Sensing The Dynamics of Small Landholding in India through Earth Observation: A Comprehensive Review

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Abstract:

Fragmentation or the breakdown of landholdings to smaller parcels has an adverse impact on crop yields and productivity because of its uneconomic operational sizes. This comprehensive review reflects the insights into the complex dynamics of small landholding (SLs) in India by leveraging earth observation (EO) based sensing technology through synthesizing existing literature, methodologies and outcomes, and technological advancements along with its challenges and limitations. This study aims to summarize the current state-of-the problems, management, and utilization of EO technology for mapping, monitoring, and parametric assessment of small-scale agricultural land holdings in India. The review also discussed about different sensing platforms, and how to utilize their varied spectrums for identifying and characterizing SLs at different geographies of India.

India, with its deeply rooted agricultural tradition dating back thousands of years, has agriculture as the primary occupation for a significant portion of its 1.4 billion population. However, a significant issue in Indian agriculture is the fragmentation of croplands into small landholdings, which results in the division of agricultural land into smaller and often uneconomical parcels. Therefore, accurate delineation and EO based sensing of SLs in India is highly necessary for precise monitoring of crop health, soil conditions, and water usage and many more, which can significantly improve productivity on small, uneconomical parcels of land to boost nations food security. The Authors believe with the efficient intervention of EO based sensing technology in SLs, farmers can make more informed decisions and maximize their yields by making more effective use of their resources. Furthermore, Earth observation can help prevent crop losses and improve food security in a nation where a large portion of the population is dependent on agriculture by helping with the early detection of pests and diseases. Our study will support the decision-making process and policy formulation in Indian agriculture system by providing comprehensive insights from EO-based sensing perspectives. Finally, this will help to create more productive and sustainable farming methods, which will be advantageous to both farmers and the national economy.

Keywords: *Croplands, Fragmentation, Small Landholding, Agriculture, Earth Observation, India*

1. Introduction

Precise and accurate delineation of croplands is crucial for identifying agricultural land-use patterns and to develop sustainable landscape management practices (Persello eta., 2019). In a country like India, with the population of 1.4 billion, fragmentation of croplands in a form of a small landholdings (SLs), is a significant issue in Indian agriculture, characterized by the division of agricultural land into smaller and often uneconomical parcels (Gulati & Ganguly., 2010; Gulati & Juneja., 2022).

India has a deeply rooted agricultural tradition dating back thousands of years, with agriculture being the primary occupation for a significant portion of its population (Mathur & Sircar., 2006). Agriculture in India contributes 15-16% (approx.) to India's Gross Domestic Product (GDP) and provides 50% (approx.) employment to the various sectors of agriculture (Wagh & Dongre., 2006). Top of that, India is one of the largest producers of several agricultural commodities (e.g. rice, wheat, sugarcane, cotton, pulses, etc.) that produces 25% of global production and feeds the global population[1]. India is the world's largest producer of milk, pulses and jute, and ranks as the second largest producer of rice, wheat, sugarcane, groundnut, vegetables, fruit and cotton[1].

The term 'small landholdings' indicates the average size of the land owned by the farmer. The same has also been used to call 'operational holdings'. The origin of land fragmentation started from British India, which created serious conceptual problems over ascribing subdivision and fragmentation solely due to population pressure (Charlesworth N., 2023). According to Arcus Policy Research, in 1970, India boasted approximately 71 million operational landholdings, with 70 percent categorized as small and marginal (according to the Agriculture Census). Fast forward to 2015-16, and these figures surged to around 146 million landholdings, with a staggering 86 percent falling under the small and marginal category[2]. Such information indicates that there are more people now owning the SLs that also indicates the increasing trend in chronological manner. Therefore, as the quantity of the SLs are increasing over the time in India, it is imperative that small landholdings must be accurately mapped using technology, in order to ensure sustainable land management practices, boost agricultural output, support rural development, and promote land tenure security (Manjunatha et al., 2013). However, smallholder farms with their irregular shapes, small sizes, and use of mixed-cropping systems, which result in ill-defined boundaries, make automated field delineation a difficult process (Persello eta., 2019). Sensing of small landholdings through technology addresses several critical needs such as precision and accuracy, efficiency, data availability, monitoring and management, inclusivity and definitely for policy formulation (Tripathi et al., 2021). Numerous opportunities exist for small landholdings in India to improve their resilience, sustainability, and productivity thanks to earth observation (EO) sensing technologies (Mahendra et al., 2014). Moreover, EO sensing of SLs holds significant potential in India by providing valuable insights into land use, crop health, environmental conditions at the field scale and many others (Verma et al., 2023; Pokhariyal et al., 2023). Leveraging of EO sensing technology can also support at the individual scale also. First, farmers can utilize the information obtained from satellite imageries provided by relevant agencies to closely monitor and manage their individual land parcels, which can be used to identify regions at risk of erosion or waterlogging, track changes in vegetation cover, and analyze the quality of the

[1] https://www.fao.org/india/fao-in-india/india-at-a-glance/en/
[2] https://arcusresearch.in/indias-small-and-marginal-farmer/#:~:text=In%20simple%20words%2C%20they%20say,million%20and%2086%20percent%20respectively.

soil. Farmers can use this knowledge to make well-informed decisions on land management techniques like crop rotation, soil conservation, and water management. Second, utilization of EO sensing techniques, individuals can monitor for pests and diseases and take prompt preventive action to safeguard their crops by spotting early indicators of infection (Lima et al., 2020). Third, EO based sensed SL data can help agricultural insurance plans and government compensation schemes by proving that natural disasters have damaged crops, which would enable small landholders to get reimbursement on time (Hu et al., 2023). This will help against false claims and misuse of government expenditures. Forth, by integrating earth EO based sensing with mobile applications and digital platforms, individuals can access and utilize this valuable information more effectively, empowering them to improve productivity, reduce risks, and enhance their resilience to environmental challenges (Dhanaraju et al., 2022).

Therefore, understanding the wide dynamics of SLs are a key factor to understand the country's agrarian economy, within the context of India's agriculture landscape to boost India’s food security as well as enhancing national security.

This extensive review attempts to provide insights into the complex dynamics of SLs in India by leveraging EO sensing technology through synthesizing existing literature, their methodologies and outcomes, and technological advancements along with the challenges and limitations. The aim of this review is to provide advanced knowledge of the opportunities and difficulties associated with EO sensing of SLs that will support the technological advancement of Indian agriculture. This review is an important source of information for developing policies that support India's small-scale agriculture. Policymakers can learn more about the geographic circumstances of SLs, the spatial distribution of agricultural activities, and resource utilization patterns by utilizing earth observation techniques to provide a nuanced understanding of the dynamics of small landholding within the nation. With this information, targeted interventions can be created to address problems small farms face, like credit availability, adoption of new technology, security of land tenure, and market connections. Furthermore, the identification of areas with high potential for intervention and sustainable agricultural practices makes it easier to prioritize resources and develop evidence-based policies that enhance the standard of living for small and marginal farmers while advancing food security and rural development. Moreover, this review article covers United Nations Sustainable Development Goals (SDG) 2 (Zero Hunger), and 15 (Life on Land). Ultimately, by bridging the gap between scientific research, policymaking, and industrial needs this review contributes to the formulation of effective strategies that empower small-scale farmers and enhance the resilience of India's agricultural sector.

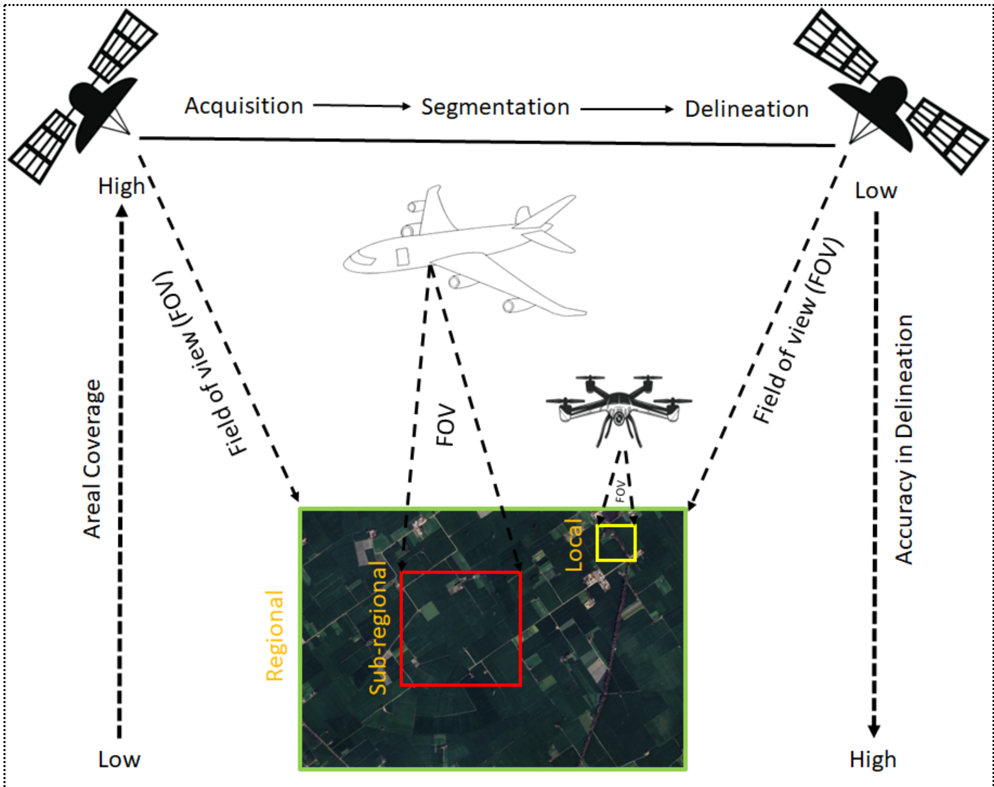

Fig 1: *Conceptual Framework for Mapping and Accuracy Estimation of Small Landholdings in Relation to Sensor Platform Altitude (Spaceborne, Airborne, UAV) in the Context of Indian Croplands.*

2. Small Landholdings and Agricultural Efficiency in India

India accounts for the second largest number of small farms after China in the Asian continent (Lowder et al., 2016). Previous studies have shown that the relationship between farm size and productivity is inverse, although some researchers have a contrary opinion (Helfand & Taylor., 2021; Deolalikar, A. B. 1981; Savastano & Scandizzo., 2017). The owners of SLs face major challenges despite playing a central role in food security, employing laborers, supporting economy but suffers with productivity constraints globally as well as in India (Deolalikar, A. B. 1981; Helfand & Taylor., 2021). Variables like size of the farm landholdings, land fragmentation, ownership of land and diversity of crop on have huge impacts on farm profit and efficiency. It is observed in some studies that fragmentation of land proportionally related to inefficiency whereas crop diversity and ownership of land are inversely correlated to inefficiency in overall productivity (Manjunatha et al., 2013). The primary cause of land pressure resulting in SLs is rapid population growth in both rural and urban areas of India. In rural India, the families over cultivate their plots to increase crop yield due to family needs and business throughout the year. Due to the pressure of over cultivation, the soil fertility is further degraded as there is no time to replenish nutrients (Maleki et al., 2021). Long term over cultivation slightly increases aridity due to amplified effect of human activities (Maleki et al., 2021). Fig. 2 depicts the cropland density in India at the district scale to understand the of diversity of croplands as per population pressure. Cropland density (m^2/person) has been estimated by the division between cropland area and number of populations. Cropland area masked from the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6.1 at 500 meters spatial resolution for the year 2022, whereas population data has been acquired from global high-resolution WorldPop data for the year 2020 computed in google earth engine.

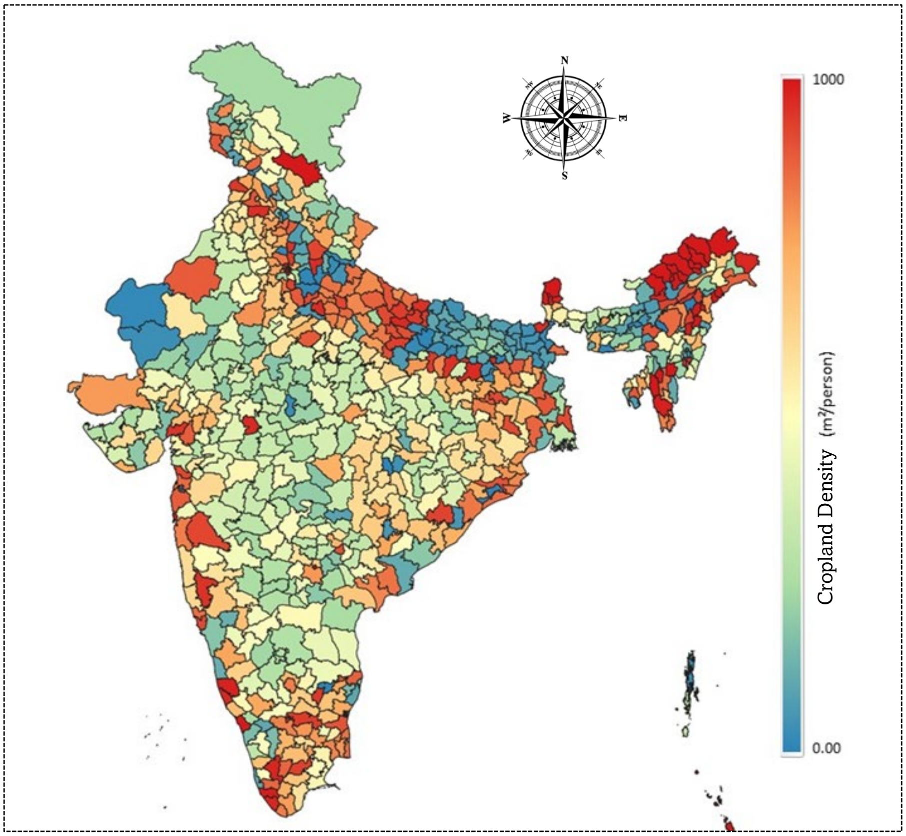

Fig 2: *District scale cropland density in India over 788 districts.*

Fig. 2 observes that districts in the eastern part of India holds higher cropland density compared to the west. Eastern Indian states like Uttar Pradesh, Bihar, West Bengal, Jharkhand, Odisha have highest number of agricultural labours whereas mentioned eastern states also have highest number of populations. The higher cropland density in eastern India, particularly in states like Uttar Pradesh, Bihar, West Bengal, Jharkhand, and Odisha, can be attributed to the fertile lands of the Indo-Gangetic plain, which support intensive agriculture. This region's high population density further contributes to the large number of agricultural laborers present there. Apart from population pressure, other factors such as farm sizes and their distribution, cropping pattern and intensity, cost of cultivation, socio-economic conditions have a significant impact on crop productivity and its yield.

Table 1 reflects the studies conducted at global as well as Indian context to provide critical insights on the impacts of farm size, distribution of farms, cropping patterns, their intensity and other factors on crop productivity and yield gradients. Below table 1 (A) and table 1 (B) illustrates critical overview on the previously published study in the perspectives of global as well as in Indian context related to low productivity of croplands due to several factors.

Global Context					
Sl. No.	**Objective**	**Experimental Site**	**Factors Affecting Productivity**	**Critical Observations**	**Reference**
1.	Examine the importance of the choice of productivity measures in the inverse relationship between farm size and productivity in development economic	Brazilian farms	• Farm Size • Choice of Productivity Measure • Modernization • Dynamic Nature	i. Farm size has an inverse relationship with land productivity, where smaller farms tend to have higher land productivity levels. This relationship remains consistent over time, as highlighted in the study on Brazilian farms from 1985 to 2006. ii. Total factor productivity shows a more dynamic relationship with farm size. With modernization and changes in agricultural practices, the relationship between total factor productivity and farm size has evolved. It has shifted towards a U-shaped or even positive trend over the years, indicating a more complex interaction between farm size and overall productivity. iii. The choice of productivity measure such as land productivity and total factor productivity is crucial in understanding the relationship with farm size. This emphasizes the importance of selecting the appropriate measure when analyzing the impact of farm size on productivity levels. iv. Factors like technological advancements, market conditions and policy changes also play a role	Helfand, S. M., & Taylor, M. P. (2021).

				in shaping the dynamic nature of productivity levels over time.	
2.	Investigate the relationship between farm size and productivity in African agriculture, specifically focusing on Rwanda	Rwanda	• Farm Size • Labor Intensity • Market Wage Rates • Land Fragmentation • Efficiency of Input Use	i. Consistent negative relationship between farm size and output per hectare was observed, indicating that smaller farms tend to be less productive ii. Factors such as land fragmentation, inefficient input use by small farmers, and market imperfections were identified as key elements influencing the productivity levels in the agricultural sector in Rwanda	Ali, D. A., & Deininger, K. (2015).
3.	Study the relationship between farm size and productivity in the context of global agriculture	Ukraine	• Unobserved Factors at District and Farm Level • Farm Expansion and Exit • Initial Distribution of Farm Sizes • Land Concentration	i. The study found that higher yields and profits were not solely due to farm expansion but rather to the exit of unproductive farms and the entry of more efficient ones, indicating the importance of farm efficiency over size.	Deininger, K., Nizalov, D., & Singh, S. (2013).
4.	Inspect the relationship between farm size and productivity in rural Vietnam	Rural Vietnam	• Farm Size • Cropping Intensity • Irrigation • Fertilizer and Seed Application • Agricultural Assets	i. Presents empirical evidence supporting an inverse relationship between farm size and land productivity in rural Vietnam. Larger farm sizes are associated with lower land productivity due to decreasing returns to scale in agricultural production	Vu, T. H., Duc, T. P., & Waibel, H. (2012, September).

			• Labor	ii. Factors such as cropping intensity, irrigation, fertilizer and seed application play significant roles in influencing both land and labour productivity in Vietnamese agriculture. These inputs contribute positively to productivity levels on farms.	

Table 1 (A): Critical overview on the global context.

			Indian Context		
1.	Investigate the relationship between farm size and productivity in the context of farming households, focusing on the cost of cultivation and the types of crops produced.	Farming households in India particularly those engaged in the cultivation of principal crops such as cotton and paddy	• Type of Crop • Costs of Cultivation • Farm Management Practices • Access to Inputs and Markets • Socio-Economic Conditions	i. Inverse relationship between farm size and productivity in the study area suggesting that small and marginal farmers are more productive in wetland cultivation (paddy), while medium and large farmers are more productive in dry land cultivation (cotton). ii. Productivity levels were influenced by the type of crop being produced, with different productivity patterns observed for cotton and paddy cultivation within the farming communities studied	Kumar, K. K., & Moharaj, P. (2023)
2.	Analyze the relationship between farm size and productivity in Indian agriculture, focusing on the persistent higher productivity of smallholdings despite concerns about modernization	India	• Technological Advancements • Soil Quality • Agro-climatic Regions • Levels of Agricultural Technology	i. Smallholdings in Indian agriculture exhibit higher productivity than large holdings, based on data from the National Sample Survey in the early 21st century, indicating the strengths of smallholders in terms of productivity.	Chand, R., Prasanna, P. L., & Singh, A. (2011).

3.	Examine the impact of land fragmentation, farm size, land ownership and crop diversity on the profit and efficiency of irrigated farms in India. The study also aims to understand the relationships between land fragmentation, crop diversity, land ownership, and inefficiency on farms, contributing to the existing knowledge on agricultural practices.	Irrigated farms in India	• Land Fragmentation • Farm Size • Land Ownership • Crop Diversity • Management Practices • Market Access	i. The study found that land fragmentation has a negative impact on farm profitability and efficiency, with smaller land parcels leading to operational inefficiencies and increased production costs. ii. Larger farm sizes were associated with higher profitability and efficiency, indicating that economies of scale play a crucial role in improving farm outcomes. iii. Secure land ownership was identified as a significant factor contributing to farm profitability and efficiency, as it encourages long-term investments in land and enhances productivity. iv. Crop diversity was found to be essential for stable profits and efficient farm operations, helping farmers mitigate risks associated with price fluctuations and climate variability. v. Effective farm management practices, such as proper irrigation techniques and technology utilization, were highlighted as key drivers of profitability and efficiency on irrigated farms.	Manjunatha, A. V., Anik, A. R., Speelman, S., & Nuppenau, E. A. (2013).
4.	Study the relationship between operational holding, productivity, and profitability in the Low Hill Zone of Himachal Pradesh, focusing on selected field crops like maize, paddy, and wheat	Low Hill Zone of Himachal Pradesh	• Operational Holding Size • Type of Crop • Profitability • Policy Implications	i. It found that there is an inverse relationship between operational holding size and productivity for maize crops. On the other hand, a constant productivity relationship was observed for paddy and wheat crops. ii. When considering all these crops together, an inverse relationship between operational holding size and productivity holds true. This suggests that as the operational holding size decreases, productivity tends to increase for these selected field crops. iii. In terms of profitability, the study indicates that only small farmers are able to convert	Kumar, S., & Kumar, K. (2022).

	their output advantages into net profitability when considering all the crops together. This implies that smaller operational holding sizes may lead to better profitability in agriculture in the study area. iv. The findings highlight the importance of land consolidation and effective implementation of development strategies to enhance agricultural production, productivity, and profitability. Managing land holdings effectively is crucial for boosting agricultural outcomes and improving the well-being of farm families in the region.	

Table 1 (B): Critical overview on the Indian context.

To measure and map the productivity patterns in India, Dayal, E. (1984) classified agricultural productivity into three indexes: (1) land productivity, (2) labor productivity, and (3) aggregate productivity. The findings showed that while irrigation, fertilizer use, and urban-industrial growth have positive trends, population density has a negative relationship with the regional variance of crop production in India. Additionally, there is a positive correlation between aggregate productivity and the use of fertilizer and irrigation, but there is an inverse relationship between population density and the number of agricultural workers.

3. Principles of Spectroscopy for Small Landholding Detection

The principles of spectroscopy play a crucial role in modern agricultural practices, particularly in precision agriculture. The principles utilized in vast aspects of agricultural applications, such as crop classification, in-season crop monitoring, crop acreage, crop health, yield estimation, productivity measurement, prediction practices including in the detection of SLs and land fragmentation mapping (Vaidya et al., 2022). State-of-art remote sensing technologies which are based on the principals of spectroscopy such as satellite imagery, aerial photography, and unmanned aerial vehicle (UAVs) imageries, have significantly boosted technology-driven agricultural practices in India as well as in global scale (Kale et al., 2024). In this context, satellites and UAV sensors equipped with moderate to high resolution spectrometers allow for efficient and accurate monitoring of SLs, facilitating better agricultural management and sustainability practices. Table 2 represents the Red (R) and Near-Infrared (NIR) bands or equivalents from optical, microwave and hyperspectral sensors, respective space agencies, and their utility for delineating croplands.

The application of light to examine and determine the composition of soil and plants in small agricultural plots is a fundamental component of spectroscopic principles for small landholding detection. Spectroscopy measures the way electromagnetic radiation interacts with matter in order to identify particular wavelengths that are absorbed or reflected by various materials (Sharma, B. K., 1981; Vitha, M. F., 2018). Thus, this technique enables the precise and nearly precise monitoring of crop types, soil health, yield, moisture content, and other significant characteristics. Moreover, high-spectral resolution imageries (e.g. hyperspectral sensors) help to study crop health and identify stress factors, estimating yield and productivity, time-series data to monitor the sowing and harvesting of crops in much detailed way. In the early period, spectroscopy applications narrowed their focus on crop type identification and acreage only. However, with the technological progress in spectroscopic applications as well as in precision agriculture, applications cover broader areas such as crop biophysical parameter estimation (e.g. leaf area, evapotranspiration potential, chlorophyll, etc.), soil components (e.g. pH, soil texture, organic matter, NPK, etc.), soil moisture and soil temperature estimation, seasonal productivity mapping and modelling, yield prediction and so on (Van Leeuwen & Huete, 1996). It quantifies the primary energy exchange on the canopy surface of a cropland. In Indian context the canopy surface could be homogeneous or heterogeneous in nature. Numerous studies of crop canopies and low stature in seasonal dynamics of crops have found an increase in reflectance in the near-infrared (NIR) region and rapid decrease in the red and short-wave-infrared (SWIR) reflectance (Attia A & Rajan N., 2016). The absorption in the visible region by leaf pigments and in the SWIR by leaf water resulted in the asymptotic nature of canopy reflectance (Hatfield et al., 2008). While the degree of this asymptotic nature of canopy reflectance resulted in the range of different biophysical parameters (e.g. LAI) of the cropland. A similar principle is also used for defining band math based spectral indices like NDVI, PRI, EVI, SAVI, etc. Such spectral indices can delineate SLs and are able to study crop growth stages, stress, and irrigation at individual scale. The Red (625nm –750nm) and Infrared (780nm and 1mm) ranges of the spectrums are most sensitive to vegetation or crop canopy and biophysical variables, due to the strong absorption of the visible lights by chlorophyll in the red band region. Similarly water content by the mid-infrared region (Bandopadhyay et al., 2023). Fig. 3 referring to the change of the reflectance of various wavelengths. It is also seen that in the visible range specifically in the red band, the absorption is highest, and the Infrared region has the peak of the reflectance curve. Table 3 shows the commonly employed indices in agriculture listed for cropland detection.

Satellite	**Sensor Category**	**Red Band (wavelength)**	**NIR Band (wavelength)**	**Space Agency**	**Application for Vegetation Monitoring and Cropland Boundary Detection**
Landsat 8	Optical	Band 4 (0.640 - 0.670 µm)	Band 5 (0.850 - 0.880 µm)	NASA / USGS	The Red band helps identify crop types and assess crop health, while the NIR band enhances the contrast between vegetation and non-vegetation areas.
Landsat 9	Optical	Band 4 (0.640 - 0.670 µm)	Band 5 (0.850 - 0.880 µm)	NASA / USGS	Similar to Landsat 8, the Red and NIR bands are crucial for monitoring cropland health, growth, and classification.
Sentinel-2	Optical	Band 4 (0.665 - 0.675 µm)	Band 8 (0.841 - 0.876 µm)	ESA	The Red band is used to detect vegetation and assess its health, while the NIR band is effective for analyzing vegetation vigor and differentiating between various types of crops.
MODIS	Optical	Band 1 (0.620 - 0.670 µm)	Band 2 (0.841 - 0.876 µm)	NASA	The Red band aids in vegetation classification, while the NIR band helps in monitoring vegetation health and biomass.
WorldView-3	Optical	Band 5 (0.650 - 0.690 µm)	Band 6 (0.770 - 0.895 µm)	DigitalGlobe / Maxar	The Red band supports crop health analysis and land cover classification, while the NIR band helps in assessing crop vigor and distinguishing between different crop types.
Landsat 7	Optical	Band 3 (0.630 - 0.690 µm)	Band 4 (0.770 - 0.890 µm)	NASA / USGS	Similar to Landsat 8 and 9, the Red and NIR bands are used for crop monitoring, health assessment, and classification.
ASTER	Optical	Band 3 (0.630 - 0.690 µm)	Band 4 (0.760 - 0.860 µm)	NASA / JAXA	The Red band helps in vegetation mapping, while the NIR band is used for assessing vegetation health and identifying different crop types.
LISS-3	Optical	Band 3 (0.630 - 0.690 µm)	Band 4 (0.770 - 0.860 µm)	ISRO	The Red band assists in vegetation classification and health monitoring, while the NIR band helps in distinguishing between different crop types and assessing vegetation vigor.
LISS-4	Optical	Band 2 (0.630 - 0.690 µm)	Band 3 (0.770 -	ISRO	Similar to LISS-3, the Red and NIR bands are used for detailed vegetation mapping,

			0.860 µm)		crop health assessment, and land cover classification.
Sentinel-1	SAR	Not applicable	Not applicable	ESA	Although Sentinel-1 does not have specific Red or NIR bands, SAR data is useful for monitoring soil moisture, crop structure, and land surface changes.
TerraSAR-X	SAR	Not applicable	Not applicable	DLR	Similar to Sentinel-1, it provides information on land surface characteristics, useful for assessing soil conditions and crop structure.
EnMap	Hyperspectral	Red (0.620 - 0.690 µm)	NIR (0.850 - 0.880 µm)	DLR	The Red band is used for crop type classification and health assessment. The NIR band helps in analyzing vegetation vigor and health.
HyMap	Hyperspectral	Red (0.620 - 0.690 µm)	NIR (0.770 - 0.890 µm)	Various	Provides detailed spectral information for precise crop health monitoring and classification.
AVIRIS	Hyperspectral	Red (0.630 - 0.690 µm)	NIR (0.850 - 0.880 µm)	NASA	The Red band helps with vegetation mapping and crop health analysis, while the NIR bands provide detailed information on crop conditions and types.

Table 2: *The table details the Red (R) and Near-Infrared (NIR) bands or equivalents from optical, microwave and hyperspectral sensors, space agencies, and their utility for delineating croplands.*

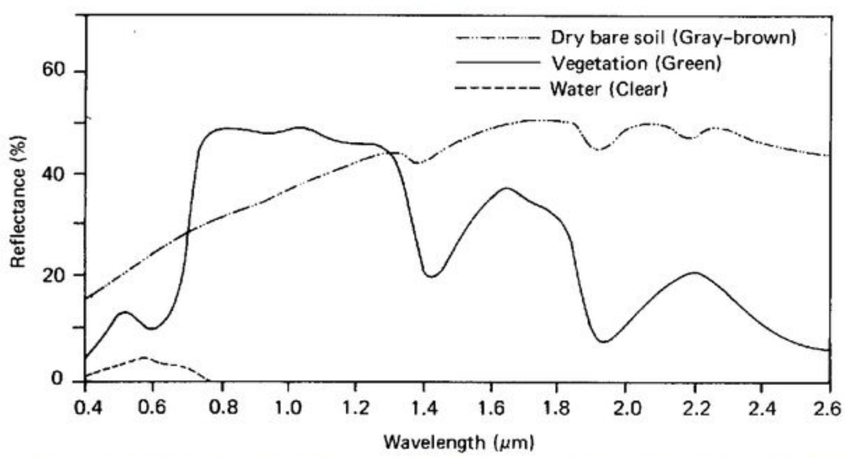

Fig 3: *The Canopy Reflectance graph at different wavelength adopted from Wright et al., 1980.*

Name	Proxy	Implementations	Formula	References
Normalized Difference Vegetation Index (NDVI)	Widely used to measure the presence and health of green vegetation by measuring the reflectance of red and infrared light.	Utilizing object-based NDVI analysis for regional-Scale mapping of agricultural land-use systems (ALUS) enhances large-scale agricultural monitoring through remote sensing.	$NDVI = \frac{(NIR+Red)}{(NIR-Red)}$	*Bellón et al., 2017* *Jeevalakshmi et al., 2016*
Enhanced Vegetation Index (EVI)	uses spectral bands with blue and red edges to reduce atmospheric effects and increase sensitivity to changes in canopy structure, making it easier to detect minute changes in vegetation.	In this study, Enhanced Vegetation Index (EVI) data from MODIS integrated with crop phenological information was employed to estimate maize cultivated area across a large scale in Northeast China.	$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + C1 * Red - C2 * B}$	*Mizen et al., 2024*
Soil Adjusted Vegetation Index (SAVI)	Enhancing vegetation index accuracy in diverse soil conditions using various constant factor also including this in various numerical model can be remove soil interference for more accurate study of leaf or crop component (i.e. Leaf N2)	No relevant study found	SAVI = $(1+0.5)*\frac{(NIR-Red)}{(NIR + Red + 0.5)}$	*Huete, 1988* *Wang et al., 2022*
Red-edge Normalized Difference Vegetation Index (NDVIre)	RedEdge of the spectrum, is highly sensitive to chlorophyll content, compared to NDVI this is more efficient in masking cropland	No relevant study found	$NDVIre = \frac{(NIR+RedEdge)}{(NIR-RedEdge)}$	*Kanke et al., 2016*

Table 3: *Table illustrates spectral indices, their proxies and implementation for studies related to cropland delineation.*

Although the retrieval of crop biophysical parameters and spectral indices from optical EO data and their application for cropland delineation, limited studies have been found that incorporate hyperspectral and microwave sensed EO data for cropland delineation. Hyperspectral sensors feature many contagious bands of narrow width and separated by modest wavelength increments.

Such sensor can accurately estimate crop biophysical and spectral indices, although no such study has been found to utilize such observations for delineating SLs. However, sensing of SLs using hyperspectral data provides detailed insights into multiple leaf parameters like chlorophyll pigments, leaf water stress, Nitrogen content, and biotic and abiotic stress, productivity which can be applied for delineating SLs over a region.

Microwave sensed EO data has become an invaluable tool in the domain of precision agriculture, especially for the identification and management of SLs. Microwave remote sensing utilizing Synthetic Aperture Radar (SAR) imaging technique which can pass through both clouds and vegetation giving high-resolution images that are necessary for accurate boundary mapping of small plots (Mengesha et al., 2024). It helps to monitor accurately in kharif season also (even during monsoon months in India with dense cloud covers) because it ranges from 1m to 10^{-3}m in the electromagnetic spectrum (EMS), which lies in the Atmospheric window, so it penetrates through intense cloud. Similarly, PolSAR uses multiple polarizations thereby differentiating various crop species, growth stage and even precise information about single crops facilitating detailed crop classification and monitoring. Thus, to address the speckle noise in PolSAR images that hampers classification and segmentation, de-speckling methods, which significantly enhance classification accuracy, are essential (Farhadiani et al., 2019). This is important in soil-crop management because multi-temporal C band L-band SAR data, acquired within a short revisiting time (1-2 weeks), can detect minute changes on the earth's surface, such as land deformation and soil moisture variation, allowing for better decisions about soil and crops (Balenzano et al., 2011). Therefore, the proposed strategy can be applied for delineating SLs with high precision. For instance, radar altimetry helps precise soil moisture mapping necessary for efficient irrigation planning (El Hajj et al., 2016). Together, these microwave sensing techniques enable development of comprehensive crop and soil parameter maps encompassing such indices, thus improving the productivity and management of small hectare agricultural lands (Mandal et al., 2020).

4. Resolution for Small Landholding Detection

Nowadays, Earth observation techniques have long been used for SLs to gain insights into numerous agronomic practices. However, Satellite imagery frequently shows blurry physical borders between smallholder farms, therefore contours must be determined by considering how the intricate textural pattern changes between fields (Persello et al., 2019). Standard edge-detection algorithms are unable to derive precise boundaries in these situations in the case of poor to moderate resolution datasets. Therefore, Earth observation sensors differ based on their spatial, spectral, radiometric, and temporal resolution characteristics.

4.1 Spatial Resolution for SL Detection

The smallest object that a satellite can identify is known as spatial resolution, and it is essential for precisely mapping small landholdings. High spatial resolution is provided by satellites like LISS-3 and LISS-4 from ISRO; LISS-3 provides 23.5 meters of resolution, while LISS-4 provides 5.8 meters. The many little fields that are typical of Indian agriculture may be precisely delineated because to this great precision. High spatial resolutions—30 meters for Landsat 8 and 10 meters for Sentinel-2—from NASA and ESA respectively are another feature that satellites like these provide globally. These resolutions are crucial for managing tiny landholdings and differentiating between adjacent plots. Precise geographic data is useful for monitoring micro-level changes, evaluating crop health, and tracking land usage.

Moreover, new age commercial sensors with very high spatial resolutions (meter to centimeter scale) also have a vital role in cropland detection for a country like India. With a 3–5-meter spatial resolution, PlanetScope satellites provide high-frequency, detailed imagery that is perfect for accurate farmland monitoring and demarcation. With its 31-centimeter panchromatic resolution and 1.24-meter multispectral band resolution, WorldView-3 enables extremely thorough examination of crop health and field borders. With a resolution of 0.25 meters, Cartosat-3 from India provides incredibly fine data that is helpful for mapping tiny landholdings and keeping a close eye on crop conditions. By improving crop classification, yield estimate, and land use mapping accuracy, these high-resolution sensors enable more efficient agricultural management.

4.2 Spectral Resolution for SL Detection

A satellite's spectral resolution affects its ability to distinguish between distinct light wavelengths, which in turn affects its ability to detect different materials. High spectral resolution is provided by Indian satellites such as HySI (Hyperspectral Imager), which can distinguish between different crops and soil types by recording fine-grained spectral bands. Similar to this, worldwide satellites with broad spectral coverage, like the hyperspectral EnMap and AVIRIS, provide accurate crop classification and health evaluation. These qualities are essential in India's heterogeneous agricultural environment, where different crops and soil types necessitate precise spectral data for efficient management and monitoring.

4.3 Radiometric Resolution for SL Detection

Radiometric resolution quantifies a satellite's capacity to identify changes in brightness or radiance. High radiometric resolution is crucial for tiny landholdings in India to detect minute variations in soil moisture and crop health. High radiometric resolution is provided by Indian satellites such as ASTER, which is essential for identifying minute fluctuations in reflectance. In a similar vein, Sentinel-2 gives 12-bit depth in its multispectral bands, and Landsat 8 has 12-bit radiometric resolution globally. With the use of these improved radiometric capabilities, tiny fields may be accurately monitored and analyzed, facilitating prompt interventions and improved resource management.

4.5 Temporal Resolution for SL Detection

Temporal resolution is the frequency with which a satellite returns to the same location. Monitoring dynamic changes in small landholdings requires regular revisits. High temporal resolution and frequent revisits are provided by the RISAT series in India, which aids in the monitoring of soil conditions and agricultural activities. Satellites like MODIS, which has a daily revisit capacity, and Sentinel-2, which has a 5-day revisit cycle, provide useful data for routine monitoring on a global scale. To maximize productivity and adapt to environmental changes, timely updates on crop growth, changes in land usage, and general agricultural management are made possible by this frequent data collecting.

5. Review of Earth observation Platforms for Delineating Small Landholdings

Near-real time monitoring of agricultural plots is needed to assess the impact of climate change and extreme events on agriculture. Delineating, mapping and monitoring of the spatial distribution of agricultural holdings plays a vital role in estimating crop production which is of importance per food security of the country. Electronic field records are of utmost importance as it is associated with detailed field information which includes the boundary and shape of the field (Fritz et al., 2015). This information helps in monitoring soil type, soil moisture, pest infestation, crop growth, and yield estimate and helps in managing fertilizer and pesticide application. However, generating and maintaining digital records of small land holdings is always tedious and has limitations. Specifically, if it comes to developing countries like India, digital field records are lacking and involve a lot of manual work with human errors (Marvaniya et al., 2021). EO technology has a lot of benefits in delineating, generating and maintaining such records with great precision. EO based images or remote sensing images contribute towards providing information and implementing a robust system in continuous monitoring of agricultural fields which serves for sustainable agricultural practice. With these advancements crop yield quality and quantity can be better estimated.

Various Earth observation platforms are available for the effective delineation of croplands. For comprehensive crop analysis and field validation, high-resolution data that is specific to local conditions is most effectively gathered through ground-based remote sensing methods. In contrast, space-based remote sensing offers broad, large-scale coverage and temporal data that are crucial for assessing cropland dynamics and regional agricultural trends. Additionally, airborne remote sensing, which includes the use of drones, provides a flexible and high-resolution approach for mapping and monitoring extensive areas.

5.1 Evidence From Ground borne Sensor

Ground-based sensing is also known as proximal sensing as the use of sensors to collect signals in contact or at close proximity to the target (within a few meters) (Pallottino et al., 2019). These sensors however, are mainly capable of monitoring and capturing information related to plant health, growth, water content, etc. (Shafi et al., 2019). Mostly the data collected from ground-based remote sensing has limited application on delineation of SLs because of the limited spatial coverage and narrow field of view (FOV).

5.2 Evidence From Airborne Sensor

However, sensors fitted on airborne platforms have a long association with agriculture mapping which goes back to 1929 (Seelan et al., 2003). Aerial remote sensing also evolved through time. Starting from simple photos taken in 1929 to imaging done through unmanned aerial vehicles (UAVs), airborne remote sensing underwent incredible advancement in technology. The use of UAVs in precision agriculture for the first time was in 1997 and this technology was widely used in Japan and South Korea for fertilizer spraying (Alexopoulos et al., 2023). Nowadays UAVs have wide applications in agriculture from collecting high-quality images to collecting information through terrestrial scanning. Chen et al., (2020) used high-resolution UAV images along with multispectral and elevation data to perform uses of agricultural land. Fetai et al., (2021) use deep learning techniques with high-resolution UAV images to detect and map land boundaries. Yallappa et al., (2017) examined the usefulness of UAVs in small agricultural holdings in India for crop management and spraying of fertilizer.

5.3 Evidence From Spaceborne Sensor

The launch of the Landsat series in the 1970s and the subsequent availability of earth observation images marked the use of satellite remote sensing in agriculture applications. For a long time, work on cropland extraction has been done on satellite images. Satellite remote sensing provides temporal and spatial continuous data, spectral crop information, and low-cost data depending on the satellite type (Georgi et al., 2018). Rydberg & Borgefors, (2001) & Evans et al. (2002) performed an automated segmentation method on Landsat images at 30 m spatial resolution to extract farmlands. Yan & Roy (2016) used Landsat time series data to extract agricultural crop fields in the U.S. and found that larger field sizes can be easily extracted. Rahman et al. (2019) extracted a multi-year agricultural field boundary using the Cropland Data Layer which has been generated from satellite images derived from Landsat, Sentinel and LISS 3 at 30 m resolution. Technical advancement with machine learning, deep learning, convolution neural network (CNN) etc. has made the task of farmland delineation much more robust. Aung et al. (2020) used spatio-temporal satellite data and delineated farm parcels using the CNN method. Singh et al., (2022) applied a deep learning method to map different agricultural land use over parts of Punjab in India using Sentinel-2 satellite data.

6. Geographic Diversity and Cropland Spatial Structures:

Spatial structure of SLs includes various aspects of the agricultural crop to identify and map individual crops and their distributions, field components assessment and mapping dependent demographic information. Spatial Structures of land holdings refers to land parcel area or size, distribution, utilization etc. Nowadays, land fragmentation and plot distribution in the rural regions have a detrimental impact on the profitability and efficiency of agricultural output (Stręk & Noga, 2019). India's diverse geography and cultural heritage have shaped different land holding structures across the region. In the fertile Indo-Gangetic Plain, characterized by intensive agriculture, small-scale farming predominates, with fragmented land holdings resulting from traditional inheritance practices. In the Northern region (comprising states such as Himachal Pradesh, Uttarakhand, and others), a traditional method of step cultivation is employed to suit the hilly terrain. Many of the Northeastern states practice shifting cultivation on small patches of agricultural land between forests. The Deccan Plateau, which relies heavily on rain-fed agriculture, has a land holding structure shaped by irrigation patterns. These regional variations in land holding, influenced by soil quality, water availability, and cultural practices, underscore the complexity of India's agricultural landscape and highlight the need for nuanced policy approaches to enhance productivity and food security. Figure 3 illustrates diversity in cropland structure based on geographic locations of India.

Fig 4: *Diversity of Crop Land Structure respect to India's geographical diversity.*

Delimiting the physical structure of SLs using modern technology serves spatial and social aspects of the developing world. Effective land-use planning and management, especially for small crop parcels, depend on precise delineation of the land boundaries (Li & Yeh, 2004). The delimitation of spatial structures within small land holdings has been modernized by the advent of new technologies, particularly handheld devices, and remote sensing techniques instead of those traditional field-based labor-intensive and time-consuming methods (Rufin et al., 2022). Using EO data and a Machine Learning (ML) approach helps delimit small landholding structures accurately.

Image classification, segmentation, Principal Component Analysis (Hotelling, 1933), edge detection, and Cluster analysis like K-mean clustering, C-mean clustering, etc. (Wiśniewski et al., 2020) methods are mostly used to study delimiting spatial structure. Such segmentation methods can be applied over any geographical location not only in India but globally. In the case of satellite imagery, there are still problems with low resolution and noise, particularly in the study of small land holdings and closely spaced plots, which requires high-resolution (below 30 x 30 meters) aerial images or drone data. Furthermore, the quality of these images might vary widely.

Land plots can be accurately classified and delineated with the use of supervised training models on annotated data, deep-learning model maps land boundaries efficiently and with a significant reduction in the amount of manual intervention required by combining satellite surface reflectance data and land records. Plot boundary detection processes may now be automated with great potential using machine learning and deep learning techniques. This automation makes the process faster and more efficient while also improving accuracy.

7. Model-Based Disentangling of Small Landholdings

Accurate data collection is fundamental to understanding and managing small landholdings, which are critical to agricultural productivity and rural development. Remote sensing technologies, when combined with advanced modeling techniques, enable precise detection, monitoring, and analysis of these small parcels of land. Just as the type of sensors installed on various platforms is crucial, the methods used to extract actionable information from the captured imageries are equally important. Traditionally, this step occurs after data collection. However, with the recent advancements in technology, particularly in model-based image classification techniques, it is now possible to extract information almost instantly as the images are captured.

7.1 Object-Based Image Analysis (OBIA)

Going from pixel-based to object-based image analysis in land use and land cover identification has greatly enhanced the accuracy of remote sensing. In a more traditional approach, the image classification would consider each pixel individually. That may generate a 'salt-and-pepper' effect, especially in categories with diverse landscapes (Ouyang et al., 2011). This happens because mixed pixel signals take place along with spectral inconsistencies. In contrast to the classical object-based remote sensing, OBIA segments a set of pixels into meaningful objects based on their spectral and spatial features and interrelations between different image parts, for instance (Hossain & Chen, 2019).. This provides a much clearer representation of the LULC categories that are of high accuracy, especially in identifying small land parcels. The process of OBIA is usually a two-step process. First, it performs a segmentation by using multiresolution or edge-based algorithms that divide the image into objects based on spectral and spatial patterns in the image. Later, these divided objects are labeled by a classifier such as decision trees or SVMs, hence enabling better and more detailed identification of small landholdings. This approach finds more and more applications nowadays, with low-altitude CubeSats (Saeed et al., 2020) and drones like the DJI Phantom 4 RTK (Ramachandran & Sangaiah, 2021).

6.2 Image Classifiers

Image classifiers work with remote-sensing sensors to extract actionable information from imagery (Mehmood et al., 2022). High-resolution imagery in several spectral bands is captured by sensors mounted on satellites, UAVs, and manned aircraft. This is the point at which the imagery is taken, and then come the image classifiers. These are either supervised or unsupervised classifiers that look into the captured data based on spectral, spatial, and temporal characteristics.

In supervised classifiers, the classifier has to be trained by an expert to correctly classify the LULC features on a labeled dataset. Some of the key supervised algorithms are the use of Support Vector Machines (SVM), Random Forest (RF), and Neural Networks (NN). Support Vector Machines look for the separating hyperplane that maximizes the margin between different classes in feature space. This algorithm is quite effective in the case where feature space is high dimensional and the classes are not linearly separable. It has a low tendency towards overfitting problems, especially on high-dimensional spaces, and yields good results with small sets of training data.

Because of the accuracy in classification and skill in handling complex boundaries between different land covers, SVM is useful in the case of small landholding detection.

Random Forests (RF) create multiple decision trees at training and output the mode of the classes (classification), and mean prediction (regression) for the individual trees. RF is robust to overfitting, like Support Vector Machine (SVM), and works well on large datasets with high dimensionality. These algorithms also provide important measures on feature importance, which helps understand the contribution of different spectral bands and indices. Such capability makes RF particularly effective to identify small landholdings, given that most of them present a mixture of different land cover types and environmental conditions.

A neural network, especially deep learning architectures such as CNNs is composed of many layers of interconnected neurons that hierarchically obtain features from the input data. Neural Networks can model complex relations and patterns of the data to achieve higher accuracy. For example, CNN does an excellent job in identifying spatial patterns and textures within high-resolution images. This ability of NNs to learn from large volumes of high-resolution data, together with their effectiveness in spatial dependencies, makes them an ideal choice for mapping small landholdings with high precision.

On the other hand, unsupervised classification methods classify similarly reflecting pixels without supervised labeling. Some common algorithms in this area include K-means clustering and ISODATA. K-means is a partitioning method that divides the dataset into K clusters based on spectral similarity, where each pixel is assigned to the cluster center that is closest to it. The application of this approach is simple and not that computationally heavy, making it useful for exploring the inherent structure of the data and identifying natural groupings. However, it has a limitation for the detection of small landholdings, since it only depends on spectral similarity, having no consideration for spatial context.

ISODATA iteratively extends K-means method by modifying the number of clusters according to user-defined criteria such as splitting and merging during iterations. Hence, compared to K-means, ISODATA is quite flexible since it will adapt more dynamically to the structure in space, yielding better results in heterogeneous and complex landscapes. However, like K-means, ISODATA still lacks the spatial context needed to identify small landholdings and may misclassify the class for complex agricultural areas.

7.3 Integration of Geospatial AI

In remote sensing, detection of small and invincible (obstructed/covered) objects has always been challenging due to the complex backgrounds and the diverse scales at which these objects appear. In recent times, AI-backed innovations such as YOLO (You Only Look Once), Segment Anything Model (SAM) from Meta AI (Kirillov et al., 2023) etc. allowed real-time and automated object detection, revolutionizing image analysis in remote sensing and solving this problem (Redmon et al., 2016). These are specifically designed to detect small objects with high accuracy and speed, which makes them very suitable for real-time disentangling of small landholdings and other applications in remote sensing.

7.4 Data Fusion

Detection of fragmented agricultural lands in India often requires the implementation of data fusion techniques. Such techniques take different types of information from different types of data sources and combine them together. For example, a multi-sensor fusion combines data from optical, radar, and LiDAR sensors, offering a holistic understanding of fragmented agricultural lands(Barbedo, 2022). Optical sensors offer valuable information regarding crop types and vegetation health, whereas radar sensors are capable of penetrating cloud cover to evaluate surface roughness and soil moisture (Abdulraheem et al., 2023). This is especially useful for South Asian countries like India, which experiences a prominent monsoon season. LiDAR data, on the other hand, provides high-resolution elevation details that support identification of terrain characteristics and changes in land cover. A fusion between these diverse datasets therefore enhances the spatial accuracy of detecting fragmented agricultural lands in India altogether. Similarly, a temporal fusion ensures the integration of data from multiple time points, facilitating the continuous monitoring of seasonal land use changes, conversions, cropping patterns, etc. These fusion techniques provide valuable insights into the dynamics of fragmented agricultural lands in India, supporting sustainable land management practices and rural development initiatives across the country.

7.5 Post-Sensing Processes

7.5.1 GIS-Based Cadastral Mapping

Geographic Information System (GIS) plays a crucial role in geospatial modeling by enabling the collection, storage, analysis, and visualization of spatial data (Ershad & Ali, 2020). In India, managing agricultural land used to rely heavily on paper-based maps which often lacked up-to-date information about the landholdings. To address this issue, the Government of India launched the National Land Records Modernization Programme (NLRMP) in 2008, which was later rebranded as the Digital India Land Records Modernization Programme (DILRMP) in 2016. This initiative aims to digitize land records across the country (Year End Review 2023, n.d.). This program promotes the use of GIS tools/environments, along with remote sensing images, to create detailed and up-to-date cadastral maps. These maps provide a clear picture of national and regional landholdings, making it easier to identify fragmented plots, analyze land use patterns, and assess the extent of land fragmentation.

7.5.2 Spatial Analysis of Fragmentation Patterns

Fragmentation matrices can be calculated using GIS environments to quantify land fragmentation, such as the number of parcels, average parcel size, and the degree of dispersion(Kilić et al., 2019). These matrices provide a quantitative basis for assessing the severity of fragmentation. For example, Parcel Size Distribution metric assesses the size distribution of land parcels within a region where smaller, more numerous parcels indicate higher fragmentation. The fragmentation index measures the degree of dispersion and disconnection among the land parcels (i.e. higher values indicate more severe fragmentation), and Proximity and Contiguity Analyses evaluate the proximity of parcels to each other along with their contiguity, which are critical for understanding the practical challenges of farming a fragmented land.

7.5.3 Optimization Models for Land Consolidation

Optimization models are utilized to create more efficient approaches in developing land consolidation programs. The objective of these models is to reshape fragmented parcels into larger, contiguous units that are more amenable to current agricultural standards, and increase productivity while providing cost savings in operations (Akkaya Aslan & Arici, 2005; Kontek et al., 2023). These optimization models are further categorized broadly as GIS-based optimization models and numerical optimization models.

7.5.3.1 GIS-based Optimization Models:

Land Suitability Modeling, and Cost-benefit Modeling are two of the most commonly used GIS-based optimization models for land consolidation. Land suitability models evaluate physical factors such as soil quality, topography, and water availability in agricultural lands and identify the most suitable areas for consolidation (Chen et al., 2023). On the other hand, oost-benefit models assess the economic feasibility of different consolidation scenarios and consider factors like infrastructure costs, potential productivity increases, and social impacts (Mittal, 2018). Through these comprehensive modeling strategies, GIS-based decision support systems (DSS) can be built which will consider physical, social, and economic factors to improve land management, enhance productivity, and minimize conflicts among landholders during the consolidation process. This will ensure fair and equitable distribution of land in developing countries like India.

7.5.3.2 Numerical Optimization Models:

As advanced numerical computations are increasingly applied, and machine learning and deep learning methodologies come into play, the performance of models used in land management has improved greatly. Various models related to Linear Programming (LP) and Integer Programming (IP) have been commonly used in land reallocation to minimize land fragmentation, while either improving productivity, or minimizing costs associated with land fragmentation, by creating more productive landholding arrangements. LP, for instance, has been applied in Rajasthan in order to re-arrange irrigable land parcels, determine appropriate crop clusters candidates, and allocate crops that maximize production (Bhatia, 2020).

Multi-Criteria Decision Analysis (MCDA) is another common optimization method to consider potential socio-economic and environmental factors associated with land consolidation decisions (Marinković et al., 2023). Procedures like Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) can evaluate multiple criteria and achieve a trade-off between multiple competing interests among the stakeholders (Marinković et al., 2023).

Heuristic and Metaheuristic Algorithms, including Genetic Algorithms (GAs) and Simulated Annealing (SA), are excellent solutions of complex land consolidation problems (Mendes et al., 2019). These algorithms are particularly useful where a large number of variables and constraints exist, essentially providing near-optimal solutions over a reasonable computational time span.

7.5.4 Game Theory and Cooperative Models

These models are very useful to examine the ways landowners/stakeholders interact with each other when making decisions about land use. Game theory considers both the incentives that encourage landowners to participate in land consolidation programs and the obstacles that may prevent them from doing so. By simulating different scenarios, game theory allows us to explore how cooperation or competition between landowners can influence the success of these consolidation efforts. For instance, it can simulate how landowners might benefit from working together or how competition between them might lead to less favorable outcomes (Barati et al., 2021). Therefore, this approach helps in designing more effective strategies for land reorganization.

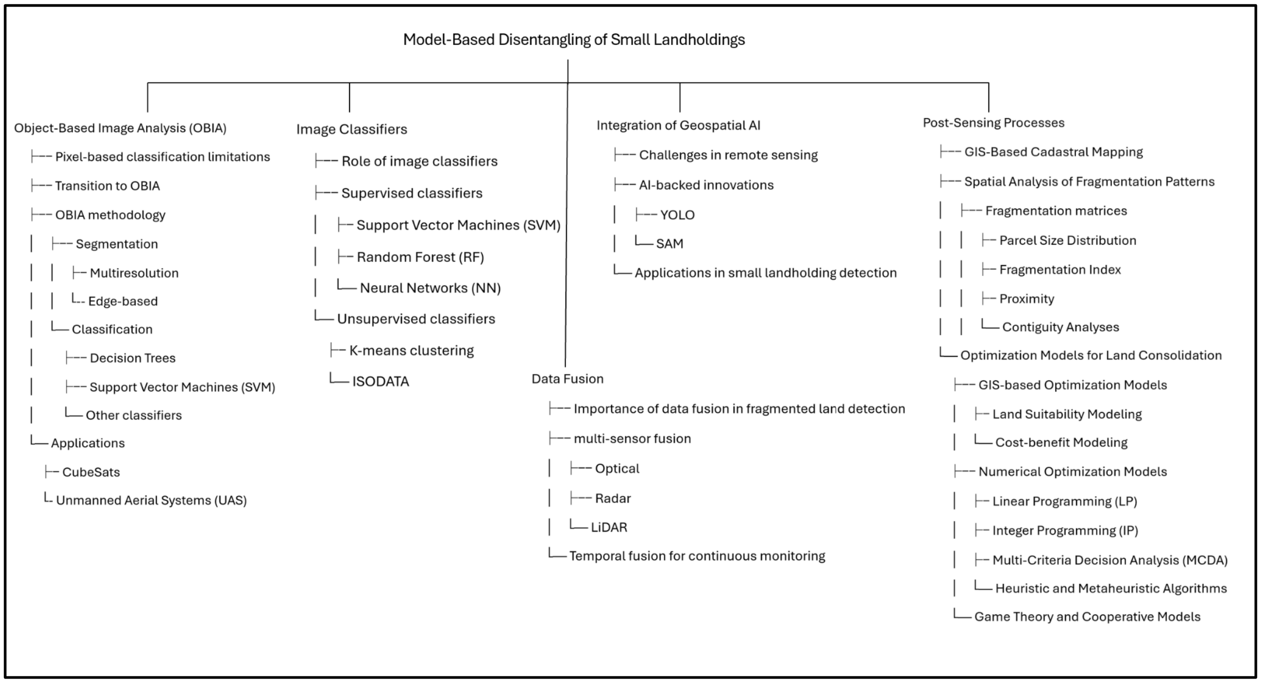

Fig 5: *Flowchart showing the diversity of model-based disentangling of SLs.*

8. Challenges and limitations in Earth-observation techniques

Automated cropland delineation is a challenging task, specifically when it comes to delineating small land holdings in a precise and accurate way. Although remote sensing have a sound capabilities in this domain, remotely sensed data poses many challenges in the delineation of SLs. These challenges can broadly be classified into two categories. Firstly, based on the type of satellite data resolution, i.e., spatial, spectral, temporal, and radiometric. Secondly, based on the type of sensor and platform used in acquiring remote sensing data, i.e., optical, microwave, thermal, UAVs, etc. The spatial resolution of the imagery plays a vital role in the delineation of small land holdings. It's very challenging to delineate agricultural fields, specifically when it comes to countries like India, where small, fragmented land holdings predominate. Wang et al., (2022) did a comparative analysis of agricultural fields in South Africa, France, and India based on the spatial resolution of Landsat-8, Sentinel-2, PlanetScope, and Airbus SPOT satellite. It has been found that bigger fields in South Africa and France are clearly visible and can be delineated with Landsat-8 (30 m) and Sentinel-2 (10 m), whereas small farmland in India requires PlanetScope (4.8 m) and Airbus SPOT (1.5 m).

Spectral resolution of satellite images enhances the edge of the field and thus has a vital role in the delineation of the fields. Small landholdings have complex geometrical characteristics, so multispectral images provide more contrast and enhance the edge more prominently than mono-spectral images. Persello et al., (2019) showed the difference between multispectral bands of WorldView-3 and Panchromatic images.

The long revisit time of the satellite over a particular region also hampers the application of cropland mapping. M. Wang et al., (2022) in their research, elaborates on the use of multi-temporal images on single-temporal satellite data.

The radiometric resolution also impacts image classification and the delineation of farmland. Verde et al., (2018)assessed the efficiency of fine and low radiometric resolution images and found that finer or higher radiometric resolution has higher image classification accuracy over low radiometric resolution. Classified images with higher accuracy can help better delineate small land holdings.

Based on the type of sensor used to capture the satellite image influences the delineation of small agricultural farmlands. Satellite images derived from optical sensors are specifically impacted by the percentage of cloud cover. Under overcast conditions, optical sensors can't capture ground signals, making it difficult to map, and this condition persists mainly in tropical countries like India (Joshi et al., 2016). Also, the presence of clouds over a region eventually reduces temporal coverage, making it difficult for continuous monitoring. Microwave remote sensing data do have advantages in capturing ground signals under cloudy conditions, but they have many physical limitations (Vreugdenhil et al., 2022). Over mountainous regions, it becomes very hard to retrieve signals as the topography alters microwave signals. Thermal images, on the other hand, can provide useful information but depend on the time of the day and weather conditions under which the data has been collected (Gan et al., 2018).

Based on the platform, there are many challenges in delineation. Airborne platforms no doubt can give precise information about the fields, specifically when it comes to delineating small land holdings, but it has many limitations. Sensors used in UAVs and airborne sensing as a whole are very expensive, and cheap sensors with low capacities have often been used (Ezenne et al., 2019). As UAVs fly in close proximity to the ground surface and within atmospheric influence, they face challenges in gathering information in bad weather with high wind flow (Mohsan et al., 2023). Even during stable weather conditions, it needs to maintain balance in order to capture images, so there is always a limitation in the number of sensors a UAV can carry (Balestrieri et al., 2021). The position and tilt of the camera are also crucial as they influence the calibration of the system, making the delineation of farmland tough. UAVs generate images with better spatial resolution, which led to the acquisition of huge amounts of data that needed a lot of processing and heavy computation facilities (Csillik et al., 2018). The delineation of agricultural fields through UAVs is still in its initial stage of development in India (Singh, 2023), and more research needs to be carried out in this domain. Images from UAVs are often costly and even not available in the public domain. The data is often considered sensitive and has limitations (Mohsan et al., 2023) on its use as it may pose security issues.

High-resolution space-borne satellite imagery is always very heavy as far as data storage and processing capacity are concerned, and it may take a lot of time to delineate small land holdings. Over large areas, satellite images can provide affordable and timely assessing and mapping of crop fields; however, when it comes to small agricultural land holdings, it comes with generating inaccurately classified maps (Kerner et al., 2024). Moreover, irrespective of the type of satellite resolution, data availability is a big question. Most of the medium and coarse spatial resolution satellite images are freely available. However, very high-resolution satellite images, even if they can serve the purpose of mapping small fields, can only be incurred with high prices from private providers like Worldview and RapidEye data (Persello et al., 2019; Cammarano et al., 2020).

Taking all the above-mentioned challenge in the delineation of small land holdings into account, the following limitations can be jotted down:-

1. Lack of freely available high-resolution images.
2. Lack of labeled data for training and validating models for delineating agricultural fields.
3. Small landholdings' geometry and spatial orientation often make delineation work arduous.
4. The level of noise in the data is like that of clouds.
5. The high volume of fine-resolution data creates digital space issues.
6. Dense and small-sized fields like those in India cannot be properly delineated for all types of satellite images.

9. Conclusion:

The review study emphasizes the importance and critical review of the methods and techniques to delineate SLs of India through the utilization of state-of-art earth observation technologies. However, delineating SLs through earth observation in a densely populated country like India is different and difficult where the numbers and density of SLs is huge. Fragmentation of lands with different shapes and sizes across India, along with different cropping patterns in different parts of the country makes the accurate delineation cumbersome (Marvaniya et al., 2021). Although there are issues with the accurate delineation of SLs, the present review paper shows the potential technologies and methods to accurately map the SLs in the Indian context even under the geographical diversity in the different parts of the country. Therefore, this extensive review discussed the potential sensing technologies in sustainable management practices for agricultural context as well as for natural resources. In the context of agriculture, in India, several programs/projects such as FASAL, CAPE, NNRMS, NADAMS, IMSD, CHAMAN, etc. and many small projects are effectively running for management of agricultural systems in one and another way (Kumar et al., 2022). The authors believed that this review paper will significantly contribute to the existing and ongoing projects related to agriculture and natural resource management to enhance country's food security and strengthening national security. We also believe that this work will also have capabilities to make a significant contribution to the future projects related to the similar field.

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Dataset Used:

1. *Population Data*: WorldPop Global Project Population Data: Constrained Estimated Age and

Sex Structures of Residential Population per 100x100m Grid Square from Google Earth Engine (Academic Version)

2. *Crop land area*: MCD12Q1.061 MODIS Land Cover Type Yearly Global 500m from Google Earth Engine (Academic Version)

Declaration of competing interest :

The authors affirm that they have no known financial or interpersonal conflicts that would have appeared to have an impact on the research presented in this study.

References

Abdulraheem, M. I., Zhang, W., Li, S., Moshayedi, A. J., Farooque, A. A., & Hu, J. (2023). Advancement of Remote Sensing for Soil Measurements and Applications: A Comprehensive Review. Sustainability, 15(21), Article 21. https://doi.org/10.3390/su152115444

Abdulraheem, M. I., Zhang, W., Li, S., Moshayedi, A. J., Farooque, A. A., & Hu, J. (2023). Advancement of Remote Sensing for Soil Measurements and Applications: A Comprehensive Review. Sustainability, 15(21), Article 21. https://doi.org/10.3390/su152115444

Akkaya Aslan, Ş., & Arici, I. (2005). GIS-supported land consolidation planning information system: ARTOP. Bodenkultur, 56, 103–110.

Akkaya Aslan, Ş., & Arici, I. (2005). GIS-supported land consolidation planning information system: ARTOP. Bodenkultur, 56, 103–110.

Alexopoulos, A., Koutras, K., Ali, S. B., Puccio, S., Carella, A., Ottaviano, R., & Kalogeras, A. (2023). Complementary Use of Ground-Based Proximal Sensing and Airborne/Spaceborne Remote Sensing Techniques in Precision Agriculture: A Systematic Review. Agronomy, 13(7), Article 7. https://doi.org/10.3390/agronomy13071942

Ali, D. A., & Deininger, K. (2015). Is There a Farm Size–Productivity Relationship in African Agriculture? Evidence from Rwanda. *Land Economics*, *91*(2), 317–343. https://doi.org/10.3368/le.91.2.317

Attia, A., & Rajan, N. (2016). Within-season growth and spectral reflectance of cotton and their relation to lint yield. *Crop Science*, *56*(5), 2688-2701.

Attia, A., & Rajan, N. (2016). Within-Season Growth and Spectral Reflectance of Cotton and their Relation to Lint Yield. *Crop Science*, *56*(5), 2688–2701. https://doi.org/10.2135/cropsci2015.05.0296

Aung, H. L., Uzkent, B., Burke, M., Lobell, D., & Ermon, S. (2020). Farm Parcel Delineation Using Spatio-temporal Convolutional Networks. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 340–349. https://doi.org/10.1109/CVPRW50498.2020.00046

Balenzano, A., Mattia, F., Satalino, G., & Davidson, M. W. J. (2011). Dense Temporal Series of C- and L-band SAR Data for Soil Moisture Retrieval Over Agricultural Crops. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 4(2), 439–450. https://doi.org/10.1109/JSTARS.2010.2052916https://doi.org/10.2307/634969

Balestrieri, E., Daponte, P., De Vito, L., Picariello, F., & Tudosa, I. (2021). Sensors and Measurements for UAV Safety: An Overview. Sensors, 21(24), Article 24. https://doi.org/10.3390/s21248253

Bandopadhyay, S., Das, B., Sánchez, A. C., Banerjee, S. P., Banerjee, B. P., & Ghosh, S. (2023). Canopy Scale High-Resolution Forest Biophysical Parameter (LAI, fAPAR, and fCover) Retrieval Through Machine Learning and Cloud Computation Approach. 2023 International Conference on Machine Intelligence for GeoAnalytics and Remote Sensing (MIGARS), 1–4. https://doi.org/10.1109/MIGARS57353.2023.10064558

Barati, A. A., Azadi, H., & Scheffran, J. (2021). Agricultural land fragmentation in Iran: Application of game theory. Land Use Policy, 100, 105049. https://doi.org/10.1016/j.landusepol.2020.105049

Barati, A. A., Azadi, H., & Scheffran, J. (2021). Agricultural land fragmentation in Iran: Application of game theory. Land Use Policy, 100, 105049. https://doi.org/10.1016/j.landusepol.2020.105049

Barbedo, J. G. A. (2022). Data Fusion in Agriculture: Resolving Ambiguities and Closing Data Gaps. Sensors (Basel, Switzerland), 22(6), 2285. https://doi.org/10.3390/s22062285

Barbedo, J. G. A. (2022). Data Fusion in Agriculture: Resolving Ambiguities and Closing Data Gaps. Sensors (Basel, Switzerland), 22(6), 2285. https://doi.org/10.3390/s22062285

Bellón, B., Bégué, A., Lo Seen, D., De Almeida, C., & Simões, M. (2017). A remote sensing Approach for Regional-Scale Mapping of Agricultural Land-Use Systems based on NDVI Time Series. *Remote Sensing*, *9*(6), 600. https://doi.org/10.3390/rs9060600

Bhatia, M. (2020). Linear Programming Approach- Application in Agriculture.

Bhatia, M. (2020). Linear Programming Approach- Application in Agriculture.

Cammarano, D., Zha, H., Wilson, L., Li, Y., Batchelor, W. D., & Miao, Y. (2020). A Remote Sensing-Based Approach to Management Zone Delineation in Small Scale Farming Systems. Agronomy, 10(11), Article 11. https://doi.org/10.3390/agronomy10111767

Chand, R., Prasanna, P. A. L., & Singh, A. (2011). Farm size and productivity: Understanding the strengths of smallholders and improving their livelihoods. Economic and Political Weekly, 46(26/27), 5–11.

Charlesworth, N. (2023). The Origins of fragmentation of landholdings in British India: a comparative examination. In Routledge eBooks (pp. 181–215). https://doi.org/10.4324/9781003461463-7

Charlesworth, N. (2023). The Origins of fragmentation of landholdings in British India: a comparative examination. In Routledge eBooks (pp. 181–215). https://doi.org/10.4324/9781003461463-7

Chen, K., Sharma, A., & Iyer, L. (2023). Suitability Evaluation of Rural Land Consolidation Based on GIS. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4608870

Chen, K., Sharma, A., & Iyer, L. (2023). Suitability Evaluation of Rural Land Consolidation Based on GIS. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4608870

Chen, P.-C., Chiang, Y.-C., & Weng, P.-Y. (2020). Imaging Using Unmanned Aerial Vehicles for Agriculture Land Use Classification. Agriculture, 10(9), Article 9. https://doi.org/10.3390/agriculture10090416

Csillik, O., Cherbini, J., Johnson, R., Lyons, A., & Kelly, M. (2018). Identification of Citrus Trees from Unmanned Aerial Vehicle Imagery Using Convolutional Neural Networks. Drones, 2(4), Article 4. https://doi.org/10.3390/drones2040039

Dayal, E. (1984). Agricultural productivity in India: a spatial analysis. Annals of the Association of American Geographers, 74(1), 98-123.

Deininger, K., Nizalov, D., & Singh, S. K. (2017). Determinants of Productivity and Structural Change in a Large Commercial Farm Environment: Evidence from Ukraine. *The World Bank Economic Review*, *32*(2), 287–306. https://doi.org/10.1093/wber/lhw063

Deolalikar, A. B. (1981). The inverse relationship between productivity and farm size: a test using regional data from India. American Journal of Agricultural Economics, 63(2), 275-279.

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable agriculture. Agriculture, 12(10), 1745. https://doi.org/10.3390/agriculture12101745

El Hajj, M., Baghdadi, N., Zribi, M., Belaud, G., Cheviron, B., Courault, D., & Charron, F. (2016). Soil moisture retrieval over irrigated grassland using X-band SAR data. Remote Sensing of Environment, 176, 202–218. https://doi.org/10.1016/j.rse.2016.01.027

Ershad, M., & Ali, E. (2020, March 26). Geographic Information System (GIS): Definition, Development, Applications & Components.

Ershad, M., & Ali, E. (2020, March 26). Geographic Information System (GIS): Definition, Development, Applications & Components.

Evans, C., Jones, R., Svalbe, I., & Berman, M. (2002). Segmenting multispectral Landsat TM images into field units. IEEE Transactions on Geoscience and Remote Sensing, 40(5), 1054–1064. https://doi.org/10.1109/TGRS.2002.1010893

Ezenne, G. I., Jupp, L., Mantel, S. K., & Tanner, J. L. (2019). Current and potential capabilities of UAS for crop water productivity in precision agriculture. Agricultural Water Management, 218, 158–164. https://doi.org/10.1016/j.agwat.2019.03.034

Farhadiani, R., Homayouni, S., & Safari, A. (2019). IMPACT OF POLARIMETRIC SAR SPECKLE REDUCTION ON CLASSIFICATION OF AGRICULTURE LANDS. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-4/W18, 379–385. https://doi.org/10.5194/isprs-archives-XLII-4-W18-379-2019

Fetai, B., Račič, M., & Lisec, A. (2021). Deep Learning for Detection of Visible Land Boundaries from UAV Imagery. Remote Sensing, 13(11), Article 11. https://doi.org/10.3390/rs13112077

Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., … Obersteiner, M. (2015). Mapping global cropland and field size. Global Change Biology, 21(5), 1980–1992. https://doi.org/10.1111/gcb.12838

Gan, H., Lee, W. S., Alchanatis, V., Ehsani, R., & Schueller, J. K. (2018). Immature green citrus fruit detection using color and thermal images. Computers and Electronics in Agriculture, 152, 117–125. https://doi.org/10.1016/j.compag.2018.07.011

Georgi, C., Spengler, D., Itzerott, S., & Kleinschmit, B. (2018). Automatic delineation algorithm for site-specific management zones based on satellite remote sensing data. Precision Agriculture, 19(4), 684–707. https://doi.org/10.1007/s11119-017-9549-y

Gulati, A., & Ganguly, K. (2010). The changing landscape of Indian agriculture. Agricultural Economics, 41(s1), 37–45. https://doi.org/10.1111/j.1574-0862.2010.00486.x

Gulati, A., & Juneja, R. (2022). Transforming Indian agriculture. In India studies in business and economics (pp. 9–37). https://doi.org/10.1007/978-981-19-0763-0_2

Hatfield, J. L., Gitelson, A. A., Schepers, J. S., & Walthall, C. L. (2008). Application of spectral remote sensing for agronomic decisions. *Agronomy Journal*, *100*, S-117.

Helfand, S. M., & Taylor, M. P. (2021). The inverse relationship between farm size and productivity: Refocusing the debate. Food Policy, 99, 101977.

Hossain, M. D., & Chen, D. (2019). Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. ISPRS Journal of Photogrammetry and Remote Sensing, 150, 115–134. https://doi.org/10.1016/j.isprsjprs.2019.02.009

Hossain, M. D., & Chen, D. (2019). Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. ISPRS Journal of Photogrammetry and Remote Sensing, 150, 115–134. https://doi.org/10.1016/j.isprsjprs.2019.02.009

Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. Journal of Educational Psychology, 24(6), 417–441. https://doi.org/10.1037/h0071325

Hu, L., Zhang, C., Zhang, M., Shi, Y., Lu, J., & Fang, Z. (2023). Enhancing FAIR data Services in Agricultural Disaster: A review. Remote Sensing, 15(8), 2024. https://doi.org/10.3390/rs15082024

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Jeevalakshmi, D., Reddy, S. N., & Manikiam, B. (2016). Land cover classification based on NDVI using LANDSAT8 time series: A case study Tirupati region. IEEE Xplore. https://doi.org/10.1109/iccsp.2016.7754369

Joshi, N., Baumann, M., Ehammer, A., Fensholt, R., Grogan, K., Hostert, P., Jepsen, M. R., Kuemmerle, T., Meyfroidt, P., Mitchard, E. T. A., Reiche, J., Ryan, C. M., & Waske, B. (2016). A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring. Remote Sensing, 8(1), Article 1. https://doi.org/10.3390/rs8010070

Kale, S. K., Sahrawat, R., Sangwan, M., Jain, S., Gautam, S. K., & Nagaraju, V. (2024). Revolutionary Technologies in Horticultural Crops: A Review. Journal of Advances in Biology & Biotechnology, 27(7), 420-436.

Kanke, Y., Tubaña, B., Dalen, M., & Harrell, D. (2016). Evaluation of red and red-edge reflectance-based vegetation indices for rice biomass and grain yield prediction models in paddy fields. *Precision Agriculture*, *17*(5), 507–530. https://doi.org/10.1007/s11119-016-9433-1

Kerner, H., Nakalembe, C., Yang, A., Zvonkov, I., McWeeny, R., Tseng, G., & Becker-Reshef, I. (2024). How accurate are existing land cover maps for agriculture in Sub-Saharan Africa? Scientific Data, 11(1), 486. https://doi.org/10.1038/s41597-024-03306-z

Kilić, J., Jajac, N., Rogulj, K., & Mastelić-Ivić, S. (2019). Assessing Land Fragmentation in Planning Sustainable Urban Renewal. Sustainability, 11(9), Article 9. https://doi.org/10.3390/su11092576

Kilić, J., Jajac, N., Rogulj, K., & Mastelić-Ivić, S. (2019). Assessing Land Fragmentation in Planning Sustainable Urban Renewal. Sustainability, 11(9), Article 9. https://doi.org/10.3390/su11092576

Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., & Girshick, R. (2023). Segment Anything (arXiv:2304.02643). arXiv. https://doi.org/10.48550/arXiv.2304.02643
Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., & Girshick, R. (2023). Segment Anything (arXiv:2304.02643). arXiv. https://doi.org/10.48550/arXiv.2304.02643
Kontek, P., Basista, I., & Maciuk, K. (2023). GIS analyses of land consolidation in case of the highly fragmentated of parcels. Folia Forestalia Polonica, 65, 136–152. https://doi.org/10.2478/ffp-2023-0014
Kontek, P., Basista, I., & Maciuk, K. (2023). GIS analyses of land consolidation in case of the highly fragmentated of parcels. Folia Forestalia Polonica, 65, 136–152. https://doi.org/10.2478/ffp-2023-0014
Kumar, K. K., & Moharaj, P. (2023b). Farm size and productivity relationship among the farming communities in India. *Outlook on Agriculture*, *52*(2), 212–227. https://doi.org/10.1177/00307270231176578

Kumar, S., & Kumar, K. (2022). Farm size and agricultural productivity in the Low Hill zone of Himachal Pradesh: a study. *Asian Journal of Managerial Science*, *11*(1), 23–28. https://doi.org/10.51983/ajms-2022.11.1.3098

Kumar, S., Meena, R. S., Sheoran, S., Jangir, C. K., Jhariya, M. K., Banerjee, A., & Raj, A. (2022). Remote sensing for agriculture and resource management. In *Natural Resources Conservation and Advances for Sustainability* (pp. 91-135). Elsevier.

Kussul, N., Lavreniuk, M., Skakun, S., & Shelestov, A. (2017). Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data. IEEE Geoscience and Remote Sensing Letters, 14(5), 778–782. https://doi.org/10.1109/LGRS.2017.2681128

Li, X., & Yeh, A. G.-O. (2004). Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. Landscape and Urban Planning, 69(4), 335–354. https://doi.org/10.1016/j.landurbplan.2003.10.033

Lima, M. C. F., De Almeida Leandro, M. E. D., Valero, C., Coronel, L. C. P., & Bazzo, C. O. G. (2020). Automatic Detection and Monitoring of Insect Pests—A Review. Agriculture, 10(5), 161. https://doi.org/10.3390/agriculture10050161

Lowder, S. K., Skoet, J., & Raney, T. (2016). The number, size, and distribution of farms, smallholder farms, and family farms worldwide. *World development*, *87*, 16-29.

Mahendra Dev, S. (2014). Small farmers in India: Challenges and opportunities.

Maleki, S., Karimi, A., Zeraatpisheh, M., Poozeshi, R., & Feizi, H. (2021). Long-term cultivation effects on soil properties variations in different landforms in an arid region of eastern Iran. Catena, 206, 105465.

Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J. M., McNairn, H., & Rao, Y. S. (2020). Dual polarimetric radar vegetation index for crop growth monitoring using sentinel-1 SAR data. Remote Sensing of Environment, 247, 111954. https://doi.org/10.1016/j.rse.2020.111954

Manjunatha, A., Anik, A. R., Speelman, S., & Nuppenau, E. (2013). Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. Land Use Policy, 31, 397–405. https://doi.org/10.1016/j.landusepol.2012.08.005

Marinković, G., Nestorović, Ž., Ilić, Z., & Božić, M. (2023). Multi-Criteria Decision Analysis and Land Consolidation Projects Ranking. 155–158. https://doi.org/10.31410/EMAN.2023.155
Marinković, G., Nestorović, Ž., Ilić, Z., & Božić, M. (2023). Multi-Criteria Decision Analysis and Land Consolidation Projects Ranking. 155–158. https://doi.org/10.31410/EMAN.2023.155
Marvaniya, S., Devi, U., Hazra, J., Mujumdar, S., & Gupta, N. (2021). Small, sparse, but substantial: Techniques for segmenting small agricultural fields using sparse ground data. International Journal of Remote Sensing, 42(4), 1512–1534. https://doi.org/10.1080/01431161.2020.1834166

Mathur, A. S., Das, S., & Sircar, S. (2006). Status of agriculture in India: trends and prospects. Economic and political weekly, 5327-5336.. https://www.jstor.org/stable/4419078

Mehmood, M., Shahzad, A., Zafar, B., Shabbir, A., & Ali, N. (2022). Remote Sensing Image Classification: A Comprehensive Review and Applications. Mathematical Problems in Engineering, 2022. https://doi.org/10.1155/2022/5880959
Mehmood, M., Shahzad, A., Zafar, B., Shabbir, A., & Ali, N. (2022). Remote Sensing Image Classification: A Comprehensive Review and Applications. Mathematical Problems in Engineering, 2022. https://doi.org/10.1155/2022/5880959
Mendes, J., Moura Oliveira, P., Neves Dos Santos, F., & Santos, R. (2019). Nature Inspired Metaheuristics and Their Applications in Agriculture: A Short Review (pp. 167–179). https://doi.org/10.1007/978-3-030-30241-2_15
Mendes, J., Moura Oliveira, P., Neves Dos Santos, F., & Santos, R. (2019). Nature Inspired Metaheuristics and Their Applications in Agriculture: A Short Review (pp. 167–179). https://doi.org/10.1007/978-3-030-30241-2_15
Mengesha, T. E., Desta, L. T., Gamba, P., & Ayehu, G. T. (2024). Multi-Temporal Passive and Active Remote Sensing for Agricultural Mapping and Acreage Estimation in Context of Small Farm Holds in Ethiopia. Land, 13(3), 335. https://doi.org/10.3390/land13030335

Mittal, S. (2018). Cost-benefit analysis of agriculture interventions in Andhra Pradesh.
Mittal, S. (2018). Cost-benefit analysis of agriculture interventions in Andhra Pradesh.
Mizen, A., Thompson, D. A., Watkins, A., Akbari, A., Garrett, J. K., Geary, R., Lovell, R., Lyons, R. A., Nieuwenhuijsen, M., Parker, S. C., Rowney, F. M., Song, J., Stratton, G., Wheeler, B. W., White, J., White, M. P., Williams, S., Rodgers, S. E., & Fry, R. (2024). The use of Enhanced Vegetation Index for assessing access to different types of green space in epidemiological studies. Journal of Exposure Science & Environmental Epidemiology. https://doi.org/10.1038/s41370-024-00650-5

Mohsan, S. A. H., Othman, N. Q. H., Li, Y., Alsharif, M. H., & Khan, M. A. (2023). Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. Intelligent Service Robotics, 16(1), 109–137. https://doi.org/10.1007/s11370-022-00452-4

Ouyang, Z., Zhang, M.-Q., Xie, X., Shen, Q., Guo, H., & Zhao, B. (2011). A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plats. Ecological Informatics, 6, 136–146. https://doi.org/10.1016/j.ecoinf.2011.01.002

Ouyang, Z., Zhang, M.-Q., Xie, X., Shen, Q., Guo, H., & Zhao, B. (2011). A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plats. Ecological Informatics, 6, 136–146. https://doi.org/10.1016/j.ecoinf.2011.01.002

Pallottino, F., Antonucci, F., Costa, C., Bisaglia, C., Figorilli, S., & Menesatti, P. (2019). Optoelectronic proximal sensing vehicle-mounted technologies in precision agriculture: A review. Computers and Electronics in Agriculture, 162, 859–873. https://doi.org/10.1016/j.compag.2019.05.034

Persello, C., Tolpekin, V. A., Bergado, J. R., & de By, R. A. (2019). Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping. Remote Sensing of Environment, 231, 111253. https://doi.org/10.1016/j.rse.2019.111253

Pokhariyal, S., Patel, N. R., & Govind, A. (2023). Machine Learning-Driven Remote Sensing Applications for Agriculture in India—A Systematic Review. Agronomy, 13(9), 2302. https://doi.org/10.3390/agronomy13092302

Rahman, Md. S., Di, L., Yu, Z., Yu, E. G., Tang, J., Lin, L., Zhang, C., & Gaigalas, J. (2019). Crop Field Boundary Delineation using Historical Crop Rotation Pattern. 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 1–5. https://doi.org/10.1109/Agro-Geoinformatics.2019.8820240

Ramachandran, A., & Sangaiah, A. K. (2021). A review on object detection in unmanned aerial vehicle surveillance. International Journal of Cognitive Computing in Engineering, 2, 215–228. https://doi.org/10.1016/j.ijcce.2021.11.005

Ramachandran, A., & Sangaiah, A. K. (2021). A review on object detection in unmanned aerial vehicle surveillance. International Journal of Cognitive Computing in Engineering, 2, 215–228. https://doi.org/10.1016/j.ijcce.2021.11.005

Rufin, P., Bey, A., Picoli, M., & Meyfroidt, P. (2022). Large-area mapping of active cropland and short-term fallows in smallholder landscapes using PlanetScope data. International Journal of Applied Earth Observation and Geoinformation, 112, 102937. https://doi.org/10.1016/j.jag.2022.102937

Rydberg, A., & Borgefors, G. (2001). Integrated method for boundary delineation of agricultural fields in multispectral satellite images. IEEE Transactions on Geoscience and Remote Sensing, 39(11), 2514–2520. https://doi.org/10.1109/36.964989

Saeed, N., Elzanaty, A., Almorad, H., Dahrouj, H., Al-Naffouri, T. Y., & Alouini, M.-S. (2020). CubeSat Communications: Recent Advances and Future Challenges (arXiv:1908.09501). arXiv. https://doi.org/10.48550/arXiv.1908.09501

Saeed, N., Elzanaty, A., Almorad, H., Dahrouj, H., Al-Naffouri, T. Y., & Alouini, M.-S. (2020). CubeSat Communications: Recent Advances and Future Challenges (arXiv:1908.09501). arXiv. https://doi.org/10.48550/arXiv.1908.09501

Savastano, S., & Scandizzo, P. L. (2017). Farm Size and Productivity: A. World Bank Policy Research Working Paper, (8127).

Seelan, S. K., Laguette, S., Casady, G. M., & Seielstad, G. A. (2003). Remote sensing applications for precision agriculture: A learning community approach. Remote Sensing of Environment, 88(1), 157–169. https://doi.org/10.1016/j.rse.2003.04.007

Shafi, U., Mumtaz, R., García-Nieto, J., Hassan, S. A., Zaidi, S. A. R., & Iqbal, N. (2019). Precision Agriculture Techniques and Practices: From Considerations to Applications. Sensors, 19(17), Article 17. https://doi.org/10.3390/s19173796

Sharma, B. K. (1981). Spectroscopy. Krishna Prakashan Media.
Singh, G., Singh, S., Sethi, G., & Sood, V. (2022). Deep Learning in the Mapping of Agricultural Land Use Using Sentinel-2 Satellite Data. Geographies, 2(4), Article 4. https://doi.org/10.3390/geographies2040042
Singh, P. (2023). Drones in Indian Agriculture: Trends, Challenges, and Policy Implications. https://doi.org/10.13140/RG.2.2.29651.35366/2
Stręk, Ż., & Noga, K. (2019). Method of Delimiting the Spatial Structure of Villages for the Purposes of Land Consolidation and Exchange. Remote Sensing, 11(11), 1268. https://doi.org/10.3390/rs11111268
Tran, K. H., Menenti, M., & Jia, L. (2022). Surface Water Mapping and Flood Monitoring in the Mekong Delta Using Sentinel-1 SAR Time Series and Otsu Threshold. Remote Sensing, 14(22), 5721. https://doi.org/10.3390/rs14225721
Tripathi, R., Kumar, A., Guru, P., Debnath, M., Mohapatra, S., Mohanty, S., Khanam, R., Shahid, M., & Nayak, A. (2021). Precision farming technologies for water and nutrient management in rice: Challenges and opportunities. Oryza, 58(Special), 126–142. https://doi.org/10.35709/ory.2021.58.spl.5
Vaidya, R., Nalavade, D., & Kale, K. V. (2022). Hyperspectral Imagery for Crop yield estimation in Precision Agriculture using Machine Learning Approaches: A review. Int. J. Creat. Res. Thoughts, 9, a777-a789.
Van Leeuwen, W. J. D., & Huete, A. R. (1996). Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices. Remote Sensing of Environment, 55(2), 123–138. https://doi.org/10.1016/0034-4257(95)00198-0
Verde, N., Mallinis, G., Tsakiri-Strati, M., Georgiadis, C., & Patias, P. (2018). Assessment of Radiometric Resolution Impact on Remote Sensing Data Classification Accuracy. Remote Sensing, 10(8), Article 8. https://doi.org/10.3390/rs10081267
Verma, B., Porwal, M., Jha, A. K., Vyshnavi, R. G., Rajpoot, A., & Nagar, A. K. (2023). Enhancing precision agriculture and environmental monitoring using proximal remote sensing. Journal of Experimental Agriculture International, 45(8), 162–176. https://doi.org/10.9734/jeai/2023/v45i82168
Vitha, M. F. (2018). Spectroscopy: Principles and instrumentation. John Wiley & Sons.
Vreugdenhil, M., Greimeister-Pfeil, I., Preimesberger, W., Camici, S., Dorigo, W., Enenkel, M., van der Schalie, R., Steele-Dunne, S., & Wagner, W. (2022). Microwave remote sensing for agricultural drought monitoring: Recent developments and challenges. Frontiers in Water, 4. https://doi.org/10.3389/frwa.2022.1045451
Vu, T. H., Duc, T. P., & Waibel, H. (2012, September). Farm size and Productivity: Empirical Evidence from Rural Vietnam. In *Conference on International Research on Food Security*.
Wagh, R., & Dongre, A. P. (2016). Agricultural Sector: Status, Challenges and it's Role in Indian Economy. Journal of Commerce and Management Thought, 7(2), 209. https://doi.org/10.5958/0976-478x.2016.00014.8
Wang, J., Dai, Q., Shang, J., Jin, X., Sun, Q., Zhou, G., & Dai, Q. (2019). Field-Scale Rice Yield Estimation Using Sentinel-1A Synthetic Aperture Radar (SAR) Data in Coastal Saline Region of Jiangsu Province, China. Remote Sensing, 11(19), 2274. https://doi.org/10.3390/rs11192274

Wang, M., Wang, J., Cui, Y., Liu, J., & Chen, L. (2022). Agricultural Field Boundary Delineation with Satellite Image Segmentation for High-Resolution Crop Mapping: A Case Study of Rice Paddy. Agronomy, 12(10), Article 10. https://doi.org/10.3390/agronomy12102342

Wang, S., Waldner, F., & Lobell, D. B. (2022). Unlocking Large-Scale Crop Field Delineation in Smallholder Farming Systems with Transfer Learning and Weak Supervision (22). Article 22.

Wiśniewski, Ł., Perdał, R., & Rudnicki, R. (2020). Proposed method for delimiting spatial structure on the example of agriculture types in Poland. Bulletin of Geography. Socio-Economic Series, 49(49), 7–18. https://doi.org/10.2478/bog-2020-0020

Wright, J., Lillesand, T. M., & Kiefer, R. W. (1980). Remote Sensing and Image Interpretation. The Geographical Journal, 146(3), 448. https://doi.org/10.2307/634969

Yallappa, D., Veerangouda, M., Maski, D., Palled, V., & Bheemanna, M. (2017). Development and evaluation of drone mounted sprayer for pesticide applications to crops. 2017 IEEE Global Humanitarian Technology Conference (GHTC), 1–7. https://doi.org/10.1109/GHTC.2017.8239330

Yan, L., & Roy, D. P. (2016). Conterminous United States crop field size quantification from multi-temporal Landsat data. Remote Sensing of Environment, 172, 67–86. https://doi.org/10.1016/j.rse.2015.10.034

Year End Review 2023: Achievement of the Department of Land Resources (Ministry of Rural Development). (n.d.). Retrieved June 24, 2024, from https://pib.gov.in/pib.gov.in/Pressreleaseshare.aspx?PRID=1989671

Year End Review 2023: Achievement of the Department of Land Resources (Ministry of Rural Development). (n.d.). Retrieved June 24, 2024, from https://pib.gov.in/pib.gov.in/Pressreleaseshare.aspx?PRID=1989671