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Article

Climate-Adaptive Potential Crops Selection in Vulnerable Agricultural Lands Adjacent to the Jamuna River Basin of Bangladesh Using Remote Sensing and a Fuzzy Expert System

Kazi Faiz Alam [1] and Tofael Ahamed [2,*]

[1] Graduate School of Science and Technology, University of Tsukuba, Tsukuba 305-8577, Japan
[2] Faculty of Life and Environmental Sciences, University of Tsukuba, Tsukuba 305-8577, Japan
* Correspondence: tofael.ahamed.gp@u.tsukuba.ac.jp

Abstract: Agricultural crop production was affected worldwide due to the variability of weather causing floods or droughts. In climate change impacts, flood becomes the most devastating in deltaic regions due to the inundation of crops within a short period of time. Therefore, the aim of this study was to propose climate-adaptive crops that are suitable for the flood inundation in risk-prone areas of Bangladesh. The research area included two districts adjacent to the Jamuna River in Bangladesh, covering an area of 5489 km^2, and these districts were classified as highly to moderately vulnerable due to inundation by flood water during the seasonal monsoon time. In this study, first, an inundation vulnerability map was prepared from the multicriteria analysis by applying a fuzzy expert system in the GIS environment using satellite remote sensing datasets. Among the analyzed area, 42.3% was found to be highly to moderately vulnerable, 42.1% was marginally vulnerable and 15.6% was not vulnerable to inundation. Second, the most vulnerable areas for flooding were identified from the previous major flood events and cropping practices based on the crop calendar. Based on the crop adaptation suitability analysis, two cash crops, sugarcane and jute, were recommended for cultivation during major flooding durations. Finally, a land suitability analysis was conducted through multicriteria analysis applying a fuzzy expert system. According to our analysis, 28.6% of the land was highly suitable, 27.9% was moderately suitable, 19.7% was marginally suitable and 23.6% of the land was not suitable for sugarcane and jute cultivation in the vulnerable areas. The inundation vulnerability and suitability analysis proposed two crops, sugarcane and jute, as potential candidates for climate-adaptive selection in risk-prone areas.

Keywords: climate change; climate adaptive crops; inundation vulnerability; land suitability; fuzzy expert system; remote sensing

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1. Introduction

A long-term change in temperature and weather patterns is referred to as climate change. Climate change impacts agriculture and food security significantly by region and crop [1]. It has become a challenge to feed everyone with the present agricultural production as the world's population continues to increase [2]. Numerous adaptation strategies are needed to ensure food security for increasing populations and to fight against the adverse effects of climate change. Climate-adaptive crop selection, changes in different cropping practices in different lands, improved crop variety development and changes in food consumption are used as strategies. Among them, land utilization for production has no alternatives, even in highly disaster-prone areas.

Bangladesh is a highly disaster-prone deltaic country and global south hotspot of climate change impact [3], where many small to large rivers flow from north to south and contribute to the Bay of Bengal. Among the four main rivers of Bangladesh, Padma flows from the northwest and merges with Jamuna. Jamuna flows from north to south and merges with Meghna, and Brahmaputra flows from north to south and merges with

Meghna. Meghna merges with the Bay of Bengal with accumulated water discharge. These rivers carry enormous amounts of water accumulated from local rainfall as well as water from upstream throughout the monsoon season. During the monsoon season, the catchment of the river becomes ten times larger than that during the dry season, inundating low-lying areas adjacent to rivers and causing serious inundation risks for agricultural land. In previous research, 44.34% of agricultural lands were reported as highly vulnerable, and 37.75% were moderately vulnerable in the 25 km territory of the main river system of Bangladesh due to the risk of inundation by flood water [4].

In the last 68 years (1954–2022), ten major flood events occurred in Bangladesh. Among them, the flood in 1987 occurred between late June and September and inundated an area of 57,000 km^2 [5]. Approximately 2.5 million houses were damaged, 1657 people died and 3.5 million tons of rice were damaged during this flood. In 1988 and 1998, Bangladesh was also affected by major floods; during that time, 35 and 51 districts out of 64 were affected, respectively. Approximately 370,000 hectares of agricultural land was fully damaged, and 391,000 hectares was partially damaged, causing drastic losses of 2 million tons of rice production during the 1998 flood [5]. According to the Department of Agriculture of Bangladesh, 24,000 farmers in the northern two districts were affected by the flood in 2022. Approximately 16,383 hectares of crops were damaged, causing a loss of USD 13 million. Most flood events occur during the premonsoon to monsoon season, which is the harvesting and planting time for rice and other cereal crops. Therefore, it is necessary to identify the lands that are considered vulnerable for agricultural use during high-risk periods to reduce the crop production losses caused by water inundation, especially in the lowland-based deltaic region. Furthermore, it is necessary to find climate-adaptive crops and conduct suitability assessments for risk-prone lands for regular crops in the monsoon season.

Deltaic regions such as Bangladesh are also facing a high risk of climate change and outbreaks in riverine areas. Rivers are directly related to the life and livelihoods of the peoples near them. Specifically, farmers are directly related to rivers, as most cultivable lands are in riverine flood plains. To assess the adverse effects of natural calamities such as riverbank erosion, cyclones, flash floods and floods, researchers have studied several areas of Bangladesh [6–10]. However, inundation vulnerability assessments for climate-adaptive crop selection in the riverine flood plains in Bangladesh are rare. For different aspects, such as suitability analysis and vulnerability analysis, multicriteria decision-making (MCDM) methods have become a very effective approach. A transparent reflection of decisions can be shown by thematic maps using the MCDM approach [11]. This MCDM approach has been applied by different researchers for the spatial analysis of land use, crop suitability and vulnerability assessment [12–14].

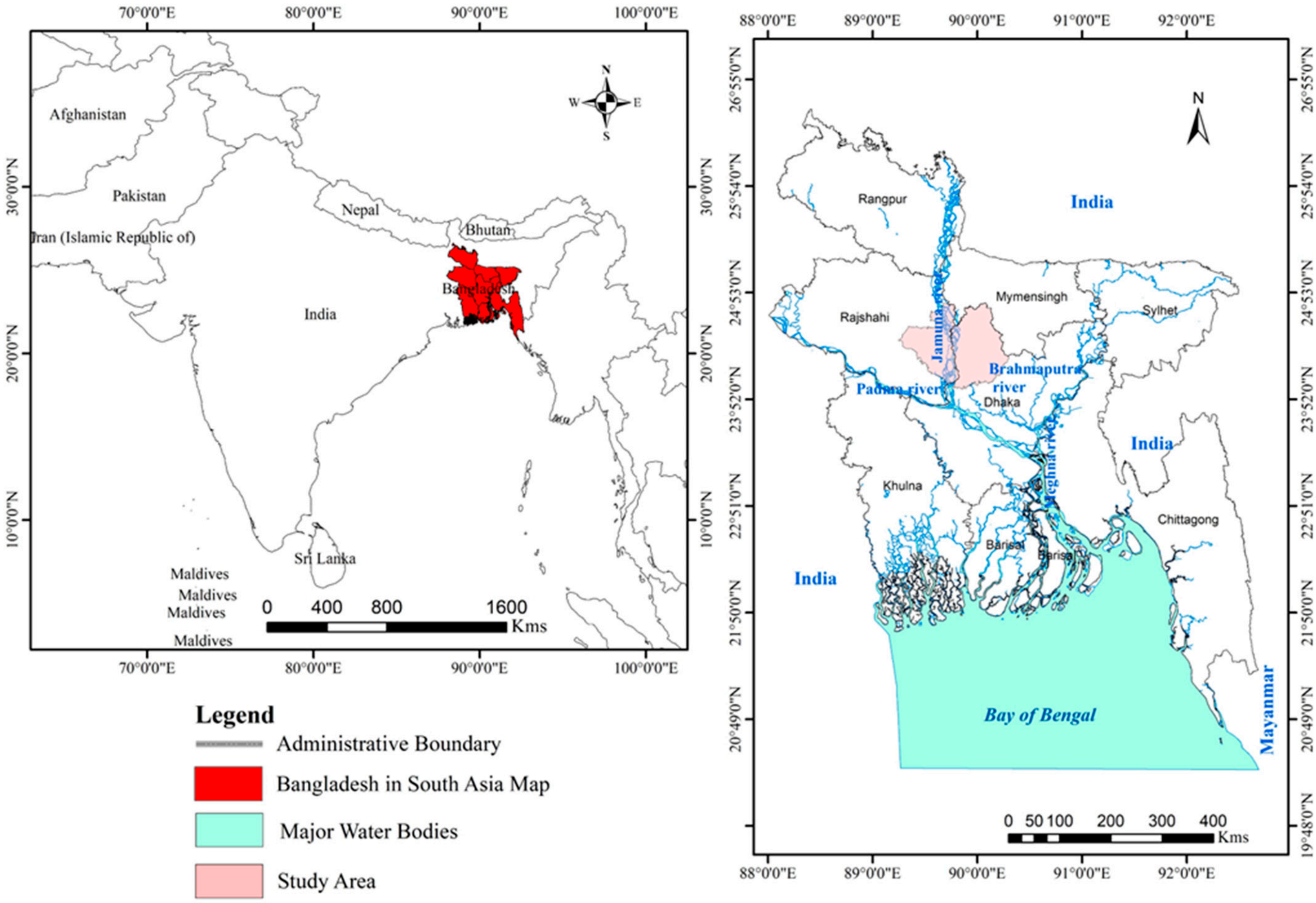
Determining the degree of land suitability and vulnerability in traditional methods is possible in any aspect, but it is very difficult, laborious and time-consuming [15]. In the field of vulnerability and suitability assessment, the application of satellite remote sensing (RS) and geographical information systems (GIS) has gained considerable attention from researchers because of their effectiveness [16,17]. In this regard, the fuzzy-based MCDM approach has been used often for crop suitability assessments by many researchers because of its improved precision and effectiveness for both single crops and multiple crops, such as maize, tea, casava, rice and other cereal crops [18–21]. Multicriteria decision-making (MCDM) methods have also been applied for suitability assessments of industrial development in suburban areas of Bangladesh [22]. However, inundation vulnerability assessments for agricultural land and suitability analyses for crops capable of tolerating flood water were rarely projected in previous studies. In this regard, our first research question was how to assess the agricultural land vulnerable to inundation risk to improve planning during the flood season on spatial and temporal scales. Additional important points of investigation were to inventory flood times, identify the crops capable of tolerating flood water and finally assess land suitability for crop cultivation. In riverine basins, satellite remote sensing can be an effective tool for assessing inundation vulnerability and land suitability for specific crops.

Therefore, the objectives of this research were to predict vulnerable agricultural land areas to recommend climate-adaptive crops during times of inundation and create land suitability maps using a fuzzy expert system and satellite remote sensing.

2. Materials and Methods

2.1. Study Area

The study area covered two administrative districts (Sirajganj and Tangail) of Bangladesh (Figure 1).



(**a**) (**b**)

Figure 1. Geographical extent of the study area in Bangladesh. (**a**) Location of the Bengal Delta in the world map. (**b**) River distribution flows from north to south toward the Bay of Bengal.

Sirajganj and Tangail districts fall under the Rajshahi and Dhaka divisions, respectively. The mighty Jamuna River flows along the boundary of both districts, and they are highly to moderately vulnerable to flooding [4]. The analysis area covered 5489 km^2 of the two administrative districts. The surface area of the two districts is composed of clay, silt, and fine- to medium-grained sand [23], which are recent floodplain deposits [24]. The most common land uses in these districts are water bodies, natural and manmade vegetation, agricultural land and urban areas. In this area, agricultural lands are in low-lying areas that are often inundated by flood water during the monsoon season. From the literature review and published online database, it was found that more than twelve major flood events occurred in Bangladesh from 1994 to 2022. Those floods mostly occurred between late June and September and were caused by the overflow of river water (premonsoon to monsoon) due to excessive rainfall in Bangladesh as well as in upstream areas. All the districts near the Jamuna and Brahmaputra Rivers were severely affected, whereas the

Sirajganj and Tangail districts in the study area were affected by every flood event. Many houses, lives and agricultural crops were damaged by the floods. Major flood events, their time of occurrence, affected area and damages are shown in Table 1.

Table 1. Major flood events in Bangladesh from 1954 to 2022.

Year of Occurrence	Month of Occurrence	Affected Area	Damage	Reference
1954	July–August	All districts near Jamuna River.	The water height at Sirajganj city was 14.22 m, damaged all crops. Dhaka district went under water.	[25]
1955	August	All districts near Jamuna River and 30% of Dhaka city.	Crops and houses	[25]
1974	March–December	Northeastern part of Bangladesh, Mymensingh, Sylhet, Sunamjang.	Significant majority of annual rice crop, one of the major causes of 1974 famines. 30,000 people died (Official data).	[26]
1987	Late June–September	57,000 km^2, about half of the area of Bangladesh.	3.5 M tons of rice, 2.5 million houses and 1657 lives,	[5]
1988	August–September	35 between 64 districts. 82,000 km^2 area (BWDB 1987 and MOI 1988).	370,000 ha fully, 391,000 ha partially damaged, 2 M tons of rice.	[5]
1998	July–August	51 of 64 districts. 75% of the country, including half of Dhaka.	30 million people and 6 million families were affected. They lost their crops and properties.	[27]
2004	July	39 of 64 districts were affected.	36 million people were affected. Agriculture, infrastructure, and health sectors were affected.	[28]
2014	August–September	Nilphamari, Lalmonirhat, Kurigram, Rangpur, Gaibandha, Jamalpur, Sirajganj, Tangail, Sunamjanj and Sylhet.	10,000 acres of crops were inundated.	[10]
2016	July–September	19 districts since July. Jamalpur, Kurigram, Sirajganj, Tangail, Gaibanda. Together, these 5 districts account for more than 70% of the affected people.	3.2 million people across 16 districts.	[29]
2017	July–August	31 districts, including Sirajganj and Tangail.	15,529 hectares of agricultural land fully and 562,594 hectares partially inundated.	[30]
2020	June–July	21 districts of Bangladesh, including Sirajganj and Tangail.	Most of the agricultural land was affected.	[31]
2022	July	Lalmonirhat, Kurigram, Thakurgaon, Panchagarh, Gaibandha, Bogra, Sirajganj, Jamalpur, Sunamganj, Brahmanbaria, Mymensingh, Tangail, Sylhet and Sunamjanj.	Most of the agricultural crops.	[32]

2.2. Datasets for Spatial Analysis

The present research was conducted using Landsat 9 multispectral datasets with a 30 m spectral resolution retrieved between October and December 2022. Different criteria maps were prepared from the satellite images to assess vulnerability due to water inundation and land suitability. Images retrieved from the Landsat 9 satellite that had less than 1% cloud coverage were utilized for map preparation. Elevation and slope maps of the study area were prepared from SRTM datasets (Table 2). An annual average precipitation map for 2021 was prepared from the CHIRPS precipitation data collected from the 1995–2022 datasets. Distance from the river was calculated utilizing the river shape file using Euclidian distance. The river shape files and administrative shape files for the research areas were collected from the Bangladesh Bureau of Statistics (BBS) updated in 2020. Soil data were retrieved from the International Soil Data Reference and Information Centre (ISRIC) data hub for preparing soil texture and pH maps (Table 2). Finally, all the prepared criteria maps were masked and analyzed in the ArcGIS 10.8.1® environment.

Table 2. Selected criteria, data types, data sources and their explanations for use in the study.

No	Data	Explanation	Types	Source of Data
1	Land Use and Land Cover (LULC) map for 2022	Developed from Landsat 9 images in Google Earth Engine Platform	Raster	USGS
2	Slope map	The Shuttle Radar Topography Mission (SRTM), resolution 1-ARC	Raster	DEM SRTM USGS, 2014 and 2015
3	Elevation map			
4	Rainfall map	CHIRPS PERSIANN-Cloud classification system, resolution of 4 km × 4 km	Raster	CHIRPS, 2020 www.chrsdata.eng.uci.edu (accessed on 15 January 2023)
5	NDWI map for 2022	Prepared from Landsat 9 (Collection 1 Tire 1 eight-days composite) in Google Earth Engine Platform	Raster	USGS
6	Soil pH	Soil texture and pH data of 250 m resolution covering 30 cm depth	Raster	ISRIC Data Hub www.isric.org/explore/isric-soil-data-hub (accessed on 15 January 2023)
7	Soil texture			
10	Administrative Boundary Shapefile		Vector	Bangladesh Bureau of Statistics (BBS)
11	River Shapefile		Vector	Bangladesh Bureau of Statistics (BBS)

2.3. Research Framework

The present study was conducted in two stages. In the first stage, an inundation vulnerability analysis was carried out based on multiple criteria. All the criteria were directly related to inundation by water. In the second stage, major flood events and their timing were analyzed from the historical database and literature. The common cropping practices by the farmers in the study area were also analyzed to identify crops that were susceptible for growing in flood-affected agricultural land. Then, potential climate-adaptive crops were proposed instead of vulnerable crops. Finally, a land suitability analysis was performed for the crops, and a land suitability map was prepared. The suitability map was prepared using eight related criteria, in which inundation vulnerability was included. The land suitability map was validated with the ground reference crop production data. In both analyses, a fuzzy-based MCDM method was implemented (Figures 2 and 3).

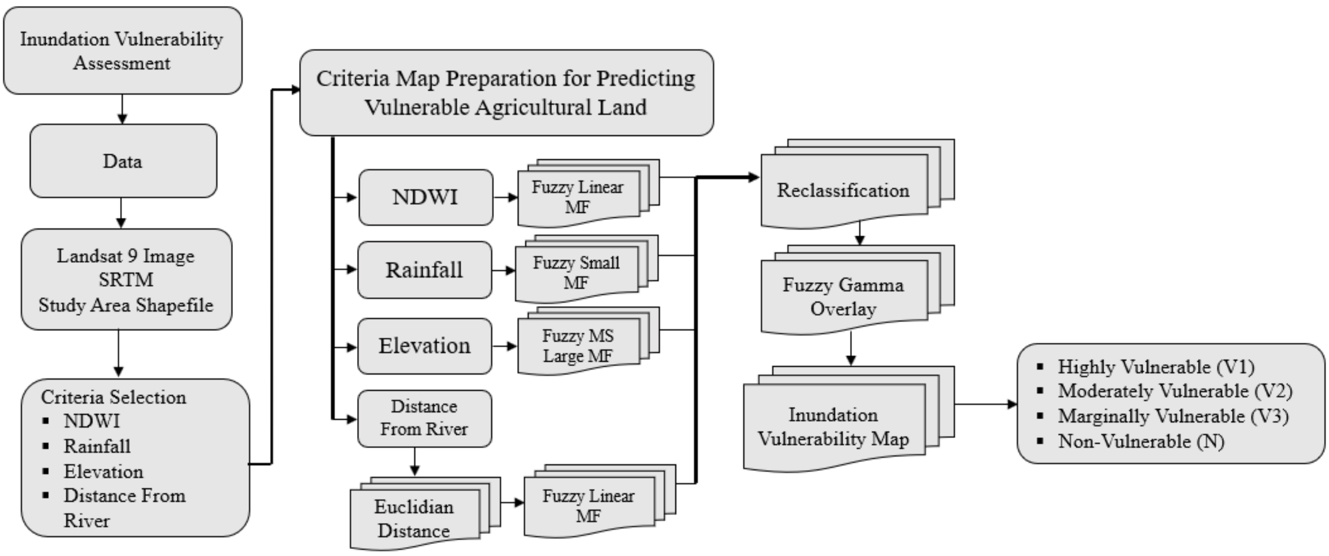


Figure 2. Stepwise workflow for inundation vulnerability assessment in the riverine area.

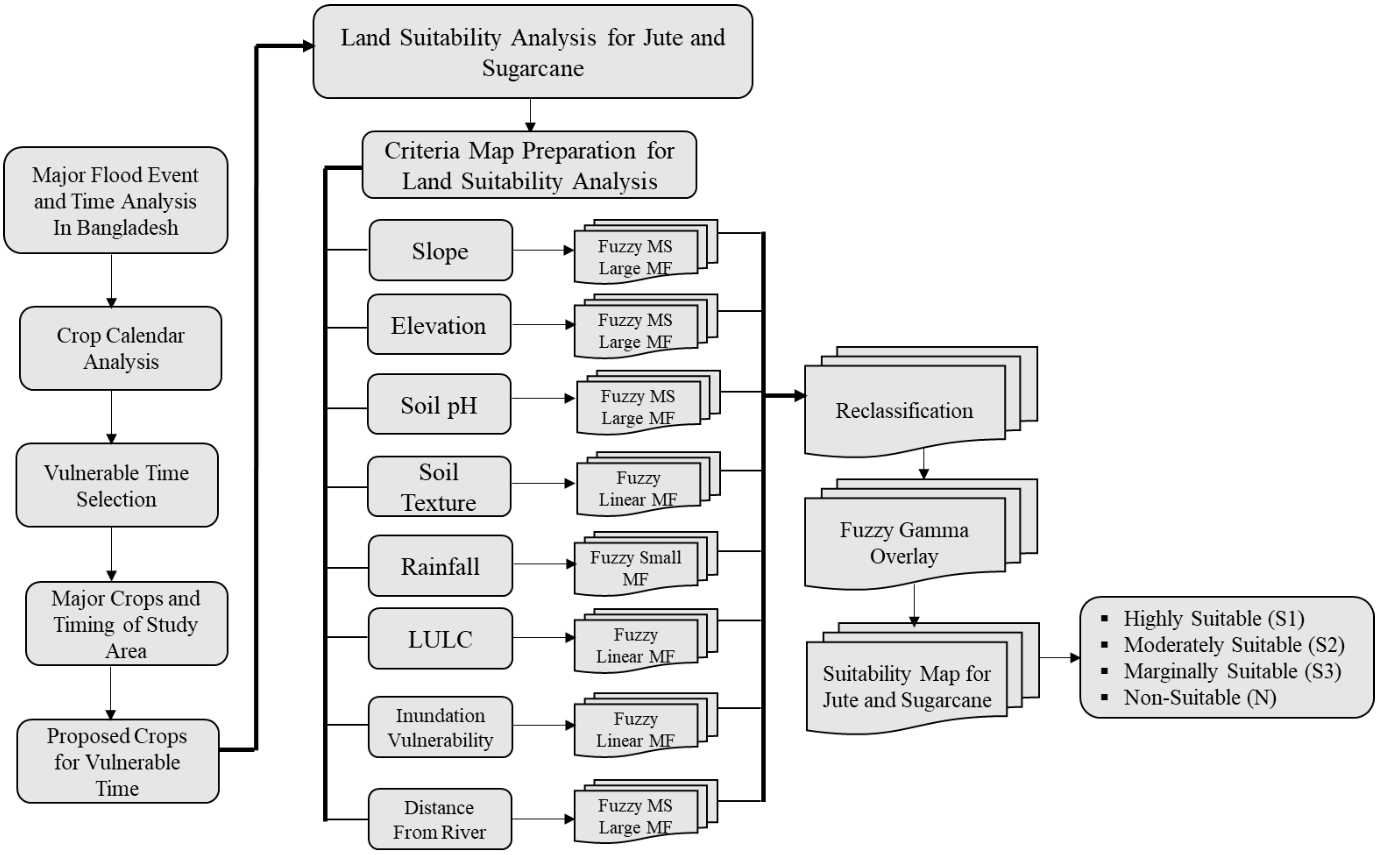


Figure 3. Stepwise workflow of land suitability assessment for jute and sugarcane.

2.3.1. Inundation Vulnerability Assessment

As a part of climate-adaptive crop selection for vulnerable agricultural land, an inundation vulnerability assessment was performed. The inundation vulnerability map was prepared using a fuzzy-based membership function by reclassification and multicriteria analysis. In the following section, the reclassification of fuzzy membership functions and the criteria considered for analysis are discussed.

Reclassification of Fuzzy Membership Function

Within a specific domain in GIS, fuzzy set theories allow the modeling of vulnerability and suitability assessment. Within a membership class or set, the fuzzy standard approach clearly defines whether they are in the class or not [33]. To accommodate a high certainty scoring method, a fuzzy membership function was used to assign the inundation vulnerability class for agricultural land use. A fuzzy membership function was also used for standardization. Seven membership functions were selected based on a literature review of which three best fitted functions were used for inundation vulnerability assessment. The selected fuzzy membership functions were linear, small and MS large, which produced standardized criteria through continuous fuzzy classifications (Equations (1)–(3)). A fuzzy linear membership function was applied to build a linear function between minimum and maximum values, whereas a fuzzy small membership function was used when a fuzzy set contained smaller input values. The fuzzy MS large membership function was used when the fuzzy set was most likely to contain larger input values. According to ESRI, the same equation was used for the fuzzy large and MS large membership functions in the ArcGIS 10.8.1® environment. The natural breaks (Jenks) method was used for the inundation vulnerability reclassification of agricultural land despite limited references concerning water inundation vulnerability assessment in riverine areas.

$$\mu(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \geq b \end{cases} \quad (1)$$

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{f1}} \quad (2)$$

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{-f1}} \quad (3)$$

In Equation (1), the values for the x coordinate are represented by a and b, where x represents the crisp value. In Equations (2) and (3), f1 and f2 represent the spread and midpoint for fuzzy small and fuzzy MS large membership functions, respectively, and x is the crisp value. The values of f1 and f2 varied for different criteria.

Criteria Selection for Inundation Vulnerability Assessment

The criteria that were directly related to inundation by water were selected for this analysis. Among the selected criteria, the normalized difference water index (NDWI) was from phenological domain, while rainfall, elevation and distance from the river were related criteria from the environmental and topographical domains. After calculating these criteria, an inundation vulnerability map was prepared and then reclassified into four classes, V1, V2, V3 and N, where V1 refers to highly vulnerable agricultural land, V2 is moderately vulnerable land, V3 is marginally vulnerable land and N refers to nonvulnerable agricultural land.

Normalized Difference Water Index (NDWI)

The NDWI was used for the inundation vulnerability assessment to identify permanent water bodies, such as rivers and permanently waterlogged areas, which are very important for vulnerability analysis. Lands near water sources such as rivers are very vulnerable to inundation by flood water as well as rainwater during the monsoon season. As our study area is near the Jamuna River and experienced many flood events in the past, the NDWI could be an important criterion for vulnerability assessment. Landsat 9 images were used to calculate the NDWI, where two spectral bands, green and NIR, were utilized for calculation in the Google Earth Engine (GEE) platform (Equation (4), [34]).

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (4)$$

Finally, the calculated *NDWI* was standardized using a fuzzy linear membership function, and the map of the study area was reclassified into four vulnerability classes (Table 3; Figure 4a).

Table 3. Fuzzy membership function for inundation vulnerability.

No	Criteria	Fuzzy Membership Function		Equation	Fuzzy Membership Type
		Midpoint	Spread		
1	Rainfall	2013.5	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{2013.50}\right)^{5}}$	Fuzzy Small
2	Elevation	22.91	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{22.91}\right)^{-5}}$	Fuzzy MS Large
3	Distance from river	7961.91	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{7961.91}\right)^{-5}}$	Fuzzy MS Large
4	Criteria	Minimum	Maximum		
	NDWI	0	0.20	$\mu(x) = \begin{cases} 0 & x \leq 0 \\ \frac{x-0}{0.20-0} & 0 < x < 0.20 \\ 1 & x \geq 0.20 \end{cases}$	Fuzzy Liner

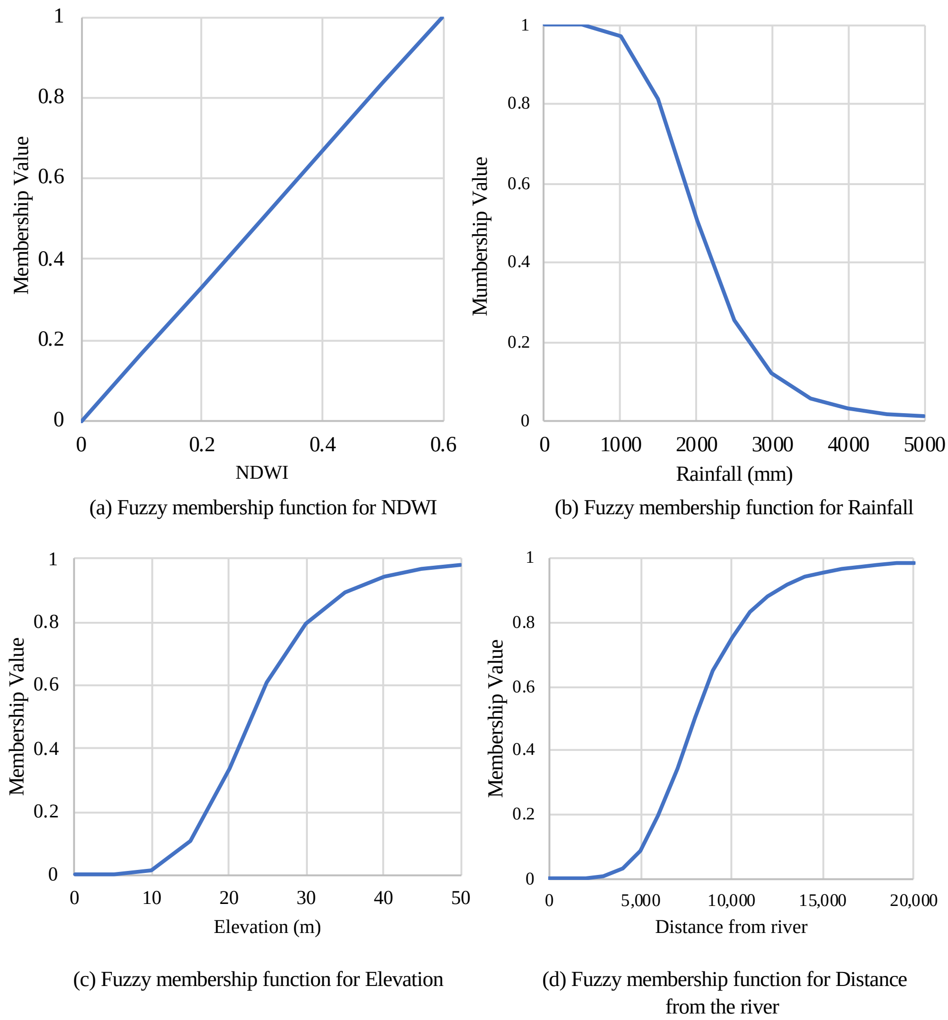


Figure 4. Fuzzy membership function for inundation vulnerability assessment: (**a**) NDWI; (**b**) rainfall; (**c**) elevation and (**d**) distance from the river.

Rainfall

The average rainfall of the investigated area for 2021 was prepared from the CHRS dataset collected from the CHRS data portal. According to the rainfall data, the lowest rainfall was 1635 mm, and the highest was 2392 mm in 2021. CHRS rainfall raster dataset of $0.04° \times 0.04°$ pixel size used to prepare the rainfall map is equivalent to $4445 \text{ m} \times 4445 \text{ m}$ spatial resolution. Then the rainfall map was resampled to $30 \text{ m} \times 30 \text{ m}$ using the resampling tool from the spatial analysis section given in ArcGIS 10.8.1®. The resampled map was then converted into point data using the conversion tool, and IWD interpolation was performed using spatial analysis tools in ArcGIS before applying the fuzzy membership function. The prepared rainfall map was standardized by applying the fuzzy small membership function in ArcGIS (Table 3, Figure 4b). Finally, the standardized rainfall map was reclassified into four vulnerability classes.

Elevation

Lands with higher elevations related to mean sea level are less vulnerable to inundation than are those with lower elevations. Elevation has a direct relationship with inundation by flood water and was selected as one of the important criteria. An elevation map was prepared by analyzing the SRTM elevation data. According to the analysis, the highest and lowest elevations were 50 m and −14 m, respectively. Most agricultural lands were in low-elevation plain areas and were vulnerable to inundation due to floods. Most agricultural lands went underwater during floods and the monsoon season, causing massive damage to crop and affecting agricultural production. The prepared elevation map was reclassified into four vulnerability classes after standardization using the fuzzy MS large membership function (Table 3; Figure 4c).

Distance from the River

As the area near the rivers has a higher inundation risk, the distance from the river was considered the most important criterion for inundation vulnerability analysis. Distance from the river was calculated using the Euclidean distance tool in the ArcGIS spatial environment using the river shape file of the study area. The river shape file was collected from the Bangladesh Bureau of Statistics (BBS), which was updated in 2020. Finally, the map was reclassified into four vulnerability classes after standardization using the fuzzy MS large membership function (Table 3; Figure 4d).

Fuzzy Overlay for Inundation Vulnerability Analysis

Fuzzy overlay tools can be used to analyze the possibility of a phenomenon belonging to multiple sets in a multicriteria overlay analysis. Fuzzy overlay tools can be used to analyze the relationships between multiple sets' memberships and to determine which sets the phenomenon is possibly present in. According to set theory, there are five types of overlay methods to combine data. The five fuzzy overlay methods are Fuzzy OR, Fuzzy AND, Fuzzy Sum, Fuzzy Product and Fuzzy Gamma. An inundation vulnerability map was produced combining the criteria maps from the fuzzy linear, fuzzy small and fuzzy MS large membership functions by conducting a Fuzzy Gamma overlay. Fuzzy Gamma can be expressed by the following equation, which is an algebraic product of the Fuzzy Sum and Fuzzy Product [35].

$$\mu(\mathrm{x}) = (\text{Fuzzy Sum})^{\gamma} \times (\text{Fuzzy Product})^{1-\gamma} \quad (5)$$

where $\mu(x)$ is calculated as the fuzzy membership function, and γ is chosen parameter in range (0, 1).

For generalizing the gamma overlay function, the default gamma value of 0.9 was used. Then, the natural breaks (Jenks) method was used to reclassify the vulnerability map into four different vulnerability classes [36]. In the database, the classes were based on inherent natural groupings [37].

2.3.2. Crop Selection for Vulnerable Agricultural Land

As a part of climate adaptation in agricultural crop models for vulnerable agricultural land, it was necessary to analyze the major flood event, affected area, time of occurrence and amount of damage. It was also necessary to analyze the major cropping practices and vulnerable time selection for those crops in terms of inundation risk by analyzing the crop calendar of the study area. Then, suitable crops for the time and area can be proposed. Three cropping seasons were reported for the central to northern parts of Bangladesh: the Rabi season (middle of October to middle of March) during the winter season, Kharif-1 (middle of March to middle of July) during the premonsoon season and Kharif-2 (middle of July to middle of October) during the monsoon season [38–41]. A crop calendar including major flooding time in Bangladesh is shown in Figure 5.

The common cropping practices during the Kharif-1 and Kharif-2 seasons are rice and maize [42]. During the Rabi season, potato, wheat, lentil, mustard, and different types of vegetables are cultivated. According to the flood event analysis, during the harvesting time of the Kharif-1 season and the planting time of the Kharif-2 season, rice and maize are severely affected by flood water inundation in low-lying areas. To reduce the losses, crops that can survive longer than rice and maize can be produced in vulnerable areas. According to the Bangladesh Jute Research Institute (BJRI), jute is grown almost in all the districts of Bangladesh, but better growing areas are Jessore, Tangail, Faridpur, Sirajganj, Dhaka, Bogra and Jamalpur. One on-farm survey was conducted in eight jute-growing subdistricts in Tanjgail during 1988–1989, which stated jute was the most common crop in low-lying areas, but practices were changed due to high production cost and high price of seeds and fertilizer [43]. The low market price of jute and competition between jute and synthetic fibers products caused changes of growing practices. In the 1960s, the major threat for jute production comes from commercial production of low-cost thermoplastic [44]. However, jute is becoming very popular worldwide in the recent time, and demand is increasing also due to its eco friendliness which is making farmers interested in jute cultivation. According to Department of Agricultural Extension (DAE), sugarcane is a very popular cash crop among the farmers of Bangladesh. As sugarcane is an annual crop and keeps the land occupied for one year, some farmers are inclined to cultivate other crops, but recently, sugarcane cultivation has been increasing in the low-lying areas. In 2022, sugarcane was cultivated in 786 ha of land in Tangail district (DAE).

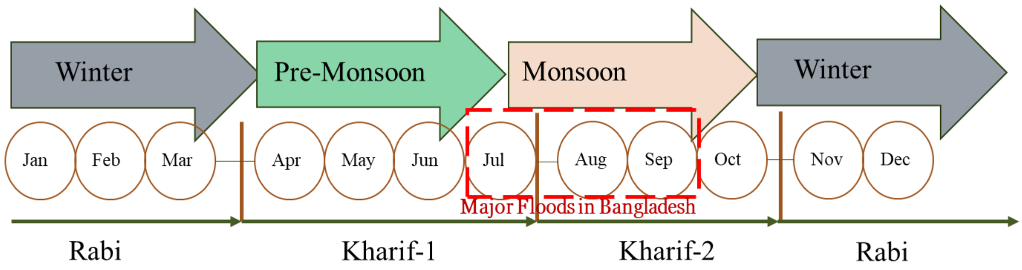


Figure 5. Crop calendar during major flooding time in Bangladesh.

Jute and sugarcane are possible crops for low-lying areas. Jute is called the golden fiber of Bangladesh and is one of the largest exports from India. Sugarcane is the only source of sugar production in Bangladesh. Therefore, the second objective of this study was to prepare a land suitability map for jute and sugarcane cultivation through a multicriteria-based suitability analysis.

2.3.3. Land Suitability Assessment for Jute and Sugarcane Production

The process of identifying lands that have the potential for certain crop production can be referred to as crop suitability analysis, which is very important for effective and sustainable agricultural planning in an area. Land suitability analysis can ensure the most suitable uses of land on a regional scale, as it is one of the bases for land use planning [45,46]. To adapt a sustainable agriculture plan, land suitability analysis for climate-resilient crops is very important. It also reduces the uncertain losses for farmers and supports increasing their income to ensure their livelihoods. Currently, many researchers are considering GIS-based multicriteria analysis, the application of satellite remote sensing techniques, the use of unmanned aerial vehicles for higher resolution and cloud computation platforms (Google Earth Engine) for land suitability analysis because of the spatial and temporal coverage as well as faster computational capabilities [47–51]. As the study area for land suitability analysis was a flood plain of the Jamuna River, a fuzzy-based multicriteria decision-making (MCDM) method was applied utilizing criteria related to the topography, soil properties, climate and geology of the area. Four land suitability classes were used to reflect the suitability classes set forth by the Food and Agricultural Organization (FAO). They were highly suitable land (S1), which can be used without any significant limitation; moderately suitable land (S2), which can be used after increasing the required input; marginally suitable land (S3), which has severe limitations for specific use; and unsuitable land (N), which cannot be used with existing facilities within an acceptable cost [52]. To adapt a climate smart model for our flood-prone study area, jute and sugarcane were selected as cash crops during the premonsoon to monsoon seasons instead of rice and maize. A stepwise framework for land suitability analysis for jute and sugar was conducted (Figure 3).

Reclassification of the Fuzzy Membership Function

All the fuzzy membership functions (fuzzy linear, near, small, MS small, Gaussian, large and MS large) were applied for each criterion in the ArcGIS 10.8.1 environment. The fuzzy membership functions, whose best fit values were on a scale between 0 and 1, were then selected for the analysis. Among the seven fuzzy membership functions, four were selected for standardizing selected criteria based on a literature review and references. The selected fuzzy membership functions were linear, small, MS large and Gaussian, which produced standardized criteria through continuous fuzzy classifications (Equations (1)–(3) and (6)). Selected criteria, fuzzy membership functions, midpoint, minimum and maximum values are listed in Table 4. The following equation represents the fuzzy Gaussian membership function:

$$\mu(x) = e^{-\left(f1 \times (x - f2)^2\right)} \tag{6}$$

where x represents the crisp value, and f1 and f2 are the spread and midpoint values, respectively.

Table 4. Fuzzy membership function of land suitability analysis for sugarcane and jute.

No	Criteria	Fuzzy Membership Function		Equation	Fuzzy Membership Type
		Midpoint	Spread		
1	Slope	22.91	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{22.91}\right)^{-5}}$	Fuzzy MS Large
2	Soil pH	5.90	0.1	$\mu(x) = e^{-\left(0.1 \times (x-5.90)^2\right)}$	Fuzzy Gaussian
3	Soil Texture	4	0.1	$\mu(x) = e^{-\left(0.1 \times (x \times 4)^2\right)}$	Fuzzy Gaussian
4	Rainfall	2013.5	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{2013.50}\right)^{5}}$	Fuzzy Small
5	LULC	2	0.1	$\mu(x) = e^{-\left(0.1 \times (x-2)^2\right)}$	Fuzzy Gaussian
6	Elevation	22.91	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{0.43}\right)^{-5}}$	Fuzzy MS Large
7	Distance from river	7961.91	5	$\mu_{(x)} = \frac{1}{1+\left(\frac{x}{7961.91}\right)^{-5}}$	Fuzzy MS Large
	Criteria	Minimum	Maximum		
8	Flooding	1	4	$\mu(x) = \begin{cases} 0 & x \leq 1 \\ \frac{x-1}{4-1} & 0 < x < 4 \\ 1 & x \geq 4 \end{cases}$	Fuzzy Liner

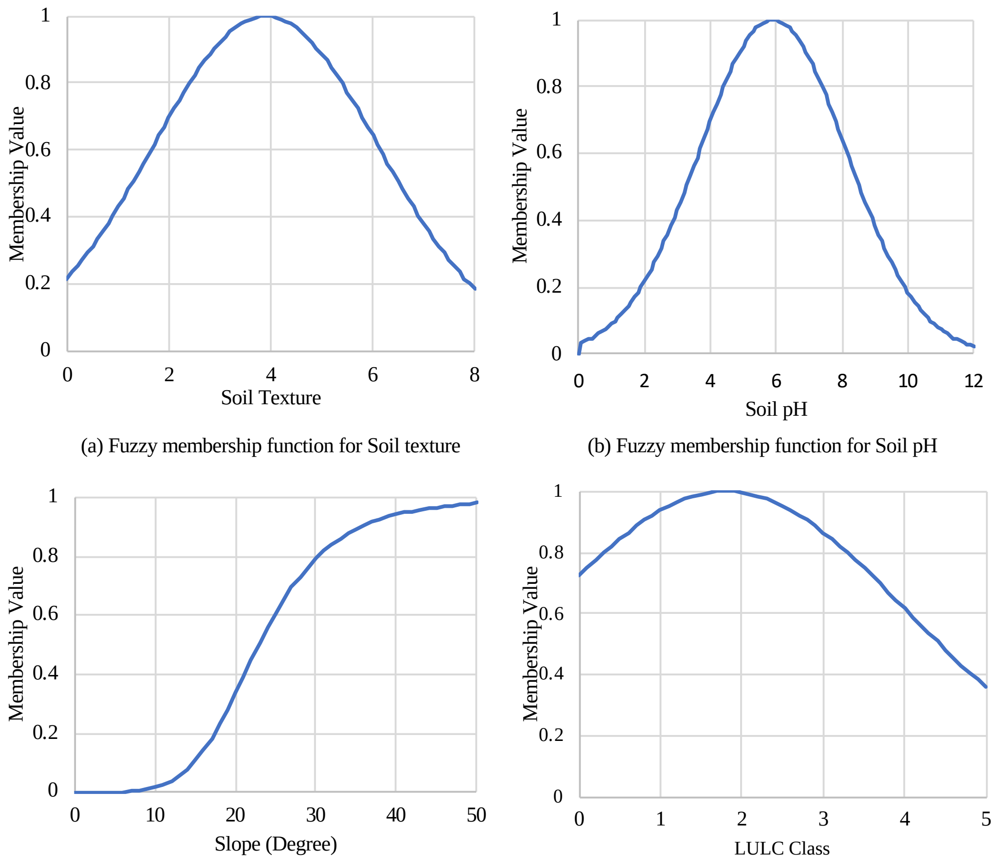
A fuzzy linear membership function was applied to build a linear function between the minimum and maximum values, whereas a fuzzy small membership function was used when a fuzzy set contained smaller input values. The fuzzy MS large membership function was used when the fuzzy set was most likely to contain larger input values. According to ESRI, the same equation was used for the fuzzy large and MS large membership functions in the ArcGIS environment. Fuzzy Gaussian membership was used when the membership was near a specific value. The natural breaks (Jenks) method was used for land suitability reclassification.

Criteria Selection

Many researchers have used different criteria for agricultural land suitability analysis. Zhang et al. [53] considered soil nutrients, climatic conditions and topography for land suitability analysis for tobacco. Soil type, flooding risk and distance from the road were the criteria selected by Bojorquez-Tapia et al. [54]. Jamil et al. [55] selected rainfall, drainage, soil properties, erosion hazard, flooding risk, distance from the road and distance from the sugar mill for a sugarcane cultivation suitability analysis. Singha and Swain [56] performed soil profile-based suitability analysis for jute cultivation. A total of eight criteria were selected based on a literature review for land suitability analysis to cultivate jute and sugarcane. All the selected criteria were related to topography, geology, soil properties and climate. After calculating all those criteria, a suitability map was prepared for each criterion, and the criteria were reclassified according to the land suitability classes S1 (highly suitable), S2 (moderately suitable), S3 (marginally suitable) and N (not suitable).

Slope

Slope refers to the degree of inclination, and lands with low, gentle slopes are much more favorable for sugarcane and jute cultivation. A slope map was prepared from the SRTM dataset in which the highest slope was found to be 1° in the study area, which means it is mostly plain land. The map was standardized using the fuzzy MS large membership function and reclassified into four suitability classes (Table 4; Figure 6a).



(a) Fuzzy membership function for Soil texture
(b) Fuzzy membership function for Soil pH
(c) Fuzzy membership function for Slope
(d) Fuzzy membership function for LULC

Figure 6. Fuzzy membership function for land suitability assessment to cultivate jute and sugarcane: (**a**) soil texture; (**b**) soil pH; (**c**) slope and (**d**) LULC.

Elevation

An elevation map was prepared from the SRTM DEM model, and data were downloaded from the USGS website. According to our analysis, the minimum and maximum elevations in the study area were from −14 m to 25 m. However, the elevation of most of the area ranged from 0–5 m, which is very suitable for jute and sugarcane cultivation. Finally, the prepared map was standardized using the fuzzy MS large membership function and reclassified into four land suitability classes (Table 4).

Soil pH

Soil pH is one of the most important factors for any type of crop cultivation. Palada and Chang [57] suggested that jute can tolerate soil pH values from 4.5 to 8.0, but pH values between 4.8 and 5.8 are the best for jute cultivation. Jamil et al. [55] suggested that slightly acidic soil is suitable for sugarcane production. A soil pH map of 250 m spatial resolution was collected from the ISRIC data hub, in which soil pH data up to a 30 cm depth were incorporated. According to our analysis and prepared map, the soil pH values were between 4.9 and 6.9, which is acidic to slightly acidic and suitable for both jute and sugarcane cultivation. The soil pH map was resampled at a 30 m resolution using resampling tool in spatial tools of ArcGIS software, then standardized using the fuzzy Gaussian membership function and reclassified into four suitability classes in the ArcGIS environment (Table 4; Figure 6b).

Soil Texture

Soil texture is another important parameter for crop cultivation, as the water retention capability of soil depends on the type of soil texture. A soil type map was collected from the ISRIC data hub with a spatial resolution of 250 m, which was updated in 2017. Then, the soil texture of the study area was classified according to the United States Department of Agriculture [58]. According to our analysis and prepared map, the study area has six types of soil textures, clay, silty clay, clay loam, silty clay loam, sandy clay loam and loam. Most of the areas are covered with clay loamy soil, which is suitable for both jute and sugarcane cultivation [55,57]. Then, the prepared map was resampled at a 30 m spatial resolution, standardized using the fuzzy Gaussian membership function and finally reclassified into four suitability classes in the ArcGIS environment (Table 4; Figure 6a).

Rainfall

The same prepared rainfall map of 30 m $\times$ 30 m spatial resolution for inundation vulnerability analysis was used in land suitability analysis for jute and sugarcane. According to the rainfall data of the study area, the lowest rainfall was 1635 mm, and the highest was 2392 mm in 2021. The rainfall range of 1600–2000 mm was suitable for jute cultivation, whereas the 1100–1500 mm rainfall range was suitable for sugarcane cultivation [53]. The prepared rainfall map was standardized by applying the fuzzy small membership function in the ArcGIS environment and was finally reclassified into four suitability classes in ArcGIS (Table 4).

Land Use and Land Cover (LULC)

Land use and land cover (LULC) provide information about cultural features, urbanization, agricultural lands and both natural and manmade vegetation [43]. Information about LULC is very important for land suitability analysis, as it provides information about the total agricultural land use of the study area. An LULC map for the study area was prepared in the Google Earth Engine (GEE) platform using Landsat 9 satellite data consisting of five classes (water body, bare land, vegetation, agricultural land and urban area). Then, the prepared map was resampled at a 30 m spatial resolution and standardized using the fuzzy Gaussian membership function in the ArcGIS environment. Finally, the map was reclassified into land suitability classes (Table 4; Figure 6d).

Flooding Vulnerability

As a part of adapting the climate smart agriculture model, an inundation vulnerability map was prepared using four related criteria in the first stage of this study. The previously prepared inundation vulnerability map was then considered one of the most important criteria for the land suitability analysis. In this suitability analysis, our concern was to propose water-resistant crops for the monsoon season when most flood events occurred. The vulnerability map was standardized using a fuzzy linear membership function and reclassified into four land suitability classes for suitability analysis to cultivate jute and sugarcane in areas highly to moderately vulnerable to water inundation (Table 4).

Distance from the River

A distance from the river map was prepared for the inundation vulnerability assessment of the study area in the first stage of this study. The same map was used for the land suitability study. Rivers are the source of water for cultivation as well as flooding. Areas closer to the river are suitable for jute and sugarcane production; however, before collecting the jute fiber, it needs to be kept under water for a certain time. The prepared map was standardized by using a fuzzy MS large membership function and reclassified into four suitability classes (Table 4).

Fuzzy Gamma Overlay

Among the five fuzzy overlay methods in the ArcGIS environment (Fuzzy OR, Fuzzy AND, Fuzzy Sum, Fuzzy Product and Fuzzy Gamma), the Fuzzy Gamma overlay was applied for land suitability map preparation combining the eight selected reclassified criteria map (Equation (5)). For generalizing the gamma overlay function, the default gamma value of 0.9 was used. Then, the Jenks natural breaks algorithm was used to reclassify the vulnerability map into four different suitability classes [36]. In the database, the classes were based on inherent natural groupings [37]. The fuzzy gamma overlay method was applied by Arab and Ahamed [51] for a land suitability analysis of extended vineyards in Afghanistan. The fuzzy gamma overlay method was also used by Shamsuzzoha et al. [9] for yield loss assessment after cyclones in the coastal region of Bangladesh. A land index was calculated in the fuzzy method that converted a 0–1 fuzzy value multiplied by 100. Then a land index value ranging 75–100 was assigned for highly suitable land (S1), 50–75 for moderately suitable land (S2), 25–50 for marginally suitable land (S3) and 0–25 for not suitable land (N) [20,51] (Figure 7).

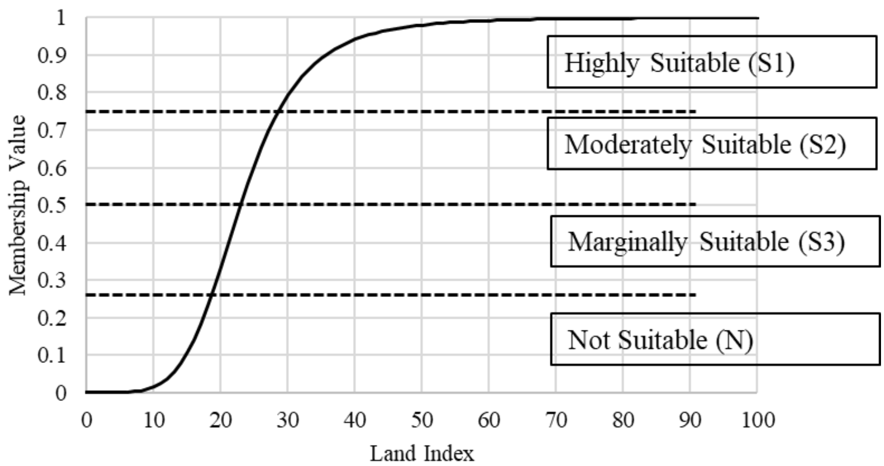
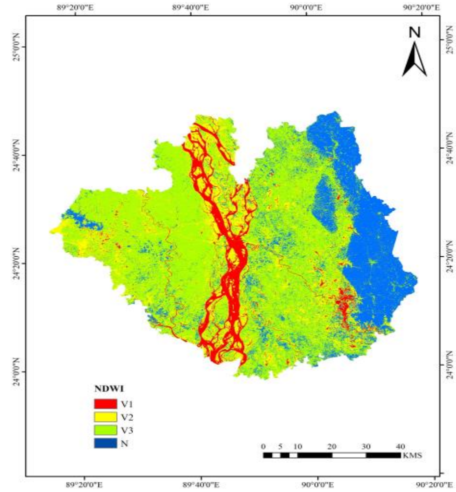


Figure 7. Land suitability class selection for jute and sugarcane cultivation using fuzzy membership function and land index.

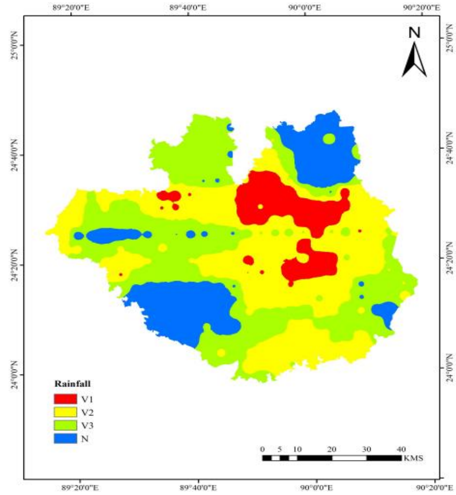
3. Results and Discussion

3.1. Inundation Vulnerability Assessment

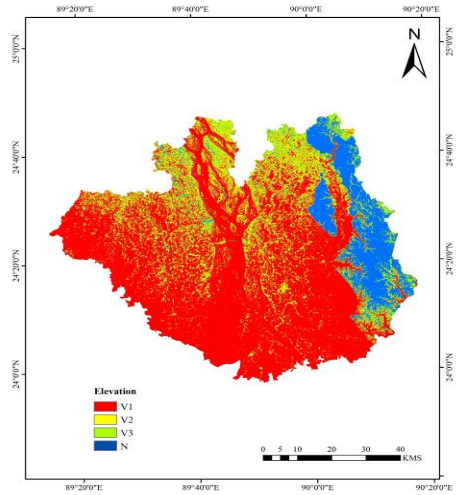
The inundation vulnerability assessment was conducted on 5489 km^2 of land, among which 0.3% and 41.9% of the area was found to be highly to moderately vulnerable to inundation by water and very susceptible to agricultural land use. In addition, 42.1% and 15.6% of the area was marginally vulnerable to nonvulnerable to inundation, respectively (Table 5). All the reclassified criteria and gamma overlay maps are given in Figure 8a–e. Previous researches also supported that the almost every flood event occurred in the study areas.



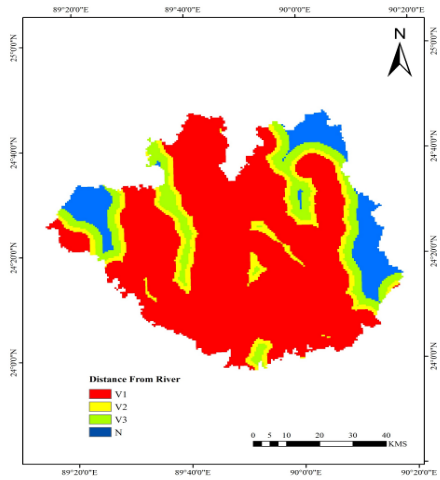
(a)



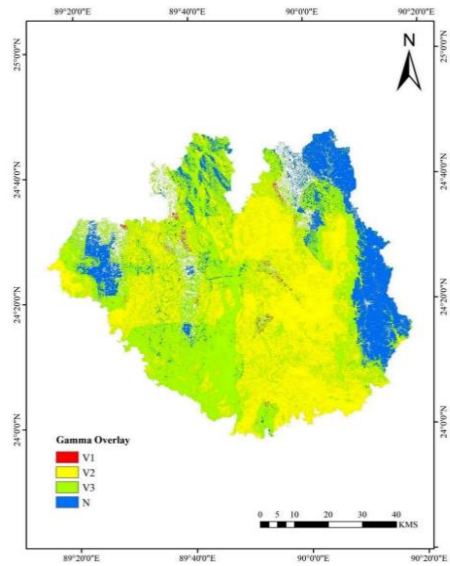
(b)



(c)



(d)



(e)

Figure 8. Reclassified vulnerability map of different indices: (**a**) NDWI; (**b**) rainfall; (**c**) elevation; (**d**) distance from river and (**e**) fuzzy gamma overlay, where V1, V2, V3 and N refer to high, moderate, marginal and nonvulnerable areas, respectively.

Table 5. Areas vulnerable to inundation according to their vulnerability classes in the Sirajganj and Tangail districts.

Vulnerability Class	Area (km^2)	Area %
V1 (Highly vulnerable area for inundation by water)	18.49	0.34
V2 (Moderately vulnerable area for inundation by water)	2304.52	41.99
V3 (Marginally vulnerable area for inundation by water)	2308.95	42.07
N (Nonvulnerable area for inundation by water)	856.70	15.61
Total	5488.66	100

3.2. Land Suitability Assessment for Jute and Sugarcane Cultivation

According to Jamil et al. [55], the most common cropping practices are rice and maize cultivation during the Kharif season, whereas potato and wheat are cultivated during the Rabi season in the Sirajganj district. According to the developed crop calendar with major floods in Bangladesh, the harvesting time of Kharif-1 (mid-April to mid-July), which is the premonsoon season, and the plantation time of Kharif-2 (mid-July to mid-September), which is the monsoon season, are vulnerable to inundation by floods (Figure 5). As rice and maize are susceptible to flood water and are damaged within a short time, jute and sugarcane can be alternative crops during this season, as they are more adaptive to floods. Jute is sown in end of February to early March and harvested in between July and September, during which major floods take place, and sugarcane is planted in August and harvested in the next year in September to November in Bangladesh.

According to the land suitability analysis, in the 5489 km^2 of analyzed area, 28.6% of lands were highly suitable, 27.9% were moderately suitable, 19.7% were marginally suitable and 23.6% of lands were not suitable for jute and sugarcane cultivation (Table 6). Moreover, highly to moderately suitable areas for jute and sugarcane cultivation were highly to moderately vulnerable to inundation by flood water. All the reclassified criteria-based suitability maps and gamma overlay maps are presented in Figure 9a–o.

Table 6. Suitable areas for jute and sugarcane cultivation according to their suitability classes in the Sirajganj and Tangail districts.

Suitability Class	Area (km^2)	Area (%)
S1 (Highly suitable for jute and sugarcane cultivation)	1573.21	28.66
S2 (Moderately suitable for jute and sugarcane cultivation)	1535.05	27.97
S3 (Marginally suitable for jute and sugarcane cultivation)	1083.89	19.75
N (Not suitable for jute and sugarcane cultivation)	1296.51	23.62
Total	5488.66	100

3.3. Validation of Suitability Map with Ground Reference Data

Total production of jute and sugarcane with the cultivated area was collected for the study area located in the Tangail and Sirajganj districts. Furthermore, data from the surrounding eight administrative districts of Natore, Pabana, Manikganj, Dhaka, Gazipur, Mymensingh, Jamalpur and Bogra were also collected from Yearbook of Agricultural Statistics-2021 [59]. Then average production was estimated from the total production and cultivated area (Figure 10). Furthermore, validation was performed using linear and polynomial regressions between the land suitability index and average production of jute and sugarcane in each administrative district.

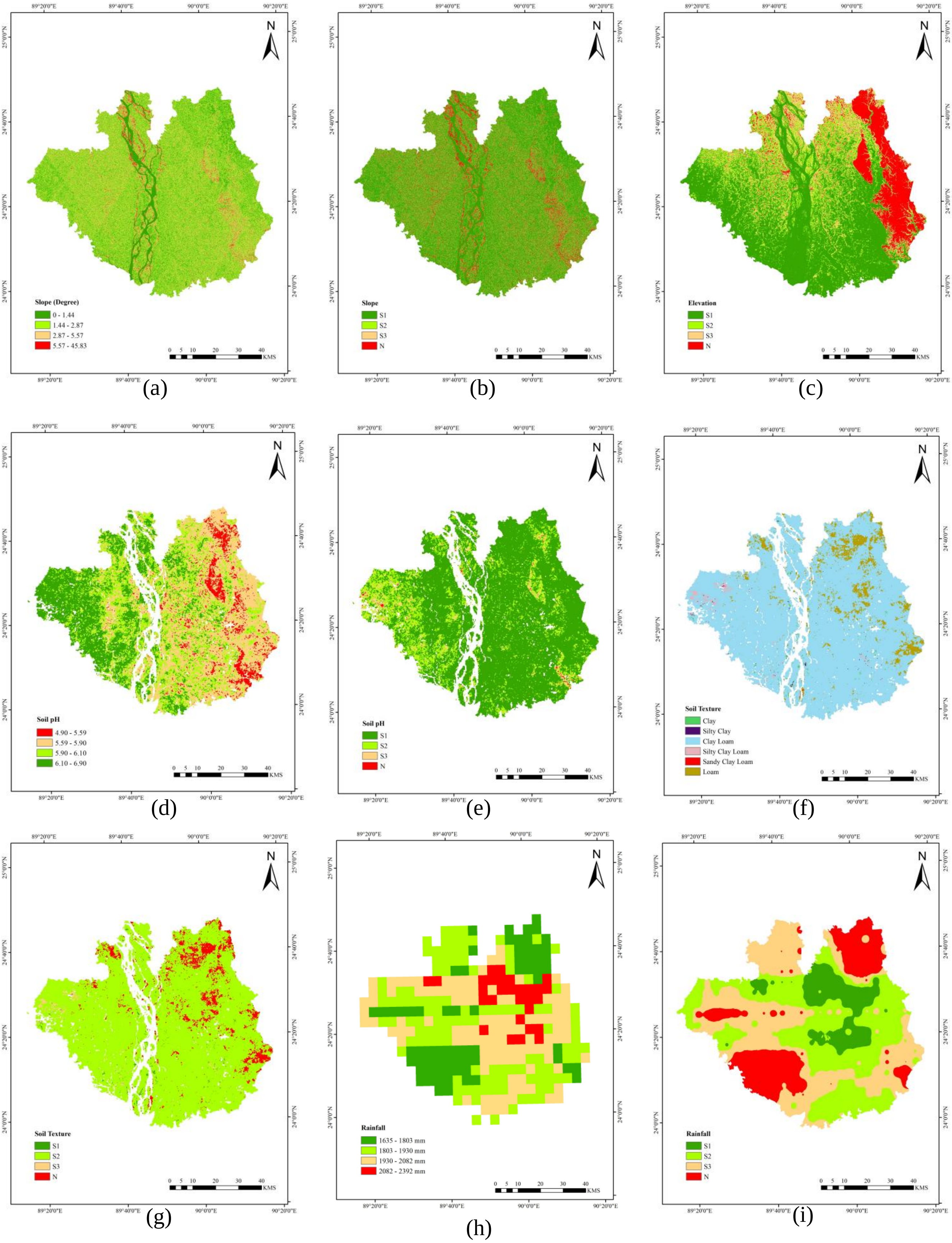


Figure 9. *Cont.*

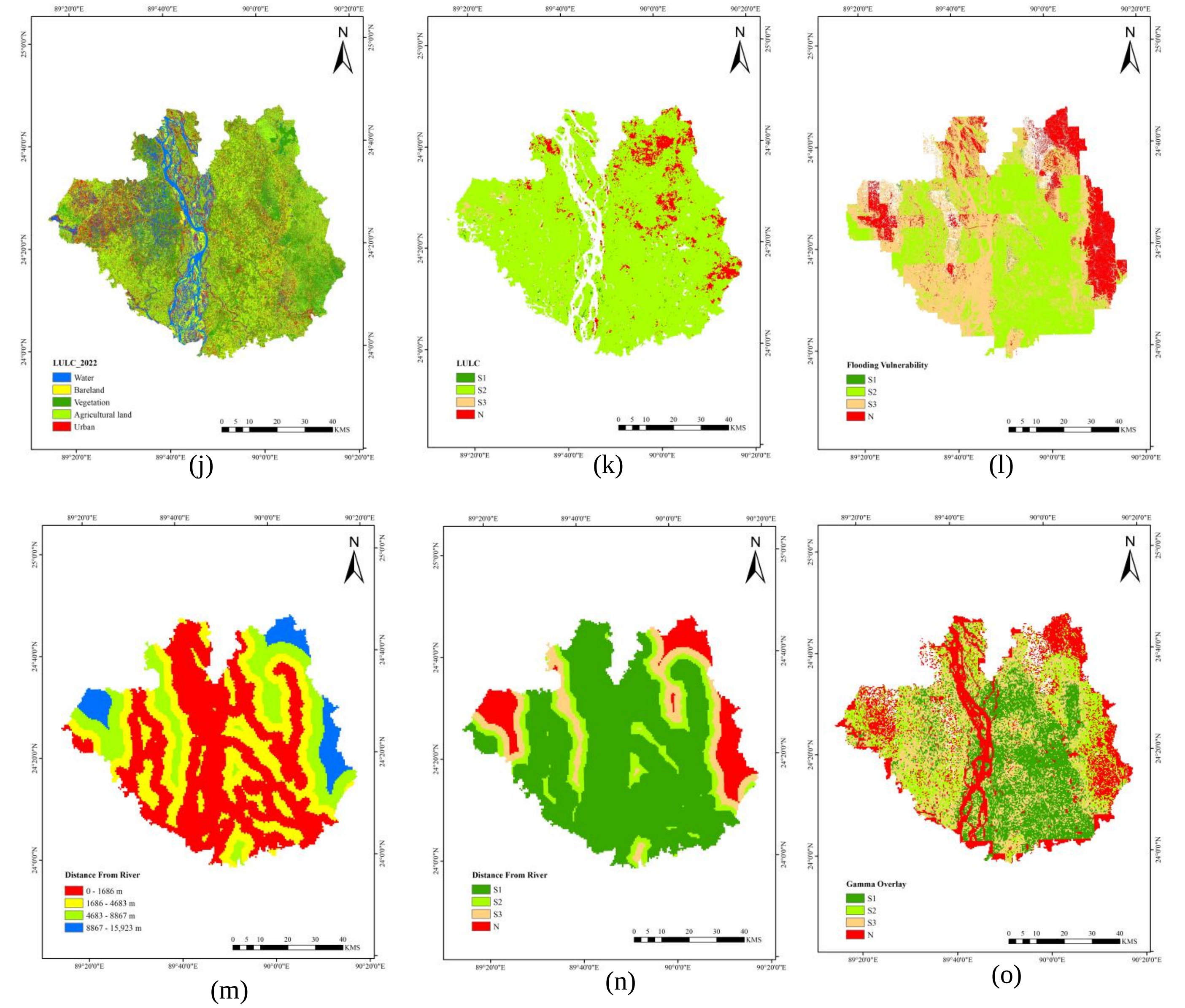


Figure 9. Reclassified suitability map of different indices for sugarcane and jute: (**a**,**b**) slope; (**c**) elevation; (**d**,**e**) soil pH; (**f**,**g**) soil texture; (**h**,**i**) rainfall; (**j**,**k**) LULC; (**l**) flooding vulnerability; (**m**,**n**) distance from river and (**o**) fuzzy gamma overlay, where S1, S2, S3 and N refer to high, moderate, marginal and suitable areas, respectively.

3.4. Validation of Fuzzy Suitability

A ground validation of suitability map was important to confirm the suitable lands for jute and sugarcane cultivation in the study areas. Validation results indicate satisfactory agreement between the land suitability index and the average production at the district level. The prepared datasets for jute and sugarcane were used for both linear regression and polynomial regression. Obtained R^2 values for sugarcane were 0.9486 and 0.9487 from linear regression and polynomial regression, respectively (Figure 11a,b). For jute, obtained R^2 values were 0.8878 and 0.8401 from linear regression and polynomial regression, respectively (Figure 11c,d). Prediction for sugarcane was the same from both regressions; however, linear regression provided higher accuracy than polynomial for jute.

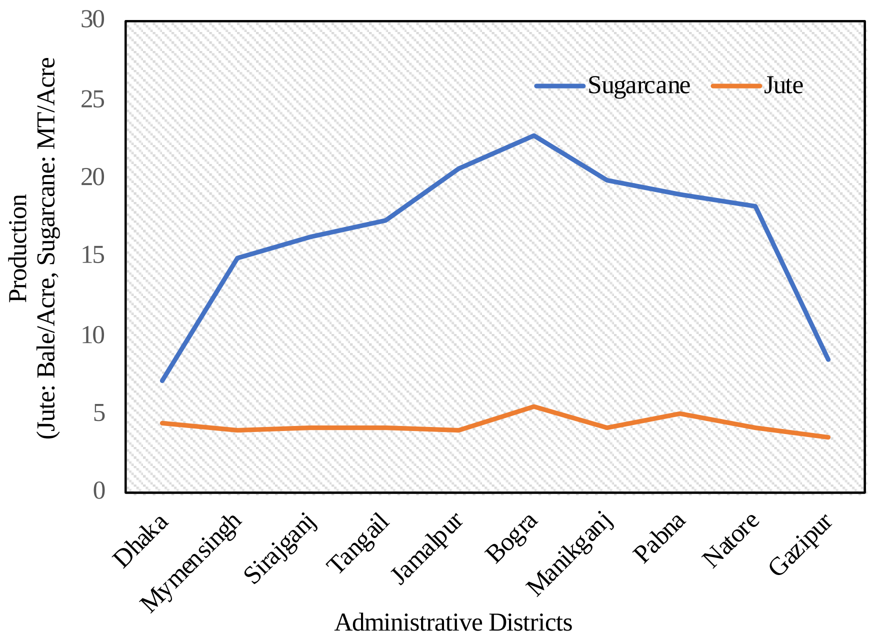


Figure 10. Average production of jute (bale/acre) and sugarcane (MT/acre) in ten administrative districts in Bangladesh during 2021.

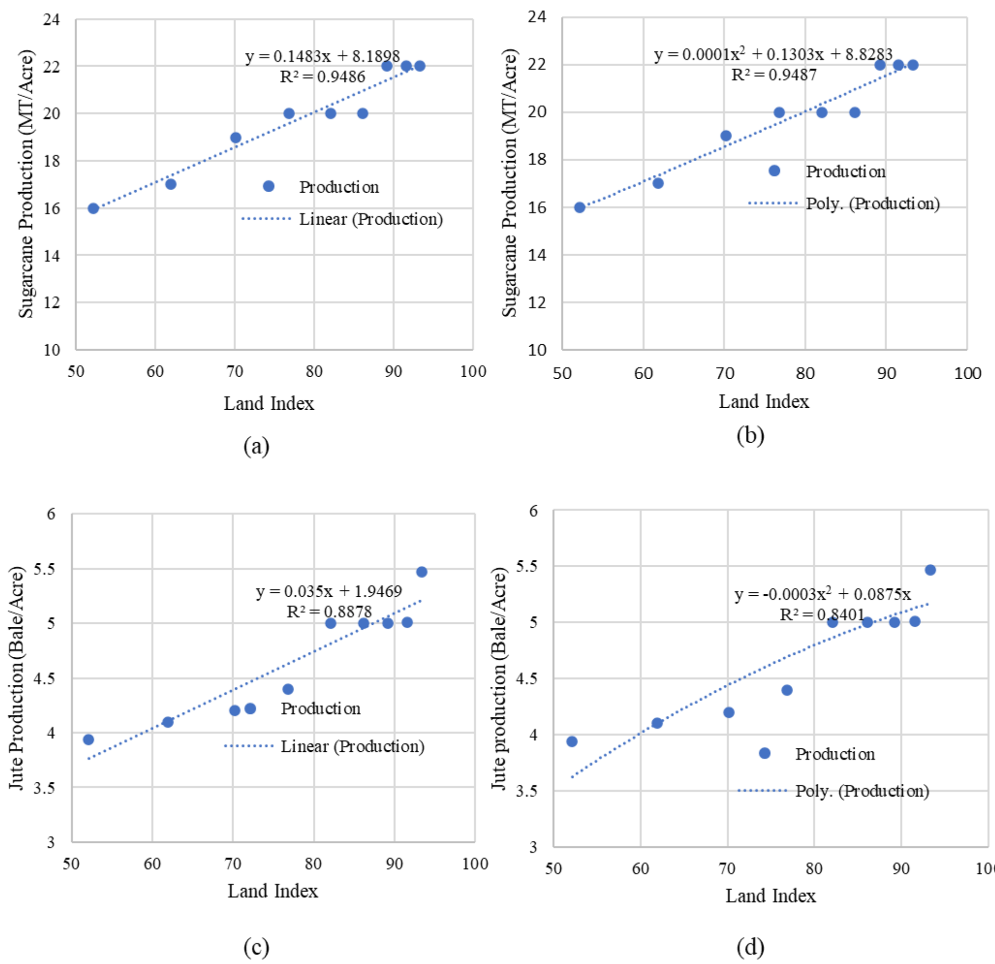


Figure 11. Validation of the fuzzy-based land suitability score referring to the average sugarcane and jute production from different administrative districts of Bangladesh. (**a**) Linear regression for sugarcane; (**b**) polynomial regression for sugarcane; (**c**) linear regression for jute and (**d**) polynomial regression for jute.

4. Conclusions

Undoubtedly, climate change is the greatest problem for the environment and humans. Deltaic areas such as Bangladesh are predicted to suffer most from climate change due to sudden adverse effects such as floods, flash floods and cyclones. As most of the cultivable lands are in the riverine flood plains of Bangladesh, they are most affected by floods and flash floods. People's lives and livelihoods related to agriculture become insecure by the detrimental consequences of these natural calamities due to climate change. To fight against the effects of climate change, alternative initiatives should be taken by authorities to secure food production and save the lives of vulnerable people. As a part of climate-adaptive crop selection in vulnerable agriculture, an inundation vulnerability assessment for the two flood-prone districts (Sirajganj and Tangail) was performed. Then, by analyzing different flood events, their damage to people and crops was determined, common cropping practices in the area were assessed and two potential alternative crops (jute and sugarcane) were proposed. Finally, land suitability assessments for jute and sugarcane cultivation were performed. According to the inundation vulnerability assessment, approximately 42.5% of the area was observed to have a high to moderate inundation risk. Additionally, 56.6% of the studied area was suitable for jute and sugarcane cultivation in areas that are most vulnerable to inundation by flood water. Therefore, the findings from this study can be helpful for adapting sustainable agricultural plans in the study area as well as in other vulnerable areas in the world in response to climate change; the results can be used to ensure the food and livelihood security of the growing population.

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Data Availability Statement: The dataset that was generated and analyzed during this study is available from the corresponding author upon reasonable request, but restrictions apply to the data reproducibility and commercially confident details.

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