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GIS-Based Assessment of Rice Transplanter Requirement in the Southern Delta of Bangladesh

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Abstract

Increased rice production is a crucial activity for food security, which is negatively impacted by the Southern Delta of Bangladesh's frequent cyclones, saline intrusion, and water shortage during the dry season. This research was done in the areas of Baratia, Khulna; Mundopasa, Barishal; Holdibaria, Patuakhali; and Charwapda, Noakhali, with the goal of precisely predicting rice transplanter requirements for mechanical rice transplanting. To improve resource planning for mechanical transplanting, the study used advanced geoinformatics approaches to precisely analyze the land use and land cover (LULC) by high-resolution Sentinel-2 satellite pictures (10m × 10m resolution). Crop fields were accurately represented and analyzed using QGIS software for satellite image research. To identify agriculture, fallow land, water bodies, and settlements, LULC maps were created using QGIS's unsupervised classification and multi-band analysis. Using QGIS tools to calculate crop hectarage in both the Aman and Boro seasons, the GIS-based methodology estimated transplanter requirements based on the crop coverage for each study area. The estimated requirements for rice transplanters were as follows: Baratia, Khulna, required 11 transplanters for Aman and 18 for Boro; Mundopasa, Barishal, required 3 for Aman and 1 for Boro; Holdibaria, Patuakhali, required 5 for Aman and 2 for Boro; and Charwapda, Noakhali, required 87 for Aman and 15 for Boro. Classification accuracies ranged from 76.47% to 85.71%, with corresponding Kappa coefficients ranging from 0.69 to 0.81, indicating substantial to excellent agreement. The results reveal a significant potential for application across larger administrative areas to determine the machinery needs for the effective

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mechanization of transplanting technology, which plays a crucial role in optimum machine use, entrepreneurship development and sustainable agricultural development in the Southern Delta region of Bangladesh.

Keywords: Agricultural Mechanization, GIS, Land Use-Land Cover, Rice Transplanter, Remote Sensing

Introduction

Agriculture is a cornerstone of Bangladesh's economy, playing an essential role in the food security and livelihood (Alam et al., 2024). Blessed with fertile land and a mild climate, Bangladesh supports a diverse range of crops (Rahman et al., 2023). Among these, rice stands as the most critical staple, cultivated across three primary seasons: Aus, Aman, and Boro (Islam et al., 2021). While the Aus and Aman seasons primarily rely on rainfall for irrigation, the Boro season depends heavily on artificial irrigation (Mainuddin et al., 2021). Remarkably, the Aus season encompasses rice varieties planted between mid-March and early April, harvested from mid-June to early July (Sarangi et al., 2021). According to recent statistics, rice production in Bangladesh reached substantial levels, totaling approximately 37.6 million MT across its three main seasons, with Aus yielding 3,285,000 MT, Aman 14,438,000 MT, and irrigated Boro 19,885,000 MT, the highest contributor respectively (Mainuddin et al., 2021; Mamun et al., 2024; Jamal et al., 2023). This outputs underscores rice's dominance as the staple crop, accounting for over 83% of total cereal food supply and pivotal to national food security (Islam et al., 2021). Despite this agricultural abundance, traditional rice cultivation faces significant challenges, particularly in transplanting. Paddy is traditionally transplanted by hand, which requires a lot of labor, demanding substantial human effort (Peramaiyan et al., 2023; Singh et al., 1985). This reliance on manual labor is increasingly unsustainable due to rising labor costs and a declining workforce interested in paddy cultivation (Asha et al., 2020; Saha et al., 2022). Mechanical transplanting using rice transplanter machines offers a viable solution, demonstrating a significant reduction in both cost and labor requirements, with machine transplanting saving up to 60% in labor costs compared to manual methods (Rahaman et al., 2022; Rashid et al., 2018). Furthermore, the combined pressures of climate change, increasing demand for food, and diminishing profits from traditional farming underscore the critical need for agricultural mechanization as a strategic approach to mitigate these adverse impacts (Vanza et al., 2024; Yuan & Huang, 2024).

The advent of smart agriculture, driven by technological advancements, offers promising pathways to address these challenges. Integrating machine learning and global information systems provides business owners with a clearer understanding of technology scalability, enabling the development of lucrative, customer-tailored enterprises (Giuggioli & Pellegrini, 2022; Li et al., 2025). Geographic information systems and remote sensing are a suitable approach for finding high-precision land use-land cover change information's (Zhao et al., 2024). GIS empowers planners who are in land use sector by providing crucial data visualization and analytical capabilities (Zhang & Li, 2022). Advanced tools like the Semi-Automatic Classification Plugin facilitate easier land cover mapping and analysis, even for users with limited background in remote sensing technologies (Congedo, 2021; Cubillas et al., 2024). This plugin facilitates the workflow from downloading remote sensing imagery through multiple processing and post-processing stages. These technological integrations facilitate the monitoring of land cover evolution, such as tracking the increase or decrease of agricultural and urban regions across different time periods (Ennouri et al., 2021; Zhang et al., 2025; Tesfaye et al., 2024). The ability of GIS to manage and interpret complex spatial data goes beyond mere information access, offering policymakers and service providers a powerful means for data representation through mapping and related calculations among multiple options. This capability is vital for determining the optimal number of transplanting machines required for a given area, thereby reducing business risks for entrepreneurs and fostering sustainable custom-hire services (Deichmann et al., 2016; Pattnaik et al., 2022; Sridevy et al., 2023). The hypothesis guiding this study posits that GIS mapping, combined with quantitative spatial modeling, can accurately identify land suitable for rice transplanter operation and enable precise equipment deployment planning.

Methodology

This study utilized several foundational methodologies to process and model changes in land cover. This study used GIS and remote sensing techniques to classify land use/land cover and estimate suitable rice-cultivated areas for mechanical transplanting. The flow chart shown below (Figure 1) summarizes the major research processes of the research. Figure 2 depicts the flow chart of estimating for the number of rice transplanter required.

The experiment was conducted with the following specific objectives:

- To identify rice-cultivated land potentially available for mechanical transplanting; and
- To estimate the number of rice transplanter required for the available land area.

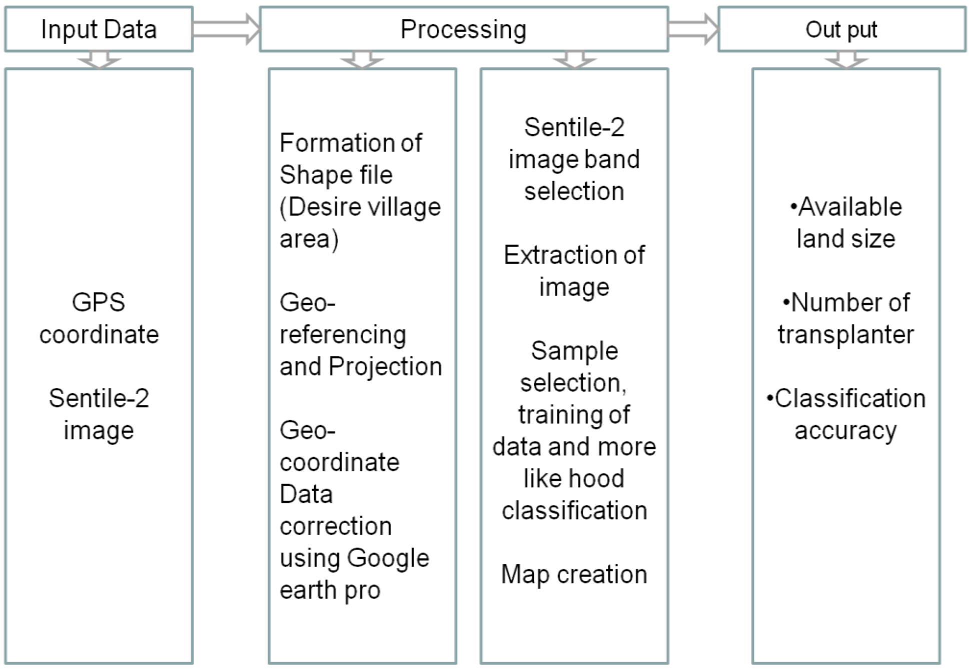


Fig. 1. Experiment flow chart

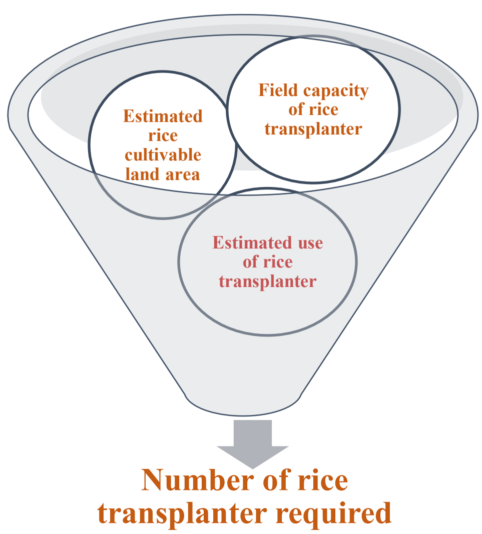


Fig. 2. Estimation model of number of rice transplanter required

Experiment areas

The experiment was carried out in four villages: Mundopasa in Wazirpur upazila in Barishal district, Baratia in Dumuria upazila in Khulna district, Holdibaria in Kalapara upazila in Patuakhali district, and No. 4 Charwapda villages in Subarnachar upazila in Noakhali district of Bangladesh's Southern Delta (Figure 3 and Figure 4).

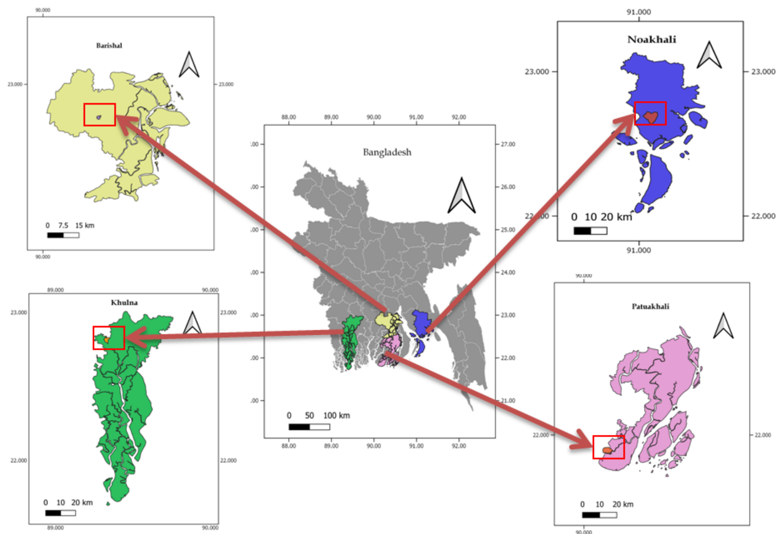


Fig. 3. Experiment locations

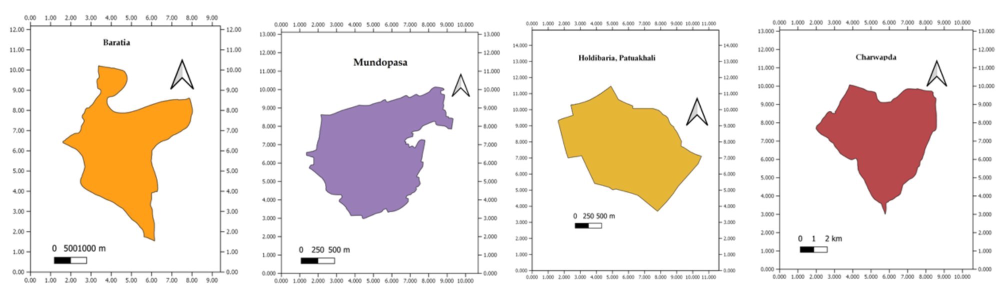


Fig. 4. Mouza maps of experiment locations

The major cropping system of the experimental area was as follows (Table 1):

Table 1. Cropping system in the study areas

Study area	Major cropping system
Mundopasa, Wazirpur, Barishal	Aman-Mungbean-Fallow
Baratia, Dumuria, Khulna	Aman-Mustard–Boro-Jute

Study area	Major cropping system
Holdibaria, Kalapara, Patuakhali	Aman-Mungbean–Fallow
Charwapda, Subarnachar, Noakhali	Aman-Watermelon/Soybean -Fallow

Remote sensing data and secondary data collection

Sentinel-2 satellite images were used in this research for visual image analysis, land use classification, and land area estimation to generate land cover and land use maps. Sentinel-2 is a European multispectral mission featuring two satellites phased at 180 degrees to provide a 5-day revisit frequency at the Equator. The system's optical instruments record 13 spectral bands with spatial resolutions set at 10 m, 20 m, and 60 m (Copernicus Data Space Ecosystem, 2026). The orbital sweep spans 290 kilometers. Both the Boro and Aman season were considered for the experiment.

Seasonal satellite data for the study regions were downloaded from the USGS Earth Explorer portal for both the Boro and Aman seasons. Table 2 shows the date of satellite data acquisition. The 2018–2019 Sentinel-2 scenes were selected because they coincided with the ground-truth field survey campaign at the four study sites, which is a precondition for reliable accuracy assessment. The acquisition dates were also chosen to align with the transplanting and early vegetative stage of Aman and Boro rice, when paddy has a distinct spectral signature compared to co-occurring crops such as mustard, jute, and mungbean, enabling rice-specific pixel identification.

Table 2. Satellite image acquirement date for the experiment

Season	Mundopasa	Holdibaria	Baratia	Charwapda
Boro	17-01-2018	06-02-2019	15-01-2018	17-01-2019
Aman	16-07-2018	20-08-2019	16-06-2018	12-07-2018

The 2018–2019 Sentinel-2 imagery was selected to match the timing of field surveys and ground-truth data collection used for classification validation. More recent rice production statistics were cited only to provide current national context regarding the importance of rice production in Bangladesh and were not used in the spatial analysis. Data for Bangladesh, including administrative boundaries of the research area and country shape files, is collected from the https://www.diva-gis.org/Data source. The administrative boundary shape files for Bangladesh were used to create the study area boundary shape files. The study regions were represented and interpreted using GPS co-ordinate points, topographical maps, and Google Earth. To identify feature classes during image classification and reclassification by overlaying the resulting land use map data, conventional software operating procedures and relevant information were utilized.

The selection of the 2018–2019 Sentinel-2 archival dataset was a strict methodological requirement to ensure perfect temporal synchronicity with the extensive ground-truth field survey and GPS data collection campaign conducted at the four primary study sites. In satellite-based land cover classification, matching the imagery acquisition date directly to the ground verification window is a prerequisite for reliable accuracy assessment and confusion matrix validation. To prevent this structural constraint from undermining contemporary planning, the spatial framework has been constructed as a dynamic, scalable model designed for periodic re-application with recent imagery datasets.

Software and plugins

Spatial data analysis and GIS-based mapping were performed with QGIS 3.10.0-A Coruña. Plugins used for the experiment were as follows:

- HCMGIS
- scpplugin
- SemiAutomatic Classification Plugin
- db_manager
- Meta Search
- Processing.

As illustrated in Figure 5, QGIS is a versatile, open-source Geographic Information System provided under the GNU General Public License. It is recognized as an official project of the Open-Source Geospatial Foundation (OSGeo) and offers extensive compatibility across Windows, Mac OS X, Linux, Unix, and Android platforms. The system provides robust functionality for managing a wide array of database, raster, and vector formats.

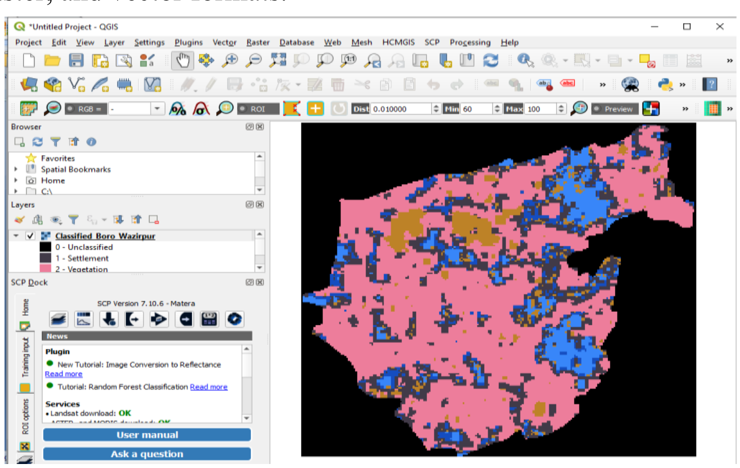


Fig. 5. QGIS software interface (screenshot)

Image classification

The analysis of remotely sensed imagery frequently utilizes digital image classification, a complex yet widely adopted method. This procedure involves the systematic categorization of image pixels to retrieve significant geographical data, which is then used to generate thematic maps detailing attributes like vegetation species and land cover categories (Matinfar *et al.,* 2007). Global classification techniques vary significantly and are often inconsistent, as there is currently no internationally unified system for defining land cover (Di Gregorio *et al.,* 1998). For the purposes of this research, a specific land cover categorization framework was established, utilizing the Semi-Automatic Classification Plugin (SCP) to perform the digital image analysis. As an open-source extension for the QGIS environment, the SCP facilitates unsupervised classification of satellite data. Unsupervised classification was selected for this study as an exploratory approach suited to the limited and spatially distributed ground-truth points available at each site; GPS data were subsequently used to manually relabel and verify the resulting spectral clusters rather than to train the classifier. This tool streamlines the entire analytical workflow, from the acquisition of open-access imagery to advanced preprocessing, raster mathematics, and final post-processing stages. These capabilities allow for the systematic extraction of thematic data from multispectral satellite imagery (Congedo, 2021).

To distinguish rice-cultivated land from other crop types, the classification process combined unsupervised spectral clustering with ancillary field information. Initially, the Semi-Automatic Classification Plugin (SCP) was used to generate spectral clusters from Sentinel-2 imagery without predefined training samples. Subsequently, each cluster was interpreted and labeled using field observations, GPS reference points, local cropping calendars, and high-resolution Google Earth imagery. The acquisition dates of the Sentinel-2 images were selected to coincide with the transplanting and early vegetative stages of Aman and Boro rice, when paddy fields exhibit characteristic spectral signatures associated with flooded or recently transplanted conditions. These signatures differ from those of mustard, mungbean, jute, soybean, and watermelon, which were either absent, harvested, or at different phenological stages during image acquisition. Therefore, spectral clusters corresponding to rice fields were identified through a combination of spectral characteristics, seasonal crop calendars, and ground-truth verification rather than spectral information alone. Similar approaches have been widely adopted in agricultural land-use classification studies where limited ground-reference data are available (Congedo, 2021; Matinfar et al., 2007; Zhao et al., 2024).

The unsupervised spectral clustering approach was deliberately coupled with precise temporal targeting. Satellite scenes were selected to coincide exactly with the transplanting and early vegetative windows of Aman and Boro rice. At this specific phenological stage, paddy fields exhibit a unique hydro-spectral signature due to field flooding and thin canopy exposure, which sharply distinguishes them from co-occurring terrestrial vegetation, fallow land, or alternative dry-season crops. This minimization of spectral mixing achieved through phenological-window targeting justifies the exploratory cluster-then-label approach over complex machine-learning classifiers when localized ground-truth coordinates are scattered.

Reclassification of the image and creating map

The process of reclassification entails modifying either the full or specific portions of a raster's dataset values. Within the QGIS environment, this technique was utilized to aggregate related raster values into unified categories (Figure 6). Following this data consolidation, the final analytical maps were produced using the comprehensive cartographic tools available in the software (Figure 7).

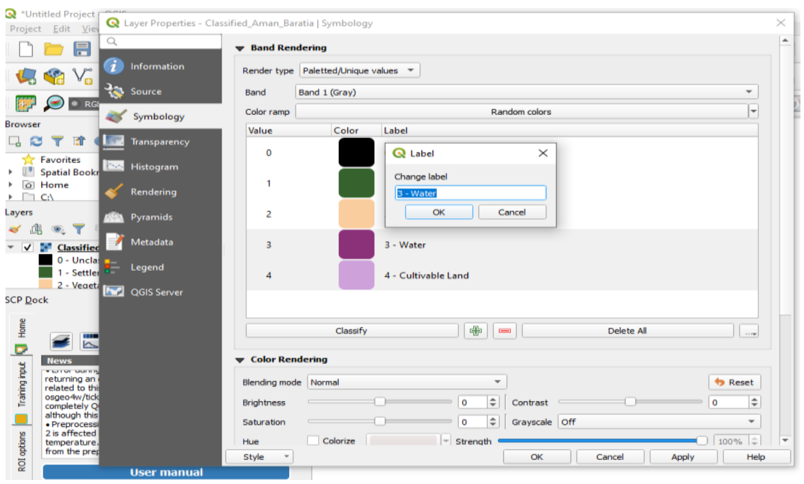


Fig. 6. Reclassification of the image (screenshot)

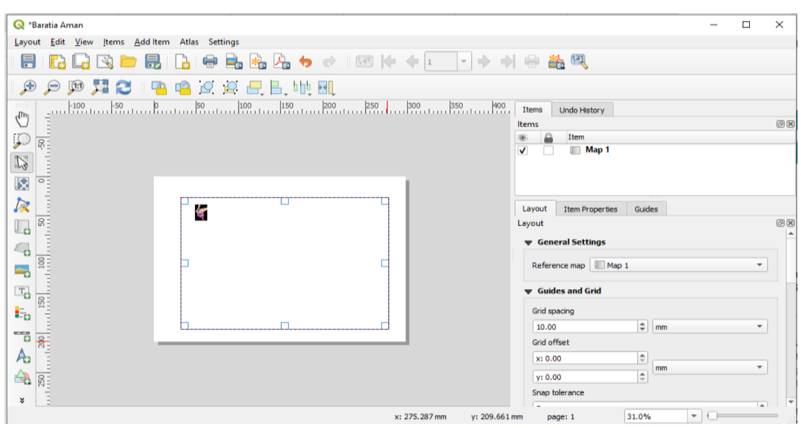


Fig. 7. Creating map in QGIS (screenshot)

Area Estimation

Classified image area was calculated from the following formula

$$\text{Classified Image Area (ha)} = \frac{\text{Count (pixel)} \times 10 \times 10}{10000} \quad \text{(i)}$$

Where:

Count (pixel) = Estimated pixel number obtained from QGIS software

10 x 10 = Image pixel size and 10000 = Conversion factor in ha.

Accuracy assessment

To verify the precision of the classification, this study employed Kappa statistics, which offer a robust statistical framework for evaluating the quality of the categorization process. This metric was specifically utilized to determine the total accuracy across all defined land classes (Tottrup and Rasmussen, 2004). As noted by Pontius and Millones (2011), a Kappa statistic exceeding 0.5 is considered a satisfactory threshold for simulations involving land-use transitions. Furthermore, Landis and Koch (1977) categorized the strength of agreement for Kappa coefficients: results above 0.79 signify excellent correlation, while those ranging from 0.6 to 0.79 reflect substantial agreement. Conversely, any value of 0.59 or lower is generally interpreted as representing moderate to weak agreement (Fosse *et al.,* 2006). The overall classification accuracy is defined as the proportion of samples within an error matrix that have been categorized correctly. This value is determined by taking the sum of all correctly identified samples and dividing it by the total count of samples used in the assessment (Cantor, 1996). It can be expressed by:

$$\text{Users accuracy (\%)} = \frac{\text{Sum of truth values in row}}{\text{Sum of values of row in each feature class}} \text{x}100 \quad \text{(ii)}$$

$$\text{Producer accuracy (\%)} = \frac{\text{Sum of truth values in column}}{\text{Sum of values of column in each feature class}} \text{x}100 \quad \text{(iii)}$$

$$\text{Overall accuracy (\%)} = \frac{\text{Sum of truth values}}{\text{Sum of sample values}} \text{x}100 \quad \text{(iv)}$$

$$\text{Cohen's Kappa Coefficient (k)} = \frac{\text{Sum of true value-Random accuracy}}{\text{1-Random accuracy}} \quad \text{(v)}$$

Calculation of the required machine number

The number of machines were estimated from the field capacity of the machine, suitable available area, and seasonal use of the machine. The equation is as follows:

$$\text{Number of machine} = \frac{\text{Area suitable for cultivation}}{\text{Area covered by a machine in a season}} \quad \text{(vi)}$$

Results

For this research, satellite data representing the Aman and Boro growing seasons for 2018 and 2019 were retrieved through a structured acquisition process from the United States Geological Survey (USGS) Earth Explorer portal. All subsequent spatial analysis, mapping, and experimental tasks were performed within the QGIS 3.10.0-A Coruña environment, utilizing its suite of open-source plugins (QGIS Development Team, 2026 and U.S. Geological Survey (USGS), 2026).

Extraction of mouza map

To perform digital analysis of satellite data, a mouza boundary mask was first superimposed on the satellite image composite band (Band No. 2, 3, 4, & 8, respectively) of each area. This allowed the extraction of all pixels that belonged to the interested area (Figures 8, 9, 10 and 11).

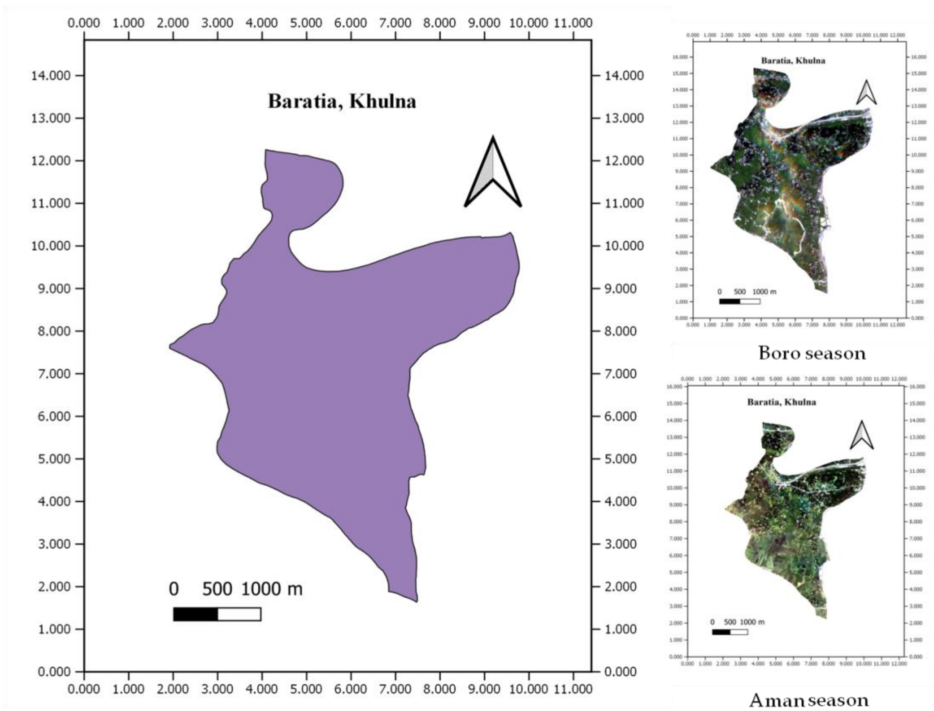


Fig. 8. Baratia, Khulna map extraction

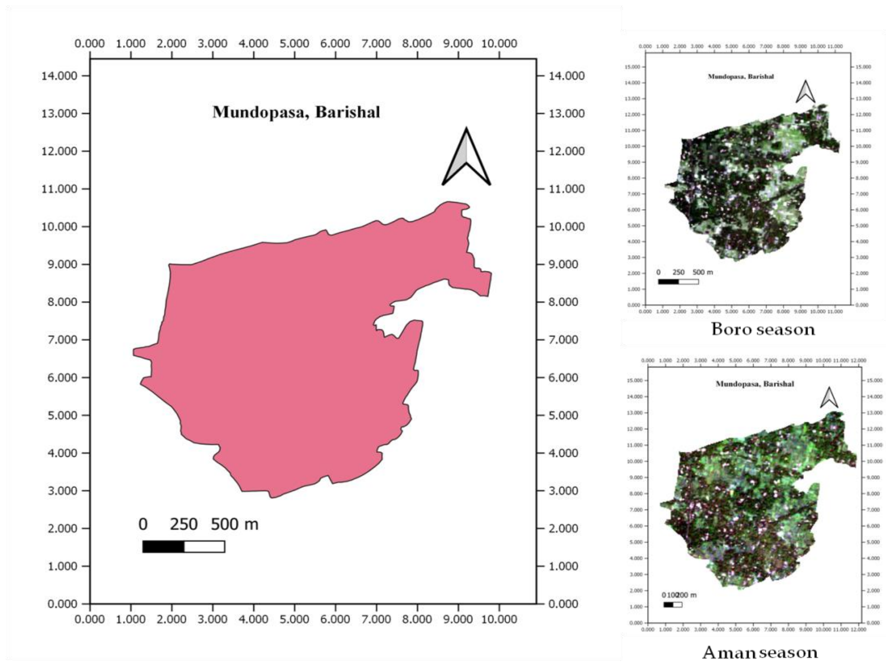


Fig. 9. Mundopasa, Barishal map extraction

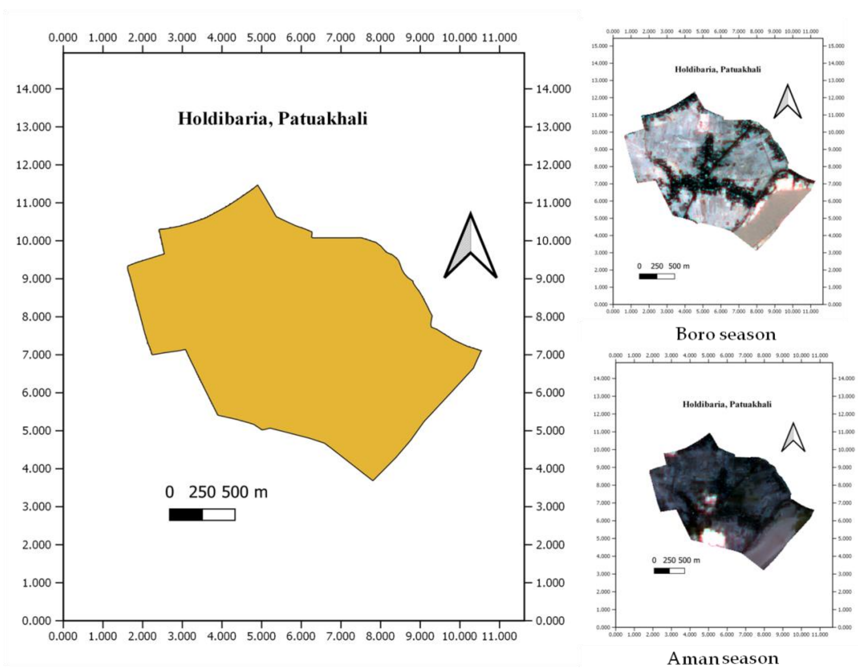


Fig. 10. Holdibaria, Kalapara map extraction

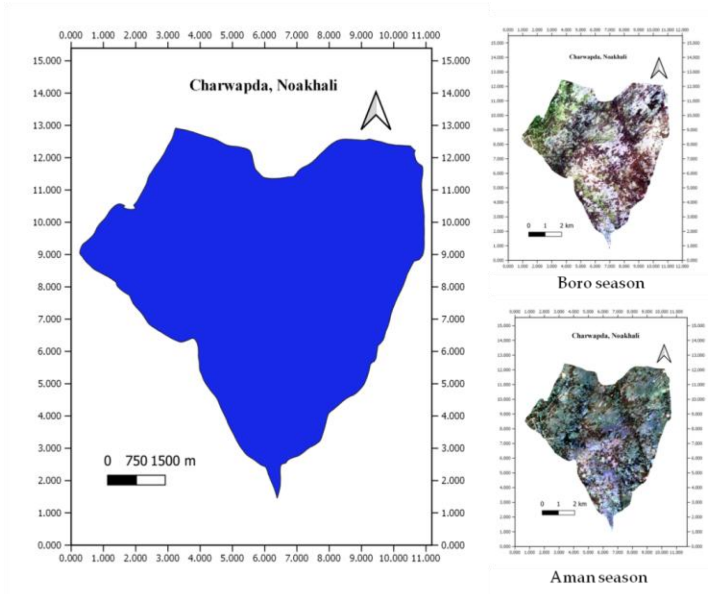


Fig. 11. Charwapda, Noakhali map extraction

Land cover classification and unsupervised map creation

The categorization of land cover was executed using an unsupervised likelihood classification technique provided by the Semi-Automatic Classification Plugin (SCP) (Congedo, 2021). This process integrated both visual and digital image assessments to generate the research maps (Figures 12, 13, 14, and 15). Through these analytical approaches, several distinct land use categories were identified across the study region, including forested areas, water bodies, urban settlements, and rice-cultivated land. A detailed description of these specific land use classes, as identified by the SCP tool, is provided in Table 3.

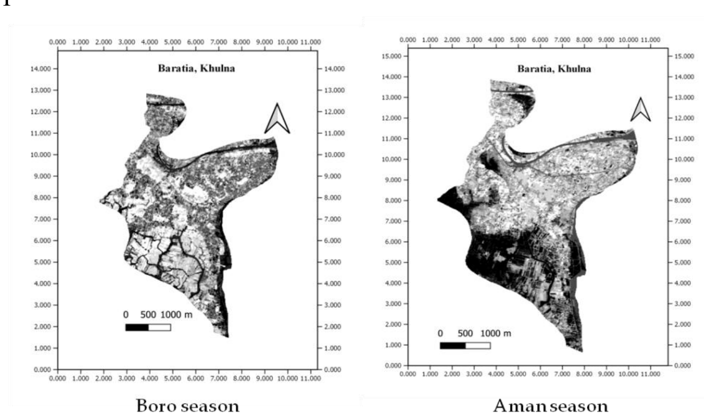


Fig. 12. Baratia, Khulna unsupervised map using SCP plugin

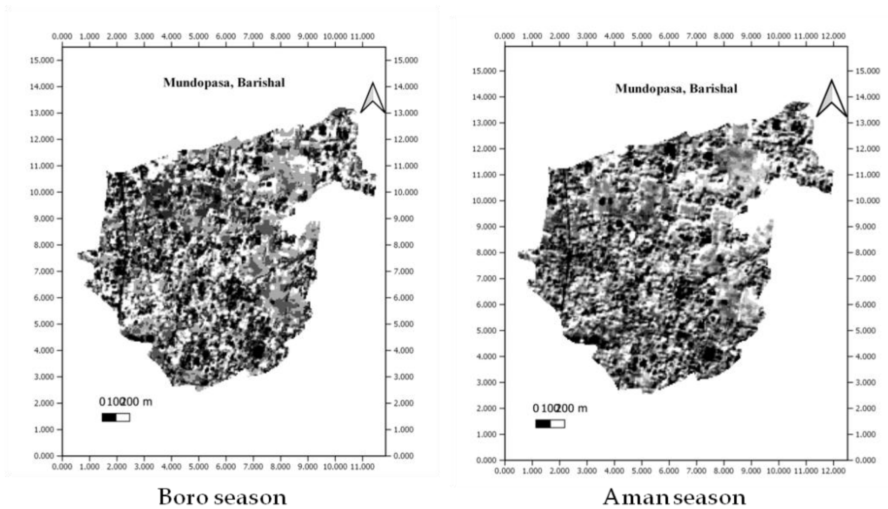


Fig. 13. Mundopasa, Barishal unsupervised map using SCP plugin

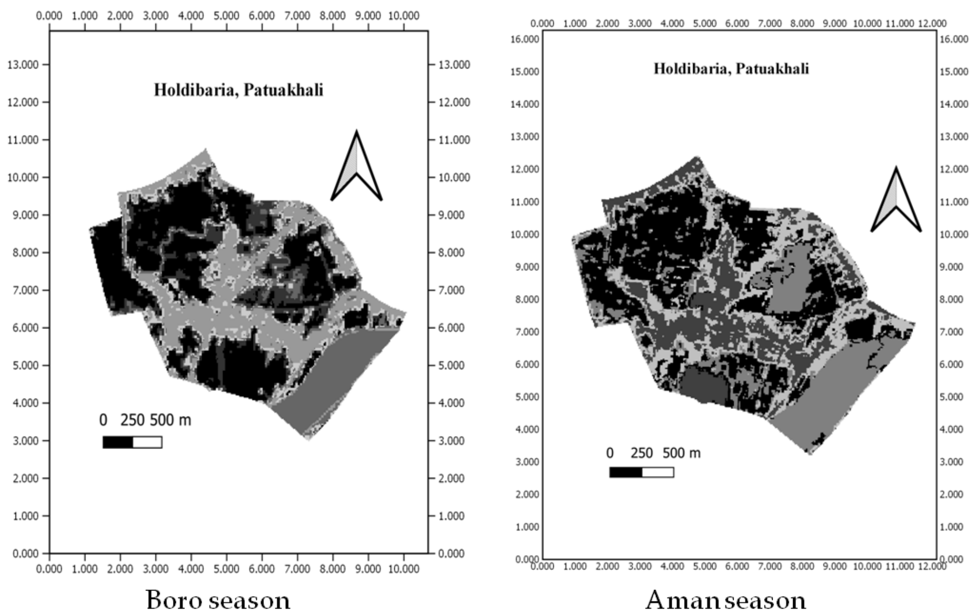


Fig. 14. Holdibaria, Patuakhali unsupervised map using SCP plugin

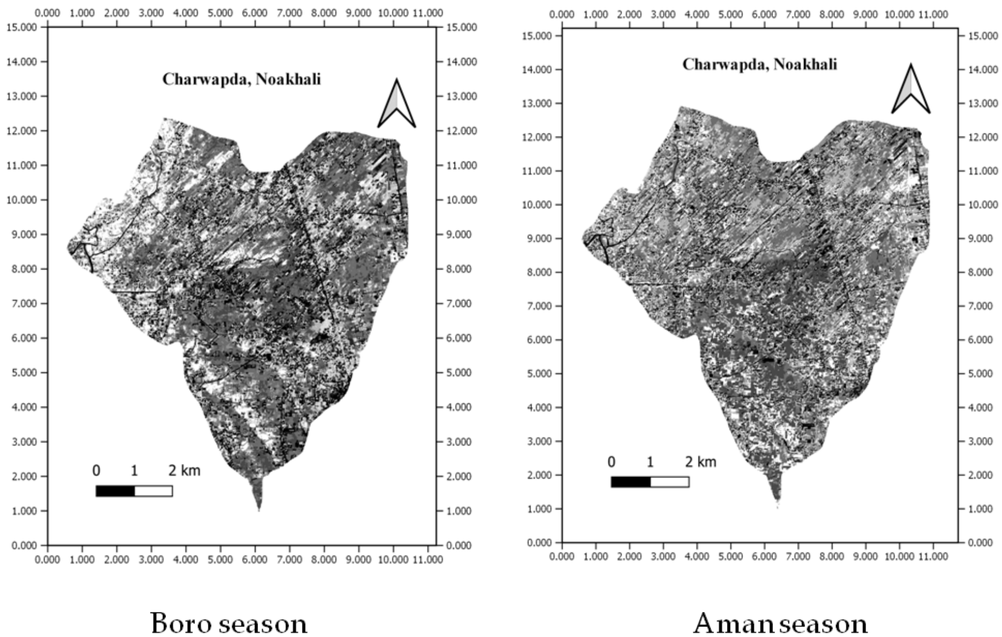


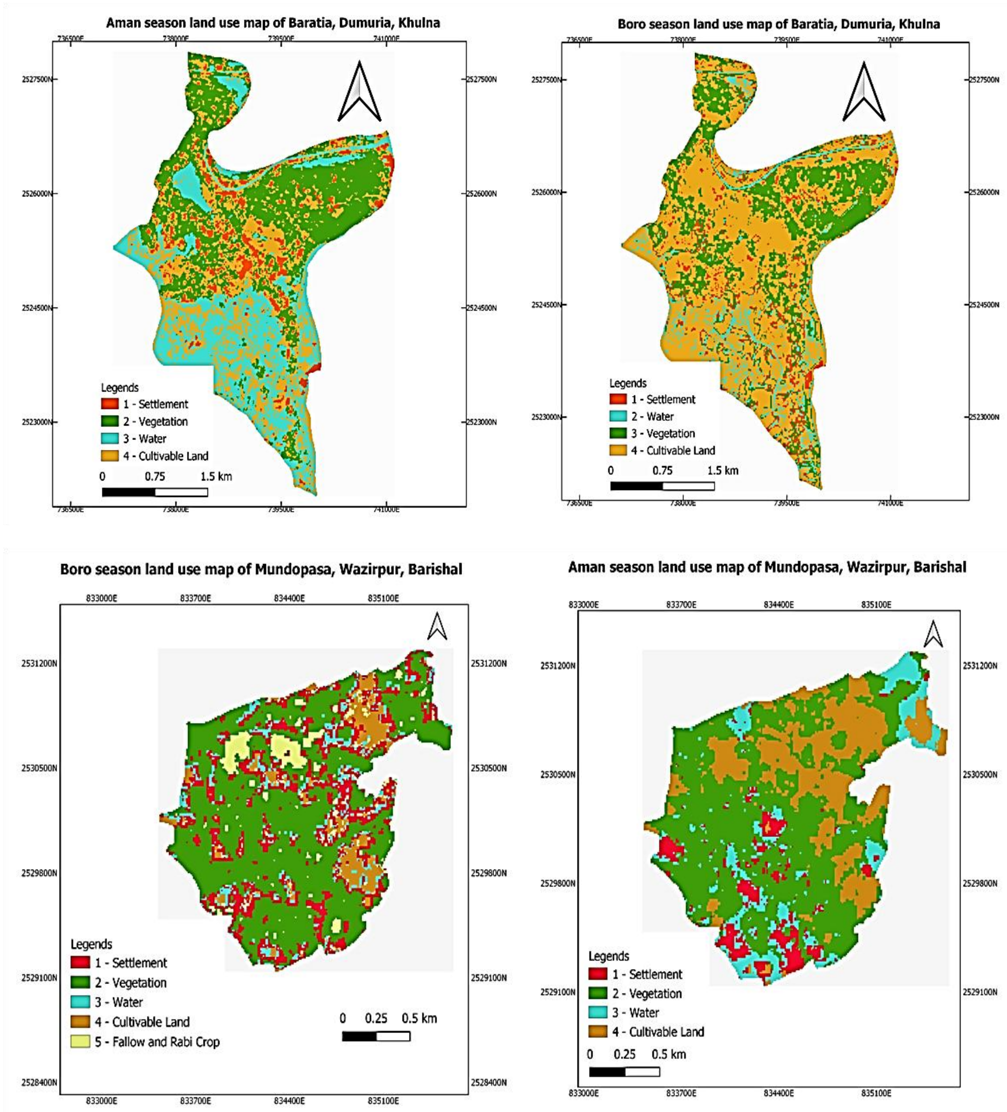
Fig. 15. Charwapda, Noakhali unsupervised map using SCP plugin

Table 3. Land covers classification

No.	Classes	Description
1	Water body	Ponds, canal, lakes, river, submerged areas
2	Settlement and structures	Permanent structures, house, roads
3	Fallow land	Fields, bare lands etc.
4	Forest and vegetation	Vegetation and forest areas
5	Rice-cultivated land	Boro and Aman paddy fields

Land cover reclassification and GIS map

The various categories were identified using ground data, including field knowledge and GPS co-ordinate datasets. The classified photos were reclassified using the SCP plugin by combining the relevant classes. Figure 16 depicts the land use maps of the research area.


Aman season land use map of Baratia, Dumuria, Khulna
Legends
1 - Settlement
2 - Vegetation
3 - Water
4 - Cultivable Land
0 0.75 1.5 km
Boro season land use map of Baratia, Dumuria, Khulna
Legends
1 - Settlement
2 - Water
3 - Vegetation
4 - Cultivable Land
0 0.75 1.5 km
Boro season land use map of Mundopasa, Wazirpur, Barishal
833000E
833700E
834400E
835100E
2531200N
2530500N
2529800N
2529100N
2528400N
Legends
1 - Settlement
2 - Vegetation
3 - Water
4 - Cultivable Land
5 - Fallow and Rabi Crop
0 0.25 0.5 km
Aman season land use map of Mundopasa, Wazirpur, Barishal
833000E
833700E
834400E
835100E
2531200N
2530500N
2529800N
2529100N
Legends
1 - Settlement
2 - Vegetation
3 - Water
4 - Cultivable Land
0 0.25 0.5 km

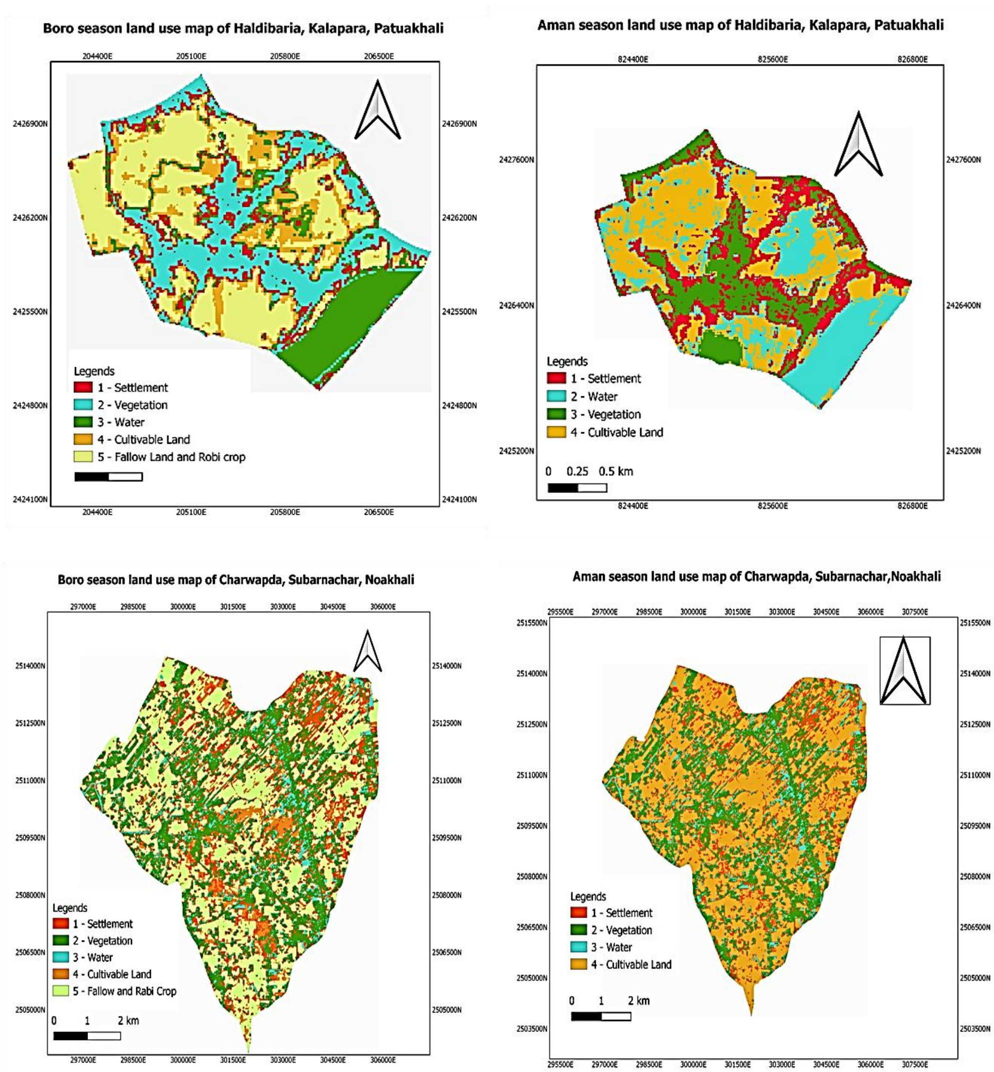


Fig. 16. Land use map of the study locations

Estimated area for mechanical rice transplanter

Utilizing GIS tools, the rice-cultivated area suitable for mechanical rice transplanting was predicted for the Aman season. The available suitable areas for mechanical rice transplanting in Baratia, Khulna, Mundopasa, Barishal, Holdibaria, Patuakhali, and Charwapda, Noakhali were 301.65 ha, 67.15 ha, 120.34 ha, and 2353.79 ha, respectively. The percentages of land available based on total area are shown in Table 4.

Table 4. Area available for mechanical transplanting in Aman season

Area	Aman		
	Rice-cultivated land (ha)	Total land (ha)	Percent of total land
Baratia, Khulna	301.65	995.32	30.31%
Mundopasa, Barishal	67.15	267.59	25.09%
Holdibaria, Patuakhali	120.34	349.08	34.47%
Charwapda, Noakhali	2353.79	5104.44	46.11%

The rice-cultivated area suitable for mechanical transplanting of rice was predicted for the Boro season using GIS techniques. In Baratia, Khulna, Mundopasa, Barishal, Holdibaria, Patuakhali, and Charwapda, Noakhali, the corresponding suitable areas for mechanical rice transplanting were 483.07 ha, 19.94 ha, 48.04 ha, and 410.49 ha (Table 5).

Table 5. Area available for mechanical transplanting in Boro season

Area	Boro		
	Rice cultivable land (ha)	Total land (ha)	Percent of total land
Baratia, Khulna	483.07	995.32	48.53%
Mundopasa, Barishal	19.94	267.59	7.45%
Holdibaria, Patuakhali	48.04	349.08	13.76%
Charwapda, Noakhali	410.49	5104.44	8.04%

Accuracy assessment

Using the QGIS environment, the SCP plugin, and ground data, the accuracy of the generated maps was evaluated. The overall accuracy and kappa coefficient were analyzed. During the Aman season in Baratia, Khulna, Mundopasa, Barishal, Holdibaria, Patuakhali, and Charwapda, Noakhali, the overall accuracy and Kappa coefficient were found to be 82.61%, 77.78%, 76.47%, 83.51%, and 0.77, 0.70, 0.69, and 0.76, respectively. Whether during Boro season in Baratia, Khulna, Mundopasa, Barishal, Holdibaria, Patuakhali, Charwapda, Noakhali, the overall accuracy and Kappa coefficient were found to be 85.71%, 80.00%, 85.71%, 83.76% and 0.79, 0.73, 0.81, 0.77, respectively (Table 6).

Table 6. Classification accuracy of the GIS maps

Area	Aman season		Boro season	
	Overall accuracy (%)	Kappa coefficient	Overall accuracy (%)	Kappa coefficient
Baratia, Khulna	82.61	0.77	85.71	0.79
Mundopasa, Barishal	77.78	0.70	80.00	0.73
Holdibaria, Patuakhali	76.47	0.69	85.71	0.81
Charwapda, Noakhali	83.51	0.76	83.76	0.77

Number of rice transplanter required for transplanting the locations

Following an evaluation of the technical specifications for available mechanical rice transplanters, this study assumed a field capacity of 0.17 hectares per hour (Saha et al., 2022). Additionally, the operational window for a single transplanting season was estimated at 20 working days (Saha et al., 2022). The 20-day operational window represents the practical transplanting period available under local cropping calendars. If the rice transplanter operates 8 hours in a day during transplanting season the total area covered by a mechanical rice transplanter was 27.2 hectares. Based on that assumption and the available rice-cultivated land area estimated by GIS technique, the needed numbers of rice transplanters for the Aman and Boro seasons in Baratia, Khulna, Mundopasa, Barishal, Holdibaria, Patuakhali, and Charwapda, Noakhali were 11, 3, 5, 87 and 18, 1, 2, 15 (Table 7).

Table 7. The needed number of rice transplanter for Aman and Boro season to cover the available cultivable land area

Locations	Required rice transplanter number	
	Aman season	Boro season
Baratia, Khulna	11	18
Mundopasa, Barishal	3	1
Holdibaria, Patuakhali	5	2
Charwapda, Noakhali	87	15

Geographic Information Systems (GIS) and remote sensing technologies have become effective tools for agricultural planning and decision-making by enabling the extraction, visualization, and analysis of spatial information related to land resources and cropping systems (Zhang & Li, 2022; Zhao et al., 2024). In the present study, GIS-based land-use classification successfully identified rice-cultivated areas suitable for mechanical transplanting across four locations in the Southern Delta of Bangladesh. The classification accuracies ranged from 76.47% to 85.71%, while

Kappa coefficients varied from 0.69 to 0.81, indicating substantial agreement and acceptable reliability of the classified maps according to the interpretation guidelines of Landis and Koch (1977) and Pontius and Millones (2011). Although some spectral overlap may exist among agricultural crops, the use of season-specific imagery, field observations, GPS verification, and local cropping-pattern information improved the reliability of rice-field identification. Consequently, the classification focused on separating rice-cultivated land from non-rice land-use categories rather than discriminating among individual non-rice crops.

The GIS analysis revealed considerable spatial variability in land availability for mechanical rice transplanting between study locations and cropping seasons. During the Aman season, the estimated suitable rice-cultivated areas were 301.65 ha in Baratia, 67.15 ha in Mundopasa, 120.34 ha in Holdibaria, and 2353.79 ha in Charwapda. In contrast, the corresponding suitable areas during the Boro season were 483.07 ha, 19.94 ha, 48.04 ha, and 410.49 ha, respectively. These differences are primarily associated with variations in cropping patterns, irrigation availability, salinity conditions, and seasonal land-use practices across the Southern Delta region (Haque, 2006; Mainuddin et al., 2021). Although the dominant dry-season cropping pattern in Charwapda is Aman–Watermelon/Soybean–Fallow, a limited portion of the area remains under irrigated Boro rice cultivation, which was identified through image classification and also Aman–Mungbean–Fallow is the dominant cropping pattern in Holdibaria, a small proportion of land remains under irrigated Boro rice cultivation.

The relatively lower availability of transplantable land in Baratia during the Aman season may be attributed to the widespread adoption of integrated rice–fish farming systems (ghers), which occupy a significant portion of agricultural land in southwestern Bangladesh (Alam et al., 2022). Conversely, Mundopasa exhibited greater land suitability during the Aman season because rice cultivation largely depends on monsoon rainfall, whereas Boro cultivation is constrained by irrigation limitations and the predominance of mungbean cultivation in the dry season (Islam et al., 2021; Rashid et al., 2018). Similarly, the reduced Boro-season rice area observed in Holdibaria and Charwapda is likely related to freshwater scarcity, salinity intrusion, and the cultivation of alternative dry-season crops, which are common challenges in coastal agroecosystems (Haque, 2006; Sarangi et al., 2021).

Based on the estimated rice-cultivated areas and the operational field capacity of a rice transplanter (0.17 ha/h), the required numbers of rice transplanters were estimated as 11, 3, 5, and 87 units for Baratia, Mundopasa, Holdibaria, and Charwapda, respectively, during the Aman season. For the Boro season, the corresponding requirements were estimated at 18, 1, 2, and 15 units. These results demonstrate the practical applicability of integrating GIS-derived spatial information with machinery planning models to estimate agricultural machinery demand at local and regional scales.

It is worth noting that the assumed field capacity of 0.17 ha/h and the resulting seasonal coverage of 27.2 ha per machine serve as an optimized baseline model. In the highly fragmented smallholder farming systems characteristic of the Southern Delta, real-world field efficiencies may decrease due to frequent turnings at plot boundaries, irregular plot geometries, and transport overhead between non-contiguous plots. Consequently, the transplanter requirements calculated here should be interpreted by agricultural extension planners as a minimum resource requirement baseline. Under highly fragmented conditions, custom-hire entrepreneurs should factor in an operational safety buffer of 10–15% additional machinery or adjusted scheduling.

Previous studies have highlighted the importance of mechanical rice transplanting in reducing labor requirements, lowering production costs, and improving timeliness of crop establishment (Rahaman et al., 2022; Saha et al., 2022; Peramaiyan et al., 2023). However, efficient deployment of transplanting machinery requires accurate estimation of service demand and spatial distribution of suitable land resources. The GIS-based framework developed in this study addresses this requirement by providing an evidence-based approach for identifying potential operational areas and estimating machinery needs. Similar applications of GIS-based decision-support systems have been recommended for optimizing agricultural investments and reducing business risks associated with mechanization services (Deichmann et al., 2016; Pattnaik et al., 2022; Sridevy et al., 2023).

Therefore, the integration of GIS and remote sensing technologies offers a robust decision-support framework for policymakers, extension agencies, entrepreneurs, and custom-hire service providers. By facilitating accurate estimation of machinery demand and spatial targeting of mechanization interventions, this approach can improve machine utilization efficiency, reduce investment risks, and contribute to the sustainable development of agricultural mechanization in the Southern Delta region of Bangladesh.

While this spatial decision-support framework successfully isolates the physical availability of suitable land resources and quantifies macro-level equipment demand, successful regional mechanization relies on secondary socio-economic variables. Factors such as smallholder purchasing power, fuel supply logistics, capital access for custom-hire entrepreneurs, and the regional availability of certified technical operators act as critical gatekeepers to actual technology adoption. Therefore, this GIS-based physical resource assessment serves as a foundational layer, intended to guide targeted credit programs and machinery subsidy allocations by showing where the infrastructure is physically viable first.

Conclusion

This research emphasizes the critical necessity of transitioning to mechanized rice cultivation in Bangladesh to counteract rising production expenses and acute labor deficits. Mechanical transplanting emerges as a viable strategy to substantially lower labor costs while maintaining planting schedules during peak periods of worker scarcity. By incorporating GIS and remote sensing methodologies, this study addresses a significant void in current academic discourse regarding the spatial allocation of agricultural machinery. The application of tools such as the Semi-Automatic Classification Plugin (SCP) within a GIS framework illustrates the software's capacity for generating high-resolution land-use datasets and defining agricultural boundaries. The results validate the hypothesis that integrating spatial mapping with quantitative modeling provides an effective decision-support system for calculating equipment requirements at the regional level. This approach offers custom-hire service providers and entrepreneurs the empirical data necessary to reduce investment risks and maximize equipment efficiency. Furthermore, by advancing from raw data collection to applied spatial modeling, this study fosters "smart agriculture" in the Southern Delta. The findings may contribute to SDG 2 and SDG 9 through improved planning of agricultural mechanization.

Limitations of the study

This study is primarily concentrated on the selected regions of Southern Delta of Bangladesh. The findings of this study may not be directly generalizable to other agro-ecological zones in Bangladesh with different cropping patterns. The reliance on remote sensing imagery and tools like the Semi-Automatic Classification Plugin may encounter challenges in perfectly resolving the highly fragmented, small landholdings characteristic of the region and in the monsoon season when heavy cloud cover may interfere. Because an unsupervised classification approach was employed, some degree of spectral confusion among agricultural crops with similar growth characteristics may have occurred. Future studies may improve crop-specific discrimination by incorporating supervised machine-learning classifiers and multi-temporal satellite imagery. This research focused on identifying physical land availability, but not prioritizes technical suitability. Although the analysis was based on validated 2018–2019 imagery, land-use patterns may have changed subsequently due to salinity intrusion, cropping-pattern shifts, infrastructure development, and expansion of aquaculture systems. Therefore, the proposed GIS framework should be periodically updated using recent satellite imagery to support current machinery-planning decisions. The 2018–2019 imagery reflects land-use conditions at the time of the ground-truth field survey. Cropping extent in the Southern Delta may have shifted since then due to salinity intrusion, gher expansion, and infrastructure change. The GIS-based framework presented here is intended for periodic re-application with current imagery rather than as a static one-time estimate. Also not consider the socio-economic variables, such as farmer purchasing power or the availability of skilled operators.

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References

Alam, M. N., Rahman, A., Rahman, M., Akhter, Mst. M., Sakib, I., Faruq, G., & Sabagh, A. E. (2024). Wheat Declining in Bangladesh: Considering Factors and Possible Solutions to Increase Its Production. doi: https://doi.org/10.20944/preprints202411.0576.v1

Alam, Md. M., Tikadar, K. K., Hasan, N. A., Akter, R., Bashar, A., Ahammad, A. K. S., Rahman, M. M., Alam, M. R., & Haque, M. M. (2022). Economic Viability and Seasonal Impacts of Integrated Rice-Prawn-Vegetable Farming on Agricultural Households in Southwest Bangladesh. Water, 14(17), 2756. doi: https://doi.org/10.3390/w14172756

Asha, K. R., Padmashree, & Ray, B. R. M. (2020). Development of Manual (Pull-type) Two-row Paddy Transplanter for the Benefit of Small Farmers' Land Holdings. *Current Journal of Applied Science and Technology*, 1. doi: https://doi.org/10.9734/cjast/2019/v38i630462

Cantor A.B (1996). Sample-size calculations for Cohen's kappa. Psychological methods 1(2) p. 150. doi: https://psycnet.apa.org/doi/10.1037/1082-989X.1.2.150

Congedo, L. (2021). Semi-Automatic Classification Plugin: A Python tool for the download and processing of remote sensing images in QGIS. *The Journal of Open-Source Software*, *6*(64), 3172. doi: https://doi.org/10.21105/joss.03172

Copernicus Data Space Ecosystem. (2026). Sentinel-2 | Copernicus Data Space Ecosystem. European Space Agency. Retrieved from https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-missions/sentinel-2

Cubillas, J. E., Torculas, R., Mayol, J., & Bajao, P. J. (2024). Land Classification Plugin for QGIS Using Pix2Pix. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 33. doi: https://doi.org/10.5194/isprs-annals-x-5-2024-33-2024

Deichmann, U., Goyal, A., & Mishra, D. K. (2016). Will digital technologies transform agriculture in developing countries? *Agricultural Economics*, *47*, 21. doi: https://doi.org/10.1111/agec.12300

Di Gregorio A, Jansen L.J (1998). A new concept for a land cover classification system. Available at: The Land 2(1) 55-65.

Ennouri, K., Smaoui, S., & Triki, M. A. (2021). Detection of Urban and Environmental Changes via Remote Sensing [Review of *Detection of Urban and Environmental*

Changes via Remote Sensing]. *Circular Economy and Sustainability*, *1*(4), 1423. Springer Nature. doi: https://doi.org/10.1007/s43615-021-00035-y

Fosse E, Johnsen S.H, Stensland-Bugge E, Joakimsen O, Mathiesen E.B, Arnesen E, Njølstad I (2006). Repeated visual and computer-assisted carotid plaque characterization in a longitudinal population-based ultrasound study: the Tromsø study. Ultrasound in medicine & biology 32(1) 3-11. doi: https://doi.org/10.1016/j.ultrasmedbio .2005.09.006

Giuggioli, G., & Pellegrini, M. M. (2022). Artificial intelligence as an enabler for entrepreneurs: a systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behaviour & Research*, *29*(4), 816. doi: https://doi.org/10.1108/ijebr-05-2021-0426

Haque S.A, (2006). Salinity problems and crop production in coastal regions of Bangladesh. Pakistan Journal of Botany 38(5) 1359-1365. Available at: www.pakbs.org/pjbot/ PDFs/38(5)/PJB38(5)1359.pdf

Islam, M. A., Sarkar, M. A. R., Rahman, M. C., & Rahaman, Md. S. (2021). Comparative Advantage of Rice Production in Bangladesh: A Long-term Quasi-Response Assessment for Aman (Wet) Season. *Fundamental and Applied Agriculture*, 1. doi: https://doi.org/10.5455/faa.82109

Islam, M., Hossain, A., Timsina, J., Saif, H. B., Sarker, M. M. R., Khan, A. S., Hasan, Md. K., Zahan, T., Sabagh, A. E., Akdeniz, H., & Barutçular, C. (2021). Feasibility and financial viability study of an intensive mustard-mungbean-transplanted Aus Rice-transplanted Aman Rice cropping system in a non-saline ecosystem of Bangladeh. Philippine Agricultural Scientist. Available at: https://www.ukdr.uplb.edu.ph/journal-articles/3981

Jamal, M. R., Kristiansen, P., Kabir, M. J., & Bruyn, L. L. de. (2023). Challenges and Adaptations for Resilient Rice Production under Changing Environments in Bangladesh. *Land*, *12*(6), 1217. doi: https://doi.org/10.3390/land12061217

Li, Y., Ring, J. K., Jin, D., & Bajaba, S. (2025). *Elevating entrepreneurship with generative artificial intelligence*. doi: https://doi.org/10.1016/j.jik.2025.100820

Mainuddin, M., Alam, Md. M., Maniruzzaman, M., Kabir, Md. J., Mojid, M. A., Hasan, M. M., Schmidt, E., & Islam, Md. T. (2021). Yield, profitability, and prospects of irrigated Boro rice cultivation in the North-West region of Bangladesh. *PLoS ONE*, *16*(4). doi: https://doi.org/10.1371/journal.pone.0250897

Mamun, M. N. H., Nihad, S. A. I., Sarker, M. R., Sarkar, M. A. R., Hossain, Md. I., & Kabir, M. (2024). Spatiotemporal mapping of rice acreage and productivity growth in Bangladesh. *PLoS ONE*, *19*(3). doi: https://doi.org/10.1371/journal.pone.0300648

Matinfar H.R, Sarmadian F, AlaviPanah S.K, Heck R.J (2007). Comparisons of object-oriented and pixel-based classification of land use/land cover types based on Lansadsat7, Etm+ spectral bands (case study: arid region of Iran). American-Eurasian Journal of Agricultural & Environmental Sciences 2(4) 448-456.

Landis JR, Koch GG (1977). The measurement of observer agreement for categorical data. Biometrics 33 159–174. Available at: https://jjcurtin.github.io/book_iaml/pdfs/ landis_1977_kappa.pdf

Pattnaik, P. K., Kumar, R., & Pal, S. (2022). *Internet of Things and Analytics for Agriculture, Volume 3*. doi: https://doi.org/10.1007/978-981-16-6210-2

Peramaiyan, P., Singh, K. P., Borgohain, R., Khandai, S., Varkey, L. M., Kumar, V., Kumar, V., Pathak, K., Kumar, V., Singh, S. S., Bhattacharya, A. K., & Kumar, V. (2023). Submergence-tolerant rice varieties and mechanical transplanting for intensification of rice-rice cropping systems in Assam. *Farming System*, *2*(1), 100068. doi: https://doi.org/10.1016/j.farsys.2023.100068

Pontius Jr R.G, Millones M (2011). Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. International Journal of Remote Sensing 32(15) 4407-4429. doi: https://doi.org/10.1080/01431161.2011.552923

QGIS Development Team. (2026). QGIS Geographic Information System (Version 3.10.0-A Coruña). Open-Source Geospatial Foundation Project. http://qgis.osgeo.org

Rahaman, H., Rahman, Md. M., Islam, A., Huda, Md. D., & Kamruzzaman, M. (2022). Mechanical Rice Transplanting in Bangladesh: Current Situation, Technical Challenges, and Future Approach. *Journal of Biosystems Engineering*, *47*(4), 417. doi: https://doi.org/10.1007/s42853-022-00161-x

Rahman, Md. B., Chakma, J. D., Momin, A., Islam, S., Uddin, Md. A., Islam, Md. A., & Aryal, S. (2023). Smart Crop Cultivation System Using Automated Agriculture Monitoring Environment in the Context of Bangladesh Agriculture. *Sensors*, *23*(20), 8472. doi: https://doi.org/10.3390/s23208472

Rashid, M., Goswami, P. C., Hossain, Md. F., Mahalder, D., Rony, M. K. I., Shirazy, B. J., & Russell, T. D. (2018). Mechanised non-puddled transplanting of boro rice following mustard conserves resources and enhances productivity. *Field Crops Research*, *225*, 83. doi: https://doi.org/10.1016/j.fcr.2018.06.006

Saha, C. K., Sarkar, S., & Alam, Md. M. (2022). Synchronized paddy cultivation using mechanical rice transplanting technology in Bangladesh. American Society of Agricultural and Biological Engineers conference, *2022 Houston, Texas July 17-20, 2022*. doi: https://doi.org/10.13031/aim.202200245

Sarangi, S. K., Mainuddin, M., Maji, B., Mahanta, K. K., Digar, S., Burman, D., Mandal, U. K., & Mandal, S. (2021). Optimum Sowing Date and Salt Tolerant Variety Boost Rice (Oryza sativa L.) Yield and Water Productivity during Boro Season in the Ganges Delta. *Agronomy*, *11*(12), 2413. doi: https://doi.org/10.3390/agronomy11122413

Singh, G., Sharma, T. R., & Bockhop, C. W. (1985). Field performance evaluation of a manual rice transplanter. *Journal of Agricultural Engineering Research*, *32*(3), 259. doi: https://doi.org/10.1016/0021-8634(85)90083-6

Sridevy, S., Devi, M. N., & Sankar, S. M. (2023). Decision support systems in agricultural industry perspective. *International Journal of Statistics and Applied Mathematics*, *8*, 29. doi: https://doi.org/10.22271/maths.2023.v8.i2sa.984

Tesfaye, W., Elias, E., Warkineh, B., Tekalign, M., & Abebe, G. (2024). Modeling of land use and land cover changes using google earth engine and machine learning approach: implications for landscape management. *ENVIRONMENTAL SYSTEMS RESEARCH*, *13*(1). doi: https://doi.org/10.1186/s40068-024-00366-3

Tottrup C, Rasmussen M.S (2004) Mapping long-term changes in savannah crop productivity in Senegal through trend analysis of time series of remote sensing data. Agriculture, Ecosystems & Environment 103(3) 545-560. doi: doi: https://doi.org/10.1016/j.agee.2003.11.009

U.S. Geological Survey (USGS). (2026). EarthExplorer. U.S. Department of the Interior. https://earthexplorer.usgs.gov/

Vanza, J., Dave, K., & Siddhapura, M. (2024). Integrating Technology and Agriculture with Advanced Machinery. *International Journal for Research in Applied Science and Engineering Technology*, *12*(5), 53. doi: https://doi.org/10.22214/ijraset.2024.61394

Yuan, J., & Huang, Z. (2024). Intelligent Agricultural Machinery and Robots: Embracing Technological Advancements for a Sustainable and Highly Efficient Agricultural Future. *Agriculture*, *14*(12), 2150. doi: https://doi.org/10.3390/agriculture14122150

Zhang, A.-G., Tariq, A., Quddoos, A., Naz, I., Aslam, R. W., Barboza, E., Ullah, S., & Abdullah-Al-Wadud, M. (2025). Spatio-temporal analysis of urban expansion and land use dynamics using google earth engine and predictive models. *Scientific Reports*, *15*(1), 6993. doi: https://doi.org/10.1038/s41598-025-92034-4

Zhang, C., & Li, X. (2022). Land Use and Land Cover Mapping in the Era of Big Data. *Land*, *11*(10), 1692. doi: https://doi.org/10.3390/land11101692

Zhao, Y., Abdelkareem, M., & Abdalla, F. (2024). Remote sensing and GIS techniques in Monitoring and mapping Land System Change in semi-arid environments. *Environmental Earth Sciences*, *83*(13). https://doi.org/10.1007/s12665-024-11706-y