

ESTIMATION OF AGRICULTURAL LANDHOLDINGS IN BHAGALPUR DISTRICT, BIHAR BY USING GEOSPATIAL TECHNOLOGY

Agriculture

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ABSTRACT

Agricultural land fragmentation and the predominance of small and marginal fields are important characteristics of India's agricultural landscape. This study aims to map and analyse agricultural field-size classes in Bhagalpur District, Bihar, using Sentinel-2 MSI and Object-Based Image Analysis (OBIA). Sentinel-2 Level-2A Surface Reflectance imagery and ESA WorldCover 2021 are used to identify agricultural areas by using Google Earth Engine Cloud Platform. Image preprocessing includes cloud masking, seasonal compositing and calculation of NDVI. Agricultural fields are delineated using Simple Non-Iterative Clustering (SNIC) segmentation, and field areas are estimated using pixel-area information. The identified fields are classified into five categories: marginal (<1 ha), small (1–2 ha), semi-medium (2–4 ha), medium (4–10 ha), and large (≥ 10 ha). The study is expected to identify the spatial distribution and concentration of small and marginal agricultural fields across Bhagalpur District. The findings will provide a spatially explicit assessment of agricultural field fragmentation and demonstrate the potential of Sentinel-2 and OBIA for field-level agricultural analysis.

KEYWORDS

Agricultural Field, Spatial, Sentinel-2 Msi; Object-based Image Analysis (obia); Snic Segmentation, Ndvi;

INTRODUCTION

Agricultural field fragmentation is an important spatial characteristic of smallholder farming systems. Conventional agricultural statistics provide information on operational holdings and aggregate agricultural area, but they do not always provide spatially explicit information on the location, shape and size of individual agricultural fields. High-resolution satellite imagery and object-based image analysis provide an opportunity to complement these statistics by delineating field-like agricultural objects and estimating their spatial extent. The present study focuses on Bhagalpur District, Bihar, and develops a Sentinel-2-based framework for mapping agricultural field-size classes and examining their spatial distribution using Google Earth engine. Although several studies have used remote sensing and GIS to investigate agricultural land Diara land , flood prone agricultural areas and land use-landcover characteristics in Bhagalpur district, limited studies are regarding the spatial delineation and classification of individual agricultural fields using high resolution Sentinel-2 imagery and object based image analysis. Literature Review

Remote sensing and GIS have become important tools for the spatial analysis of agricultural landscapes. The development of cloud-based platforms and high-resolution satellite data has improved the ability to process large datasets and undertake field-level agricultural analysis. Gorelick et al. (2017) introduced **Google Earth Engine (GEE)** as a cloud-based platform for planetary-scale geospatial analysis, providing access to large remote-sensing datasets and high-performance computational facilities. Its capacity for large-scale image processing makes it suitable for agricultural monitoring and spatial analysis. Sentinel-2 MSI imagery, with its relatively fine spatial resolution and multispectral bands, provides suitable data for identifying agricultural areas and variations in vegetation conditions. The use of Normalized Difference Vegetation Index (NDVI) can further assist in distinguishing vegetated agricultural areas from non-agricultural surfaces. The European Space Agency (ESA **WorldCover**) of 10 m 2021 v200 dataset provides standardized land-cover information, including a cropland class, and can therefore be used as ancillary information for agricultural-area extraction (Zanaga et al., 2022). Object-based approaches are particularly useful for field delineation because agricultural fields represent spatially coherent units rather than independent pixels. Achanta and Süssstrunk (2017) developed **Simple Non-Iterative Clustering (SNIC)**, an efficient segmentation method that generates connected image objects and supports polygonal partitioning. In agricultural studies, SNIC can therefore be integrated with Sentinel-2 imagery to delineate individual field objects and estimate their areas. Government of India agricultural statistics classify operational holdings into marginal (<1 ha), small (1–2 ha), semi-medium (2–4 ha), medium (4–10 ha) and large (≥ 10 ha) categories. These classifications provide a useful framework for categorizing satellite-derived agricultural field sizes. However,

satellite-derived field objects should not automatically be considered equivalent to operational holdings, as one farmer may operate multiple parcels. Thus, integrating Sentinel-2, NDVI, WorldCover, SNIC and GEE provides a suitable methodological framework for **spatially explicit agricultural field-size mapping**, with validation against agricultural statistics or cadastral information where available.

STUDY AREA

Bhagalpur district is located in eastern Bihar, India within the fertile plains of Ganga river basin. The river district extends from **25°07'–25°30' N latitude and 86°37'–87°30' E longitude** and covers an area of about **2,569 km²**. **The Ganga river divides the district into two geographical belts into -Diara land and Fertile land.**

FIG-1



MATERIALS AND METHODS

Datasets

The present study employs an integrated remote sensing and GIS approach for mapping the spatial distribution of agricultural field size classes. Sentinel-2 Multispectral instrument (MSI) Level-2A Surface Reflectance Harmonized imagery (Copernicus/S2_SR_Harmonised) is used as the principal satellite dataset. Sentinel-2 provides multispectral observations with high temporal frequency and spatial resolutions of 10, 20, and 60m making it particularly suitable for agricultural monitoring and the delineation of relatively small agricultural fields (European Space Agency {ESA}, 2024; Google Earth Engine, 2026).

Image Preprocessing

The Sentinel-2 imagery undergoes a systematic preprocessing procedure before agricultural field-size extraction. First the Bhagalpur District boundary is used to define the Area of Interest, Sentinel-2 observations are spatially filtered and clipped to the study area. The Level-2A Surface Reflectance product is used because atmospheric correction already been used in the product, independent atmospheric correction is not carried out on the GEE platform. (European Space

Agency {ESA},2024; Google Earth Engine,2026) Cloud and cloud shadow contaminated pixels are subsequently removed using the Scene Classification layer(SCL). Pixels classified as cloud shadow (Class 3), medium-probability cloud (Class 8), high-probability cloud (Class 9), cirrus (Class 10), and snow/ice (Class 11) are excluded. This procedure reduces atmospheric contamination and prevents cloud-related artefacts from affecting agricultural field delineation (Google Earth Engine, 2026).Following cloud masking, the Sentinel-2 surface-reflectance bands are converted from their scaled digital values into reflectance values using the scale factor provided with the dataset. In Google Earth Engine, this is generally implemented by dividing the relevant reflectance bands by **10,000** (Google Earth Engine, 2026). After preprocessing , multiple cloud free Sentinel-2 observations are combined to generate a representative image composite . A median composite can be used to reduce the influence of residual cloud contamination and anomalous observations. The **Normalized Difference Vegetation Index (NDVI)** is subsequently calculated using the Red (B4) and Near-Infrared (B8) bands:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

NDVI is widely used for vegetation monitoring because healthy vegetation strongly absorbs red radiation while reflecting near-infrared radiation (Rouse et al., 1974). In the present study, NDVI is used to distinguish vegetated agricultural areas from non-vegetated surfaces. An initial agricultural mask is then generated by combining the **WorldCover cropland class (Class 40)** with an NDVI threshold. For example, cropland pixels having NDVI values greater than 0.20 may be retained as agricultural vegetation. However, this threshold should be regarded as an empirical parameter and should be evaluated against field-reference data and the local agricultural calendar rather than being considered a universal threshold. Following agricultural-area extraction, **Simple Non-Iterative Clustering (SNIC)** segmentation is applied to generate spatially homogeneous agricultural field objects. SNIC is an object-based superpixel segmentation method that generates connected image objects based on spectral and spatial similarity (Achanta & Süsstrunk, 2017). In the present study, B2, B3, B4, B8, B11 and B12 are used as input spectral bands for segmentation. The resulting segments are subsequently restricted to the agricultural mask to obtain satellite-derived agricultural field objects.

Field area = $\sum$ Pixel area

The area of each segmented agricultural object is calculated from the number and area of constituent pixels.

TABLE-1

FIELD SIZE CATEGORY	AREA
Marginal sized	<1 ha
Small -sized	1-2 ha
Semi-medium sized	2-4 ha
Medium -sized	4-10 ha
Large -sized	≥ 10 ha

These categories correspond broadly to the conventional size classification used in Indian agricultural statistics.

RESULTS AND DISCUSSION

The spatial distribution of agricultural landholding-size classes in Bhagalpur District for 2025 is presented in FIG-1.

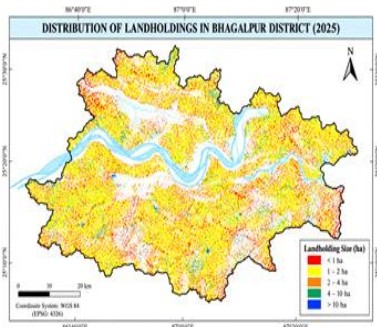


Figure 2.

The spatial analysis indicates that **Bhagalpur District is characterized predominantly by small agricultural field units, particularly those in the 1–2 ha category**

TABLE-2

FIELD SIZE CATEGORY	AREA (%)
Marginal sized	36
Small-sized	29
Small-Sized	20
Medium-sized	10
Large -sized	5

accompanied by numerous marginal-sized (<1 ha) patches. Medium and large agricultural units occur considerably less frequently and are spatially scattered. The resulting pattern reflects a fragmented agricultural landscape in which small-sized field units cohere concentration of small fields is not completely uniform. Some areas exhibit relatively dense concentrations of small polygons, whereas other areas contain more heterogeneous mixtures of the 1–2 ha, 2–4 ha and larger classes. This spatial heterogeneity suggests that the structure of agricultural land is influenced by local physical and socioeconomic conditions. nstitute the dominant spatial structure. The spatial occurrence of **medium (4–10 ha) and large (>10 ha) units is comparatively limited.** The green and blue classes appear only as isolated patches on the map. Their limited occurrence indicates that large contiguous agricultural fields are not a dominant feature of the district's agricultural landscape. Spatially, the agricultural field-size distribution of Bhagalpur District exhibits distinct zones of concentration. The northern part of the district, comprising the Naugachhia subdivision and the blocks of Bihpur, Narayanpur, Kharik, Naugachhia, Gopalpur, Ismailpur and Rangrachowk, represents an important riverine agricultural zone where small and marginal field units are extensively distributed. The central part of the district, particularly Sabour, Goradih, Jagdishpur and Nathnagar, is characterized predominantly by small-sized agricultural fields, with scattered semi-medium units. In the southern agricultural belt, including Shahkund and Sultanganj, a mixed pattern of marginal, small and semi-medium fields is observed. The eastern part, represented by Kahalgau, Pirpanti and Sanhaua, also shows a predominance of smaller agricultural units, although relatively larger field patches occur locally. Overall, the spatial pattern indicates that small and marginal agricultural field units are distributed extensively across the district, whereas medium and large units occur as isolated and discontinuous patches

CONCLUSIONS-

The analysis demonstrates that agricultural land in Bhagalpur is spatially heterogeneous, with considerable variation in the size and distribution of agricultural field units. The spatial pattern indicates the presence of **marginal, small, semi-medium, medium and large field-size categories**, with smaller agricultural units occurring as numerous fragmented patches and relatively larger units occurring in more spatially concentrated or isolated locations. The distribution is also influenced by the distinctive physical geography of Bhagalpur, particularly the Ganga River and associated riverine agricultural landscapes. An important contribution of the study is that it moves beyond conventional land-use/land-cover classification, in which agricultural land is generally represented as a single category. The geospatial approach enables agriculture to be examined in terms of its **internal spatial structure and field-size variability**. Consequently, the methodology can provide useful information for identifying areas of agricultural fragmentation and understanding the spatial organization of agricultural land at the district level. The findings have important implications for **agricultural planning and rural development**. Spatial information on field-size distribution can assist in identifying areas where land fragmentation may affect mechanization, irrigation development, agricultural infrastructure and farm-management practices. The approach can also provide a baseline for monitoring future changes in agricultural field structure using repeated satellite observations.

However, the study also highlights an important distinction between **satellite-derived agricultural field size and actual farmer landholding or operational holding size**. A remotely sensed field object does not necessarily represent a single farmer's ownership or operational holding. Therefore, the estimated field-size classes should be validated with **Agricultural Census data, cadastral records, Bhu-Naksha, revenue records and field-level surveys** wherever available. Such validation would improve the reliability of the

estimated landholding structure. Overall, the study establishes a **practical and replicable geospatial framework for estimating and analysing agricultural landholding-size patterns in Bhagalpur District**. The integration of remote sensing and GIS provides an efficient means of generating spatial information that can complement conventional agricultural statistics. Future studies should extend the analysis to **block-wise estimation, multi-temporal monitoring, cadastral validation and integration with socioeconomic variables** to develop a more comprehensive understanding of agricultural fragmentation and landholding dynamics in Bhagalpur District and other parts of Bihar.

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