

Agro-Geoinformatics-based approach for predicting requirements of BARI seed planter machine in the southern region of Bangladesh

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ABSTRACT: To promote agricultural mechanization, proper resource planning and information management are needed for sustainable crop production to ensure food security. Advanced geoinformatics-based techniques such as remote sensing and geographical information systems can be of great use for enhancing agricultural mechanization goals and management. In this regard, this proposed study was to delineate the major crop types along with the statistics for predicting the tillage-cum-seeding machinery required to cultivate them using high-resolution Sentinel-2 satellite imagery (10m×10m) in the four selected areas of Bangladesh. After the preprocessing of satellite images, the imagery was classified into land use and land cover (LULC) classifications through an unsupervised classification algorithm of multiple-band images using ArcGIS 10.3.7 software. The LULC analysis of the study areas has been attempted based on thematic mapping of the areas consisting of fallow land, water bodies, settlements and targeted cropland using the satellite image. Using ancillary data, visual interpretation, and accurate knowledge of the area through GIS further refined the classification results. Among the estimated LULC classes, the area covered by major crops was derived from the average result of three different seasons. Based on the average crop hectareage estimation result, the number of BARI seed planter machine was worked out as 1, 2, 3 and 12, respectively, that would be needed for crop cultivation during a cropping season in the study areas. The resulted classification accuracy was found satisfactory (i.e., overall accuracy ranges from 72% to 86% with Kappa values ranging from 0.65 to 0.85) and hence the classified image was found robust for further research. The study experience creates an opportunity for future study in larger areas such as upazila, district, or country level for making the best decisions for appropriate modern agricultural technology adoption, dissemination, and management planning in order to ensure proper agricultural mechanization.

Keywords: BARI seed planter machine, GIS, LULC mapping, Remote sensing, Sentinel-2

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I. INTRODUCTION

Bangladesh needs to produce more food on the same land to satisfy the demand of an ever-increasing population. At the same time, the country's more viable alternative kinds of employment are lessening farm labor requirements [1]. To address this issue, Bangladesh has to adopt appropriate-scale agricultural machinery technology suitable for the smallholder farming community, as this category of farm holdings is overwhelmingly dominating the agricultural sector of Bangladesh. According to Tiwari et al., [2], the use of

efficient machinery saves 20-30% of operation time and labor, 15-20% of seed and fertilizer, a 5-20% rise in cropping intensity, 10-15% greater yield, and a reduction in the drudgery of farm laborers, particularly women. However, among all agricultural machinery activities, land tilling is one of the most power-intensive operations for successful crop production. In traditional systems, 4 to 8 tillage passes are preferred to establish the major crops in Bangladesh [3]. Especially to establish the Rabi crop following rice, farmers typically use 4 to 5 passes by two-wheeled tractors or power tillers (PT) in the cultivation of land in Bangladesh. This conventional repetitive tillage approach depletes soil organic carbon and diminishes soil fertility [4], wastes irrigation water and soils [5], and harms the ecological environment [4]. Again, traditional tillage necessitates considerable amounts of fuel and energy [6], resulting in higher production costs and lower profit [7], as well as environmental degradation. In other words, this existing full-tillage system for seed sowing is being delayed by 15-20 days, which reduces yield significantly [8]. The innovation of the BARI-developed tillage-cum-seed planter machine is to avoid repeated tilling of the soil, which saves time, energy, and labor. This machine accomplished three operations simultaneously: single-pass shallow tillage (up to 60 mm), placement of seed in a furrow, and leveling and pressing at the optimum moisture content of 15 to 30% of the soil moisture level [9]. The use of this machine improves the timeliness of the sowing of crops, reduces 30-40% irrigation water [7], saves fertilizer by about 30% [10], requires 30-55% less labor by 35-60% less fuel consumption [11], and reduces the cost of crop production. Based on this criterion, there is a big prospect for accelerating or scaling up such technology in the farmers' level. A BARI seed planter machine was developed, and, tested and found efficient in the northern and north-western regions of Bangladesh [7]. But it is only limitedly practiced in the southern region, where the soils and environment are quite different from those in other regions of the country. Keeping in view the importance and benefits of this modern agricultural technology, the development and implementation of selected adaptive measures have emerging need for taking decisions about popularization, adoption, or dissemination program planning according to the different climate and soil conditions of southern region of Bangladesh. Following this concern, appropriate resource planning is needed with proper information management infrastructure [12], which requires a systematic effort towards proper agricultural planning. The introduction of computer-aided geospatial technology, i.e., remote sensing (RS) and geographic information systems (GIS) is a powerful set of tools and spatial decision support systems for those adaptive applications. Today, GIS-RS-based spatial data analysis techniques are now emerging in agriculture, which enable to organize the organization of data sets for analysis and decision-making processes. These geospatial techniques have the potential to provide quantitative and timely information on agricultural crops over large areas. The prime use of RS-GIS lies in the map-making and digitizing specific crop fields. Digitizing the map data of the crop field assists in the decision-making and/or planning of the field. It applied to explore agricultural applications such as crop identification and area estimation, crop condition monitoring, soil moisture assessment, yield prediction, agriculture water management, farm machinery management, argil-meteorological, etc. However, this study is focused on the integration of GIS and RS with farm machinery management, which emerge as inevitable tools for enhancing modern agricultural mechanization. In the view of modern agricultural mechanization, the timeliness of an operation such as tillage, harvest, fertilization, etc. is an important factor in determining successful crop production. Timely operation requires a sufficient number of machinery units associating with the machine field capacity and size. RS and GIS techniques could be capable of providing quantitative and timely information about the number of machines and units required for the selected crop in a given season over large areas [13]. In Bangladesh, traditionally, farm machinery statistics are derived on thorough enumeration by the Department of Agricultural Extension (DAE), and/or by national and multi-national research organizations, personal assessments by local NGOs, and private sector. This traditional method acquiring and updating farm machinery statistics is mostly based on sampling surveys and statistical reports. This method is not only costly, labor-intensive, tedious, time-consuming, and biased, but it also produces incorrect findings and/or delayed updating. At different times, this concept was represented by different researchers such as Lazzaria and Mazzetto [14]; Bol [15]; Alam et al. [16], Dash and Sirohi [17]; Dubey [18], Yousif et al. [19]; Pathak et al. [20] and others using Computer model development for agricultural machinery selection and management. But RS and GIS-based assessments of agricultural machinery estimation are not available. With this backdrop, this study has been designed to promote the utilization of GIS and satellite RS techniques for mapping specific crop land areas that extend to making accurate and precise estimates of the BARI-developed eco-friendly seed planting technology in a given season at the regional level. Through this type of study, an agricultural planner and policymaker can take important decisions with respect to purchasing, storing, public distribution, exports, imports, and other related issues for sustainable agricultural mechanization planning.

II. MATERIALS AND METHODS

This chapter deals with the research methodology followed to achieve the objective of the present study. This study was carried out on the methodological basis developed by the author. The materials and methods include materials and equipment used, a description of the study areas, the collection of data, and analytical

techniques. The methods for land use land cover (LULC) mapping based on the collection and analysis of remote sensing data are also described in this section. The collected data have been analyzed systematically using suitable statistical techniques.

DETAILS OF MACHINE

BARI seed planter machine designed and developed by Farm Machinery and Postharvest Process Engineering Division (FMPE) of Bangladesh Agricultural Research Institute (BARI) is named power tiller operated seeder (PTOS) or BARI seed planter or BARI inclined plate planter([21]-[25]) as shown in Fig.1. This machine was powered by a Dongfeng or Saifeng 12-16 horsepower power tiller (PT) or two-wheel tractor (2WT). This seed planter machine consists of 48 Chinese C-type rotating blades arranged in a face-to-face alternate outside configuration for pulverizing soil at shallow depth with very high speed (450-500 rpm) and having an inverted ‘T’ furrow opener for furrow opening and seed dropping in the furrow properly. Seeds are drilled at regular intervals in rows, and the depth of sowing can be maintained. Three types of combined conservation tillage and seeding operations, such as zero tillage, strip tillage, and reduce tillage, can be performed well with this machine by arranging tines at the optimum moisture content of 15 to 30% of the soil moisture level ([9], [25]). This machine was tested and evaluated for the planting of different crops like maize, jute, wheat, pulses, and oilseeds in field conditions. Inclined plate-type seed metering devices were used for planting different crops directly. Most of the seeds (wheat, lentil, mungbean, maize, rice, chickpea, groundnut, and jute) can be sown by the same machine by arranging furrow openers with small changes, such as for jute seeding, mixing rice husk with a 6:1 ratio [10]. It can complete planting operations in a single pass, and average field capacity is 0.10-0.12 ha/h and the average annual area coverage of the machine is 30 ha [26]. This machine can complete planting operations on the same day as previous crop harvest, whereas with conventional methods, it takes 7-9 days from harvest to seeding. Haque et al. [27] presented that using this machine to cultivate various crops produced 13%, 12%, 18%, and 11% higher yields for wheat, jute, onion, and garlic, respectively compared to the conventional system (PT). This also increased farmers' net income by 30%, 23%, 46%, and 45% for the above crops, respectively [28]. The detailed specification of the BARI seed planter is shown in Table 1.

Table(1). Specifications of a BARI seed planter machine

Items	Value
Dimension	: 720 mm×1320 mm×700 mm
Weight	: 136 kg
Number of rotary blades	: 48 (C type for Reduce tillage) 24 (Tip angle 15° for strip tillage)
Power requirement	: Power tiller (9-12 KW)
Number of rows	: 6 (line number adjustable)
Furrow opener	: Inverted ‘T’ type
Row spacing	: 200 mm (adjustable)
Normal working speed	: 1.0-2.5 km/h
Working width	: 1200 mm
Normal seeding depth	: 50-60 mm
Type of seed meter	: Inclined plate
Speed of blade	: 450–500 rpm



Fig.1 Pictorial view of A) BARI seed planter machine, B) Field operation and C) Standing crop field

DESCRIPTION OF STUDY AREAS

Four villages, including Mundopasha village (22.86341N and 90.26278E) of Wazirpurupazila in Barishal district of Barishal division; Baratiavillage(22.82152N and 89.33117E) of Dumuriaupazila in Khulna district of Khulna division; Holdibaria village(21.91571N and 90.14235E)in Kolaparaupazila in Patuakhali district of Barishal division;and 4 No. Charwapdavillage (22.70029N and 91.10641E)inSubarnacharupazila of

Noakhali district of Chattogram division; were selected as the study areas of the southern region of Bangladesh (Fig.2). These areas were selected purposefully based on their diverse cropping patterns, landtype, topography, soil, and climatic conditions, i.e., altered rainfall patterns [29].The study areas are dominated by rain-fed dryland cropproduction systems. Agriculture in these areas uses traditional to semi-mechanized techniques and equipment. The power supply is usually a two-wheeled tractor, popularly known as a power tiller. Rainwater is the main water resource in the region, where gravity irrigation is predominant. The agro-ecology of the southern region of Bangladesh is different from other areas. Generally, farmers are greatly dependent on climate-sensitive crop production and cultivate their land during three seasons: (i) *Kharif-1* (mid-March to mid-June, summer crops), (ii) *Kharif-2* (mid-July to mid-October, monsoon crops), and (ii) *Rabi* (mid-October to mid-March, winter crops) in this region. The major cropping patterns of the selected areas are shown in Table 1. Agriculture in this region is characterized by low productivity due to salinity, waterlogging, less practice of modern technologies, inadequate control over water resources, and repeated crop losses due to natural calamities. Again, this region is under the constant threat of soil and water salinization. These are having a negative impact on soil fertility and crop productivity, which underpins the rural economy of coastal Bangladesh. Conversely, drought, heavy rainfall, soil and water salinity, tidal floods, and waterlogging cause delays in *Rabi* crop cultivation and sometimes damage crops during the harvesting period. So, the average cropping intensity in the coastal areas is about 130%, whereas the national average cropping intensity is 198% [30]. About 30-50% of net cropped areas remain fallow in *Rabi* and *Kharif-1* seasons in this region, mainly due to high soil and surface water salinity, the unavailability of freshwater for irrigation, drought and uneven or heavy rainfall during crop cultivation, etc. [31].

Table(2). Major cropping patterns in the study areas

Study area	Major cropping pattern	Major non-rice crop
Mundopasha, Wazirpur, Barishal	T.Aman-Mungbean-Fallow	Mungbean
Baratia, Dumuria, Khulna	T.Aman-Mustard-Boro-Jute	Jute
Holdibaria, Kolapara, Patuakhali	T.Aman-Mungbean-Fallow	Mungbean
Charwapda, Subarnachar, Noakhali	T.Aman-Watermelon/Soybean -Fallow	Watermelon, Soybean

Source: Authors survey (2017-2019)

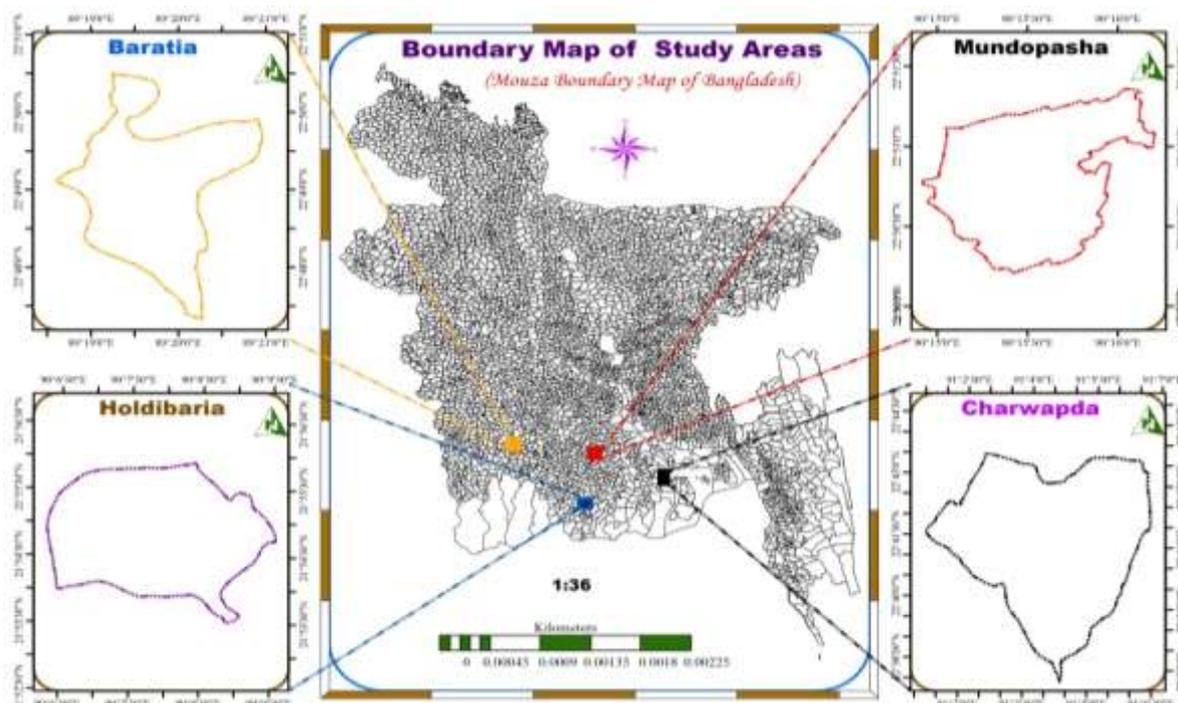


Fig.2 Locations and boundary map of the study areas

DATA COLLECTION

Both qualitative and quantitative data were collected from the study areas. The collection of data is split into two major types: primary (i.e., satellite imagery, GPS coordinates) and secondary (i.e., administrative boundaries of area of interest (AOI), published and unpublished literature such as books, technical reports, and journals, etc.).

SATELLITE DATA ACQUISITION AND ANCILLARY DATA COLLECTION

In this study, the main spatial data performed was Sentinel-2 satellite imagery, which launched by the European Space Agency (ESA) and consists of two satellites namely Sentinel-2A (launched on 23rd June 2015) and Sentinel-2B (launched on 7th March 2017) ensuring better data continuity than other relevant satellites, such as SPOT and Landsat satellite series [32], due to its high spatial resolution and short revisit time (5-10 days). These twins' satellites are the most popular and advanced satellites for long-term high-frequency remote sensing applications, equipped with Multispectral Instruments (MSI) capable of acquiring 13 bands of information at different spatial resolutions (10m, 20m and 60 m). The band information for Sentinel-2A and Sentinel-2B is shown in Table 3. According to ESA [33], the different band specifications can be described as (i) the four bands at 10 m resolution (three in the visible, i.e., blue, green and red, and one in the near-infrared (NIR)) satisfy user requirements for basic land cover classification; (ii) the four bands at 20 m resolution (three in the 'red edge', one in narrow NIR, and two in SWIR) address requirements for enhanced land cover classification and the retrieval of biophysical parameters, and (iii) the two Short-Wave Infrared (SWIR) bands at 20 m and the remaining bands at 60 m show high contrast between moisture and dry content. In this study, ten bands of the spatial resolution of 10 m (B2, B3, B4, and B8, respectively) and 20 m (B5, B6, B7, B8A, B11, and B12, respectively) in blue/green/red/red edge/VIS/NIR/VNIR/SWIR were used from among the 13 bands. The single date satellite imageries were freely acquired between early February and early April from the open-access hub USGS (United States Geological Survey) earth explorer website (<https://earthexplorer.usgs.gov/>) for each study area during the peak vegetative stage (March and middle June) of the crop for 2017, 2018 and 2019. The acquired images were selected based on the temporal coverage with minimal to no or less than 10% cloud cover and unwanted shade-free conditions. Imagery with clouds and unwanted shade substantially reduces the accuracy of the image classification work. It should be addressed that in Bangladesh, November to February is the winter season and March to early April is the transitional period from winter to summer. Again, the monsoon period (June to August) in Bangladesh is cloudy, and days in winter are most of the time cloud-free. Despite the increased temporal resolution of Sentinel-2 data, the presence of clouds significantly reduced the number of available scenes. For this reason, satellite imagery could not be acquired in the same month throughout the whole study period. On the other hand, crop growth (seedling-vegetative-maturity stage) is started in the middle of January to the middle of February for mungbean cultivation, first in April to the middle of May for jute cultivation, and end in December to the middle of January for soybean cultivation, respectively. Sometimes cultivation times might be changed due to vulnerable natural calamities. So, March is the peak season for mungbean and soybean crops, and July is for jute, which covers most of the crop areas. So, the satellite image was acquired during the growth period of the crop. The satellite data acquisition dates are shown in Table 4.

Other ancillary data, including the administrative boundary of Mouza (village land map), union, upazila, district, division, and country-level shapefile of Bangladesh, are now available and could be freely downloaded from internet sources (<https://www.diva-gis.org/Data>). The mouza boundary shape, which contained one or two villages corresponding to a specific land area of each study area, was clipped from Bangladesh administrative boundary shapefile. This type of map is very important as it comprises the boundaries of all land parcels and contains methodically arranged information regarding ownership, land use, and area details, as well as showing the boundaries of all land parcels on a large scale, generally in 1m by 3.96 km. Other related data sources, such as a topographical map and Google Earth, were used as a base map to identify the feature classes during reclassification and illustrate the rural road network map. GPS co-ordinate points of each land use/cover class were collected from the field during field visits and used as ground truth data for accuracy assessment.

Table 3: Sentinel-2 spectral bands characteristics (ESA, 2020)

Band No.	Wavelength (nm)	Spatial resolution (m)	Bandwidth (nm)
Band 1 – Coastal aerosol	443	60	20
Band 2 – Blue	492	10	65
Band 3 – Green	560	10	35
Band 4 – Red	665	10	30
Band 5 – Vegetation red edge	705	20	15
Band 6 – Vegetation red edge	740	20	15
Band 7 – Vegetation red edge	783	20	20
Band 8 – NIR	842	10	115
Band 8A – Narrow NIR	865	20	20
Band 9 – Water vapour	945	60	20
Band 10 – SWIR – Cirrus	1375	60	20
Band 11 – SWIR	1610	20	90
Band 12 – SWIR	2202	20	180

Table(4). Satellite image acquisition dates with respective seasons of study areas

Baratia		Mundopasha		Holdibaria		Charwapda	
Season	Date	Season	Date	Season	Date	Season	Date
Kharif-1 2017	15-05-2017	Rabi 2017	23-03-2017	Rabi 2017	23-03-2017	Rabi 2017	23-03-2017
Kharif-1 2018	16-06-2018	Rabi 2018	18-03-2018	Rabi 2018	08-03-2018	Rabi 2018	18-03-2018
Kharif-1 2019	16-07-2019	Rabi 2019	28-03-2019	Rabi 2019	23-03-2019	Rabi 2019	28-03-2019

GROUND TRUTH DATA ACQUIRING

Ground truth data is of vital importance to perform accuracy assessments. More than 80 GPS coordinates or geo-referenced points, combination of all land use/cover classes of each study area were recorded by conducting various field trips using an Android smartphone (version 5.1.1) at the peak vegetative stage of crops. Generally, GPS-enabled smartphones are typically accurate to within a 4.9 m (16 ft) radius under the open sky (<https://www.ion.org/>) and determine approximately 98% of their GPS points within 10 m of their true positions and approximately 59% within 5 m [34]. So, a position correction algorithm was needed in that instance. In fact, a mobile GPS receiver works in any weather as long as the device has a clear line of sight to the satellites and extract location coordinates from the satellites by using related mobile network resources. For this reason, this type of GPS receivers usually has low accuracy in positioning. The high-resolution imagery from the Google Earth Pro application (<http://earth.google.com>) is a free and acceptable open source of information in order to evaluate the positional accuracy of GPS coordinate points. This form of application provides, in addition to its valuable ground imagery, point coordinates in local UTM system and ground profiles that can be easily obtained. The collected GPS coordinate data samples were therefore checked to minimize the position error based on knowledge of each land cover class in each area by visual interpretation. Indeed, these data have an important function in determining information about specific feature classes, interpreting decisions, and assessing accuracy of the results in land use classification algorithms.

METHODOLOGY

The methodology used in this study is aimed at land use identification with digital high-resolution Sentinel-2 satellite image classification in order to develop the ultimate LULC maps. The overall approach involves four main phases, i.e., image pre-processing, classification analysis, evaluation for assessing the classification accuracy and then the area estimation phase, respectively. The following methodological workflow (Fig. 3) is adopted in the present study to fulfill the objectives:

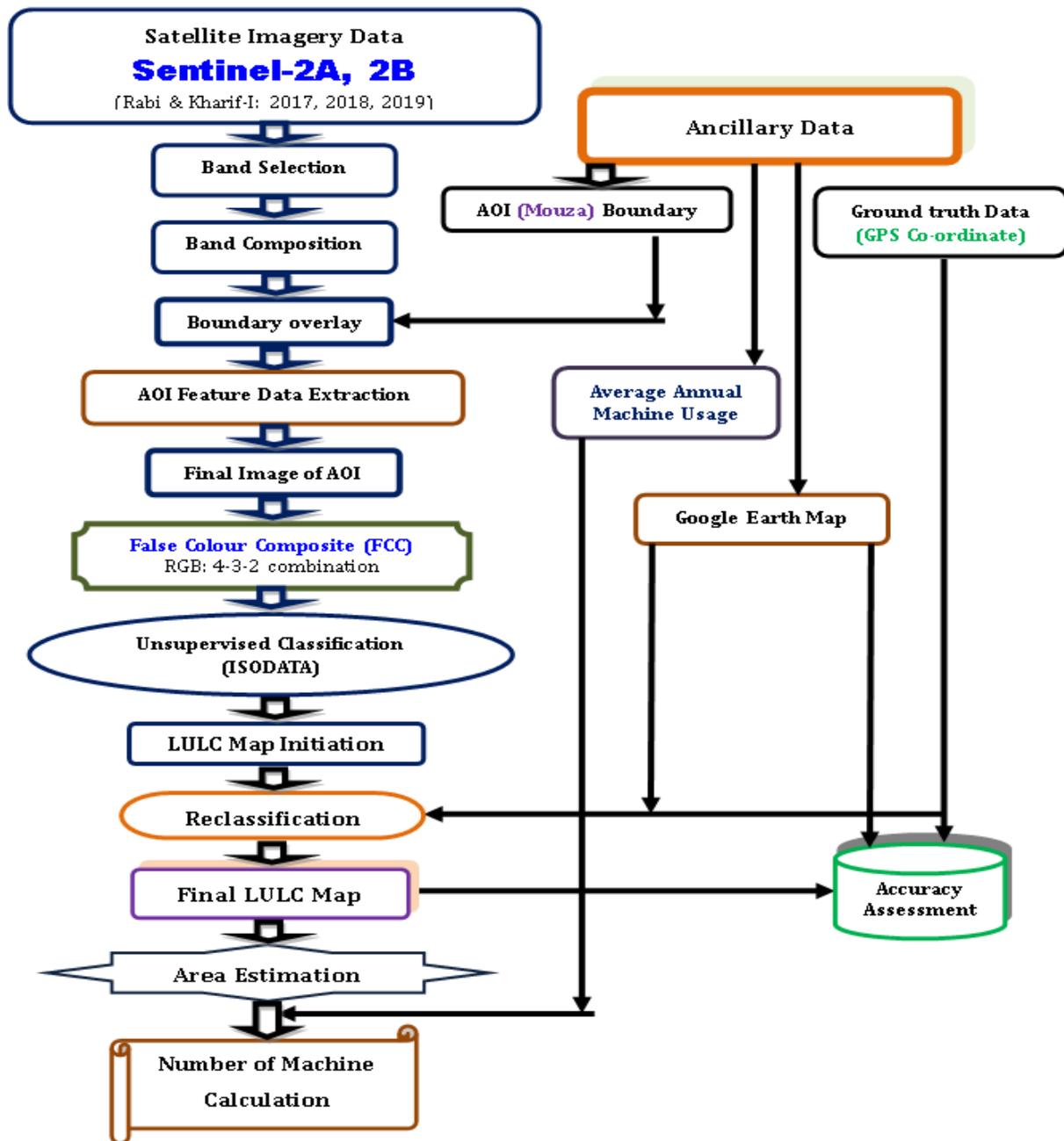


Fig. 3Thematic workflow of methodology

SOFTWARE'S USED

In order to achieve the above-mentioned methodological workflow, some different types of software were used for digital image acquisition, processing, analysis, data storage, statistical analysis, validation of work, etc. For example, Microsoft Office (version 2019) was used for database preparation, and ArcGIS software (version 10.3.7.) was used for spatial data composition, masking or sub-setting, image classification, crop identification, area estimation, and the final LULC thematic generation of maps.

SATELLITE IMAGE PRE-PROCESSING

The satellite imagery pre-processing is mainly related to resampling, atmospheric correction, geometric correction, band composition and sub-setting, etc.[35]. Atmospheric correction, radiometric correction, geometric corrections, and image geo-referencing are integrated parts of the process of Sentinel-2 satellite image processing when acquired [32]. Multi-band composition or layer stacking of the satellite imageries was performed to convert from selected bands (2, 3, 4, and 8, respectively) of image files into a single layer in order

to join together to form a single layer image file (.tiff), and they all have a similar spatial resolution of 10 m x 10 m. Then, from the stacked satellite image, the specific AOI was extracted by overlaying the mouza boundary over the respective multi-band composite image to extract all feature data from each image during the respective crop growing seasons of 2017, 2018, and 2019 for spatial analysis.

DEVELOPMENT OF LULC MAP

Extracting LULC information is a crucial exercise for agricultural land, which is most useful for the decision support system, planning, and development in agriculture [36]. Satellite imagery classification was performed in order to assign different spectral signatures from the satellite datasets to different LULCs. This was done based on the reflection characteristics of the different LULC types. In this regard, it is important to delineate the land cover class theme based on the purpose of the study prior to attempting a classification. The LULC class for the study areas was divided into the following theme classes, as shown in Table 4.

Table 4: Description of LULC classes

No.	Classes	Description
1	Water Bodies	Ponds, canals, lakes, rivers, lowland, fisheries/Gher, riverbank, Charland, waterlogged area, Boro rice field, wetland forest
2	Settlement	Small houses, back/front yards, parking area, large space house, road & roadside, natural vegetation and planted trees, playground, lawn, grass, and bush vegetation, betel leaf yard
3	Fallow land	Open space, bare and exposed soil, mixed barren land, dry pond, canal, wetland, fodder crop field, agricultural fallow land (seasonal) after Boro rice harvesting in Khulna and fallow after Aman rice harvesting in Patuakhali, Barishal, Noakhali,
4	Forest	Forest plantations, scrub forests and degraded forests
5	Crop land	Mungbean, jute, watermelon, soybean, and vegetable field

IMAGE CLASSIFICATION APPROACH

Digital image classification in remote sensing is the detection and clustering of similar image pixels into the same information categories, which are produced from several spectral bands of a satellite image [37]. The major steps of image classification may include the determination of a suitable classification system, image pre-processing, selection of suitable classification approaches, post-classification processing, and accuracy assessment [38]. Prior to image classification, a false-color composite (FCC) band combination of 4-3-2 was selected for the RGB color composite, i.e., band 4 in the red, band 3 in the green, and band 2 in the blue, after a literature review and lab examination. This type of color infrared composite (a combination of near-infrared, red, and green) is displayed by placing the infrared, red, green in the red, green, and blue frame buffer memory, which facilitates obtaining useful information for the classification of land and crops based on the analysis of satellite images. Then the classification of the image was derived by using an unsupervised classification algorithm. In this classification algorithm, spectral classes are grouped first based on the numerical information and then matched. There are various studies, using supervised or unsupervised algorithms, dedicated to cropland mapping from time series or single-date remote sensing images [39]. It should be noted that agriculture is more diverse in the study areas. In some areas, there are green plants (vegetative stage) and ploughed fields together, while both are agricultural but have a different spectral reflection. Different reflectance pixels have significantly changed their spectral signature between growth and fallow seasons. So, the collection of training samples for supervised classification is challenging due to this type of heterogeneous area. Therefore, an unsupervised classification algorithm is more suitable to extract this class. The crops and other associated features of each LULC class were identified using ground truth data (GPS) as well as Google Earth Pro as a guided map. For all land use types, expert knowledge of the study areas was used in decision rules to remove understandable classification errors.

DATA POST-PROCESSING

The classified images were subjected to a post-processing process in order to obtain results with high accuracy. Post-classification refinement was done to improve classification accuracy and reduce misclassifications [40]. After the classification of the image, ground verification was done in order to check the precision of the classified LULC map. Based on the ground verification, necessary corrections, adjustments, and improvements to the classified LULC map were made. After the processing of all indices, descriptive statistics were calculated and exported as an excel sheet as described as pixel count, a unit of area, percentage, and mean for delineating the selected LULC classes.

CLASSIFICATION ACCURACY ASSESSMENT

Assessing the accuracy of digital image classification output is very important. A classification error occurs when an image pixel that belongs to one category is incorrectly assigned to another category. Then, accuracy assessment was carried out in combination with field observation GPS data, manual interpretation of

Sentinel-2 images, and Google Earth high-resolution images. Also, the accuracy of the obtained pixel-based classification was evaluated through a confusion or error matrix consisting of overall accuracy, producer's accuracy, user's accuracy metrics [41], and kappa coefficient [42].

LULC AREA ESTIMATION

Remote sensing technology is capable of preparing maps for crop identification and classification. Cropland mapping through image classification provides statistical and spatial information, such as crop area estimation, offering important decision support in agriculture [43]. Mapping crop type dynamics requires multi-temporal image data covering different crop growing seasons and involves sets of interpretation techniques [44]. In this study, after classification, the agriculture and open land-use area in different three years, i.e., 2017, 2018, and 2019 was calculated. The pixel-based unsupervised classification was used to classify the main crop types within the cropland area. The area covered by each class of LULC in three different years was calculated after image classification. This is performed by pixel-based area calculations. In pixel counting, the total number of pixels allocated to each land cover class was counted. By knowing the area covered by the pixel, the area of that class can be obtained following the formula provided by Gallego [45].

$$A_{ha} = \frac{N \times a}{10000}$$

Where, A_{ha} = Each land cover class area in a hectare, N = Counted pixel of each cover class and a = Area covered by a pixel and obtained from the spatial resolution of the sensor

NUMBER OF MACHINE(S) ESTIMATION

The number of the machine(s) is calculated as follows:

$$\text{Number of machines, } M = \frac{a}{A}$$

Where, M = Number of machines required; a = Estimated average crop area and A = Annual area coverage of machine

DATA FINALIZATION

The final stage of the overall process illustrated was the calculation of LULC maps. The study's results were shown as digital maps of restricted satellite images in a GIS setting, along with ground-truthing and cross-tabulation validation. The GIS-based maps contained all the user-friendly information, such as legend, direction, and scale. Maps were interpreted using simple and understandable language for wider acceptance by policymakers, extension managers, and researchers. Besides, statistical tables and graphs were also generated using Microsoft Excel. In the case of accuracy assessment, the existing software was unable to import the points necessary for accuracy assessment for each unsupervised classification. To mitigate this technical difficulty, all accuracy assessments, were completed in Microsoft Excel.

III. RESULTS

LULC MAPPING

Based on the methodological procedure, the satellite imageries from each study area of three different years, i.e., 2017, 2018, and 2019, were first classified and an appropriate LULC classification map was generated from the integration of remote sensing data. The result is a new image that shows the locations of all combinations of the feature classes in the original images. The image was classified into five LULC classes, i.e., cropland, forest, water bodies, fallow land, and settlement. The maps were prepared using visual and digital image interpretation, which gave a general idea of the forms of LULC classes in those areas. Furthermore, the different LULC classes' area was estimated based on a group of pixel counts and estimated using the pixel grid cell method. The graphical illustration of (A) LULC classified maps, (B) variation of crop cultivated area, (C) percent of area distribution under different LULC categories, and (D) area covered by crops (i.e., jute, mungbean and soybean) over three different years in the study areas is shown in Fig.s5, 6, 7, and 8, respectively.

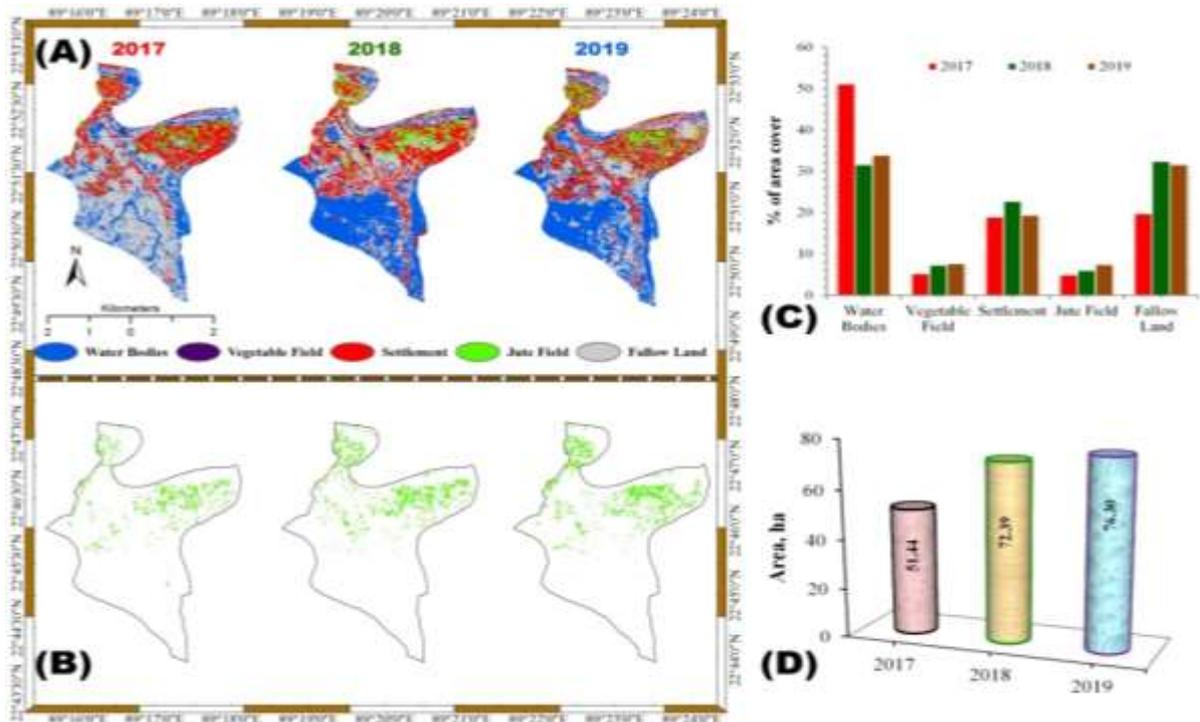


Fig.5 Graphical representation of (A) LULC classified maps, (B) year-wise variation of jute cultivated area, (C) percent of area distribution under different LULC categories, and (D) area covered by jute over three different years at Baratia, Dumuria, Khulna

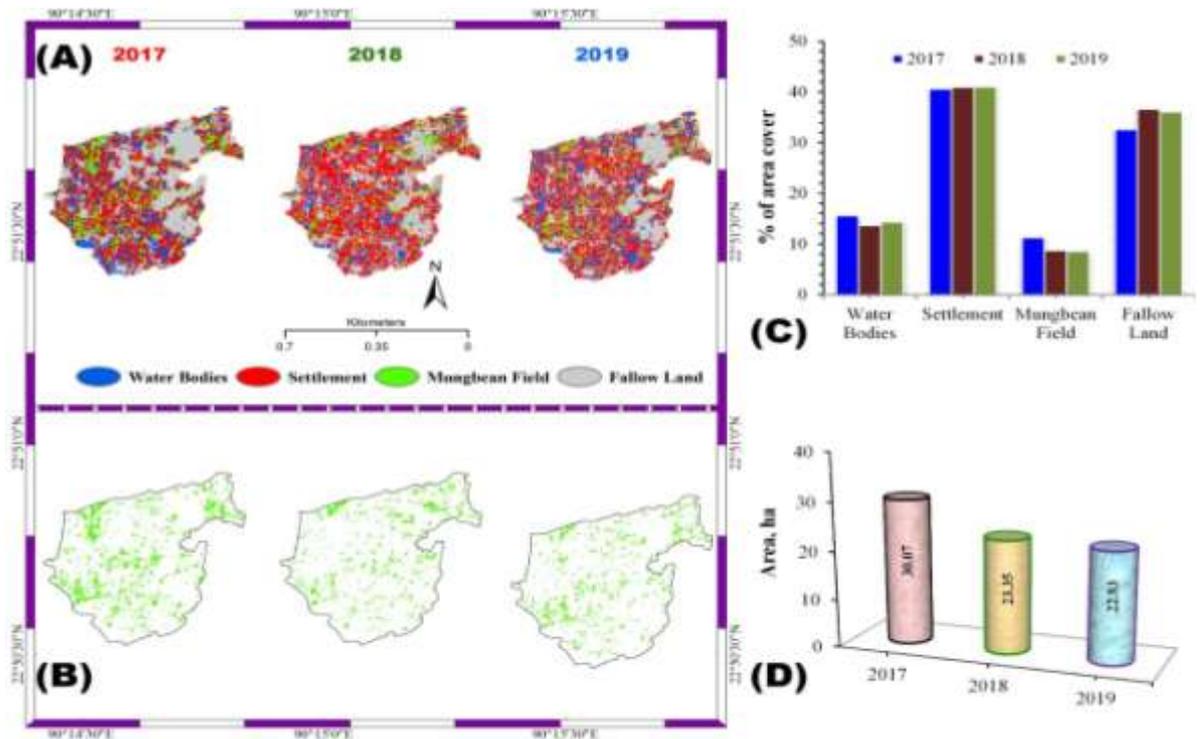


Fig.6 Graphical representation of (A) LULC classified maps, (B) year-wise variation of mungbean cultivated area, (C) percent of area distribution under different LULC categories, and (D) area covered by mungbean over three different years at Mundopasha, Wazirpur, Barishal

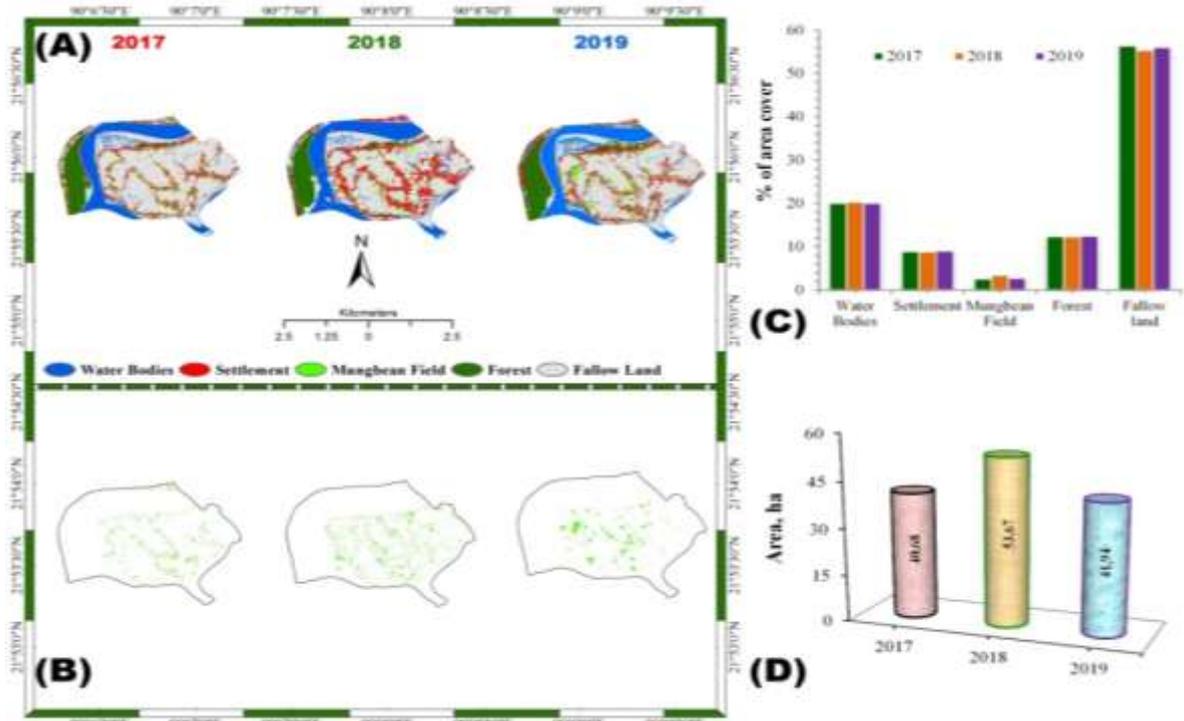


Fig.7 Graphical representation of (A) LULC classified maps, (B) year-wise variation of mungbean cultivated area, (C) percent of area distribution under different LULC categories, and (D) area covered by mungbean over three different years at Holdibaria, Kalapara, Patuakhali

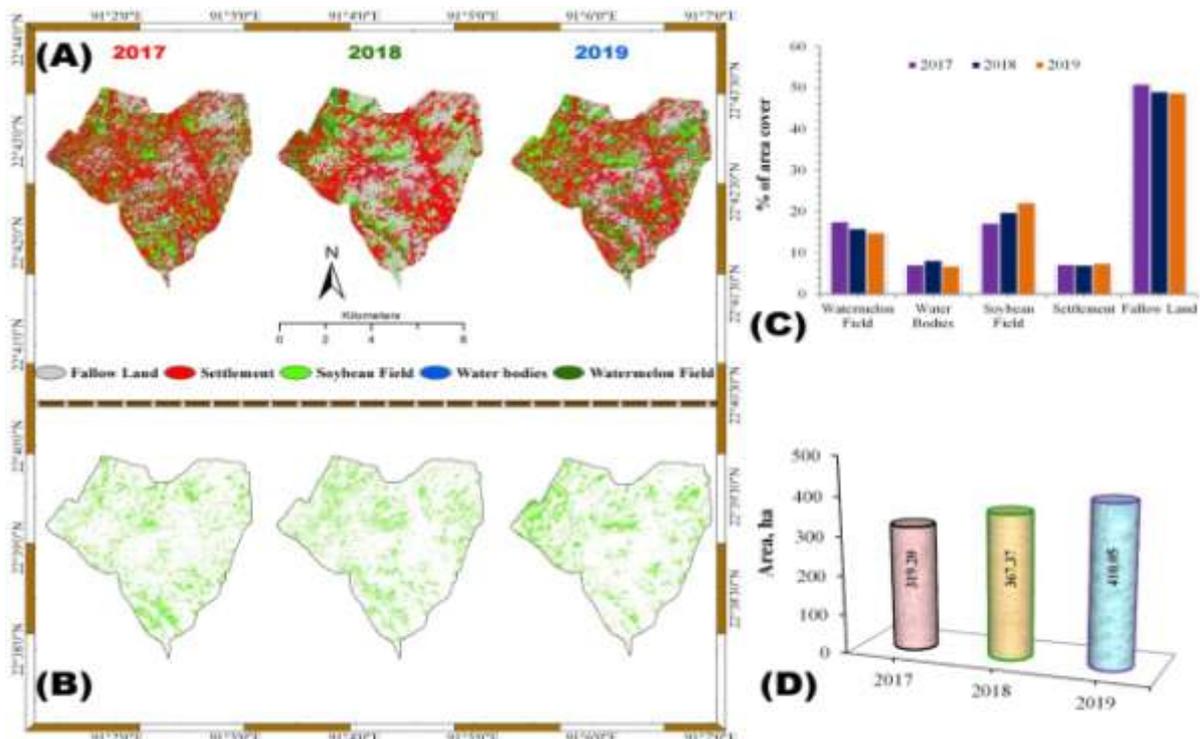


Fig.8 Graphical representation of (A) LULC classified maps, (B) year-wise variation of soybean cultivated area, (C) percent of area distribution under different LULC categories, and (D) area covered by soybean over three different years at Charwapda, Subarnachar, Noakhali

ACCURACY MEASUREMENT OF ANALYSIS

Since image heterogeneity presents a major challenge in land cover classification, accuracy assessment was then carried out in combination with field observation GPS data, manual data along with the visual interpretation of satellite images, and Google Earth Pro in order to examine the accuracy and consistency of the area estimated. In this regard, a random stratified sampling method was used to prepare the ground reference data that eliminated the possibility of bias [41]. This sampling method allocates the sample size for each land use based on its spatial extent [46]. However, one of the most common ways to express classification accuracy is by preparing of a classification error matrix, which is also known as a confusion or error matrix. Error matrix comparison was done based on the class-by-class division. In this classification, the overall classification accuracy and kappa coefficient were calculated for the three different time frames (2017, 2018, and 2019) found from the accuracy assessment, are shown in Table 5. It should be noted that the value of accuracy is expected to meet the requirements of greater than 60% (Green et al., 2000) so that the results of the percentage of overall accuracy values obtained can be used as proof of the accuracy of the image classification. The results show that the percentage range of the overall classification accuracy for the land cover classes was between 72% and 76% for Baratia, 84% to 89% for Mundopasha, 76% to 81% for Holdibaria, and 74% to 86% for Charwapda, respectively, from satellite image classification in different three years. In this study, the average overall classification accuracy was found to be in the range of 74-86%. Besides, in this study, the average value of Kappa, which was used to check accuracy in classification, was estimated to range 0.65 to 0.85 which indicate a strong to the fair agreement between thematic maps generated from image analysis data and the reference data. A kappa coefficient is a popular approach to map comparison in remote sensing [47]. Values of Kappa greater than 0.80 indicate strong agreement; beyond chance, values between 0.40 and 0.79 indicate fair to good; and values below 0.40 indicate poor agreement [42].

Table(5).Classification accuracy for the remote sensing classification result

Study area	LULC class	Season											
		2017				2018				2019			
		PA (%)	UA (%)	OA (%)	Ks	PA (%)	UA (%)	OA (%)	Ks	PA (%)	UA (%)	OA (%)	Ks
Baratia	Water bodies	60	85.71	73%	0.66	75	93.75	72%	0.65	85	89.47	76%	0.70
	Fallow land	80	88.89			85	100.00			90	100.00		
	Settlement	80	59.26			65	46.43			70	53.85		
	Vegetable field	75	71.43			60	70.59			70	77.78		
	Jute field	70	70.00			75	68.18			65	68.42		
Mundopasha	Water bodies	90	100.00	89%	0.85	85	100.00	84%	0.78	95	100.00	85%	0.80
	Fallow land	85	100.00			85	80.95			85	89.47		
	Settlement	95	76.00			95	76.00			80	72.73		
	Mungbean field	85	85.00			70	82.35			80	80.00		
Holdibaria	Water bodies	70	87.50	80%	0.75	80	88.89	81%	0.76	75	78.95	76%	0.70
	Forest	85	70.83			95	73.08			85	85.00		
	Fallow land	90	78.26			80	88.89			75	62.50		
	Settlement	85	73.91			85	68.00			80	76.19		
	Mungbean field	70	100.00			65	100.00			65	81.25		
Charwapda	Water bodies	75	93.75	74%	0.68	85	100.00	86%	0.83	75	88.24	80%	0.75
	Fallow land	80	100.00			90	85.71			75	100.00		
	Settlement	80	59.26			90	81.82			85	65.38		
	Watermelon field	60	63.16			80	88.89			75	78.95		
	Soybean field	75	68.18			85	77.27			90	78.26		

Note: PA= Producer's accuracy, UA= User accuracy, OA= Overall accuracy, and Ks= Kappa statistic

CROP AREA ESTIMATION

The main purpose of this study is to generate the LULC map, which shows how much land there is for major upland crop production compared to any other LULC features. These maps give an idea about the utility of multiyear data for not only mapping the cropping area but also studying the variation in crop phenology. Land use classification was carried out to discriminate between cropland areas and non-agricultural areas such as fallow land, water bodies, settlement, etc. The analysis showed that most of the study areas are agricultural crop areas. During the classification, among the water bodies classified were rivers. Again, agriculture and open land are merged with fallow land as well as the vegetation classified as settlements. The year-wise crop cultivated area over three different years along with mean data in the study areas are tabulated in Table(6). As well, the specific crop-wise area distribution of each study area over three different years is described in the following section.

Table(6).Year-wise variations of crop cultivated area in the study areas over three different years

Study area	Crop name	Cultivated area (ha)			Mean
		2017	2018	2019	
Baratia	Jute field	51.44	72.39	76.30	67
Mundopasha	Mungbean field	30.07	23.35	22.83	26
Holdibaria	Mungbean field	40.68	53.67	41.94	46
Charwapda	Soybean field	319.20	367.37	410.05	366

In Baratia, farmers are cultivating jute. It is observed from the above table that the highest total areas of jute were estimated at 76.30 ha, which covered 7.67% of the total area in 2019, followed by 72.39 ha (7.27% of total area) in 2018. The lower jute area was obtained as 51.44 ha (5.17% of the total area) during the season of 2017. Again, mungbean is the major mono-upland crop in the rabi season in the Mundopasha, Wazirpur, Barishal, and Holdibaria, Kalapara, Patuakhali areas. The area coverage of mungbean was observed as 30.07 ha (11.24% of total area), 23.35 ha (8.73% of total area) and 22.83 ha (8.53% of total area) in Mundopasha, while 40.68 ha (2.55% of total area), 53.67 ha (3.36% of total area), and 41.94 ha (2.63% of total area) in Holdibaria, respectively for three different years of 2017, 2018, and 2019, respectively, as seen in Table 6. The result indicates that the lowest spatial distribution area was found as 22.83 ha and 40.68 ha in Mundopasha for 2019 and in Holdibaria for 2017, respectively. Conversely, soybean is mainly a rainfed crop in Charwapda, Subarnachar, Noakhali. The result reveals that the highest soybean area of coverage was observed at 410.05 ha (22.11% of the total area) in 2019, followed by 367.37 ha (19.81% of total area) in 2018. A significantly lower area was found at 319.20 ha (17.21% of total area) in 2017. Therefore, it can be summarized that the average jute, mungbean, and soybean cultivation areas were calculated as 67, 26, 46, and 366 ha, respectively, in Baratia, Mundopasha, Holdibaria and Charwapda, respectively, which could be identified using single-date satellite imageries data from Sentinel-2.

NUMBER OF THE MACHINE(S) REQUIRED

Based on the estimated average targeted crop area and annual use of the machine, the quantity of BARI seed planter machines for each study area was worked out during a cropping season, as shown in Table(7). The table shows that around 12 machines are required for soybean cultivation at Charwapda. On the other hand, a few amounts of the machines (1 and 2, respectively) are required for mungbean cultivation at Mundopasha and Holdibaria. In Baratia, three machines are needed for jute cultivation.

Table(7).Machine estimation based on major crop area

Study area	Average area (ha)	Annual use of the machine (ha)	Quantity of machine (nos.)
Baratia	67		3
Mundopasha	25	30	1
Holdibaria	45		2
Charwapda	366		12

SENSITIVITY ANALYSIS

Sensitivity analysis is the study of the impacts of fluctuations in the parameters of a system on the outputs [48]. In other words, this analysis is a calculating procedure used for the prediction of the effect of changes in input data on the output results of one form. In this study, a sensitivity analysis was conducted and showed how sensitive the BARI seed planter machine estimation was for a decision-maker and how vulnerable that estimation is to changes in the total number of machines that can result from changes in the decision. In this regard, the scenarios on total crop cultivation area and annual use of machines were varied to test the effect on the results shown in Table(8).

Table(8).Impact of changing cropping area and annual use of the machine on BARI seed planter machine estimation

SL. No.	Scenario	Quantity of machine (nos.)			
		Baratia	Mundopasha	Holdibaria	Charwapda
1	Base parameter	3	1	2	12
2	Crop area increase 20%and annual use of machine constant	3	1	2	15
3	Crop area increase 50% and the annual use of machine decrease 10%	4	1	3	20
4	Crop area increase 30% and the annual use of machine decrease by 20%	4	1	2	20
5	Crop area decrease 20% and the annual use of machine decrease 10%	3	1	2	18
6	Crop area decrease 50% and annual use of machine decrease 10%	1	0	1	7
7	Crop area increase 30% and the annual use of machine decrease by 20%	2	1	1	11
Average=		3	1	2	15

The result reveals that further analysis was performed to measure the sensitivity of the results to changes in the major six scenarios such as total crop area increased by 20% and annual use of machine remained constant, total crop area increased by 50% and annual use of machine decreased by 10%, total crop area increased by 30% and annual use of machine decreased by 20% (Scenarios 2 to 4), respectively while total crop area decreased by 20% and annual use of machine decreased by 10%, total crop area decreased by 50% and annual use of machine decreased by 10%, total crop area decreased by 30% and annual use of machine decreased by 20% (Scenarios 5 to 7), respectively of BARI seed planter machine estimation decision. The result implies that among all scenarios, the most likely scenario 2, and scenario 7 are highly feasible during decision-making because the indicator measures would remain above or close to the base parameter, which is an acceptable benchmark.

IV. DISCUSSION

The primary goal of this research was the mapping of practiced cropland in the study areas, considering remote sensing image classification for the estimation of BARI seed planter machine needs in different farming practices. In this regard, cloud-free single dates along with atmospherically corrected Sentinel-2 satellite imageries were applied to a pixel-based unsupervised classification algorithm to define LULC classes for selected areas. The classification has been done based on five separate LULC classes, such as water bodies, forests, fallow land, settlements and location-specific major non-rice cropland. Each class was marked with the color defined for classification purposes, including blue color water bodies, green for forest, grey for fallow land, lime for cropland, and red for settlement. The result demonstrated that the RS of the satellite dataset of Sentinel-2 has been used for crop area estimation of the small area of different types of crops, i.e., jute, mungbean, and soybean. The RS technique plays a vital role in identifying and classifying different crop areas. The observation, with the help of image interpretation and field experience, revealed that the areas under study were predominantly agricultural regions. According to the findings of the LUCC, there are some reasons to identify and classify the croplands. Proper identification and discrimination of crops during their existing cropping season is very beneficial for crop area estimation. Based on field knowledge supported by the collected GPS coordinate point dataset, it was also used as ground truth to identify the land cover classes. The spatial distribution data analysis (2017, 2018, and 2019) of Baratia shows that the jute cultivation area has gradually increased over the past two years as the jute farmers are getting fair prices for their products and consumption of jute leaves as a vegetable is increasing over time. Conversely, the opposite scenario at Mundopasha and Holdibaria showed that decreased mungbean area coverage was observed in the seasons of 2019 and 2017. The reason was that the mungbean faced drought at the growing stage in Mundopasha during the season of 2019. Again, the crop was damaged due to heavy rainfall, which created waterlogging conditions at the pod ripening stage during the same season. As a result, the mungbean pod could not be harvested on time. Therefore, total production was reduced, and farmers lost interest in mungbean cultivation. Besides this, farmers are giving their attention to Boro rice cultivation. The same situation occurred in Holdibaria during the season of 2017. It should be addressed that farmers in those study areas have a preference for mungbean cultivation adjacent to road or homeside area and choose comparatively high land because of attacks from cattle, birds as well as easy harvesting. In Charwapda, the disparity in the spatial distribution of soybean area coverage was observed in three different years because heavy rains occurred during the ripening stage of the last week of April 2017, and then the maximum crop field was submerged in water for five to seven days. As a result, the crop was damaged, and farmers could not withdraw their investment at that time. Again, in the same season, soybean seedlings were

damaged due to high soil salinity at the seedling stage. Because no rainfall was occurred for more than three months (Middle December-Middle March). Besides, watermelon was the most competitive crop of soybean in this study area, and farmers earned a good return from watermelon cultivation in the 2017 season. At these points of view, farmer changed their mind about next season soybean cultivation. Consequently, accuracy assessment was carried out using the confusion matrix in order to examine the accuracy and consistency of the area estimated. With this backdrop, the accuracy of the classified maps was analyzed and represented by estimating the Kappa value and overall accuracy. In this study, several classes were incorrectly classified in the classification method of LULC, that ensure significant overlapping between the classes in all image layers due to their similarities in spectral characteristics, resulting in comparatively lower overall accuracy. The major reason for the lower accuracy of the image was misclassification or poor performance of the classification algorithm, overlapping, and errors in visual interpretation in distinguishing some LULC classes. Another reason was that the reference points were located in different areas for the assessments, i.e., many reference points were located in the border of two classes when assessing the classified image, so it was hard to identify the right class, which probably decreased the overall accuracy measure as well. For example, in Mundopasha and Holdibaria areas, the high misclassification rate of the mungbean field class was caused by the confusion with fallow land (with weeds) and tree shadows. Again, in Charwapda, it has been misclassified as an in-between soybean and watermelon field or as a settlement, as well as a low land/dry fishing pond that was shown as fallow land, and in some instant jute fields, it overlapped with the vegetable field and settlement in Baratia. Again, it was observed from the findings that the value of accuracy is expected to meet the requirements of greater than 60% [49], so that the results of the percentage of overall accuracy values obtained can be used as proof of the accuracy of image classification. Besides, the average value of Kappa, which was used to check accuracy in classification, is estimated to range from 0.65 to 0.85, which indicates a strong to good agreement between thematic maps generated from image analysis data and the reference data, which is quite satisfactory. Therefore, it can be summarized that the results of this research contribute to the understanding of the applications of satellite imagery classification and also the integration of RS with GIS. Also, the findings reveal that LULC mapping and area estimation of small crop areas using an unsupervised algorithm might be a better option for crop area identification. Subsequently, based on the estimated crop area and average annual use of the machine, the BARI seed planter machine quantity prediction was worked out for major crop cultivation during a cropping season. The study experience creates a wide opportunity for future studies in larger areas such as upazila, district, or country-level for the planning of agricultural mechanization, especially for the sustainable adoption of BARI seed planter machines. Moreover, the sensitivity analysis showed how sensitive the BARI seed planter machine estimation was for a decision-maker and how vulnerable that estimation is to changes in the total number of machines that can result from changes in the decision. This methodology also serves as a pre-season planning and management tool for a policymaker about the future forecasting of the agricultural machinery business market situation through mathematical instruments.

V. CONCLUSION

The empirical results of this study show that a method of integrated GIS and RS data as, well as the associated analytical approaches, have been usefully and powerfully used to identify crop identification and crop area estimation. In this study, a mouza-level LULC classification and estimates of area under a specific crop using Sentinel-2 satellite data with high precision were carried out for three different years at four study areas through an unsupervised classification approach in the GIS environment to define land use types for the areas. According to the spectral tone and texture of the classified image, LULC was mapped for uses of land such as fallow land (wetland, barren land, agricultural land), land under crop cultivation, water bodies, and land not available for cultivation (settlement/urban/built-up, etc.). Although accurately mapping agricultural resources in Bangladesh is a difficult assignment because of the characteristics of smallholder farms, such as smaller cropland sizes, irregularly shaped fields with often indistinct boundaries, strong seasonal variations in surface reflectance, predominantly rain-fed practices that naturally coincide with a high incidence of clouds, high spatiotemporal dynamics, etc. However, the investigation of the multi-temporal satellite imagery dataset was adequate to accurately identify the cropped area and to assess the performance of the methodology used that produced a satisfactory LULC thematic map generated from image analysis data. Furthermore, a methodology has also been applied for predicting the number of BARI seed planter machines based on estimated crop area and average annual use of machine for major upland crop cultivation in the study areas during a cropping season. Therefore, the results conclusively reveal that the efficiency and applicability of computer-aided geospatial analysis techniques for identifying and estimating crop areas of specific crop types could be necessary and useful, particularly to provide a better insight to the policymaker as to how many and what type of agricultural machinery need to be introduced either by adoption or replacement for crop cultivation.

CONFLICT OF INTEREST

The authors confirm that the content of this article has no conflicts of interest.

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REFERENCE

- [1]. Gurung, T. R., Kabir, W. and Bokhtiar, S. M. (eds.). [2017] “Mechanization for Sustainable Agricultural Intensification in SAARC Agriculture Centre” Dhaka, Bangladesh pp.302
- [2]. Tiwari P. S., Gurung, T. R., Sahni R. K. and Kumar, V. [2017] In: Gurung T. R., Kabir, W., Bokhtiar S. M. (Eds.) “Mechanization for Sustainable Agricultural Intensification in SAARC Agriculture Centre” Dhaka, Bangladesh Pp.302.
- [3]. Wohab, M. A., Roy, K. C., Haque, M. E. and Amin, M. N. [2007] “Adaption of minimum tillage seeder as high-speed rotary tiller for upland farming” Bangladesh Journal of Agricultural Research Vol. 31: pp.525–531.
- [4]. Grace, P. R. [2003] “Rice-wheat system and climatic change. In Addressing Resource Conservation Issues in Rice-Wheat Systems of South Asia: A Resource Book, Rice-Wheat Consortium for the Indo-Gangetic Plains” International. Maize and Wheat Improvement. Center, New Delhi, India. Pp.63-67.
- [5]. Sayre, K. D. and Hobbs, P. R. [2003] “Raised bed system of cultivation. Bed planting course” CIMMYT, Apdo. # 370, P.O. Box 60326, Houston.
- [6]. Aravindakshan, S., Rossi, F. and Krupnik, T. J. [2015] “What does benchmark of wheat farmers practicing conservation tillage in the eastern Indo-Gangetic Plains tell us about energy use efficiency? An application of slack-based data envelopment analysis” Energy Vol. 90: pp.483-493.
- [7]. Gathala, M. K., Timsina, J., Islam, M. S., Krupnik, T. J., Bose, T. R., Islam, N., Rahman, M. M., Hossain, M. I., Rashid, M. H. A., Ghosh, A. K., Hasan, M. M. K., Khayer, M. A., Islam, M. Z., Tiwari, T. P. and McDonald, A. [2016] “Productivity, profitability, and energetics: A multi-criteria assessment of farmers’ tillage and crop establishment options for maize in intensively cultivated environments of South Asia” Field Crops Research Vol. 186: pp.32–46. Doi.org/10.1016/j.fcr.2015.11.008
- [8]. Jat, L. K., Singh, S. K., Latore, A. M., Singh, R. S. and Patel, C. B. [2013] “Effect of dates of sowing and fertilizer on growth and yield of wheat (*Triticum aestivum*) in an Inceptisol of Varanasi” Indian Journal of Agronomy Vol. 58: Issue 4, pp.168-171.
- [9]. Miah, M. M. A., Haque, M. E., Baksh, M. and Hossain, M. I. [2010] “Economic analysis of power tiller operated seeder operation at farm level” Journal of Agricultural Engineering Vol. 38/AE: Issue 1, pp.19–24.
- [10]. Hossain, M. I., Sarker, M. J. U. and Hoque, M. A. [2015] “Status of conservation agriculture-based tillage technology for crop production in Bangladesh” Bangladesh Journal of Agricultural Research Vol. 40: Issue 2, pp.235-248.
- [11]. Gathala, M. K., Timsina, J., Islam, M. S., Rahman, M. M., Hossain, M. I., Rashid, M. H., Ghosh, A. K., Krupnik, T. J., Tiwari, T. P. and McDonald, A. [2015] “Conservation agriculture-based tillage and crop establishment options can maintain farmers’ yields and increase profits in South Asia’s rice–maize systems: evidence from Bangladesh” Field Crops Research Vol. 172: pp.85–98.
- [12]. Ahamed, T., Takigawa, T., Koike, M., Hossain, M. M., Houq, M. M. and Faruk, M. O. [2003] “Assessment of energy status by GIS for agricultural mechanization. A case study of Bangladesh” Japanese Journal of Farm Work Research Vol. 38: Issue 4, pp.221–236. Doi.org/10.4035/jsfwr.38.221.
- [13]. Rathinavel, S., Balaji, Kannan, Kavitha, R. and Ramachandran, J. [2023] “Application of GIS in Farm Mechanization” Just agriculture pp.9-12
- [14]. Lazzaria, M. and Mazzetto, F. [1996] “A PC model for selecting multicropping farm machinery systems” Computers and Electronics in Agriculture Vol. 14: Issue 1, pp.43-59. Doi.org/10.1016/0168-1699(95)00036-4.
- [15]. Bol, M. B. [1996] “Development of a Computer Model for Machinery Selection and Management” M.Sc. thesis, university of Gezira, wad Madeni, Sudan.
- [16]. Alam, M., Awal, M. A. and Hossain, M. M. [2001] “Selection of Farm Machinery by Using Computer Programme” Agricultural Mechanization in Asia, Africa and Latin America, AMA Vol. 32: Issue 1, pp.65 - 69.
- [17]. Dash, R. C. and Sirohi, N. P. S. [2008] “A computer model to select optimum size of farm power and machinery for paddy wheat crop rotation in northern India” Agricultural Engineering International Vol. 8: Issue X, pp.1-9.
- [18]. Dubey, A. [2010] “Decision support system for farm mechanization with the use of computer modeling for paddy-wheat crop rotation in Jabalpur district of Madhya Pradesh” Ph.D. thesis, JNKVV, Jabalpur, India.
- [19]. Yousif, L. A., Dahab, M. H. E. and Ramlawi, H. R. [2013] “Crop-machinery management system for field operations and farm machinery selection” Academic journals Vol. 5: Issue 5, pp.84-90. DOI 10.5897/JABSD2013.0205
- [20]. Pathak, U., Shrivastava, A. K. and Naik, R. K. [2019] “Computer programme for selecting farm machinery for tomato crop in central region of Madhya Pradesh” The Pharma Innovation Journal Vol. 8: Issue 6, pp.35-40
- [21]. Wohab, M. A., Ziauddin, A. T. M., Amin, M. N., Ahmed, S. and Roy, K. C. [2003] “Development of a power tiller operated minimum tillage seeder” Journal of the Institution of Engineers, Bangladesh Vol. 30/AE(1).
- [22]. Ahmed, S., Matin, M. A., Roy, K. C., Amin, M. N., Islam, M. S. and Islam, M. S. [2005] “Field performance test of power tiller operated planter for maize, wheat and pulses crop” Annual Research Report, Bangladesh Agricultural Research Institute (BARI), Joydebpur, Gazipur-1701, Bangladesh.
- [23]. Matin, M. A., Roy, K. C. and Amin, M. N. [2008] “Performance of BARI developed planter for establishment of maize” Agricultural Engineering International: the CIGR Ejournal. Manuscript PM 07 023 X January.
- [24]. Hoque, M. A. [2017] “Energy use efficiency of different conservation agriculture-based crop management practices” PhD Dissertation. Department of Farm Power and Machinery, Bangladesh Agricultural University. Mymensingh-2202.
- [25]. Mottalib, M. A., Hossain, M. A., Hossain, M. I., Amin, M. N., Alam, M. M. and Saha, C. K. [2019b] “Enhancing economically and eco-friendly jute production through appropriate conservation agricultural tillage cum seeding methods in the southwestern coastal region of Bangladesh” International Journal of Engineering Inventions Vol. 8: Issue 1, pp.27-46
- [26]. Mottalib, M. A., Hossain, M. A., Hossain, M. I., Amin, M. N., Alam, M. M. and Saha, C. K. [2019a] “Assessment of cost-benefit parameters of conservation agricultural machinery for custom hires entrepreneurship in the southern region of Bangladesh” Agricultural Engineering International: CIGR Journal Vol. 21: Issue 3, pp.94–103.

- [27]. Haque, M. E., Rahman, S. N. and Bell, R. W. [2013] "Smallholders' Minimum Tillage Planter Adoption in Bangladesh: A successful case of private sector involvement for technology commercialization" Proceedings paper: 1st CIGR Inter-regional Conference on Land and Water Challenges - Water, Environment and Agriculture: Challenges for sustainable development, Bari, Italy, 2013
- [28]. Miah, M. A. M. and Alam, Q. M. [2008] "Adoption and relative profitability of mustard production in Bangladesh" Annual Research Report 2007-08, Oilseed Research Centre, BARI, Joydebpur, Gazipur.
- [29]. Knorr, W., Jiang, L. and Arneith, A. [2016] "Climate, CO₂ and human population impacts on global wildfire emissions" *Bio-geosciences* Vol. 13: pp.267–282, DOI:10.5194/bg-13-267-2016
- [30]. BBS (Bangladesh Bureau of Statistics) [2022] "Statistical Year Book of Bangladesh" Statistics Division, Ministry of Planning, Government of the People's Republic of Bangladesh, Website: www.bbs.gov.bd
- [31]. Sikder, M. U., Haque, M. A., Jodder, R., Kumar, T. and Mondal, D. [2016] "Polythene Mulch and Irrigation for Mitigation of Salinity Effects on Maize (*Zea mays* L.)" *A Scientific Journal of Krishi Foundation. The Agriculturists* Vol. 14: Issue 2, pp.01-13.
- [32]. Zhang, T., Su, J., Liu, C. and Chen, W. H. [2017] "Band Selection in Sentinel-2 Satellite for Agriculture Applications" Proceedings of the 23rd International Conference on Automation & Computing, University of Huddersfield, Huddersfield, UK, 7-8 September, pp.1-7.
- [33]. ESA (European Space Agency) [2020] "Sentinel-2 MSI technical guide" Retrieved July 28, 2020 from <https://sentinel.esa.int/web/sentinel/technical-guides/sentinel-2-msi>.
- [34]. Merry, K. and Bettinger, P. [2019] "Smartphone GPS accuracy study in an urban environment" *PLoS ONE* Vol. 14: Issue 7, e0219890. Doi.org/10.1371/journal.pone.0219890.
- [35]. Adel, S. and Moghanm, F. S. [2015] "Assessment of urban sprawl on agricultural soil of northern Nile Delta of Egypt using RS and GIS" *Chinese Geographical Science* Vol. 25: Issue 3, pp.274–282.
- [36]. Soni, S. K. [2011] "Crop Area Estimation for Bundi Tahsil of Rajasthan using Remote Sensing and GIS Technique" *Geospatial World Forum*, Hyderabad, India, pp.18-21.
- [37]. Paiboonvorachat, C. and Oyana, T. J. [2011] "Land-cover changes and potential impacts on soil erosion in the Nan watershed, Thailand" *International Journal of Remote Sensing* pp.1-23. Doi:10.1080/01431161.2010.512935
- [38]. Lu and Weng [2007] "A survey of image classification methods and techniques for improving classification performance" *International Journal of Remote Sensing* Vol. 28: Issue 5, pp.823-870. Doi.org/10.1080/01431160600746456.
- [39]. Xiong, J., Prasad, S., Thenkabail, P. S., Gumma, M. K., Teluguntla, P., Poehnel, J., Congalton, G. R., Yadav, K. and Thau, D. [2017] "Automated cropland mapping of continental Africa using Google Earth Engine cloud computing" *ISPRS Journal of Photogrammetry and Remote Sensing* Vol. 126: pp.225–244. Doi.org/10.1016/j.isprsjprs.2017.01.019.
- [40]. Harris, P. M. and Ventura, S. J. [1995] "The integration of geographic data with remotely sensed imagery to improve classification in an urban area" *Photogrammetric engineering and remote sensing* Vol. 61: pp.993-998.
- [41]. Congalton, R. G. [1991] "A review of assessing the accuracy of classifications of remotely sensed data" *Remote Sensing of Environment* Vol. 37: pp.35–46.
- [42]. Cohen, J. [1960] "A coefficient of agreement for nominal scales" *Educational and psychological measurement* Vol. 20: Issue 1, pp.37-46.
- [43]. Torres-Sánchez, J., López-Granados, F., De Castro, A. I. and Peña-Barragán, J. M. [2013] "Configuration and Specifications of an Unmanned Aerial Vehicle (UAV) for Early Site-Specific Weed Management" *PLoS ONE* Vol 8: Issue 3, e58210. <http://doi.org/10.1371/journal.pone.0058210>.
- [44]. Cai, X., Thenkabail, P. S., Biradar, C. M., Platonov, A., Gumma, M., Dheeravath, V., Cohen, Y., Goldshleger, N., Ben-Dor, E., Alchanatis, V., Vithanage, J. and Markandu, A. [2009] "Water productivity mapping using remote sensing data of various resolutions to support "more crop per drop" *Journal of Applied Remote Sensing* Vol. 3: pp.335-03357. Doi: 10.1117/1.3257643
- [45]. Gallego, F. J. [2004] "Remote sensing and land cover area estimation" *International Journal of Remote Sensing* Vol. 25: pp.3019-3047. Doi:10.1080/01431160310001619607.
- [46]. Shalaby, A. and Tateishi, R. [2007] "Remote sensing and GIS for mapping and monitoring landcover and land-use changes in the Northwestern coastal zone of Egypt" *Applied Geography* Vol. 27: pp.28–41
- [47]. Foody, G. M. [2006] "GIS: Health applications. Progress in Physical Geography" *Earth and Environment* Vol. 30: Issue 5, pp.691-695. Doi:10.1177/0309133306071152.
- [48]. Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M. and Tarantola, S. [2008] "Global Sensitivity Analysis: The Primer" John Wiley & Sons: Chichester, UK.
- [49]. Green, E. P., Mumby, P. J., Edwards, A. J. and Clark, C. D. [2000] "Remote sensing handbook for tropical coastal management" UNESCO, Paris.