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REVIEW

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Earth observation technologies for agricultural risk management in fragmented croplands of India

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Abstract
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. Fragmentation, or the breakdown of landholdings into smaller parcels, has an adverse impact on crop yields and productivity due to its uneconomic operational sizes. Therefore, accurate mapping of small landholdings (SLs) is necessary for precise monitoring of crop health, soil conditions, water usage, and many other factors, which can significantly improve the productivity of fragmented land parcels and sustain the country's's food security. This comprehensive review provides insights into the complex dynamics of SLs in India by leveraging Earth Observation (EO) based remote sensing data and technology, synthesizing the existing literature, methodologies, and outcomes, as well as technological advancements, their challenges and limitations.This study aims to synthesize the current challenges, management practices, and applications of Earth Observation (EO) technologies for mapping, monitoring, and parametric assessment of small-scale agricultural landholdings in India. The review also discussed different remote sensing platforms and how to utilize their varied spectrums for identifying and characterizing SLs at different geographies in India. By incorporating EO approaches into Disaster Risk Reduction (DRR) frameworks, the study highlights how fragmented croplands can be better identified, monitored, and safeguarded against disasters and climate-induced agricultural risks. This study will support the decision-making process and policy formulation in the Indian agricultural system by providing comprehensive insights from EO-based sensing perspectives. Finally, this will help to plan 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

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1 Introduction

Precise and accurate delineation of croplands is crucial for identifying agricultural land-use patterns and for developing sustainable landscape management practices [101]. In a country like India, with a population of 1.4 billion, fragmentation of croplands in the form of small landholdings (SLs) is a significant issue in Indian agriculture, characterized by the division of agricultural land into smaller and often uneconomical parcels [54, 55].

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 [88]. Agriculture in India contributes 15%–16% to the country's Gross Domestic Production (GDP) and employs approximately 50% of the workforce [128]. On top of that, India is one of the largest producers of several agricultural commodities (e.g., rice, wheat, sugarcane, cotton, pulses, etc.) that produce 25% of global production and feed 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, groundnuts, vegetables, fruits, and cotton.

The term 'small landholding' indicates the average size of the land owned by a farmer. It is also used interchangeably with the term 'operational holdings'. . The origin of land fragmentation dates back to British India, which created serious conceptual problems in ascribing subdivision and fragmentation mainly due to population pressure [21]. According to Arcus Policy Research, in 1970, India had approximately 71 million operational landholdings, and 70% of them were categorized as small and marginal landholdings (according to the agriculture census). By the year 2015-16, the numbers surged to around 146 million landholdings, with a staggering 86% falling under the small and marginal category[2]. This information suggests that more people now own SLs, indicating a massive temporal increase in land ownerships. Therefore, as the number of SLs is increasing over time in India, it is imperative that small landholdings be accurately mapped using technology to ensure sustainable land management practices, boost agricultural output, support rural development, and promote land tenure security [85]. However, the fragmented farms, with their irregular shapes, small sizes, and mixed-cropping systems oftenresult in ill-defined boundaries, and make automated field delineation efforts challenging [101]. Identifying and delineating such small landholdings using technology addresses several critical needs, including precision and accuracy, efficiency, data availability, monitoring and management, inclusivity, and policy formulation [119]. Many opportunities exist for small landholdings in India to enhance their resilience, sustainability, and productivity through the application of earth observation (EO) sensing technologies (Mahendra S., 2014[82]). Recent efforts have increasingly emphasized the role of digital EO-based tools in strengthening climate-resilient agricultural systems [7, 48]. Moreover, EO sensing of SLs holds significant potential in India, providing valuable insights into land use, crop health, and environmental conditions at the field scale, among other applications [102, 124]. Figure 1 illustrates a multi-scale remote sensing workflow from data acquisition to segmentation and delineation of croplands using space-borne (satellite), and airborne (air craft and UAV) remote sensing platforms. It shows that a satellite provides large areal coverage but low delineating

[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%2 C%20they%20say, million%20and%2086%20percent%20respectively.

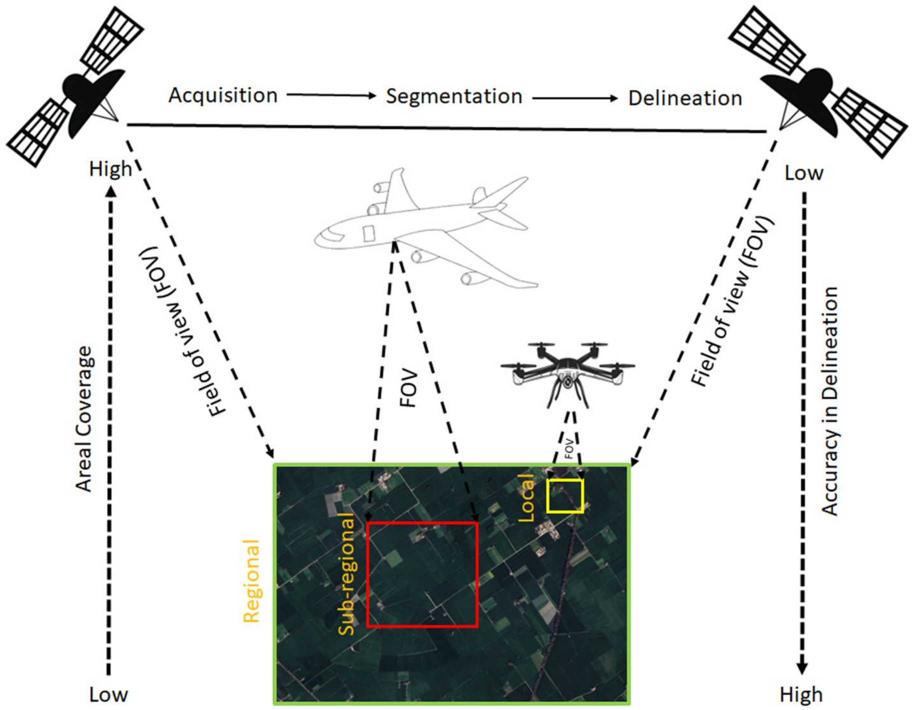

Fig. 1 Conceptual framework for mapping and accuracy estimation of small landholdings in relation to sensor platform altitude (Spaceborne, Airborne, UAV) in the context of Indian croplands

accuracy, while UAVs offer higher accuracy at a local scale with limited coverage due to smaller field-of-view (FOV). While airborne platforms bridge this gap at sub-regional scales, they highlight the trade-off between field of view, spatial details, and mapping accuracy across platforms. Multi-scale EO data integration enables precise mapping and exposure assessment across local to sub-regional and regional scales, strengthening disaster risk reduction (DRR) efforts through timely and evidence-based insights. By translating these EO-derived risk products into standardized spatial indicators, policymakers can formulate targeted mitigation strategies, land-use regulations, and early-warning frameworks.

The paper highlights the importance of precise SL delineation as an important step for assessing agricultural risk under compound disaster conditions, particularly in highly dynamic river basins such as the Ganga–Brahmaputra–Meghna (GBM) basin [49, 72]. In such regions, fragmented croplands are frequently exposed to recurrent flooding, seasonal drought, riverbank erosion, and climate variability. Accurate EO-based boundary detection improves exposure quantification, supports sub-field vulnerability assessment, and enables Machine Learning (ML) frameworks capable of capturing such compound disaster dynamics in SL-dominated landscapes. Moreover, Leveraging of EO sensing technology can also support at the individual scale. First, farmers can utilize the information obtained from satellite imagery 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 soil. Farmers can utilize this knowledge to make informed decisions about land management techniques, such as crop rotation, soil conservation, and water management. Second, the utilization of EO sensing techniques allows individuals to monitor for pests and diseases and take prompt preventive action to safeguard their crops by spotting early indicators of infection [78]. Third, EO-based remotely sensed SL data can help agricultural insurance plans and government compensation schemes by verifying whether or not a natural disaster has damaged the crops, enabling small landholders to get their reimbursements on time [61]. This will help countering false claims, insurance frauds, and misuse of government expenditure. Fourth, by integrating 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 [32].

Given this, understanding the wide dynamics of SLs is crucial in comprehending India's agrarian economy within the context of itst agricultural landscape, which can significantly enhance the food and national security of the country. This extensive review attempts to provide insights into the complex dynamics of SLs in India by leveraging EO sensing technology. It synthesizes existing literature, methodologies, and outcomes, discusses technological advancements, and addresses associated challenges and limitations. This review aims to provide an advanced understanding of the opportunities and challenges associated with EO sensing of SLs, which 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 EO techniques to provide a nuanced understanding of the dynamics of small landholdings within the country. With this information, targeted interventions can be developed to address the challenges that small farms face, including access to credit, adoption of new technologies, land tenure security, 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 ensuring food security and rural development.

Lastly, this review addresses United Nations Sustainable Development Goal 2 (Zero Hunger) and Sustainable Development Goal 15 (Life on Land). By bridging the gap between scientific research, policymaking, and industry needs, it contributes to the development of effective strategies that empower small-scale farmers and strengthen the resilience of India's agricultural sector.

2 Small landholdings and agricultural efficiency in India

India accounts for the second-largest number of small farms in Asia, after China [80]. Previous studies have shown that the relationship between farm size and productivity is inverse, although some researchers have a contrary opinion [31, 58, 111]. The owners of SLs face major challenges despite their central role in food security, employment, and the economy. They face productivity constraints globally and in India [31, 58]. Variables such as the size of farm land, land fragmentation, land ownership, and crop diversity significantly impact the profits and farming efficiency. Some studies have found that land fragmentation is inversely related to overall productivity, whereas crop diversity and land ownership are positively correlated with it [85]. The primary cause of land fragmentation resulting in SLs is rapid population growth in both rural and urban areas of India. In rural India, families often over cultivatetheir plots to increase crop yields, driven by both family needs and business requirements year-round. Due to the pressure of over-cultivation, the soil fertility is further degraded as there is no time to replenish nutrients [83]. In long-term, overcultivation gradually increases the aridity of the land [83]. Broader agricultural stress factors such as groundwater overexploitation and residue burning further complicate crop system dynamics, especially in northern India [110]. Figure 2 illustrates the cropland density in India at the district scale, enabling an understanding of the diversity of croplands in relation to population pressure. Cropland areas were masked from the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6.1 data at 500 m spatial resolution for the year 2022; and the population data has been acquired from global high-resolution WorldPop data for the year 2020, computed in Google Earth Engine.

Figure 2 shows that districts in the eastern part of India have higher cropland density than those in the western part. Eastern Indian states, such as Uttar Pradesh, Bihar, West Bengal, Jharkhand, and Odisha, have the highest number of agricultural labourers, and they also have the highest populations. The higher cropland density in eastern India, particularly in states such as 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 labourers present there. Apart from population pressure, other factors such as farm sizes and their distribution, cropping patterns and intensities, cultivation costs, and socio-economic conditions have a significant impact on crop productivity and yield.

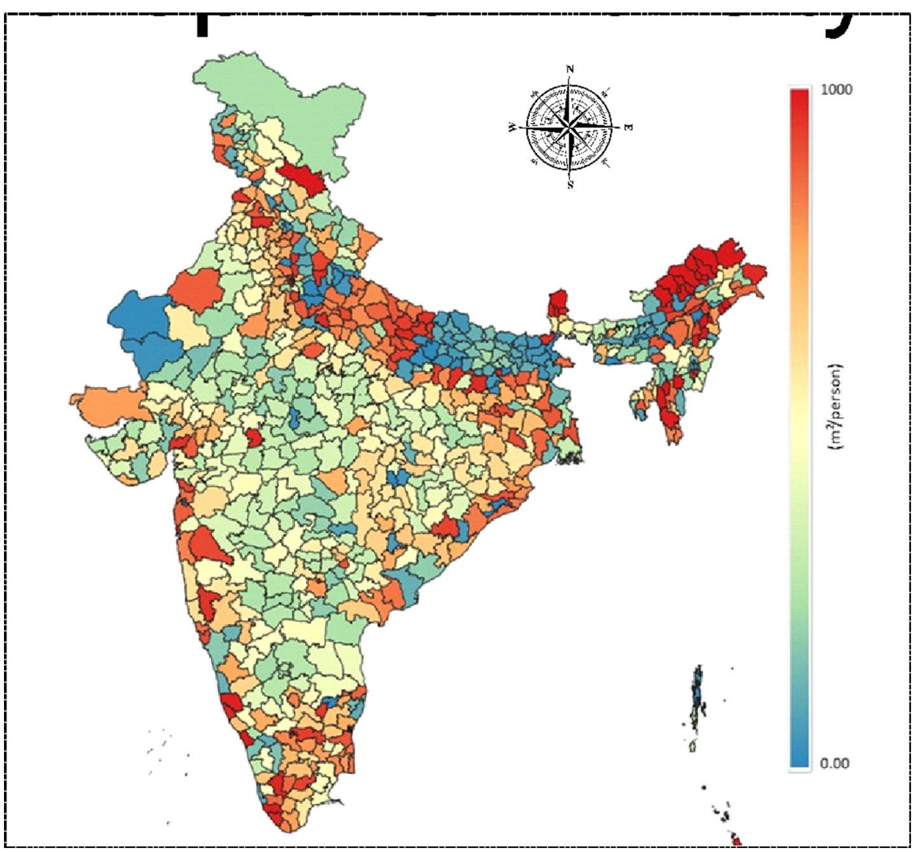

Fig. 2 District scale cropland density in India over 788 districts

Tables 1 and 2 presentstudies conducted in both global and Indian contexts to provide critical insights into the impacts of farm size, farm distribution, cropping patterns, their intensity, and other factors on crop productivity and yield gradients.

To measure and map the productivity patterns in India, Dayal [27] classified agricultural productivity into three indices: (1) land productivity, (2) labour productivity, and (3) aggregate productivity. His 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. 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 (Fig. 3).

3 Principles of spectroscopy for small landholding detection

The principles of spectroscopy are essential in modern agriculture, especially in precision farming. These principles are utilized in broader aspects of agricultural applications, such as crop classification, in-season crop monitoring, crop acreage, crop health, yield estimation, productivity measurement, prediction practices, including the detection of SLs and land fragmentation mapping [120]. State-of-the-art remote sensing technologies, based on spectroscopy principles, such as satellite imagery, aerial photography, and unmanned aerial vehicle (UAV) imagery, have significantly enhanced technology-driven agricultural practices in India and around the world [65]. In this context, satellites and UAV sensors equipped with moderate- to high-resolution spectrometers enable efficient, accurate monitoring of SLs, facilitating improved agricultural management and sustainability practices. Table 3 presents the available Red (R) and Near-Infrared (NIR) bands (typically used for vegetation remote sensing) or their equivalents from different microwave and optical (i.e. multispectral and hyperspectral) satellite-based sensors, as well as their 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 detecting small landholdings. Spectroscopy measures the interaction of electromagnetic radiation with matter to identify specific wavelengths that are absorbed or reflected by various materials [114, 125]. Thus, this technique enables the precise and nearly precise monitoring of crop types, soil health, yield, moisture content, and other significant characteristics. High-spectral resolution images (e.g., hyperspectral sensors) help studying crop health, identify stress factors, estimate yield and productivity, and analyze time-series data to monitor the sowing and harvesting of crops in more detail In the early period, spectroscopy applications initially focused on crop type identification and acreage alone. However, with the technological advancements in spectroscopy and precision agriculture, the applicability extended to broader areas such as crop biophysical parameter estimation (e.g., leaf area, evapotranspiration potential, chlorophyll-a, 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 [121]. It quantifies the primary energy exchange on the canopy surface of a cropland. In the 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

Table 1 Critical overview of the global context

Sl. No.	Global context				
	Objective	**Experimental site**	**Factors affecting productivity**	**Critical observations**	**Reference**
1.	Examine the importance of selecting appropriate productivity measures in the context of the inverse relationship between farm size and productivity in developing economies	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 measures, 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 in shaping the dynamic nature of productivity levels over time	Helfand and Taylor [58]
2.	Investigate the relationship between farm size and productivity in African agriculture, with a specific focus on Rwanda	Rwanda	• Farm size • Labour intensity • Market wage rates • Land Fragmentation • Efficiency of Input Use	i. A 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 and Deininger [5]
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 et al. (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 • Labor	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 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 positively contribute to farm productivity	Vu et al. [127]

Table 2 Critical overview of the Indian context

SI no.	Indian context				
	Objective	**Experimental site**	**Factors affecting productivity**	**Critical observations**	**Reference**
1.	Investigate the relationship between farm size and productivity among farming households, focusing on cultivation costs 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 and Moharaj [73]
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 et al., [20]
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 et al., [85]

Table 2 (continued)

Sl no.	Indian context				
	Objective	Experimental site	Factors affecting productivity	Critical observations	Reference
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. 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 shows that only small farmers are able to convert their output advantages into net profitability when considering all the crops together. This suggests that smaller operational holding sizes may lead to improved profitability in agriculture within 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	Kumar and Kumar, [74, 75]

a rapid decrease in the red and short-wave-infrared (SWIR) reflectance [8]. Absorption by leaf pigments in the visible region and by leaf water in the SWIR region leads to the asymptotic behavior of canopy reflectance. [56]. The degree of this asymptotic nature of canopy reflectance resulted in a range of different biophysical parameters (e.g., LAI) of the cropland. A similar principle is also used for defining spectral indices, such as NDVI, PRI, EVI, SAVI, etc. Such spectral indices can be used to delineate SLs and to study crop growth stages, stress, and irrigation. The Red (625–750 nm) and Infrared (780 nm and 1 mm) ranges of the electromagnetic spectrum are most sensitive to vegetation, crop canopy, and biophysical variables due to the strong absorption of the visible light by chlorophyll in the red band region, and water content in the mid-infrared region [12]. Figure 4 illustrates the change in reflectance at various wavelengths. It is also seen that in the visible range, specifically in the red band, absorption is highest; and in the infrared region, the reflectance curve peaks. Table 4 shows the commonly employed indices for cropland detection.

Although optical EO data have been widely used to retrieve crop biophysical parameters and spectral indices for cropland delineation, relatively few studies have incorporated hyperspectral and microwave EO data for this purpose.

Hyperspectral sensors feature many contiguous bands of narrow width and separated by moderate wavelength increments. Such sensors can accurately estimate crop biophysical and spectral indices, although no such study has been found to utilize such observations for delineating SLs. Sensing SLs using hyperspectral data provides detailed insights into multiple leaf parameters, such as chlorophyll pigments, leaf water stress, nitrogen

Table 3 The table highlights the spectral ranges of the Red (R) and Near-Infrared (NIR) bands, which are primarily used in crop land delineation and monitoring

Satellite	Sensor category	Red band (wavelength)	NIR band (wavelength)	Space agency	Application for vegetation monitoring and cropland boundary detection
Landsat 8	Multispectral	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	Multispectral	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	Multispectral	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	Multispectral	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	Multispectral	Band 5 (0.650–0.690 µm)	Band 6 (0.770–0.895 µm)	Digital-Globe / Maxar	The Red band supports crop health analysis and land cover classification, while the NIR band helps in assessing crop vigour and distinguishing between different crop types
Landsat 7	Multispectral	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	Multispectral	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	Multispectral	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 vigour
LISS-4	Multispectral	Band 2 (0.630–0.690 µm)	Band 3 (0.770–0.860 µm)	ISRO	Similar to LISS-3, the Red and NIR bands are used for detailed vegetation mapping, crop health assessment, and land cover classification
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

Table 3 (continued)

Satellite	Sensor category	Red band (wavelength)	NIR band (wavelength)	Space agency	Application for vegetation monitoring and cropland boundary detection
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

It details the spectral ranges employed by various multispectral and hyperspectral sensor agencies and their utility in accurately delineating croplands and associated informations.

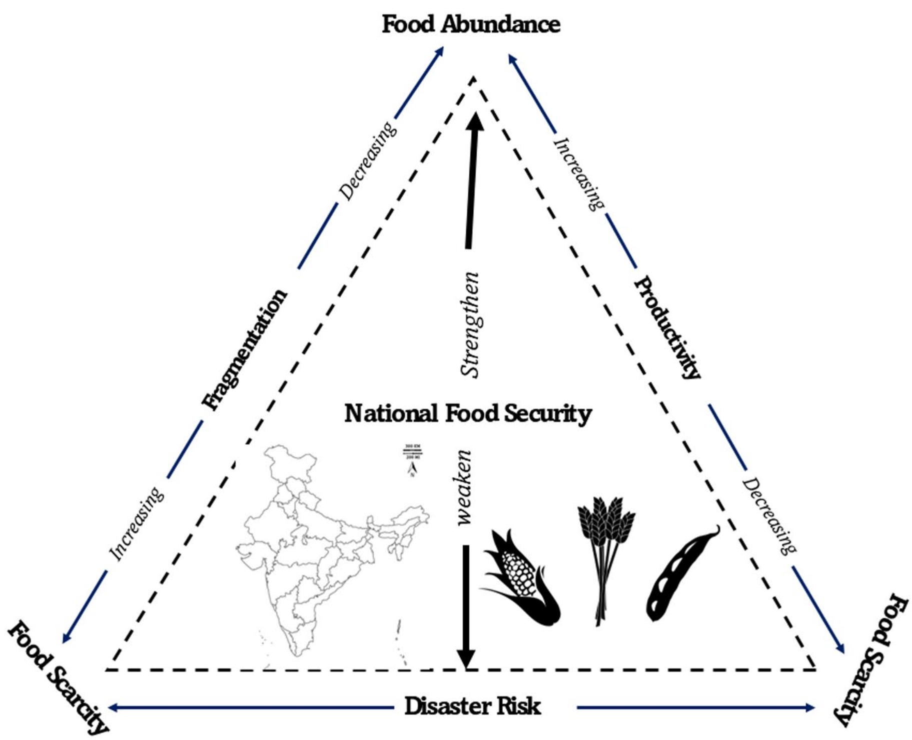

Fig. 3 Conceptual framework linking cropland fragmentation, productivity, and disaster risk with national food security

content, and biotic and abiotic stress, as well as productivity, which can be applied to delineate SLs over a region [106].

Similarly, 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 technique utilizes radar technology (e.g., Synthetic Aperture Radar (SAR), can pass through both clouds and vegetation, giving high-resolution images that are necessary for accurate boundary mapping of small agricultural plots [91]. It also helps in crop monitoring during kharif season (covering the monsoon months in India with dense cloud covers). Microwaves utilized in this technology typically ranges from 1 to 10^{-3} m in the electromagnetic spectrum (EMS), which lies within the atmospheric

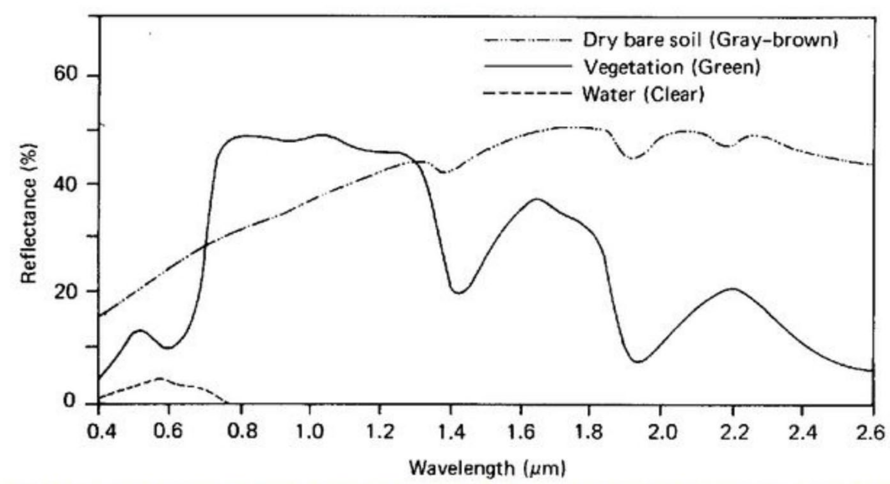

Fig. 4 The canopy reflectance graph at different wavelength adopted from [133]

window, allowing it to penetrate through intense clouds. Similarly, PolSAR uses multiple polarizations thereby differentiating various crop species, growth stages and even precise information about single crops, facilitating detailed crop classification and monitoring. To address accurate monitoring of crop informations, speckle noise in PolSAR images that hampers classification and segmentation, de-speckling methods, which significantly enhance classification accuracy, are essential [39]. This is important in soil and crop management because multi-temporal C-band L-band SAR data, acquired within a short revisiting time (1-2 weeks), can detect minute -level changes on the earth's surface such as land deformation and soil moisture variation, allowing for better decisions about soil and crops [10]. Therefore, the proposed strategy can be applied for delineating SLs with high precision. For instance, radar altimetry facilitates precise soil moisture mapping, which is essential for effective irrigation planning [36]. Together, these microwave sensing techniques enable the development of comprehensive crop and soil parameter maps that encompass such indices, improving the productivity and management of small agricultural lands [84].

4 Resolution for small landholding detection

Earth observation techniques have long been used for SL detection and to gain insights into numerous agronomic practices. However, satellite imagery frequently shows blurry physical borders between small-sized farms; therefore, contours must be determined by considering how the intricate textural pattern changes between fields [101]. Standard edge-detection algorithms are unable to derive precise boundaries in these situations, particularly with datasets of poor to moderate resolution. Therefore, different earth observation sensors with different spatial, spectral, radiometric, and temporal resolution are needed to be utilized.

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. Satellites like LISS-3 and LISS-4 from ISRO provide high spatial resolution. LISS-3 offers a resolution of 23.5 m, while LISS-4 provides a resolution of 5.8 m. The many little fields that are typical of Indian

Table 4 Spectral indices, their proxies and implementation for studies related to cropland delineation

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. [16] Jeevalakshmi et al. [63]
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 were employed to estimate maize cultivated area across a large scale in Northeast China	$EVI = 2.5 * \frac{(NIR-Red)}{(NIR+C1*Red-C2*Blue*1)}$	Mizen et al. [94]
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, [62]; Wang et al. [129]
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. [66]

agriculture may be precisely delineated because of this great precision. The ISRO sensors like LISS-3 and LISS-4 provide free access through the National Remote Sensing Centre–Bhuvan and the MOSDAC data portals used by global researchers for agricultural research without incurring any costs. The radiometric correction and geometric correction of LISS-3 and LISS-4 sensors required standard preprocessing steps used routinely in Indian EO studies and have been well documented. Although there are currently no GEE catalogs available for hosting LISS-III/IV data systematically, users may upload the datasets to cloud platforms to facilitate a scalable analytical approach to LISS-3/4 data. Thus, accessibility, cost-effectiveness, and cloud-based integration are feasible for ISRO sensors like LISS, though dependent on user-driven preprocessing workflows. Similarly, high spatial resolutions(30 m) for Landsat 8 and 10 m 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.

Furthermore, advanced commercial sensors with extremely high spatial resolutions, ranging from meters to centimeters, are crucial for cropland detection in 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 cm 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 m, Cartosat-3 from India provides incredibly fine data that is helpful for mapping small landholdings and closely monitoring crop conditions. By improving crop classification, yield estimation, 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 [122].

4.4 Temporal resolution for SL detection

Temporal resolution refers to the frequency at which a satellite returns to the same location. Monitoring dynamic changes in small landholdings requires regular revisits. The RISAT series provides high temporal resolution and frequent revisits in India, which aids in the monitoring of soil conditions and agricultural activities. Satellites like MODIS, which have 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, this frequent data collection makes changes in land usage, and general agricultural management possible.

Table 5 represents a decision table that summarizes a variety of EO sensors across high and low spatial resolution used for mapping smallholder agricultural data in India. This decisional matrix highlights the trade-offs looking at spatial detail, temporal frequency, cloud resilience, and cost. The decision table is a practical tool to help to select the best combination of optical, SAR, and multi-resolution EO sensors based on the field size being mapped and the mapping goals, thereby enabling scale to be obtained from analyzing data at the field level to monitor national policy.

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 the spatial distribution of agricultural holdings play a vital role in estimating crop production, which is crucial for the country's food security. Electronic field records are of utmost importance because they provide detailed field information, including the field boundary and shape [41]. This information helps in monitoring soil type, soil moisture, pest infestation, crop growth, and yield estimation, and helps in managing fertilizer and pesticide application. However, generating and maintaining digital records of small landholdings is always tedious and has limitations. Specifically, in developing countries like India, digital field records are lacking and involve considerable manual work, which is prone to human errors [87]. EO technology offers numerous benefits in delineating, generating, and maintaining such records with great precision. EO-based or remote sensing images provide information and enable a robust system for continuous monitoring

Table 5 Decision table: optimal EO sensor combinations for Indian smallholder mapping

Mapping objective	Spatial scale / field size	Resolution category	Key sensors	Strengths	Limitations	Recommended use strategy
Field boundary delineation	< 1 ha	Very High (≤ 1 m)	WorldView, GeoEye, Cartosat-2	Accurate parcel boundaries	High cost, low revisit, clouds	Training, validation, pilot studies
Crop type & phenology mapping	1–5 ha	High (10 m)	Sentinel-2, LISS-4	Free, high spectral detail	Cloud sensitive	Primary dataset for smallholder mapping
All-season monitoring	1–5 ha	High SAR (10 m)	Sentinel-1	Cloud independent	Speckle noise	Fuse with optical during monsoon
Historical trends & district stats	5–25 ha	Moderate (20–30 m)	Landsat, LISS-3	Long time-series	Mixed pixels	Temporal consistency & trend analysis
National monitoring & early warning	> 25 ha	Coarse (250 m–1 km)	MODIS, VIIRS	High temporal frequency	Not field-scale	Policy dashboards, drought monitoring

of agricultural fields, supporting sustainable agricultural practices. With these advancements, crop yield quality and quantity can be better estimated.

Various Earth observation platforms are available for accurately delineating 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, also known as proximal sensing, involves the use of sensors to collect signals in contact with or at proximity to the target (within a few meters) [99]. These sensors, however, are primarily capable of monitoring and capturing information related to plant health, growth, and water content, among other factors [113]. Mostly, the data collected from ground-based remote sensing have limited application in the delineation of SLs due to their limited spatial coverage and narrow field of view (FOV).

5.2 Evidence from airborne sensor

However, sensors fitted on airborne platforms have a long history of association with agricultural mapping, dating back to 1929 [112]. 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 has undergone incredible advancements in technology. The use of UAVs in precision agriculture first occurred in 1997, and this technology was widely used in Japan and South Korea for fertilizer spraying [3]. Nowadays, UAVs have a wide range of applications in agriculture, from collecting high-quality images to gathering information through terrestrial scanning. Chen et al. [23] used high-resolution UAV images along with multispectral and elevation data to perform agricultural land use classification. Fetai et al. [40] use Deep Learning (DL) techniques with high-resolution UAV images to detect and map land boundaries. Yallappa et al. [134] examined the usefulness of UAVs in small agricultural holdings in India for crop management and spraying of fertilizer.

5.3 Evidence from spaceborne sensors

The launch of the Landsat series in the 1970s and the subsequent availability of Earth observation imagery marked the adoption of satellite remote sensing for agricultural applications. For a long time, work on cropland extraction has been done on satellite images. Satellite remote sensing provides continuous temporal and spatial data, spectral crop information, and low-cost data, depending on the satellite type [46]. Rydberg and Borgefors [108] and Evans et al. [37] performed an automated segmentation method on Landsat images at 30 m spatial resolution to extract farmlands. Yan and Roy [135] utilized Landsat time series data to extract agricultural crop fields in the U.S. and found that larger field sizes could be easily identified. Rahman et al. [103] 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 advancements in ML, DL, and convolutional neural networks (CNNs), among other areas, have significantly enhanced the robustness of the task of farmland delineation. Aung et al. [9] utilized spatiotemporal satellite data and delineated farm parcels using a CNN method. Singh et al. [115] employed a DL method to map various agricultural land uses across parts of Punjab, India, utilizing Sentinel-2 satellite data.

6 Geographic diversity and cropland patterns

The spatial structure of SLs encompasses various aspects of crops, enabling the identification and mapping of individual crops and their distributions, as well as the assessment and mapping of field components and dependent demographic information. Spatial structures of land holdings refer to land parcel area or size, distribution, utilization, etc. Land fragmentation and plot distribution in rural regions have a detrimental impact on the profitability and efficiency of agricultural output [117]. India's diverse geography and cultural heritage have shaped different landholding 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 rainfed agriculture, has a landholding structure shaped by irrigation patterns. These regional variations in landholding, 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 5 illustrates diversity in cropland structure based on the geographic locations of India.

The physical structure of SLs, enhanced through modern technology, effectively addresses the spatial and social dimensions of the developing world.Effective land-use planning and management, particularly for small crop parcels, rely on the precise delineation of land boundaries [77]. 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 the traditional field-based labour-intensive and time-consuming methods [107]. Using EO data and a ML approaches help accurate delineation of small landholding structures.

Image classification, segmentation, Principal Component Analysis [60], edge detection, and Cluster analysis, such as K-means clustering and C-means clustering [132], are primarily used to study the delimitation of spatial structure. Such segmentation methods can be applied to any geographical location, not only in India but globally. In the case of satellite imagery, issues with low resolution and noise persist, particularly in the study of small landholdings and closely spaced plots, which require high-resolution images (below 30 × 30 m) 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. A DL model efficiently maps land boundaries by combining satellite surface reflectance data and land records, resulting in a significant reduction in manual intervention. Plot boundary detection processes may now be automated with great potential using ML and DL techniques. This automation streamlines the process,

Fig. 5 Diversity of crop land structures of India, observed in the different parts of the country

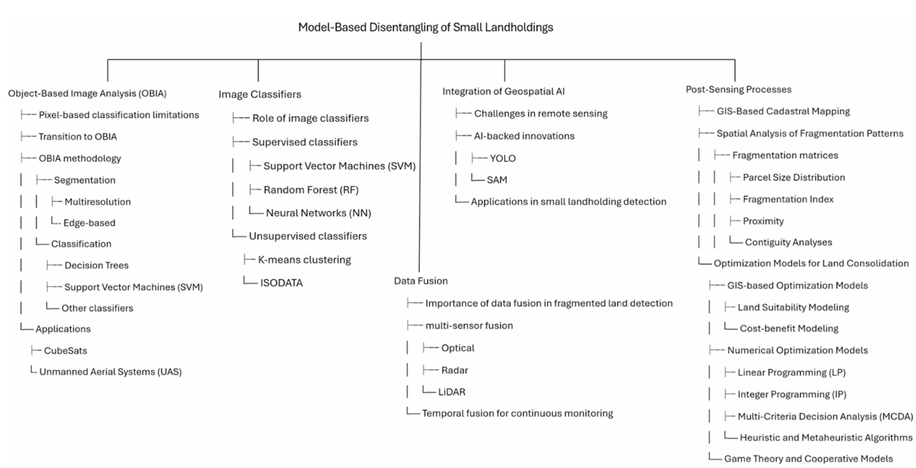

Fig. 6 Flowchart showing the diversity of object-based image analysis (OBIA), image classifiers, data fusion, GeospatialAI, post-sensing processes for disentangling of SLs

making it faster, more efficient, and more accurate. The next section presents a more detailed discussion of these concepts, focusing on their implementation within the proposed geospatial framework.

7 Image models assisting in disaggregation of small landholdings

Accurate data collection is essential for understanding and managing small landholdings, which are crucial to agricultural productivity and rural development. Remote sensing technologies, when combined with advanced modeling techniques (Fig. 6), enable precise detection, monitoring, and analysis of these small parcels of land. Just as the types of sensors installed on various platforms are crucial, the methods used to extract actionable information from captured imagery are equally important. Traditionally, this step occurs after data collection. However, with recent advances in technology, particularly in model-based image classification techniques, it is now possible to extract information almost instantly as 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 dramatically 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 [98]. This occurs because mixed pixel signals are present alongside spectral inconsistencies. In contrast to classical object-based remote sensing, OBIA segments a set of pixels into meaningful objects based on their spectral and spatial features, as well as the interrelations between different image parts [59]. This provides a more precise representation of the LULC categories, particularly in terms of high accuracy, especially when identifying small land parcels. The process of OBIA typically involves a two-step approach. First, it performs segmentation using multiresolution or edge-based algorithms that divide the image into objects based on spectral and spatial patterns within the image. Later, these divided objects are labelled 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 [109] and drones like the DJI Phantom 4 RTK [104].

7.2 Image classifiers

Image classifiers work with remote-sensing sensors to extract actionable information from imagery [89]. 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 the image classifiers come into play. 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 must be trained by an expert to accurately classify the LULC using the features in a labelled dataset. Some of the key supervised algorithms include Support Vector Machines (SVMs), Random Forests (RFs), and Neural Networks (NNs). Support Vector Machines look for the separating hyperplane that maximizes the margin between different classes in feature space. This algorithm is quite effective in cases where the feature space is high dimensional, and the classes are not linearly separable. It has a low tendency to overfit, especially in high-dimensional spaces, and yields good results with small training datasets. Due to its classification accuracy and skill in handling complex boundaries between different land covers, SVM is particularly useful for detecting small landholdings.

Random Forests (RF) create multiple decision trees during training and output the mode of the classes (classification) and the mean prediction (regression) for each tree. RF is robust to overfitting, like the Support Vector Machine (SVM), and works well on large, high-dimensional datasets. These algorithms also provide important measures of feature importance, which help understand the contribution of different spectral bands and indices. Such capability makes RF particularly effective at identifying small landholdings, as most of them exhibit a mix of land cover types and environmental conditions.

A neural network, particularly deep learning architectures such as CNNs, is composed of multiple layers of interconnected neurons that hierarchically extract features from the input data. Neural networks can model complex relations and patterns in the data to achieve higher accuracy. For example, CNNs excel at 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 labelling. Some standard 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 straightforward and computationally lightweight, making it useful for exploring the inherent structure of the data and identifying natural groupings. However, it has a limitation in detecting small landholdings because it relies solely on spectral similarity without considering spatial context.

ISODATA iteratively extends K-means by adjusting the number of clusters based on user-defined criteria, such as splitting and merging during iterations. Hence, compared to K-means, ISODATA is more flexible, as it adapts more dynamically to the spatial structure, yielding better results in heterogeneous and complex landscapes. However, like K-means, ISODATA still lacks the spatial context necessary to identify small landholdings and may misclassify classes in complex agricultural areas.

7.3 Integration of geospatial Artificial Intelligence (GeoAI)

Geospatial Artificial Intelligence (GeoAI) integrates artificial intelligence and ML methods with geospatial data to analyze complex spatial and spatiotemporal patterns. By combining satellite observations, GIS-based data, and spatial context with data-driven learning algorithms, GeoAI enables automated feature extraction and improved representation of heterogeneous landscapes. In remote sensing, the detection of small and invisible (obstructed/covered) objects has always been challenging because of 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 ([70]. 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, making them well suited for real-time disentangling of small landholdings and other applications in remote sensing.

7.4 Data fusion for better imaging

Detection of fragmented agricultural lands in India often requires the implementation of data fusion techniques. Such techniques gather various types of information from different data sources and combine them. For example, a multi-sensor fusion combines data from optical, radar, and LiDAR sensors, offering a holistic understanding of fragmented agricultural lands [14]. Optical sensors provide valuable information about crop types and vegetation health, whereas radar sensors can penetrate cloud cover to assess surface roughness and soil moisture [1, 100]. This is especially useful for South Asian countries, such as India, which experience a prominent monsoon season. LiDAR data, on the other hand, provides high-resolution elevation data that support the identification of terrain characteristics and land cover changes. A fusion of these diverse datasets, therefore, enhances the spatial accuracy of detecting fragmented agricultural lands in India. Similarly, temporal fusion ensures the integration of data from multiple time points, facilitating the continuous monitoring of seasonal land use changes, conversions, and yield estimation, cropping patterns, among other factors (Ranjan and Parida., 2021[105]). These fusion techniques offer valuable insights into the dynamics of fragmented agricultural lands in India, supporting sustainable land management practices and rural development initiatives nationwide.

7.5 A comparative synthesis: suitability for Indian context

Due to the size, diversity, and complexities of the Indian landscape, it is hard to find or recommend a blanket solution. The trend is therefore moving toward Hybrid Workflows. For instance, researchers are increasingly using SAM to generate initial segments (objects) [68] and then passing those objects into a CNN or RF classifier [68, 118]. This bypasses the tedious "Scale Parameter" tuning required in traditional OBIA while maintaining the high spatial accuracy needed for plots that are often smaller than the 10 m resolution of a single Sentinel-2 pixel, even in mixed-pixel scenarios [118]. However, the application of advanced models or techniques often incurs a high computational cost. Therefore, investigators are advised to weigh convenience, accuracy, and computational cost when executing a task and choose accordingly. Table 6 provides a comparative analysis of traditional classifiers, ML, and DL models, evaluating their performance across four critical metrics, i.e. accuracy, data requirements, computational cost, and scalability.

A critical methodological challenge for EO-based disaster risk reduction in fragmented smallholder landscapes is the limited availability of reliable ground truth and labeled training data. Small, irregular field geometries and heterogeneous cropping practices substantially increase the cost and complexity of field-level annotation, while cadastral datasets, where available, are often outdated, inconsistently georeferenced, or administratively restricted [43, 101]. These limitations constrain the scalability and generalizability of ML models across India's diverse agro-climatic zones, particularly for flood and drought impact assessment at sub-field scales [76]. Emerging approaches such as weak supervision, transfer learning, and hybrid EO–field campaigns offer partial solutions but remain underexplored in operational DRR applications. Addressing training data scarcity is therefore essential for ensuring that EO-driven assessments used in SDG-oriented disaster risk reduction are both robust and transferable.

8 Decision support frameworks assisting in disaggregation of small landholdings

8.1 GIS-based cadastral mapping

A Geographic Information System (GIS) plays a crucial role in geospatial modelling by enabling the collection, storage, analysis, and visualization of spatial data [4]. 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

Table 6 Strengths and limitations of different image-based models for Indian agricultural landscapes

Criteria	Random Forest (Pixel-based)	OBIA (Object-Based)	CNN-based (U-Net, ResU-Net)	AI Models (SAM)
Field Boundary Delineation Accuracy	Low - Moderate. Pixel-level classification often produces salt-and-pepper noise and poorly defined field boundaries, especially in fragmented smallholder systems common across India [15, 44].	Moderate - High. Can generate sharp agricultural field boundaries when segmentation scale is carefully tuned; performance varies across agro-climatic zones and cropping patterns [18, 35].	Very High. Effectively captures irregular field shapes and spatial context; studies in smallholder-like systems report F1-scores > 0.9 when sufficient training data are available [33, 76].	High but Variable. Strong zero-shot boundary detection for fields, but tends to over-segment heterogeneous cropland mosaics without prompts or post-processing [70, 97].
Training Data Requirements	Moderate. Requires hundreds to a few thousand labeled pixels; practical for India due to ease of sample collection and compatibility with GEE workflows [15].	Low - Moderate. Requires fewer labeled field objects but depends heavily on very high-resolution imagery (e.g., Cartosat-2), which is not uniformly available nationwide [18].	Very High. Requires thousands of annotated field polygons or masks; data preparation is challenging due to limited cadastral availability and regional diversity in India [81].	Minimal (Zero-shot). No local training data needed for initial field segmentation; task-specific prompts or limited fine-tuning improve relevance for Indian crops [70].
Computational Cost	Low. Efficient on CPUs and cloud platforms (e.g., Google Earth Engine); well suited for operational, pan-India crop monitoring [15].	Medium. Segmentation is memory-intensive and difficult to scale nationally without tiling and region-specific parameter tuning [57].	Very High. Training and inference require high-end GPUs and long runtimes, limiting operational scalability for national agricultural programs [81].	High (Inference). Transformer-based inference is computationally heavy, especially for high-resolution agricultural imagery over large areas [70].
Scalability (Pan-India)	Excellent. Proven scalability across diverse agro-ecological zones and cropping seasons (Kharif/Rabi) using Sentinel-2 time series [44].	Limited to moderate. Segmentation parameters do not easily transfer across India's diverse agricultural landscapes [35].	Moderate. Scales well after training, but model generalization across regions and seasons remains challenging without domain adaptation [81].	Moderate–High. Enables rapid large-area inference, but consistency varies with crop diversity, phenology, and field size heterogeneity [68].
Best Use Cases in Indian Context	National/state-level crop-type mapping, acreage estimation, seasonal crop monitoring, and baseline agricultural statistics.	Field boundary extraction in selected regions using VHR imagery; pilot studies and local-scale applications.	High-precision crop mapping, yield estimation, crop stress assessment, and climate–agriculture interaction studies.	Rapid field boundary delineation in data-scarce regions, exploratory mapping, and pre-processing for downstream crop classification.

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 imagery, to create detailed, 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.

8.2 Spatial analysis of fragmentation patterns

Fragmentation matrices can be calculated in GIS environments to quantify land fragmentation, including the number of parcels, average parcel size, and degree of dispersion [69]. These matrices provide a quantitative basis for assessing the severity of fragmentation. For example, the 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 land parcels (i.e., higher values indicate more severe fragmentation). Proximity and contiguity analyses evaluate the proximity of parcels to one another and their contiguity, which are critical for understanding the practical challenges of farming on fragmented land.

8.3 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, increase productivity, and provide operational cost savings [2, 71]. These optimization models are further categorized broadly as GIS-based optimization models and numerical optimization models.

8.3.1 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 [22]. On the other hand, cost-benefit models assess the economic feasibility of different consolidation scenarios and consider factors such as infrastructure costs, potential productivity gains, and social impacts [93]. 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.

8.3.2 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 significantly improved. 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 crop cluster candidates, and allocate crops that maximize production [17].

8.3.3 Multi-criteria decision analysis (MCDA)

This is another common optimization method to consider potential socio-economic and environmental factors associated with land consolidation decisions [86]. Procedures such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) can evaluate multiple criteria and achieve a trade-off between competing interests among stakeholders [86]. Heuristic and Meta-heuristic Algorithms, including Genetic Algorithms (GAs) and Simulated Annealing (SA), are excellent solutions to complex land consolidation problems [90]. These algorithms are particularly useful when a large number of variables and constraints exist, providing near-optimal solutions within a reasonable computational time frame.

8.3.4 Game theory and cooperative models

These models are useful for examining how landowners and stakeholders interact when making land-use decisions. 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 enables us to explore how cooperation or competition between landowners affects 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 favourable outcomes [13]. Therefore, this approach helps in designing more effective strategies for land reorganization.

9 Challenges and limitations of fragmented cropland mapping

Automated cropland delineation remains challenging in fragmented smallholder systems. Although remote sensing provides strong capabilities for agricultural mapping, several technical and operational constraints limit its precision in delineating SLs. These challenges can broadly be grouped into (i) data resolution constraints (spatial, spectral, temporal, and radiometric) and (ii) sensor and platform-related limitations. Spatial resolution plays a decisive role in detecting small agricultural parcels. In highly fragmented landscapes such as India, medium-resolution imagery often fails to capture precise boundaries. Wang et al., [130, 131] compared agricultural fields across South Africa, France, and India using Landsat-8, Sentinel-2, PlanetScope, and Airbus SPOT data, showing that while larger fields in South Africa and France can be delineated using Landsat-8 (30 m) and Sentinel-2 (10–20 m), small Indian fields require very high-resolution imagery such as PlanetScope (4.8 m) and Airbus SPOT (1.5 m). Spectral resolution further enhances field-edge detection, as multispectral imagery provides greater contrast than panchromatic data [101]. Temporal resolution affects monitoring continuity, where longer revisit intervals necessitate multi-temporal integration strategies [130]. Radiometric resolution also influences classification accuracy, with finer radiometric detail improving delineation outcomes (2018). Sensor characteristics introduce additional constraints. Optical sensors are highly sensitive to cloud cover, reducing both data quality and temporal availability, particularly in tropical regions such as India [64]. Microwave sensors mitigate cloud interference but may suffer terrain-induced distortions, especially in mountainous areas [126]. Thermal imagery provides complementary information but is dependent on acquisition timing and atmospheric conditions [45]. Platform-based limitations further complicate delineation. UAVs and airborne systems offer very high spatial resolution but face economic, operational, and regulatory constraints. Payload limits, wind sensitivity, calibration challenges, high processing requirements, and limited public accessibility restrict large-scale deployment [11, 26, 38, 95]. In India, UAV-based delineation remains in its early developmental phase and faces security and data access limitations [95, 116]. While high-resolution spaceborne imagery can improve boundary precision, it is computationally intensive and often expensive, limiting accessibility for large-area operational mapping [19, 67, 101]. Overall, key limitations include restricted access to freely available high-resolution imagery, scarcity of labelled training data, irregular field geometries, atmospheric noise, and the substantial computational burden associated with fine-resolution datasets. Beyond technical optimization, scalability challenges also include harmonizing EO-derived products within national agricultural data systems and ensuring interoperability with administrative datasets. Furthermore, the effective deployment of EO systems must account for socio-economic asymmetries, including differential access to insurance schemes, digital platforms, and formal land records, which mediate how risk information translates into action.

From a forward-looking perspective, the principal research frontier for EO-enabled disaster risk reduction in smallholder systems lies not in further sensor refinement alone, but in the integration of EO products with institutional workflows, scalable data infrastructures, and equity-aware decision frameworks. Persistent challenges include the generalization of EO-based models across agro-climatic zones, the operational integration of EO-derived indicators into insurance and compensation mechanisms, and the development of standardized validation protocols for fragmented landscapes (Lobell et al., [79]; Verburg et al., [123]) [7, 42]. Recent evidence further demonstrates the increasing occurrence of compounding climate extremes affecting agricultural systems [49]. Future research must therefore prioritize interdisciplinary approaches that couple EO analytics with governance, policy, and social science perspectives to ensure that technological advances translate into measurable SDG outcomes, particularly for vulnerable smallholder populations exposed to climate extremes.

10 Fragmented cropland and disaster risk reduction

Extreme weather events have profound implications for agriculture and food production, as well as a wide range of broader impacts on the livelihoods and well-being of affected communities. Over the last two decades, floods and droughts have been identified as two of the most devastating consequences for agricultural production. Agricultural insurance was dominated by indemnity-based insurance, which provides coverage based on actual losses (Sandmark et al., 2013). While farmers in developed countries rely on agricultural insurance and other financial products to manage risk, these products are less accessible to farmers in developing countries. Another advantage of index insurance is that payouts are based on a standardized index that ensures a faster indemnity payment (Leeuw et al., 2014[79]). By linking payouts to an external index, index insurance avoids the need for costly on-site verification, which can otherwise discourage farmers from fully disclosing their losses (Miranda & Farrin, 2012[30]).

However, despite the potential to improve farmer livelihoods, there are several limitations in the practical implementation of index insurance. First, basic risk remains a significant obstacle. Poorly designed indices can lead to situations in which farmers experience losses but receive no payouts, thereby reducing their trust in insurance. Different types of basis risk problems arise depending on the index's structure. For instance, spatial basis risk occurs when the index measurement does not accurately reflect the conditions experienced by individual farmers due to spatial variations. Index insurance can, however, be reinforced using bundled solutions in different ways (Mukherjee et al., [96]), like (i) credit bundling, (ii) input bundling, (iii) contract farming, and (iv) insurance bundling. In credit bundling, loans/credit to farmers are bundled with agricultural insurance. Bundling index-based insurance with credit helps to address these challenges by providing a means to pre-finance or defer premium payments, thus facilitating access to credit (Giné et al., [92]). In recent years, digital technologies have become a prominent option for scaling bundled index insurance using remote sensing data, communication networks, and AI/ML algorithms. Different data on weather, crops, and agronomy are key to designing robust products. Integration through digital platforms enables the collection and storage of more granular, comprehensive data, thereby making the design more robust. Mapping of croplands using Earth observation enables spatially explicit identification of crop types, growth stages, and stress conditions across fragmented landscapes. EO technology supports index-based crop insurance in several ways, such as (1) defining homogeneous risk zones based on agro-climatic and cropping patterns; (2) monitoring vegetation indices (e.g., NDVI, EVI) to trigger payouts when anomalies indicate crop failure; (3) reducing ground verification costs through satellite-derived proxies for yield and weather impact; (4) improving transparency and timeliness in claim settlement by linking payouts to objective, remotely sensed indicators. Such efforts will essentially transform insurance from a reactive compensation model to a proactive resilience approach.

In the Indian context, the contribution of EO-based smallholder mapping to Sustainable Development Goal-aligned disaster risk reduction is most effective when embedded within existing agricultural risk governance frameworks. For example, EO-derived field boundaries and crop condition indicators increasingly support yield estimation and loss assessment under the Pradhan Mantri Fasal Bima Yojana (PMFBY), particularly through initiatives such as Yield Estimation using Space, Technology and Analytics (YES-TECH), where satellite-based vegetation indices and phenological metrics complement traditional Crop Cutting Experiments at the insurance unit (village or cluster) level (YES TECH Manual [136, 137]). Improved spatial representation of fragmented croplands helps reduce basis risk in index-based insurance products by strengthening the alignment between remotely sensed indicators and actual cultivated areas, while remaining consistent with India's administratively aggregated payout mechanisms [25]. In addition, EO-based parcel delineation complements the Digital India Land Records Modernization Programme (DILRMP) by providing auxiliary spatial layers for land-use planning and post-disaster damage verification in regions where cadastral digitization remains incomplete [28, 29]. Importantly, EO-based mapping functions as a decision-support input rather than a substitute for statutory land records or administrative validation, ensuring that EO-enabled DRR interventions remain aligned with India's legal and institutional structures.

11 Sustainable development goals (SDG) and disaster risk reduction

Disaster risk management is an important aspect of achieving several SDGs, including Goals 9 (Industry, Innovation, and Infrastructure), 11 (Sustainable Cities and Communities), 13 (Climate Action), and 15 (Life on Land). Disaster risk management is essential for achieving the SDGs on climate events, agricultural stress, health, and nutrition. Lowering the risk of disasters and safeguarding livelihoods may involve investing in early warning systems, strengthening infrastructure, and promoting sustainable land use practices. Recent efforts have increasingly emphasized the role of digital EO-based tools in strengthening climate-resilient agricultural systems [7, 48]. EO-based flood monitoring applications have been successfully deployed across major river basins in South and Southeast Asia [52].

Flood and drought maps/products serve as critical tools for addressing disaster risks and supporting SDGs [53, 138]. These resources, developed by national agencies, NGOs, and international organizations, provide real-time data, forecasts, and risk assessments for effective disaster management. They enable governments, humanitarian agencies, and local communities to prepare for and respond to floods and droughts, which are among the most pressing challenges in the region. The geospatial maps/products can play a significant role in helping to achieve the SDG goals in various ways:

i. Early warning systems

Maps and products related to flooding and drought help advise communities and government agencies in advance of approaching disasters. This lessens the impact of catastrophic events on infrastructure and communities by enabling prompt response and preparedness. This may accomplish goals about climate action (SDG 13) and disaster risk reduction (SDG 11).

ii. Planning and preparedness

Access to accurate flood and drought maps/products can help plan and prepare for these events. Governments and organizations can use this information to develop strategies for water management, agricultural planning, and infrastructure development that are resilient to the impacts of floods and droughts. This can contribute to achieving goals related to sustainable cities and communities (SDG 11), clean water and sanitation (SDG 6), and responsible consumption and production (SDG 12).

iii. Risk assessment and decision making

Maps and products related to flooding and drought can provide important information for risk assessment and informed decision-making. Governments and organizations can make well-informed decisions promoting sustainable development by prioritizing investments in vital infrastructure, allocating resources for vulnerable populations, and identifying places susceptible to flooding or drought. This aid can attain SDGs 1 and 2, i.e.,zero hunger and resilient infrastructure;and SDG 9.

While EO-based mapping provides critical spatial intelligence for disaster risk reduction, its effectiveness in smallholder systems is strongly mediated by socio-economic and institutional constraints. In India, uneven digital literacy and limited access to smartphones or internet services restrict direct farmer engagement with EO-derived advisories, causing reliance on intermediaries such as extension workers, cooperatives, and farmer producer organizations. Land tenure insecurity further complicates EO-enabled interventions, as a significant proportion of smallholders cultivate land under informal tenancy or sharecropping arrangements without formal titles, limiting their eligibility for insurance payouts and post-disaster compensation despite being visible in EO-based exposure maps [28, 47]. Gender disparities also influence EO adoption, with women farmers often underrepresented in land records and facing lower access to digital services, thereby inadvertently excluding them from EO-enabled risk management mechanisms (Doss et al., [34]). These factors highlight that while EO technologies enhance hazard visibility and monitoring capacity, their contribution to SDG-aligned disaster risk reduction depends on parallel institutional and social inclusion mechanisms.

12 Conclusion

Delineating SLs through EO in a densely populated country like India is a distinct and challenging task, given the large numbers and high density of SLs. This review emphasizes the increasing potential of EO data and analytical methods for mapping smallholder landscapes and evaluating agricultural risks in various geographical locations, notwithstanding these limitations. Disasters like floods, droughts, and pest outbreaks frequently impact fragmented smallholder lands more severely, as limited resources and adaptive capacity increase their vulnerability. Integrating EO-derived information within DRR frameworks is therefore critical for improving vulnerability assessment, preparedness, and resilience, ultimately contributing to national food security and sustainable land management. Regional drought monitoring frameworks using EO data have demonstrated strong potential for strengthening water security and climate adaptation in South Asia [6, 24, 50]. Looking ahead, several key knowledge gaps remain. These include limitations in resolving sub-field heterogeneity in highly fragmented landscapes, insufficient ground-based validation data for EO-derived products, and the limited integration of socio-economic factors that influence smallholder risk exposure and decision-making. Additionally, most existing approaches emphasize post-season assessment, while early and intra-seasonal risk detection remains underexplored, particularly for smallholder-dominated systems.

Building on the synthesis presented in this review, future research must prioritize the development of EO- and ML-based frameworks capable of capturing compound agricultural risks arising from interacting hydro-climatic stressors. Integrating high-resolution spatial delineation with time-series analytics can improve sub-field assessment of sequential flood–drought events and climate-induced yield variability. Such approaches are particularly relevant in hazard-prone regions such as the GBM basin, the Lower Godavari River Basin [52], and eastern coastal states such as West Bengal and Odisha, where fragmented croplands are frequently exposed to monsoon variability, riverine flooding, drought episodes, and groundwater stress. Equally important is the translation of EO-derived risk indicators into operational decision-support systems that inform insurance mechanisms, early warning platforms, and district-level disaster management planning. Strengthening these science–policy linkages will be critical for ensuring that technological advances meaningfully enhance resilience in India's smallholder agricultural landscapes.

Future research should leverage emerging technologies and methodological synergies, including the fusion of high-resolution optical and SAR data, advances in ML and DL for sub-field analysis, and improved exploitation of time-series data for early warning of climate and pest-related stresses. Integrating EO data with participatory ground observations and mobile-based platforms also offers promising avenues to enhance model calibration and relevance at the farm scale.

Finally, translating EO-based research into scalable and policy-relevant applications will require closer alignment with national agricultural and disaster management frameworks. Standardized EO-derived indicators that are transparent, interpretable, and operationally feasible are essential for uptake by government agencies, insurers, and extension services. Strengthening research-policy linkages and institutional capacity will be crucial to ensuring that advances in EO and geospatial technologies effectively support risk mitigation, resilience building, and sustainable intensification in India's fragmented agricultural landscapes.

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Declarations

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Not applicable. This study is a review article based on previously published literature and publicly available datasets. This article does not contain any studies with human or animal participants. Consent to participate is not applicable.

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