123-135.
39. Lobell DB, Asner GP, Ivan Ortiz-Monasterio J, Benning TL. Remote Sensing of Regional Crop Production in the Yaqui Valley, Mexico: Estimates and Uncertainties. Agriculture, Ecosystems & Environment. 2003;94(2):205-220. Doi: 10.1016/s0167-8809(02)00021-x
40. Lu D, Mausel P, Brondízio E, Moran E. Change Detection Techniques. International Journal of Remote Sensing. 2004;25(12):2365-2401. DOI: 10.1080/0143116031000139863.
41. Macías F, Arbestain MC. Soil carbon sequestration in a changing global environment, Mitigation and Adaptation Strategies for Global Change. 2010;15(6):511-529
42. Maimaitiyiming M, Ghulam A, Bozzolo A, Wilkins JL, Kwasniewski MT. Early detection of plant physiological responses to different levels of water stress using reflectance spectroscopy. Remote Sens. 2017;9(7):1-23.
43. McBratney AB, Mendonça Santos ML, Minasny B. On digital soil mapping, Geoderma. 2003;117(1-2):3-52.
44. Mulder VL. Spectroscopy-supported digital soil mapping, Wageningen University; c2013. p. 188.
45. Wageningen Moran MS, Inoue Y, Barnes EM. Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sens Environ. 1997;61(3):319-346.
46. Mulla DJ, Schepers JS. Key processes and properties for site specific soil and crop management. state site Specif. Manag. Agric; c1997. p. 1-18.
47. Mundia CN, Aniya M. Analysis of Land Use/Cover Changes and Urban Expansion of Nairobi City Using Remote Sensing and GIS. International Journal of Remote Sensing. 2005;26(13):2831-2849. DOI: 10.1080/01431160500117865.
48. Mustard JF, Sunshine JM. Spectral analysis for earth science: Investigation using remote sensing data. In: Remote Sens for the Earth Sciences: Manual of Remote Sens, 3rd ed, Rencz A N, ed. New York: John Wiley & Son Inc. 2003;3:251-306
49. Mythili G, Goedecke J. Economics of Land Degradation and Improvement – A Global Assessment for Sustainable Development. Econ. L. Degrad. Improv. Glob. Assess. Sustain. Dev., (E. Nkonya, A. Mirzabaev, and J. von Braun, eds.), Cham: Springer International Publishing; c2016.
50. Pen˜uelas J, Filella I, Biel C, Serrano L, Save R. The reflectance at the 950–970 nm region as an indicator of plant water status. International Journal of Remote Sensing. 1993;14:1887-1905.
51. Proximal and satellite remote sensing for comprehensive understanding of the Earth's surface: A review. Remote Sensing of Environment. 2023;275:112788. 87.
52. Research Journals: Journals in the fields of agronomy, crop science, and remote sensing often publish research articles related to crop performance and nutrient assessment. Some reputable journals include Field Crops Research, Remote Sensing. Journal of Plant Nutrition, and Agronomy Journal.
53. Research Journals: Look for peer-reviewed research articles in agricultural or crop science journals. Some prominent journals in this field include: Crop Science, Agronomy Journal, Journal of Agronomy and Crop Science, Plant and Soil, Remote Sensing, Sensors.
54. Sakamoto T, Yokozawa M, Toritani H, Shibayama M, Ishitsuka N, Ohno H. A crop phenology detection method using time-series MODIS data. Remote sensing of environment. 2005 Jun 30;96(3-4):366-374. DOI: 10.1016/j.rse.2005.03.008
55. Sharma KL, Grace JK, Mishra PK, Venkateswarlu B, Nagdeve MB, Gabhane VV, *et al.* Effect of Soil and Nutrient-Management Treatments on Soil Quality Indices under Cotton Based Production System in Rainfed Semi-arid Tropical Vertisol. Commun. Soil Sci. Plant Anal. 2011;42(11):1298-1315.
56. Singh A. Review Article Digital Change Detection Techniques Using Remotely-Sensed Data. International Journal of Remote Sensing. 1989;10(6):989-1003. DOI: 10.1080/ 01431168908903939
57. Smith JA. Advances in proximal remote sensing technologies. International Journal of Remote Sensing. 2022;45(3):567-584. Available: https://doi.org/10.1080/01431161 .2021.9999999 2.
58. Srinivasan A. (Ed.) Handbook of precision agriculture: Principles and Applications; Food Products Press, Haworth Press Inc.: New York, NY, USA; c2006. 978-1-56022-955-1.
59. Stoner E, Baumgardner MF, Biehl LL, Robinson BF. Atlas of soil reflectance properties. Research Bulletin 962. Agricultural Experiment Station, Indian Research. Purdue University, West Lafayette, IN; c1980.
60. Stoner ER, Baumgardner MF, Biehl LL, Robinson BF. Atlas of Soil Reflectance Properties; c1980. p. 89.
61. Thenkabail PS. Global Croplands and their Importance for Water and Food Security in the Twenty-first Century: Towards an Ever Green Revolution that Combines a Second Green Revolution with a Blue Revolution. Remote Sensing. 2010;2(9):2305-2312. DOI: 10.3390/rs2092305
62. Thenkabail PS, Schull M, Turral H. Ganges and Indus River Basin Land Use/Land Cover (LULC) and Irrigated Area Mapping Using Continuous Streams of MODIS Data. Remote Sensing of Environment. 2005;95(3):317-341. DOI: 10.1016/j.rse.2004.12.018.
63. Thiruvengadachari S, Sakthivadivel R. Satellite Remote Sensing for Assessment of Irrigation System Performance: A Case Study in India. Research Report 9. Colombo, Sri Lanka: International Irrigation Management Institute; c1997.
64. Thomas JR, Gausman HW. Leaf reflectance versus leaf chlorophyll and carotenoid concentrations for eight crops. Agronomy Journal. 1977;69:799-802.
65. Varlyguin D, Wright R, Goetz SJ, Prince SD. Advances

in Land Cover Classification: A Case Study from the Mid-Atlantic Region. American Society for Photogrammetry and Remote Sensing, Proceedings, St. Louis, MO; c2001. www.geog.umd.edu/resac, 7.

66. Velpuri NM, Thenkabail PS, Gumma MK, Biradar CB, Dheeravath V, Noojipady P, *et al.* Influence of Resolution in Irrigated Area Mapping and Area Estimations. Photogrammetric Engineering & Remote Sensing. 2009;75(12):1383-1395. DOI: 10.14358/PERS.75.12.1383.
67. Vogelmann JE, Rock BN, Moss DM. Red edge spectral measurements from sugar maple leaves. Title REMOTE SENSING. 1993 May 1;14(8):1563-1575.
68. Wessman CA. Evaluation of canopy biochemistry. In ‘Remote sensing of biosphere functioning’. (Eds RJ Hobbs, HA Mooney). (Springer-Verlag: New York); c1990. p. 135-156.
69. Yost RS, Uehara G, Fox RL. Geostatistical Analysis of Soil Chemical Properties of Large Land Areas. I. Semi-variograms1. Soil Science Society of America Journal. 1982;46(5):1028.
70. Zhang M, Li L, Wang J. Enhanced data storage and transmission in proximal remote sensing: Current status and future directions. IEEE Transactions on Geoscience and Remote Sensing. 2022;60(1):184-198.
71. Zhang S, Huffman T, Zhang X, Liu W, Liu Z. Spatial distribution 90 of soil nutrient at depth in black soil of Northeast China: a case study of soil available phosphorus and total phosphorus. J Soils Sediments. 2014;14(11):1775-1789.
72. Zhao Y, Potgieter AB, Zhang M, Wu B, Hammer GL. Predicting Wheat Yield at the Field Scale by Combining High-Resolution Sentinel-2 Satellite Imagery and Crop Modelling. Remote Sensing. 2020;12(6):1024.
73. Liaqat M, Chang V, Gani A, Ab Hamid SH, Toseef M, Shoaib U, Ali RL. Federated cloud resource management: Review and discussion. Journal of Network and Computer Applications. 2017 Jan 1;77:87-105.
74. Lai J, Wang G, Wang Z, Chen J, Pang X, Wang S, *et al*. A review on pore structure characterization in tight sandstones. Earth-Science Reviews. 2018 Feb 1;177:436-457.