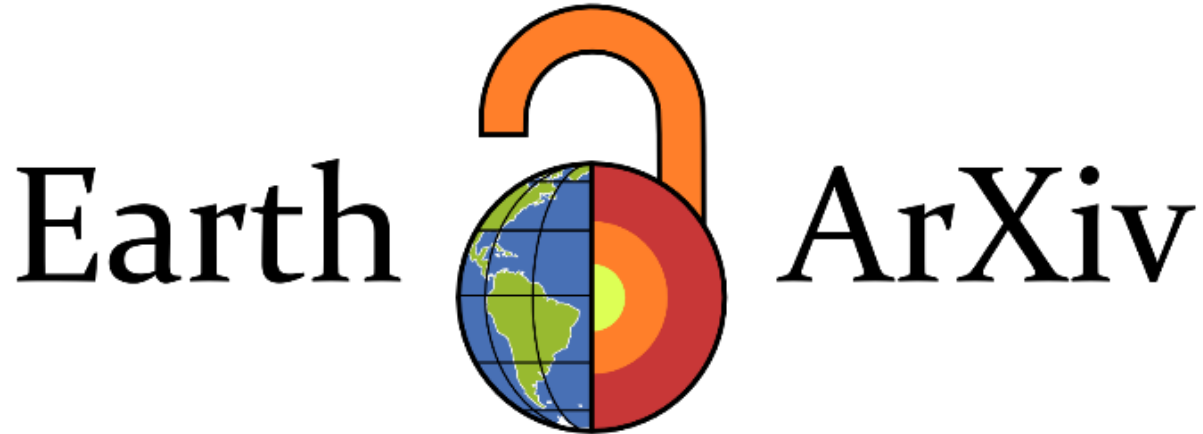




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Synergistic Use of Multitemporal SAR and Optical Data with Random Forest Approach for Rice Mapping in Bangladesh

Abstract: Accurate in-season crop mapping is vital for national food security, yet traditional ground-based estimation methods in Bangladesh often lack precision. This study develops a robust machine-learning framework to map Boro rice in the Manikganj district by integrating Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical imagery. To overcome the challenge of seasonal cloud cover, Sentinel-1 VH polarization was utilized to identify unique backscatter reductions during the transplantation phase (late February to early March) caused by specular reflection from flooded fields. By combining these SAR signatures with high-resolution spectral indices (NDVI, EVI, and BSI) from Sentinel-2 during peak growth stages, the research captures the distinct phenological signatures of paddy rice. A pixel-based Random Forest algorithm was applied within the Google Earth Engine (GEE) platform, utilizing about 200 field-verified reference points per sub-district (1,385 in total) for training and validation. The results demonstrated high classification performance, with overall accuracies ranging from 88.1% to 94.9% across the seven sub-districts. Furthermore, a comparison with official government statistics revealed a minimal total area difference of only 2.34%, underscoring the reliability of this integrated satellite approach for operational crop monitoring.

1. Introduction

The agricultural sector is the fundamental pillar of the Bangladesh economy, employing about 45% of the national labor force [1] and supporting the roughly 60% of the population that resides in rural areas. Although its share of national output has declined as the economy has industrialized, agriculture still contributes about 11% of GDP [2]. Although 42% of the country consists of potentially irrigable land with favorable soil conditions, production remains heavily dependent on weather patterns.

Within this landscape, rice is the nation's most valuable commodity and primary staple, making Bangladesh the world's third-largest producer [3]. Rice continues to dominate the crop sub-sector, both in cultivated area and in the diet of the population. To ensure national security and independence from unreliable external supplies, successive governments have prioritized food grain self-sufficiency, making it the foundation of all national agricultural strategies.

However, maintaining this self-sufficiency is increasingly challenged by environmental and demographic pressures. Rice production is becoming highly vulnerable to the impacts of climate change, with Bangladesh facing a range of threats including unpredictable rainfall, temperature extremes, increased salinity, droughts, and devastating floods [4]. These climate-related factors, compounded by the loss of agricultural lands due to overpopulation, risk reducing crop yields by up to 30%. While climate-related factors pose a severe threat, the accurate monitoring of these vulnerabilities is becoming a global priority for maintaining food stability. Earth Observations (EO) play a critical role in supporting food security by providing objective data to manage agricultural risks at scale [5].

To ensure food security, precise in-season assessments of rice area and yields are vital for informing evidence-based policies regarding exports and import requirements [5]. While traditional field-based sampling and eye-estimation were used historically, modern challenges require more robust methodologies. Remote sensing provides a sophisticated framework to accurately map the spatial distribution and dynamics of rice cultivation across the country's diverse sub-districts. At the national level, the Bangladesh Bureau of Statistics (BBS) is officially responsible for crop area estimation and has traditionally relied on conventional methodologies, such as eye-estimation and manual crop-cut surveys [6]. These statistical approaches are often cumbersome, inefficient, and labor-intensive, requiring extensive manual field data collection and significant post-processing before reliable statistics can be released, delays that hinder modern disaster risk management and timely food policy planning. To address these limitations, the Department of Agricultural Extension (DAE) is strengthening the national estimation process by operationalizing Earth Observation technologies. Using Google Earth Engine for land cover classification provides high efficiency and accuracy for national-level agricultural assessments [7], and a key driver of this modernization is the partnership between DAE and the International Centre for Integrated Mountain Development (ICIMOD) under the SERVIR Hindu Kush Himalaya (SERVIR-HKH) initiative.

Previous research has demonstrated the value of EO for rice mapping along three main lines. SAR-based methods exploit the sensitivity of C-band backscatter to flooded soils and canopy structure: multi-temporal SAR captures the sharp drop in backscatter at transplantation caused by specular reflection from standing water, followed by a rise with canopy volume scattering [8–10], and operational demonstrations across Asia and the Mekong Delta have confirmed the reliability of C-band SAR, including Sentinel-1, for rice monitoring [11–13]. Optical-based methods instead track vegetation indices through the growing season: time-series NDVI and related indices from optical sensors such as MODIS reveal the transplanting, vegetative, and senescence stages that distinguish paddy rice from other crops, and phenology-based algorithms implemented in Google Earth Engine have mapped paddy rice across Northeast Asia at continental scale [14–16]. A third line of work fuses the two sensor types, combining the cloud-penetrating capacity of SAR with the high spatial and spectral resolution of optical imagery, which has been shown to outperform either sensor alone in humid tropical deltas [17–19].

Despite this progress, three gaps remain, particularly for operational national use in Bangladesh. First, most fusion studies are experimental in nature: they demonstrate a method for a single season but are seldom validated against official national statistics, so their utility for food balance-sheet preparation is unknown. Second, operational deployment inside a government agency with field staff collecting training data, standard quality control, and a dissemination platform usable by planners is rarely reported. Third, the smallholder, fragmented field structure of rural Bangladesh places specific demands on sampling design and classifier configuration that generic studies do not address.

Beyond these operational gaps, several broader challenges remain open in the Bangladesh literature. Most prior studies are geographically restricted to small pilot areas and lack validation across the country's diverse agro ecological zones, such as the coastal saline belt, haor wetlands, and hilly terrains, leaving the regional transferability of these frameworks largely untested. Existing rice mapping efforts also predominantly focus on Boro rice, while the Aman and Aus varieties, which collectively contribute nearly half of national rice production, remain insufficiently mapped, particularly due to persistent monsoon cloud contamination. Furthermore, most studies rely on single year datasets, limiting the ability to capture inter annual variability, climate driven phenological shifts, and long-term cropping pattern dynamics. Additionally, the full polarimetric potential of Sentinel 1, including VV polarization, VH/VV ratios, and SAR texture features remains underutilized, and integration with ancillary datasets such as climate variables, soil moisture, and topographic data is rarely attempted. Finally, current frameworks largely stop at area estimation, with limited progress toward yield prediction, uncertainty quantification, feature importance analysis, and adaptive phenology detection. The present study does not try to solve all of these broader challenges; it focuses on the three operational gaps identified above, and the remaining challenges are discussed as limitations and future work in Section 6.3.

This study addresses the three operational gaps through three objectives: (1) to develop and validate a Random Forest framework that fuses multi-temporal Sentinel-1 SAR and Sentinel-2 optical data for in-season Boro rice mapping at 10 m resolution in the Manikganj district; (2) to evaluate the framework quantitatively against independently collected field data and against official BBS area statistics; and (3) to package the workflow in the RiceMapEngine, a web-based application designed for operational use by the Department of Agricultural Extension. The novelty of the work lies not in a new algorithm but in the end-to-end operational demonstration stratified field sampling by extension officers, a validated multi-sensor classification, agreement with official statistics within 2.34%, and a delivery platform aligned with institutional practice which provides a replicable model for satellite-based crop statistics across Bangladesh.

2. Study Area

Manikganj is a strategically significant district located in central Bangladesh within the Dhaka Division. Spanning an area of approximately 1,384 km², the district is administratively divided into seven sub-districts (Upazilas): Manikganj Sadar, Saturia, Singair, Shibalaya, Harirampur, Ghior, and Daulatpur. Agriculture serves as the primary economic mainstay for the local population. The district's land-use pattern is characterized by high intensity, with nearly 50% of the total cultivated land undergoing double cropping, while 40% is dedicated to single cropping, and the remainder is utilized for triple cropping or other agricultural activities.

The region follows a distinct seasonal crop cycle. Table 1 outlines the phenological periods from sowing to harvesting for the five predominant crops that define the agricultural landscape of Manikganj.

Table 1: Phenological cycle of major crops in Manikganj District

Crop Type	Sowing/Transplanting	Harvesting	Remarks
Mustard	November	January	Major oilseed
Wheat	November	February	Winter cereal
Maize	November	March	High-yield fodder/grain
Boro Rice	February	June	Primary dry-season crop
Aman Rice	June	October	Monsoon-dependent crop

During the dry season (February–June), Boro rice is the dominant cultivar. According to the Bangladesh Rice Research Institute (BRRI), Boro rice is the most critical rice variety in the country, contributing to more than 50% of the total national rice production. Furthermore, the role of Boro rice extends beyond production targets to national food availability. Addressing the yield gap in Boro rice is a primary strategy for feeding a bigger Bangladesh in the coming decades [20, 21]. The importance of this crop is reflected in the district's recent performance; in the latest agricultural cycle, Manikganj exceeded its annual cultivation target of 49,000 hectares by an additional 775 hectares. This expansion underscores the district's vital role in contributing to the national foodgrain surplus and highlights the necessity for accurate, satellite-based monitoring to manage these high-intensity production zones. Field data points shown in Figure 1.

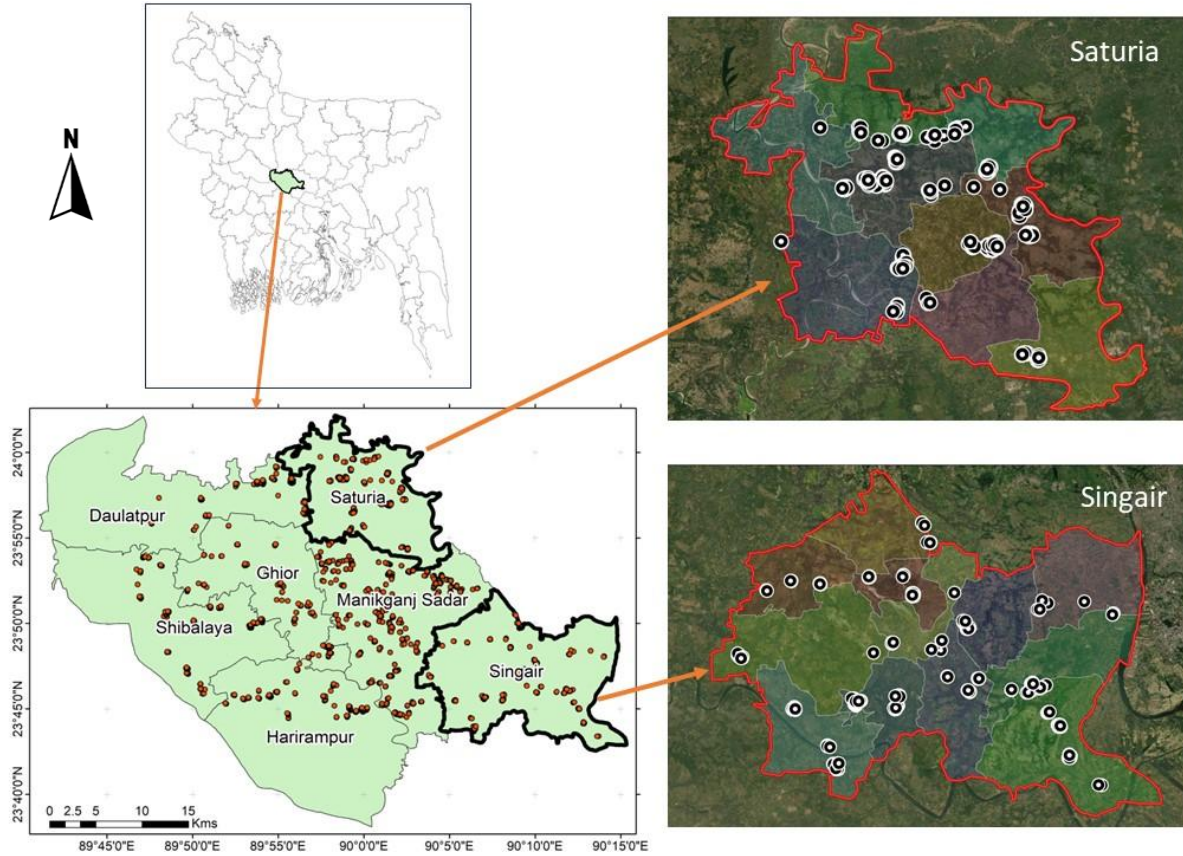


Figure 1: Field data points collected from the 7 sub-districts of Manikganj.

3. Materials and Methods

3.1 Experimental and Technical Design

The methodological framework for mapping Boro rice follows a structured workflow designed to integrate multi-source satellite data with field-based observations. The process begins with the preparation of ground-truth reference data, which is essential for training and validating the machine learning models. A critical preliminary step is the application of an agricultural mask: the **ESA Worldcover 10 m v200 product** (reference year 2021) [22] was used to extract the cropland extent of Manikganj. Because the reference year (2021) precedes the study season (2023), the stability of the mask was assessed: cropland change in central Bangladesh over this interval is dominated by gradual built-up encroachment rather than cropland gain or loss, and any residual change is confined to non-crop classes excluded by the mask, so it cannot inflate the rice area estimate. This masking process isolates potential croplands, thereby reducing spectral noise from non-agricultural features such as water bodies, forests, and urban infrastructure.

The core of the classification strategy relies on a synergistic analysis of both optical and radar satellite data to capture the unique phenological stages of Boro rice. **Sentinel-1 (SAR)** backscatter values are utilized to analyze crop growth stages, with a specific focus on the transplantation period. During this time, the specular reflection from flooded paddy fields creates a distinct radar signature that allows for the identification of rice-planting activities, even under heavy cloud cover. Simultaneously, **Sentinel-2** optical imageries are processed to derive key vegetative indices, including the **Normalized Difference Vegetation Index (NDVI)**, **Enhanced Vegetation Index (EVI)**, and **Bare Soil Index (BSI)**. These indices are used to map the crop's phenology during its peak vegetative and reproductive stages.

By collectively analyzing Sentinel-1 data from the transplantation and harvesting windows alongside Sentinel-2 signatures from the growing period, the model can effectively differentiate Boro rice from other vegetation types. The final outputs are validated using the 30% hold-out field samples, and crop area estimation is derived through pixel-count analysis based on the 10m spatial resolution. To ensure the practical utility of this research, the framework is operationalized through the **RiceMapEngine**, a customized web-based GIS application designed for the dissemination of high-resolution crop statistics to agricultural stakeholders. Figure 2 shows the overall methodology.

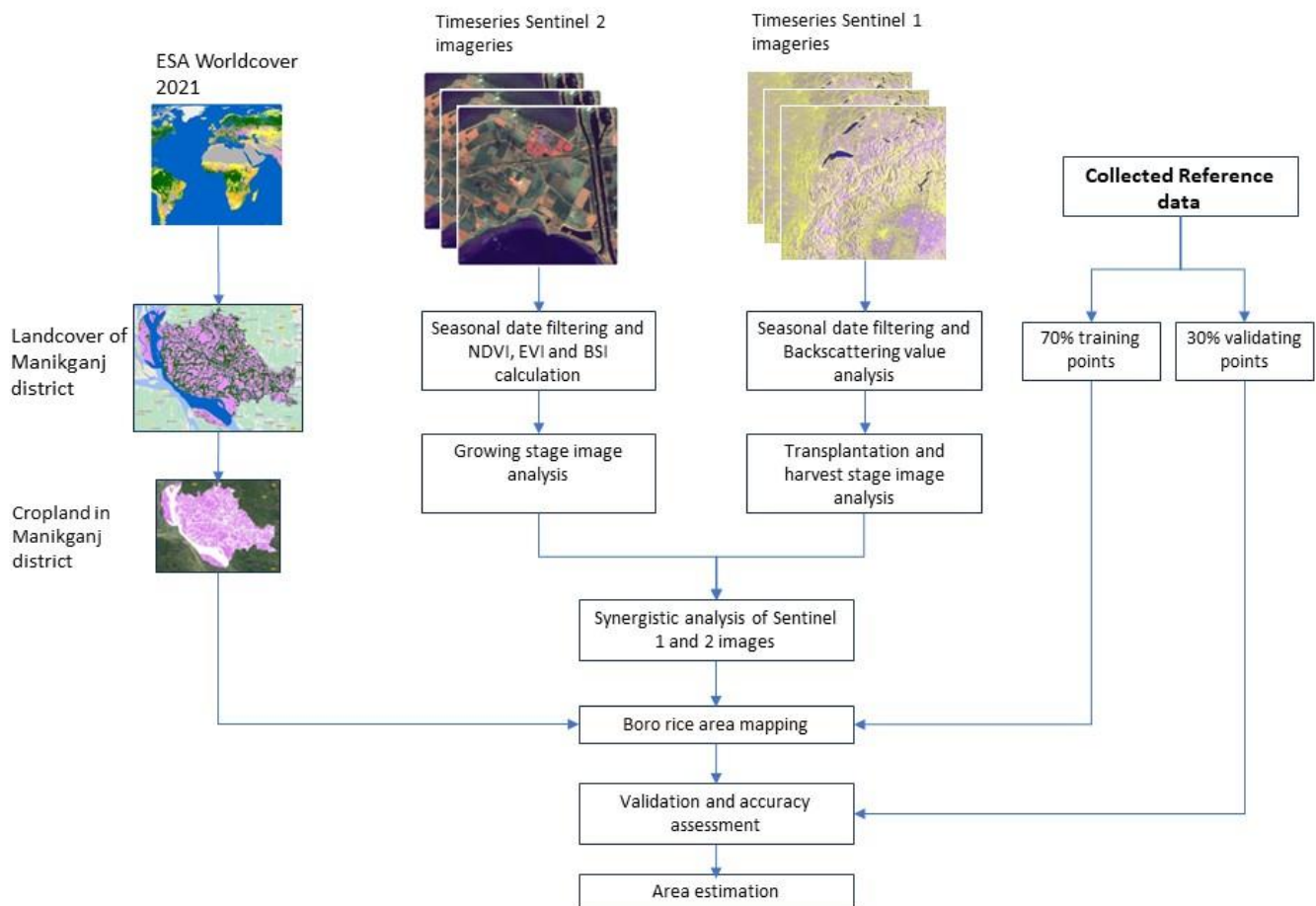


Figure 2: Flowchart of the methodology

3.2 Reference Data Preparation

Robust remote sensing-based crop mapping is highly dependent on the quality and quantity of ground-truth reference data. The sampling followed a stratified design: within each sub-district, upazila-level agricultural maps and the previous season's crop statistics were used to divide the area into strata dominated by the major land cover and crop types, and reference points were then located purposively inside contiguous fields of at least 0.4 ha, with the number of points per stratum proportional to its approximate areal share, so that all classes were represented in proportion to their occurrence across the district. The design is stratified-purposive rather than random, because the operational objective was to characterize every land cover class adequately rather than to estimate class areas from the sample; classification accuracy, not sample-based area estimation, is the product of the sampling. For this study, approximately 200 usable field points for each upazila were used across each sub-district using Geofairy, a specialized mobile application designed for geospatial data acquisition as shown in Table 2.

Table 2: No. of useable points used for this research

Upazila	Field points
Sadar	192
Saturia	154
Ghior	162
Daulatpur	173
Shibalaya	252
Harirampur	192
Singair	260

To ensure data integrity, a comprehensive training program was conducted for 60 agricultural extension officers from the seven sub-districts of Manikganj. These officers were tasked with collecting field data according to a strict set of technical criteria:

Points were required to be situated within croplands with a minimum contiguous area of 0.4 hectares to align with satellite resolution, and data collection was strategized to ensure points were distributed representatively across the diverse landscapes of the Manikganj sub districts. To avoid “edge effects” and mixed pixel contamination, all points were collected at a minimum depth of 20–30 meters inside the field boundaries. Furthermore, samples were gathered from various vegetation and land cover types to provide the model with sufficient contrast between rice and non-rice classes.

Following the collection phase, the raw dataset underwent a rigorous quality assurance and data-cleaning process. This involved a cross-comparison of field-recorded coordinates with high-resolution **Google Earth** imagery and site photographs. Points found to be erroneously placed outside crop boundaries were either adjusted or removed to maintain the purity of the training set. Finally, the cleaned reference points were randomly partitioned into two independent subsets: **70%**

of the samples were allocated for training the supervised machine learning algorithm, while the remaining **30%** were reserved for the final validation and accuracy assessment.

Reference classes and class balance. Field points were recorded under six reference classes: Boro rice, fallow land, grass, maize, vegetables, and others (homestead vegetation, orchards and minor crops). The five main classes are used in Figures 3 and 5 to examine the spectral and backscatter separability of Boro rice during different phenological stages, particularly at transplantation and during subsequent crop growth. After field data quality control, the final number of points per upazila ranged from 154 to 260 (Table 2). Because the operational aim of the Department of Agricultural Extension is the net Boro rice area, the non-rice classes were merged for the final map, which is reported with three classes: Boro rice, Other vegetations, and Water bodies (Figures 7 and 8). Open water was not one of the field-recorded classes, so water body samples were added by visual interpretation of very high resolution Google Earth imagery and checked against their Sentinel-1 VH backscatter. Points were allocated to classes in proportion to their approximate areal share in each sub-district, so Boro rice, the dominant dry season crop, made up the largest share of the points (about 55–65%), while the remaining points were spread across the competing crops and fallow land to give representative non-rice samples. Class imbalance was limited in three ways: the ESA WorldCover cropland mask removed non-agricultural classes (urban areas, forest and permanent water) before classification (Section 3.3.3); the 70/30 split was drawn from this class-proportional sample, so the validation set keeps approximately the same class ratios as the training set; and the bootstrap sampling of Random Forest handles moderate imbalance without synthetic oversampling. Class-wise producer's and user's accuracies of the Boro rice class, derived from the error matrix of each sub-district, are reported in Table 3, so that the effect of class imbalance on the rice class can be checked directly.

3.3 Satellite Data Preparation

In this remote sensing-based study for Boro rice area mapping, a multi-sensor approach was adopted, utilizing both **Sentinel-1 Radar** and **Sentinel-2 Optical** imageries. The selection of data was strategically aligned with the Boro rice phenological cycle (January to July), covering the entire duration from land preparation and transplantation to peak vegetative growth and eventual harvest. Accurate temporal alignment is critical in remote sensing, as it allows for the construction of time-series signatures that differentiate specific crop types based on their unique growth patterns.

3.3.1 Sentinel-1 Synthetic Aperture Radar (SAR) Data

Sentinel-1 operates as an active sensor providing dual-polarization C-band SAR data at a frequency of 5.405 GHz. For this research, Ground Range Detected (GRD) scenes which are pre-calibrated and ortho-corrected were utilized. The operational capabilities of the Sentinel-1 mission, including its systematic acquisition and high revisit frequency, make it a cornerstone for modern environmental monitoring [23]. Pre-processing in GEE followed the standard GRD workflow: thermal noise removal, radiometric calibration to sigma-nought, and terrain correction using the SRTM digital elevation model. Speckle was reduced through multi-temporal compositing, the median of the available acquisitions within each phenological compositing window which is more

effective than spatial filtering for time-series crop classification because it suppresses speckle while preserving the temporal signal. To guarantee a consistent incidence-angle geometry across the time series, only descending-orbit acquisitions were used; mixed-orbit time series were avoided because incidence-angle differences alter backscatter independently of crop state.

The primary advantage of Sentinel-1 is its "all-weather" capability; unlike optical sensors, SAR can penetrate thick cloud cover, which is frequent during the early stages of the Boro season. SAR data is highly sensitive to the physical structure of plants and the dielectric properties of the surface (such as water content). The sensitivity of SAR to plant structure and water conditions is well-documented. Multi-temporal C-band SAR is highly effective at capturing rice-plant variables, providing the physical basis for detecting flooded transplantation stages [9].

To overcome the challenge of seasonal cloud cover, a time-series of **VH (Vertical-Horizontal) polarization** was fetched directly from the **Google Earth Engine (GEE)** image collection. The backscatter coefficients were extracted for each field reference point and analyzed to identify the "specular reflection" signature a sharp drop in backscatter that occurs during the transplantation phase when fields are flooded. During this period, the transition from bare soil to flooded fields creates specular reflection, resulting in a significant reduction in backscatter [12, 13].

3.3.2 Sentinel-2 Optical Data and Vegetative Indices

Sentinel-2 provides high-spatial-resolution (10–20 m) multi-spectral imagery with a high revisit frequency. For this study, a time-series of cloud-free images (defined by a <30% cloud cover threshold) was acquired through GEE for the January–July window. To capture the spectral characteristics of the Boro rice canopy, three primary vegetative indices were calculated from the Sentinel-2 imagery, including the Normalized Difference Vegetation Index (NDVI) [14], the Enhanced Vegetation Index (EVI) [24], and the Bare Soil Index (BSI) [25].

- **Normalized Difference Vegetation Index (NDVI):** This index is the standard for quantifying vegetation greenness and density. It is calculated as the normalized ratio between the Near-Infrared (NIR) and Red bands (Equation 1):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where NIR and Red are the surface reflectance of Sentinel-2 Band 8 (near infrared) and Band 4 (red), respectively.

NDVI is instrumental in monitoring the biomass accumulation and general health of the rice crop throughout the growing season.

- **Enhanced Vegetation Index (EVI):** To address the limitations of NDVI, such as atmospheric noise and saturation in high-biomass regions, EVI was calculated.

It is computed with Equation (2):

$$EVI = G \times \frac{NIR - Red}{NIR + C_1 \times Red - C_2 \times Blue + L} \quad (2)$$

where $G = 2.5$ is the gain factor; $C_1 = 6$ and $C_2 = 7.5$ are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band; $L = 1$ is the canopy background adjustment, which accounts for non-linear, differential NIR and red radiant transfer through the canopy; and Blue is the surface reflectance of Sentinel-2 Band 2. NIR and Red are as defined for Equation (1).

- EVI provides a more sensitive signal in the dense canopy stages of Boro rice, effectively de-coupling the background soil signal from the vegetation.
- **Bare Soil Index (BSI):** This numerical indicator combines Blue, Red, NIR, and Short-Wave Infrared (SWIR) bands to capture soil variations. It is particularly useful during the pre-planting and post-harvest stages and is computed with Equation (3):

$$BSI = \frac{(SWIR + Red) - (NIR + Blue)}{(SWIR + Red) + (NIR + Blue)} \quad (3)$$

where SWIR is the surface reflectance of Sentinel-2 Band 11 (short-wave infrared, 20 m, resampled to 10 m), and the other bands are as defined for Equations (1) and (2).

NDVI and EVI quantify canopy greenness and are low at transplantation, when water and soil remain visible between the young seedlings; they rise steeply through tillering and vegetative growth, peak at flowering, and decline as the canopy senesces before harvest. BSI behaves inversely: it is high during land preparation and after harvest, when soil is exposed, and low under a closed canopy. In combination, NDVI and BSI therefore separate fallow land from actively growing rice fields, while EVI remains sensitive in the dense-canopy stages where NDVI saturates. These index trajectories, together with the VH backscatter trajectory described in Section 3.3.1, constitute the phenological signature that the classifier learns. We note that atmospheric-correction algorithms such as FLAASH correct aerosol effects but do not remove clouds: where the sensor never observed the ground, no optical method can recover surface reflectance. The workflow therefore applies rigorous cloud masking (the QA60 cloud mask in GEE) to retain only cloud-free pixels for the indices, and relies on Sentinel-1 SAR for the cloudy transplantation and late-season windows, the central design choice of this study.

3.3.3 Agricultural Land Masking

To ensure high classification accuracy and minimize spectral confusion, the **ESA Worldcover 10m** dataset was utilized to extract the specific cropland extent of Manikganj [22]. This extracted layer served as a robust agricultural land mask. By restricting the machine learning analysis solely to these areas, the study prevented misclassifications that often arise from non-crop features such as evergreen forests, urban built-up areas, and permanent water bodies which may occasionally exhibit temporal dynamics similar to those of rice during its various growth phases. This masking

process refined the Area of Interest (AOI) and significantly improved the reliability of the final area estimations.

3.4 Crop Classification

The geospatial analysis and image processing for this study were conducted using the Google Earth Engine (GEE) cloud-based platform [26]. GEE provides a massive library of Earth observation data and the computational power required for planetary-scale analysis. To map crop extent, a pixel-based supervised **Random Forest (RF) machine-learning algorithm** was applied within the **Google Earth Engine (GEE)** environment. This classification utilized a synergistic integration of Sentinel-1 and Sentinel-2 datasets, covering the entire phenological cycle from sowing to harvest. The RF approach is an ensemble learning technique that constructs a multitude of decision trees during the training phase. Random Forest was selected over alternative supervised algorithms for four reasons. First, comparative benchmarks consistently show RF matching or exceeding support vector machines and shallow neural networks for optical/SAR crop classification with limited training data, while requiring no feature scaling and few hyperparameters [27, 28]. Second, RF provides an internal out-of-bag (OOB) error estimate and per-variable importance, which SVM lacks. Third, gradient-boosting and deep-learning architectures require substantially larger and better-balanced training sets together with careful tuning, which are impractical for a 1,385-point operational dataset collected by field officers. Fourth, RF is natively implemented and computationally efficient in GEE, a practical requirement for national-scale operational deployment.

The input feature stack per pixel comprised: (i) VH backscatter composites for the transplantation (late February–early March), peak vegetative (April), and harvest (June) windows and (ii) NDVI, EVI, and BSI medoid composites for the first half of March and the first and second halves of April, giving $p = 12$ input features (3 VH and 9 index features) stacked as bands of one 10 m image in GEE. Principal Component Analysis was not applied: RF ranks and splits on individual features, is insensitive to feature scaling and multicollinearity, and PCA would destroy the physical interpretability of the phenological features without improving accuracy. The RF was configured with 200 trees, $mtry = \lfloor \sqrt{p} \rfloor = 3$ variables per split, and a minimum leaf population of 1.

The **RF classifier** is an ensemble learning method that operates by generating individual trees using a bootstrap aggregating process, where each tree is built from a random subset of the training data. To ensure diversity and reduce correlation between the trees, the **RF model** selects a random subset of predictors typically defined as $\sqrt{p}$, where p represents the total number of input features to determine the optimal split at each node. By averaging the outputs of these independent trees, the model effectively minimizes variance and reduces the risk of overfitting compared to traditional decision tree methods [28, 29].

For the training and validation phase, the collected reference data was partitioned into a 70/30 ratio, where 70% of the samples were utilized to train the RF model enabling it to learn the distinct spectral and backscatter signatures of the target crops while the remaining 30% of the samples were held out for an independent accuracy assessment to rigorously validate the classifier's performance. The number of trees and $mtry$ were fixed through a sensitivity test in which the out-of-bag (OOB) error was computed for 50, 100, 200, 300 and 500 trees and for $mtry = 2, 3, 4$ and

6. The OOB error changed by less than 0.5 percentage points beyond 200 trees, and $mtry = 3$ gave the lowest error, so 200 trees and $mtry = 3$ were used [28]. To check that the accuracies do not depend on one particular train/validation split, a stratified 5-fold cross-validation was also run for each sub-district on the full reference set; the mean and standard deviation of the cross-validated overall accuracy are reported in Table 3, and the OOB error of the final models in Section 5.1.

3.5 Accuracy Assessment

Accuracy assessment is a critical phase in the remote sensing workflow, involving a quantitative evaluation of the classified output against independent reference data to determine the reliability of the resulting map. In this study, a multi-faceted validation approach was implemented to assess the performance of the machine learning classifier for Boro rice mapping. This assessment utilized two primary methodologies: statistical metrics derived from an error matrix and qualitative verification through multi-source ground truth data. The sub-district-level classification accuracy metrics (overall accuracy, Kappa coefficient, and producer's and user's accuracies of the Boro rice class) are reported in Table 3, and the comparison between satellite-derived acreage and official statistics is presented in Table 4.

3.5.1 Statistical Validation: Error Matrix and Cohen's Kappa Coefficient

The primary statistical tool used for validation is the **Error Matrix** (also known as a confusion matrix). This is a cross-tabulation table where rows represent the predicted classes from the classification model and columns represent the actual classes from the reference samples. This matrix provides a comprehensive view of classification performance, allowing for the calculation of several key parameters [30].

Among these metrics, Producer's Accuracy (PA) measures the probability that a certain land cover of an area on the ground is classified as such, indicating how well the classifier can identify specific classes (representing the error of omission). Conversely, User's Accuracy (UA) measures the probability that a pixel classified into a given category actually represents that category on the ground (representing the error of commission). Finally, Overall Accuracy (OA) represents the percentage of correctly classified pixels across all categories relative to the total number of validation samples.

While OA provides a general summary, it can be misleading if class distributions are uneven. Therefore, this study employed the Kappa coefficient to provide a more robust measure of classification quality. The Kappa coefficient accounts for the agreement occurring by chance, offering a more rigorous evaluation of the inter-class arrangement [31].

The Kappa coefficient (κ) is computed with Equation (4):

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad (4)$$

where P_o is the observed agreement, i.e., the proportion of validation samples on the diagonal of the error matrix (equal to OA), and P_e is the agreement expected by chance, computed

from the row and column totals of the error matrix as $P_e = \sum(n_{i+} \times n_{+i})/N^2$, where n_{i+} and n_{+i} are the row and column totals of class i and N is the number of validation samples. $\kappa = 1$ means complete agreement between the map and the reference data, and $\kappa = 0$ means agreement no better than chance.

3.5.2 Complementary Qualitative Verification

In addition to the quantitative accuracy assessment of Section 3.5.1, the classified map was examined qualitatively using the geo-tagged photographs collected with the Geofairy application and very high-resolution Google Earth imagery. These checks interpret they do not independently re-estimate the error matrix above: photographic evidence was used to resolve spectral ambiguities between rice and similar-looking winter crops at specific coordinates, and visual interpretation of field boundaries and land-use patterns in Google Earth confirmed that the mapped rice clusters match the agricultural landscape of the sub-districts as captured by the RiceMapEngine outputs.

4. Results

4.1 Phenological Analysis using Optical and Radar Time-Series

The classification of Boro rice relied on a detailed comparative analysis of the temporal profiles of rice versus other vegetation types, utilizing both **Sentinel-1 (SAR)** and **Sentinel-2 (Optical)** imageries [17].

4.1.1 Optical Phenology (Sentinel-2)

The temporal profile of the **Normalized Difference Vegetation Index (NDVI)** revealed distinct growth patterns. In **Figure 3**, the boxplot analysis shows that Boro rice exhibits a characteristically low NDVI value during late February and early March. This period corresponds to the transplantation phase, where the presence of water and soil at the surface results in a lower spectral response compared to established winter crops like mustard or wheat. As the crop enters its vegetative growth phase in April, the NDVI values for Boro rice increase significantly, reaching a peak that effectively differentiates it from other agricultural land covers. This phenological mapping approach is consistent with international research, such as the work by Dong et al. [16], who utilized phenology-based algorithms in Google Earth Engine to map paddy rice across Northeast Asia with high precision.

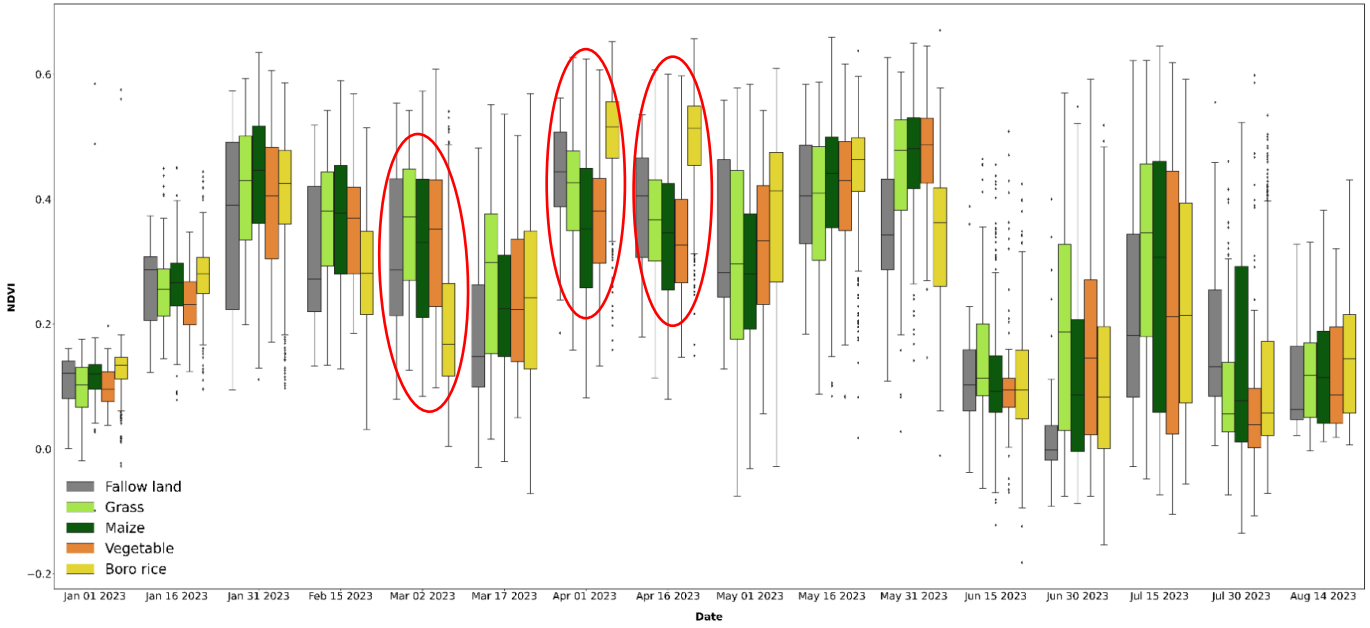


Figure 3: Boxplot showing the NDVI value from different agricultural fields. The dots represent the outliers in each event or date and the lines in the box are the median. The lower and upper edges of each box are the 25th and 75th percentiles, and the whiskers extend to the most extreme values that are not outliers. The red marker shows the increase in NDVI with the growth of the vegetation

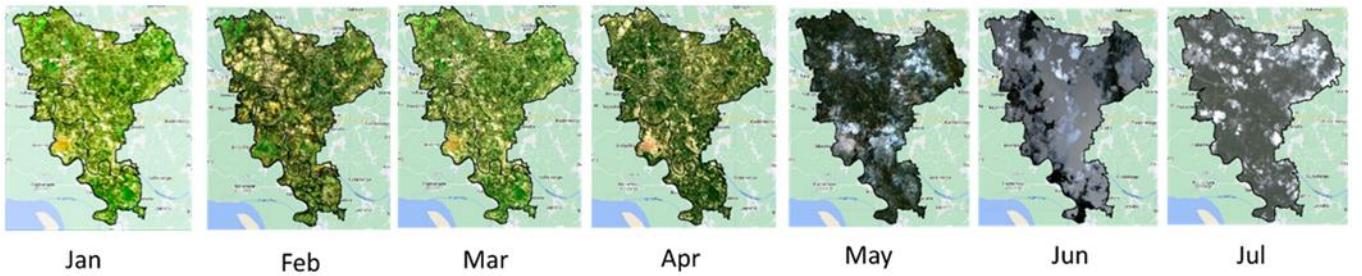


Figure 4: Sentinel 2 imageries from January to July 2023

A comparison between Figure 3 and Figure 4 highlights the limitations of optical data during the later months of the cycle. While Boro rice remains in the field through June and July, the Sentinel-2 imageries for this period are heavily contaminated by cloud cover, making indices unreliable. Consequently, the high-quality, cloud-free optical imageries from March and April were prioritized to calculate the vegetative indices required for the final classification model.

4.1.2 Radar Phenology (Sentinel-1)

Because Sentinel-1 is an active SAR sensor, it provided a robust temporal profile unaffected by the weather conditions that hampered optical data. The backscatter signatures shown in **Figure 5** illustrate the unique interaction between radar pulses and the rice canopy. During the transplanting phase (late February to early March), Boro rice displays significantly lower backscatter values

compared to other crops. This phenomenon is caused by **specular reflection**; the flooded fields act as a mirror, reflecting the majority of the incident radar energy away from the sensor [10].

Visually, this is represented in **Figure 6**, where transplanted rice fields appear as dark pixels within the agricultural landscape. This specific "water-on-land" signature is a primary indicator for identifying Boro rice. Previous research supports this, identifying SAR-based techniques as one of the most reliable options for monitoring rice phenology and water sources from local to global scales [11]. SAR data is particularly sensitive to variations in rice texture and flood conditions [8], and capturing the flood stage at the precise time of transplantation is essential for accurate identification [12]. Similar success in rice monitoring has been observed in other major deltas. Nguyen et al. [13] effectively used multi-temporal Sentinel-1 data in the Mekong Delta, mirroring the success of SAR-based identification used in this study for the Manikganj district.

As the crop reaches the reproductive and ripening stages, the backscatter values increase due to the volume scattering of the dense rice canopy. While the backscatter values of Boro rice and other vegetation types become more similar during the peak growing stage, a second window of differentiation occurs during the harvest period, which the Sentinel-1 sensor successfully captures despite seasonal cloud cover.

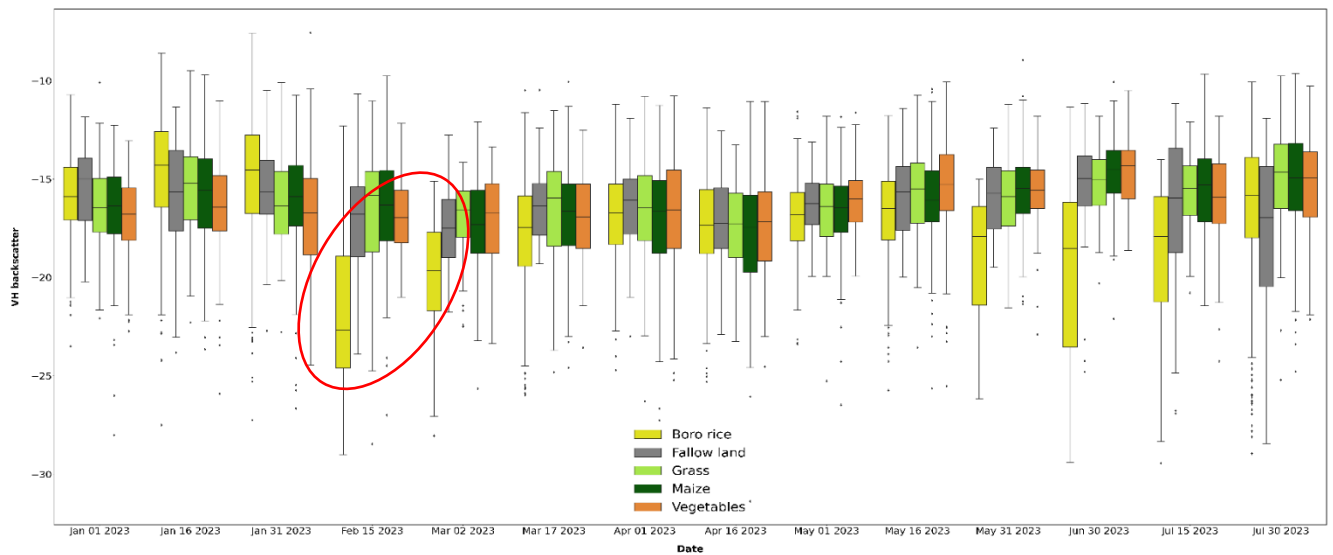


Figure 5: Boxplot showing the backscatter value from different agricultural fields. The dots represent the outliers in each event or date and the lines in the box are the median. The lower and upper edges of each box are the 25th and 75th percentiles, and the whiskers extend to the most extreme values that are not outliers. The red marker shows the increase in backscatter value with the growth of the vegetation

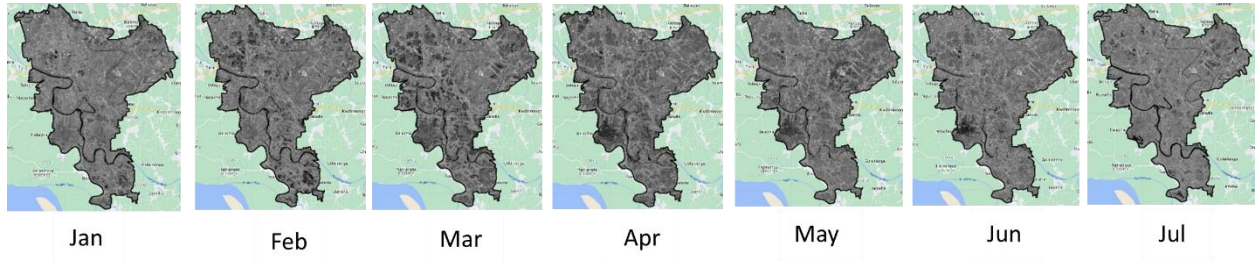


Figure 6: Sentinel 1 imageries from January to July 2023

4.2 Synergistic Classification and Area Estimation

By integrating the optical signatures from the peak vegetative growth stage with the SAR backscatter profiles from the transplantation and harvest periods, a highly accurate supervised classification was achieved. The synergistic use of these datasets allowed the model to overcome the individual limitations of each sensor specifically cloud cover for Sentinel 2 and spectral ambiguity for Sentinel 1 during mid-season. Using this integrated methodology, the spatial distribution of Boro rice across the Manikganj district was mapped with high resolution (10m). The final classification result is shown in Figure 7. Furthermore, Figure 8 presents detailed area distributions for each of the seven sub-districts: Manikganj Sadar, Saturia, Singair, Shibalaya, Harirampur, Ghior, and Daulatpur. This framework demonstrates that leveraging multi sensor temporal dynamics provides a superior basis for national agricultural statistics compared to traditional, non-spatial estimation methods.

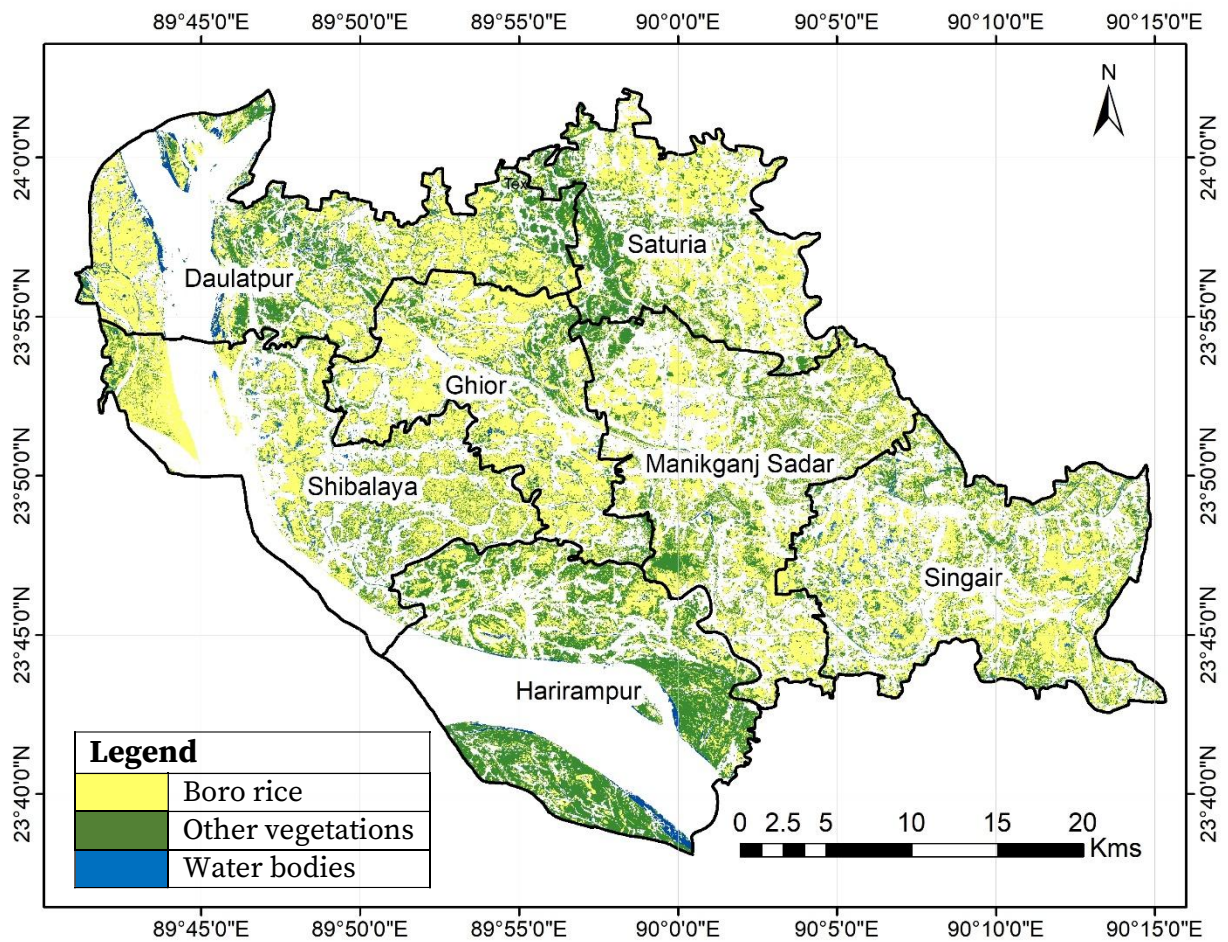


Figure 7: Boro rice area of Manikganj district

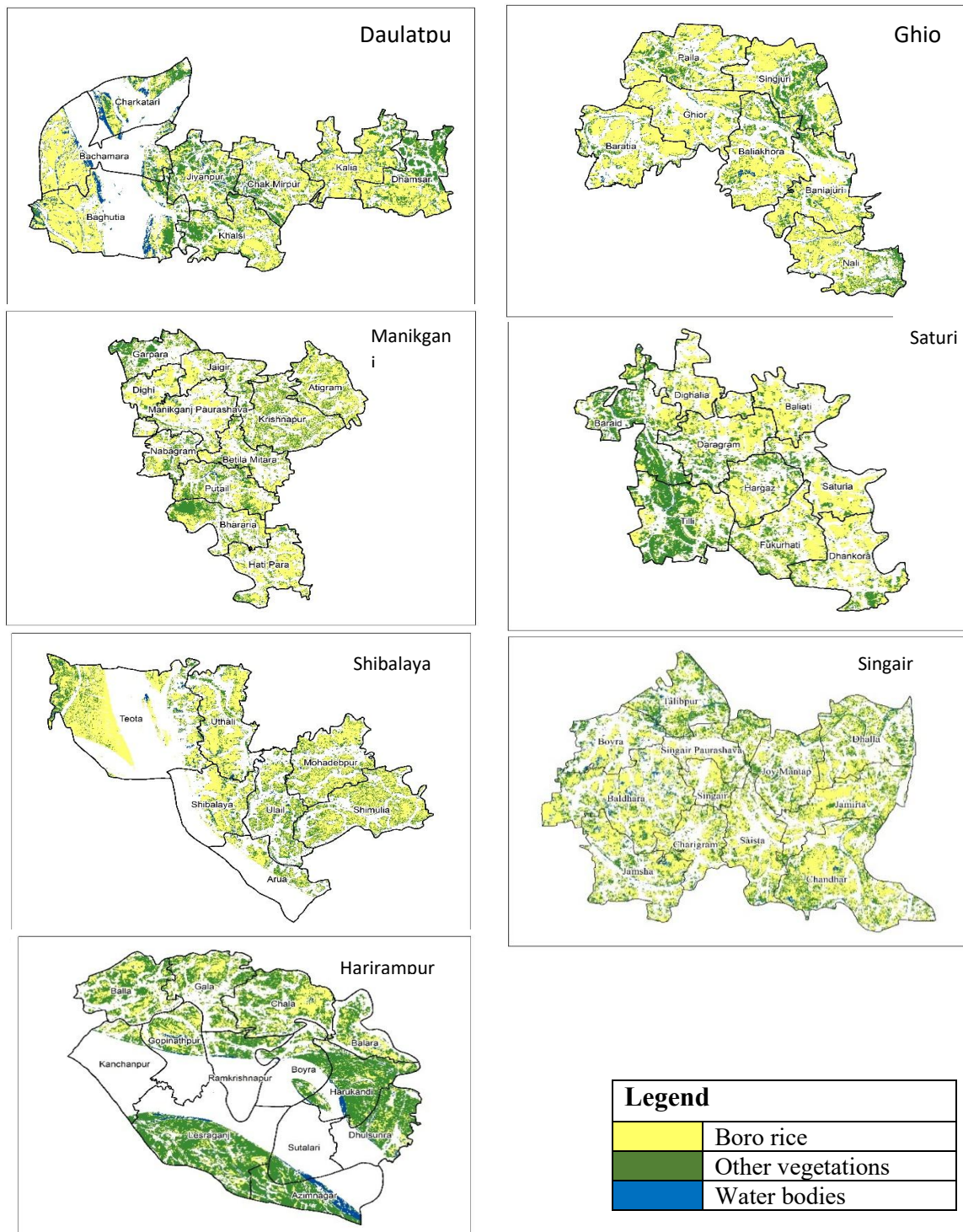


Figure 8: Sub-district level Boro rice distribution visualizations for Manikganj district exported from the interactive RiceMapEngine application

5. Validation and Area Assessment

The reliability of the Boro rice classification produced through the **Random Forest (RF)** algorithm was rigorously evaluated using standard remote sensing validation metrics. A sub-district-wise accuracy assessment was conducted to ensure the model's performance remained consistent across the diverse landscapes of Manikganj.

5.1 Classification Accuracy Assessment

The performance of the classifier was quantified using an error matrix, from which the **Overall Accuracy (OA)** and **Kappa Coefficient** were derived for each of the seven sub-districts. As summarized in Table 3, the classification results demonstrate a high level of precision. The analysis reveals that **Singair** achieved the highest classification performance with an overall accuracy of 94.87% and a Kappa coefficient of 0.87, indicating "almost perfect" agreement [32] between the classified map and ground truth data. Across the entire district, the Kappa values were all at or above 0.75, confirming that the integrated Sentinel-1 and Sentinel-2 approach is highly effective at differentiating Boro rice from spectrally similar non-rice classes.

For the Boro rice class, producer's accuracy ranged from 87.10% to 94.74% and user's accuracy from 84.21% to 94.74% (Table 3); most of the remaining errors were confusion with vegetables and late-sown maize. The 5-fold cross-validated overall accuracies were 1.96 to 2.29 percentage points lower than the hold-out accuracies, a small and consistent gap across all sub-districts, and the OOB error of the final models ranged from 5.13% to 11.94%, which shows that the reported accuracies do not depend on one particular train/validation split.

Table 3: Sub-district wise classification accuracy on the 30% hold-out set: overall accuracy (OA), Kappa coefficient, producer's (PA) and user's (UA) accuracy of the Boro rice class, and 5-fold cross-validated OA (mean $\pm$ SD)

No.	Sub-district	OA (%)	Kappa	Boro rice PA (%)	Boro rice UA (%)	5-fold CV OA (%)
1	Manikganj Sadar	92.59	0.84	91.30	91.30	90.5 $\pm$ 1.2
2	Saturia	88.24	0.75	88.89	84.21	86.2 $\pm$ 1.5
3	Singair	94.87	0.87	94.74	94.74	92.8 $\pm$ 0.9
4	Ghior	91.67	0.82	90.48	90.48	89.5 $\pm$ 1.3
5	Daulatpur	90.16	0.80	90.00	87.10	88.2 $\pm$ 1.4
6	Shibalaya	90.79	0.81	91.30	87.50	88.5 $\pm$ 1.1
7	Harirampur	88.06	0.77	87.10	84.38	85.9 $\pm$ 1.6

5.2 Satellite-Based Area Estimation

In remote sensing-based assessments, the total area for a specific class is determined by calculating the sum of pixels identified as that class and multiplying it by the area of one pixel of the classified map. For this study, Equation (5) was used to estimate the Boro rice area:

$$A = \frac{P \times R^2}{10,000} \quad (5)$$

where A is the Boro rice area (ha), P is the number of pixels classified as Boro rice, R is the pixel size (10 m, so one pixel covers 100 m²), and 10,000 converts square metres to hectares. Based on this pixel-based calculation, the total spatial distribution of Boro rice in Manikganj for the 2023 season was estimated. The spatial results, visualized in Figure 8, provide a high-resolution map of rice-growing clusters, which is essential for local-level agricultural planning.

5.3 Comparison with Official Agricultural Statistics

To evaluate the practical utility of the Random Forest model for national-level planning, the satellite-derived rice area estimates were compared with the official figures published by the Bangladesh Bureau of Statistics. The results showed close agreement, with only a 2.34% deviation from the reported area for the 2022-2023 Boro season [33]. As shown in Table 4, the total estimated Boro rice area for the district was 47,611 hectares (Ha).

Table 4: Comparison between Satellite-Based Estimates and Government Statistics (2023)

Sub-districts	Govt. Statistics (Ha)	Remote Sensing (Ha)	Difference (%)
Manikganj Sadar	9,120	8,503	-6.77
Saturia	5,699	5,319	-6.67
Singair	8,450	8,381	-0.82
Ghior	7,000	6,854	-2.09
Daulatpur	7,560	7,836	+3.65
Shibalaya	7,095	7,071	-0.34
Harirampur	3,830	3,647	-4.78
Total	48,754	47,611	-2.34

The comparison reveals a low total difference of only **-2.34%** between the satellite-derived data and the official government records. In several sub-districts, such as **Singair (-0.82%)** and **Shibalaya (-0.34%)**, the difference was less than 1%, highlighting the precision of the machine

learning model. While slight discrepancies exist possibly due to the differences between administrative boundary definitions and pixel-based cropping intensities the close agreement demonstrates that Earth Observation data can serve as a reliable, objective, and timely alternative to traditional eye-estimation for national food security assessments.

6. Discussion

6.1 Spatial variation of classification accuracy

The overall accuracies range between 88.1% in Harirampur and 94.9% in Singair, and this pattern is explained by common causes of classification errors in subsistence agriculture landscapes. In the case of Harirampur, located along the Padma River, the plots are relatively small and irregular, thus making a 10m pixel likely to fall across a field boundary or bund, increasing proportion of mixed pixels and consequently omission and commission errors. By comparison, the fields in Singair are very big and contiguous, representing Boro crops grown in similar conditions in terms of irrigation management. This leads to spectral homogeneity and high overall accuracies. The confusion with spectrally similar crops like winter crops – specifically vegetables and late-sown maize – is responsible for the rest of errors, since their NDVI curves are similar to the early-season rice but different in VH flood signal, which allows distinguishing these crops in a fusion classifier.

6.2 Comparison with official statistics

Of the seven sub-districts, six have negative deviations, meaning that the satellite estimate is smaller than the BBS statistic. The primary cause of the systematic difference is almost certainly that of boundary effects: the BBS statistics are computed based on upazila levels, and they use all land that has been classified as a crop, even though the land is close to the upazila boundaries, located on narrow strips or within homesteads which fall below the minimum field size of 0.4 ha used for reference sampling. Daulatpur has an exception of a positive deviation (+3.65%), and there are two possible causes. First, the expansion of Boro cultivation in Daulatpur on irrigated chars and riverbank along the Jamuna; newly added fields may be picked up by satellite before being reported into the official statistics. Second, due to boundary effects along the Jamuna, some rice fields might get counted under wrong upazilas, which is more important where the area is small. We do not interpret the sign of deviation of each sub-district as an indication of errors in the two sources; the overall -2.34% agreement is what matters in practice.

6.3 Limitations

There are four limitations to this study, which determine the direction of future research. The first one is related to the use of only one polarization (VH), whereas adding more polarizations (VV, VH/VV ratios, texture), will help to improve rice canopy discrimination from other dense canopies. The second limitation of this study is related to the pixel-based classification, which leads to the appearance of salt-and-pepper noise in fragmented areas. Object-based classification would be appropriate for such smallholders' agriculture as rural Bangladesh has. The third limitation is associated with not using any ancillary data and uncertainty quantification. In order to use the method for operational acreage statistics, it is necessary to apply probabilistic output from Random Forest at each pixel to obtain area uncertainties. The fourth limitation is related to the fact that the study considered only one season in one district of Bangladesh.

6.4 Implications for National Food Security Planning

The practical application of this research is that the satellite-based estimates of Boro rice agree with official statistics to within 2.34% at district level, yet they can be produced much earlier and at 10 m resolution. Applied country-wide, the RiceMapEngine procedure will be directly connected to the requirements of the food security governance in Bangladesh. Rice areas estimations provided on the district level within the growing season could become input data for the food balance sheet calculated by the Ministry of Food, which will allow for timely decision-making on procurement, import, and distribution of public stocks; these maps could also be combined with flood forecast products from the Flood Forecasting and Warning Centre for fast damage assessment after the disaster instead of time-consuming manual estimation of the extent of the damages afterwards. The work also supports Sustainable Development Goal 2 (Zero Hunger) and SDG 13 (Climate Action), the Sendai Framework for Disaster Risk Reduction, and national plans such as the Bangladesh Delta Plan 2100 and the National Agriculture Policy 2018. The scaling-up process from Manikganj to the entire 64 districts is more about institutional and logistical issues, duplicating the training of officers and sample collection methodology than scientific matters, which is exactly why the current framework is a replicable one.

7. Operationalizing the RiceMapEngine

To facilitate the practical application of satellite-based monitoring, this research utilizes the **RiceMapEngine**, a sophisticated web-based application built upon the **Google Earth Engine** (GEE) API [34]. The engine is designed to handle the complex computational requirements of large-scale remote sensing data, providing a user-friendly interface for agricultural officers and policymakers. The architecture of the **RiceMapEngine** consists of three specialized modules that streamline the rice-mapping workflow:

Phenology Explorer (PE): This module serves as the primary tool for data quality control and exploratory analysis. It allows users to inspect ground-truth samples against the temporal phenological signatures produced by Sentinel sensors. By cross-referencing field data with remote sensing profiles, users can differentiate between true rice signatures and spectral outliers. Furthermore, the PE module is used to establish empirical thresholds for various growth stages, providing the quantitative basis for rule-based classification.

Empirical Thresholding (ET): The ET module offers a rapid classification method based on defined value ranges for specific phenological phases. These thresholds, often derived from previous regional studies or the Phenology Explorer, allow for the generation of rice maps without the immediate need for new training samples. This method is particularly valuable for quick-look assessments or in regions where ground-truth collection is logistically challenging.

Supervised Classification (SC): This module represents the robust machine learning component of the system. It employs advanced algorithms, such as Random Forest, to train models using the high-quality ground-truth samples collected via the Geofairy application. This approach provides the highest level of accuracy and was the primary method used to generate the 10m-resolution maps for the Manikganj district.

As demonstrated in **Figure 9**, the RiceMapEngine effectively visualizes the spatial extent of Boro rice at the sub-district level (e.g., Satoria). Beyond simple visualization, the platform acts as a dissemination hub, allowing stakeholders to access agricultural statistics and spatial datasets in real-time. The framework is inherently scalable; if field samples are provided for other seasons, the engine can be configured to map Aman or Aus rice varieties, making it a versatile tool for strengthening the national food security management system.

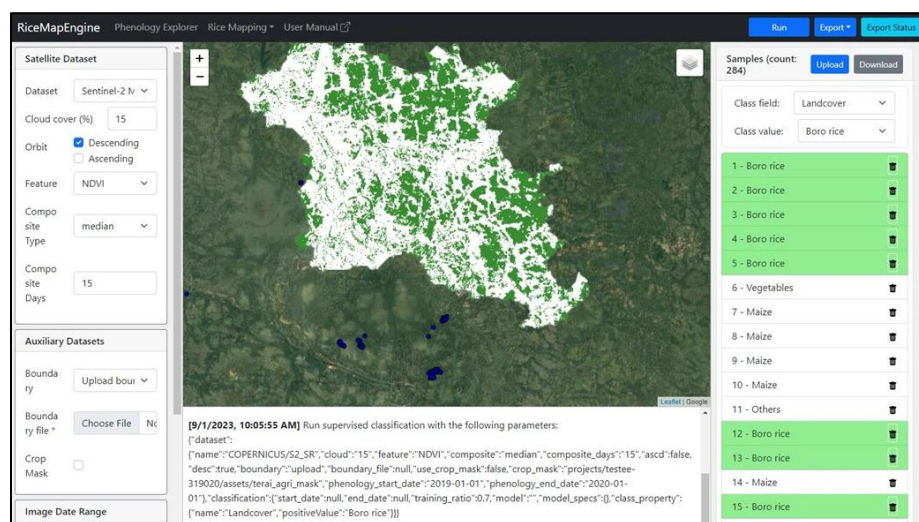


Figure 9: RiceMapEngine visualizes the spatial extent of Boro rice at the sub-district level

8. Conclusion and Way Forward

The collaborative initiative between the Department of Agricultural Extension (DAE) and ICIMOD's SERVIR-HKH initiative represents a milestone in modernizing Bangladesh's agricultural monitoring capabilities. By shifting from traditional, labor-intensive "eye estimation" to a satellite-driven machine learning framework, this study provides a more accurate, timely, and cost-effective methodology for crop acreage estimation. The results of this study confirm that the synergistic use of Sentinel-1 (SAR) and Sentinel-2 (optical) datasets, processed through a pixel-based Random Forest algorithm, provides exceptional classification accuracy. The minimal variance of only 2.34% compared to official government statistics [33] underscores the reliability of this remote sensing approach for operational use. This framework successfully addresses historical challenges such as persistent cloud cover and spectral ambiguity offering a scientific knowledge base for evidence-based decision-making. Moving forward, the potential for this methodology extends far beyond the Manikganj District. The current framework serves as a scalable model that can be adapted for national expansion by rolling out the "RiceMapEngine" across all 64 districts of Bangladesh to provide a unified, satellite-based agricultural inventory. It can also be utilized for seasonal mapping to monitor the Aman and Aus rice cycles, ensuring year-round food grain security monitoring. Furthermore, the framework supports disaster resilience by integrating the system with flood and drought monitoring tools to provide rapid damage assessments following extreme weather events. In conclusion, the integration of Earth Observation (EO) technologies into institutional practices is a significant step toward achieving national food self-sufficiency. This research provides the essential tools and scientific foundation required to transform agricultural planning in Bangladesh into a data-driven, sustainable, and climate-resilient process.

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Author Contributions

M. F. Perveen conceived the research idea, designed the study, and provided overall supervision for the project. S. Shrestha performed the preliminary analysis. A. A. Mehadi was responsible for the writing, revision, and editing of the manuscript. S. Kazmina conducted the software and technical analysis and contributed to the writing. A. A. Saem performed software analysis. All authors have read and agreed to the published version of the manuscript.

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Ethics declaration

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Data Availability

The Google Earth Engine workflow scripts and ground-truth reference datasets generated and analyzed during this study were developed under a collaborative initiative between the Department of Agricultural Extension (DAE), Bangladesh, and the International Centre for Integrated Mountain Development (ICIMOD). These data are available from the corresponding author upon reasonable request. The RiceMapEngine platform utilized in this research is documented in [34].

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