Land Suitability Evaluation and Drought Stress Assessment of Tea Estates Using Satellite Remote Sensing-based Multi-Criteria Decision Support System

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Land Suitability Evaluation and Drought Stress Assessment of Tea Estates Using Satellite Remote Sensing-based Multi-Criteria Decision Support System

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Abstracts

Land suitability evaluation aims at finding suitable lands in order to optimize the land resource planning and management and drought stress assessment provides guidance to minimize the climate change effects for increasing tea production. Bangladesh is considered one of the major tea producing countries in the world. However, land under tea cultivation in Bangladesh has not been increased significantly to increase production. In addition, adverse global climate change effects, especially, the reduction in rainfall that results in drought have been challenging the optimal tea production in this country. Therefore, it is crucial to identify the suitability of the existing cultivable lands and assessing the drought stress in order to foster better land use decisions and climate change-focused tea production strategies in Bangladesh. However, adequate information is unavailable in the existing literature regarding land suitability evaluation and drought stress assessment for tea production in Bangladesh. Therefore, this study focused on developing a land suitability model for increasing tea production using multi-criteria decision support systems and assessing the drought severity including drought classification for tea estates in Bangladesh.

To meet the research objectives, the land suitability evaluation followed by subsequent validation of suitability classes using time-series yield information was performed to classify lands as well as to select the suitable lands for sustainable tea production in the north-eastern part of Bangladesh. According to the review of literature and field survey, twelve criteria were selected for the land suitability evaluation. The AHP was used as a MCA technique to incorporate expert's opinion for prioritizing the criteria. The study area was classified into four categories- "Highly suitable", "Moderately suitable", "Marginally suitable" and "Not suitable". This research utilized the phenological datasets of remote sensing, geospatial datasets of soil-plant bio-physical properties, and expert's opinion. The Sentinel-2 satellite images were processed to obtain the layers for the Land Use and Land Cover (LULC) and normalized difference vegetation index (NDVI). Data of Shuttle Radar Topography Mission (SRTM) were used to generate the elevation layer. The vector layers of edaphic, climatic, topographic, and accessibility parameters were processed in the ArcGIS 10.7.1® software for respective raster layers. Finally, suitability classes were determined using spatial analysis of the reclassified raster layers along with the consideration of result of multi-criteria analysis. Results of this study showed that 41,460 hectares lands (3.37 % of the total lands) were under highly suitable class. The proportion of moderately suitable, marginally suitable and not-suitable classes of lands for tea cultivation in the study area were 9.01 %, 49.87 %, and 37.75%, respectively. Thirty-one tea estates were in highly suitable areas, 79 were in moderately suitable, 24 in marginally suitable, and only one in a not suitable area. There are two important vegetative parameters for yield estimation in tea viz. NDVI and LAI were selected for the validation of suitability classes. The results of yield estimation using time-series yield information shows the NDVI (R^2 = 0.69, 0.66, and 0.67), and LAI (R^2 = 0.68, 0.65, and 0.63) for 2017, 2018, and 2019, respectively.

The aim of the study on the assessment of drought stress for tea estates was to measure the drought severity in tea plantation areas using optical and thermal remote sensing technology with the Standardized Precipitation Index (SPI). To calculate the SPI, rainfall data for the Sylhet and Sreemangal station was gathered from the Bangladesh Meteorological Department (BMD). Landsat 8 OLI/TIRS images were processed to develop the maps for Land Surface Temperature (LST), and Soil Moisture Index (SMI). The Normalized Difference Moisture Index (NDMI) maps were developed from the Sentinel 2 satellite images. The drought frequency was calculated from the classification of droughts utilizing SPI. The results of the study demonstrated that the drought frequencies for the Sylhet station was 38.46% for near normal, 35.90% for normal, and 25.64% for moderately dry months. In contrast, the Sreemangal station showed the frequencies: 28.21%, 41.02%, and 30.77%, for near normal, normal, and moderately dry months, respectively. The correlation coefficient between the SMI and NDMI were observed as 0.84, 0.77, and 0.79 for the drought period of 2018-2019, 2019-2020 and 2020-2021, respectively, indicates a strong relationship between soil and plant canopy moisture. The results of yield prediction with respect to drought incidence in tea estates demonstrated that 61%, 60%, and 60% of estates in the study area provides lower yield than the observed yield during drought, which accounted for 7.72%, 11.92% and 12.52% yield loss in 2018, 2019, and 2020, respectively.

In conclusion, geospatial datasets have been proved to be a reliable source for land suitability evaluation with validation of suitability classes as well as drought stress assessment for tea plantation. This study suggests that the remote sensing technology with the multi-criteria decision support system could be used by scientists, land policy makers, and agricultural land use planners to select suitable lands as well as to measure the magnitude of drought stress in tea estates for increasing tea production

Keywords: Tea, Land suitability evaluation, Remote sensing, Sentinel-2, Landsat-8, OLI (Operational Land Imager), TIRS (Thermal Infrared Sensor) MCA (Multi-criteria Analysis), AHP (Analytical Hierarchy Process), Phenological datasets, NDVI (Normalized Difference Vegetation index), LAI (Leaf Area Index), Validation of yield, Drought, SPI (Standardized Precipitation Index).

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List of Abbreviations

AHP	Analytical Hierarchy Process
AVHRR	Advanced Very High Resolution Radiometer
BARC	Bangladesh Agricultural Research Council
BMD	Bangladesh Meteorological Department
BTB	Bangladesh Tea Board
CI	Consistency Index
CR	Consistency Ratio
ETM	Enhanced Thematic Mapper
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GIS	Geographical Information System
GPS	Geographic Positioning System
ITC	International Tea Committee
LAI	Leaf Area Index
LSA	Land Suitability Analysis
LSE	Land Suitability Evaluation
LST	Land Surface Temperature
LULC	Land use and land cover
MCA	Multi-criteria Analysis
MSI	Multispectral Instrument
NDMI	Normalized Difference Moisture Index
MODIS	Moderate Resolution Imaging Spectroradiometer
OA	Overall accuracy
OLI	Operational Land Imager

PA	Producer Accuracy
SAVI	Soil Adjusted Vegetation Index
SMI	Soil Moisture Index
SPI	Standardized Precipitation Index
SRTM	Shuttle Radar Topography Mission
SWIR	Short-Wave Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
UA	User Accuracy
USGS	United States Geological Survey
VIIRS	Visible and Infrared Scanner
WSN	Wireless Sensor Network

List of Nomenclatures

C_{11}	The value of row *i* (the 1st row) and column *j* (the 1st column) in the pairwise comparison matrix
x_{ii}	is number of observations in row *i*, column *i*
X_{ij}	The normalization matrix for pair-wise comparison of AHP
W_{ij}	The weight matrix of AHP
λ_{max}	Principal eigenvector
n	Number of criteria
R	Reflectance
α	Shape parameter
β	Scale parameter
$\Gamma(\alpha)$	Gamma function

CHAPTER 1

Introduction

1.1 Background

Tea (*Camellia sinensisL.* (O.) Kuntze) is valuable cash crop as well as a popular beverage all over the world. Tea is an evergreen shrub belongs to the botanical family Theaceae, native to the east Asia and originated in the borderland of south-western China and northern Myanmar. There are two major varieties (*C. sinensis* var. *sinensis)*, and (*C. s.* var. *assamica)* and their hybrids are grown to produce green, oolong, black, white and yellow teas using twigs and tender leaves. Tea plants can reach a height up to 15 meters, however, pruned down to less than 2 meters to produce enormous green tender leaves as well as for the convenience of harvesting. The plant favors a mild and rainy weather in tropical, subtropical, and Mediterranean regions. Tea is renowned for its nutritional, medicinal, antimicrobial, and anticancer properties throughout the world, contains caffeine, which increases the strength of the heartbeat and stimulates the production of gastric acid. All types of teas also have theanine with caffeine, which affect the brain to boost mental alertness. The health-promoting substances in tea are polyphenols especially, catechins and epicatechins have the antioxidant and anti-inflammatory properties promotes a lower risk of cardiovascular diseases and diabetes.

Bangladesh is one of the world's major tea-producing countries ranking 9th (**Figure 1.1**) The country has 167 tea estates that produce approximately 96.07 million kilograms of tea annually with an average yield of 1768.52 kg/ha. Tea is the second largest export-oriented cash crop in Bangladesh after jute. The tea industry of Bangladesh annually earns roughly USD 20.874 million (0.81% of GDP) in foreign currencies, exporting 18 million kilograms of tea (1.37% of the export of the global tea trade). Once a major exporter, Bangladesh is at present a net importer of tea due to increasing demand in country as well. In addition to this, the production of tea is not increasing due to climate change, especially reduction in rainfall as well as using the marginally suitable lands for tea cultivation.

Tea-producing districts of Bangladesh are Moulvibazar, Habiganj, Sylhet, Brahmanbaria, Chattogram, Rangamati, Bandarban, Panchagarh, Thakurgaon and Dinajpur. Among those districts, most of the tea is produced in three districts of the Sylhet division: Moulvibazar, Habiganj, and Sylhet. The country has around 115,441 hectares of land for tea cultivation, raised from 28,734 hectares in 1947 (BTB 2020). To solve the various problems in tea cultivation, the Bangladesh Tea Research Institute (BTRI) governed by the Bangladesh Tea Board (BTB) was established in Sreemangal on 28 February 1957. The BTRI released 21 high-yielding and high-quality tea clones named BT1 to BT21. Among those varieties, the

BT2 have a good touch of flavor called "Darjeeling flavor". The BTRI also developed five hybrid varieties used as biclonal and polyclonal stocks.

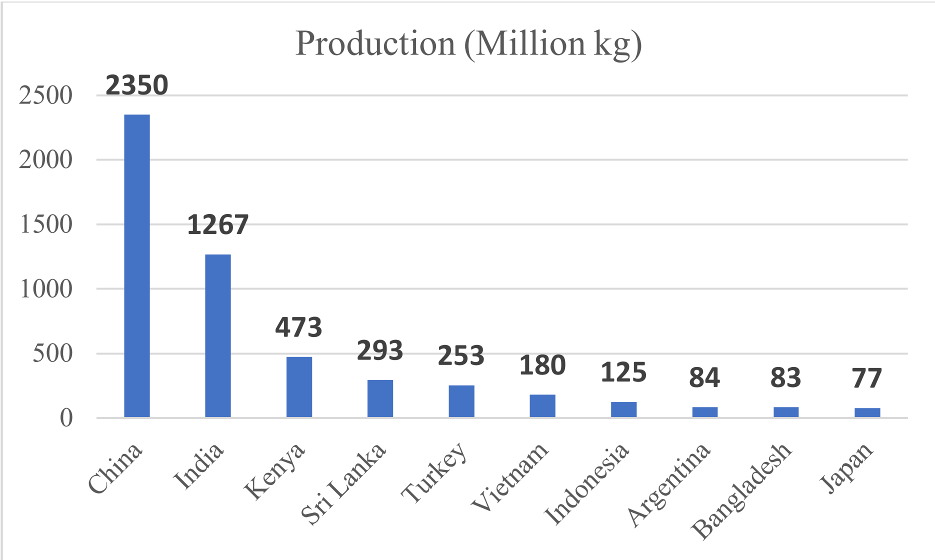


Figure 1.1 World Production of tea (ITC 2017)

1.2 Problem Statement, Justification, and Novelty of Research

The rapidly growing population of Bangladesh exerts considerable pressure on scarce land and water resources. The country is at present facing the challenges of increased crop production under stress of decreasing potential land resources due to the adverse climate change effects. Lower production of tea in Bangladesh is due to the effects of land degradation caused by climate change, especially changes in rainfall and temperature. Global tea production has increased tremendously over the last 50 years. However, tea production in Bangladesh is lower than other major producing countries (83 million kg). Demand of tea has also been increased in country.

Those problems could be solved adopting the climate smart agriculture system. The climate Smart Agriculture is an inevitable approach to sustainably increase the crop production finding the alternative ways with the changing climate to generate income as well as adapting resilience to the environment. The aim of climate smart agriculture is to mitigate the effects of climate change where agricultural production is being reduced and affecting the national economy.

Land suitability evaluation is the basis for sustainable land resource planning and management to find out optimal land for crop production (Sys et al, 1991). Therefore, it is imperative to identify new land and climate for cash crops to enrich the economy of the country. In Bangladesh, we have a lot of fallow lands and islands, which could be included under cultivation area. According to an initiative of the Government of Bangladesh, agricultural land management is of utmost importance for higher productivity of crops. A limited number of researches have been done for land suitability evaluation and zoning of some traditional crops were performed by the Bangladesh Agricultural Research Council (BARC). Furthermore, no studies regarding land suitability evaluation for tea has been performed yet. Therefore, it was urgent to find out suitable lands for tea cultivation using GIS and Satellite Remote Sensing tools considering various climatic, edaphic, topographic, accessibility, and remote sensing parameters. The novelty of this research is the validation of suitability classes using remote sensing parameters, where time-series yield information of individual tea estates was correlated with the phenological and biophysical indices.

Besides, drought is a natural hazard, which affects production in tea growing countries. The tea estates of Bangladesh face the adverse effects of drought during winter months from December to February. To the best of our knowledge, no studies regarding drought stress assessment in large scale for tea estates has been performed. Therefore, the land suitability evaluation and drought stress assessment for tea plantation areas were important for sustainable tea production in Bangladesh.

1.3 Research Objectives

1. To develop a land suitability model for increasing tea production in Bangladesh using multi-criteria decision support systems
2. To perform yield estimation of tea plantation using vegetation phenological and biophysical parameters
3. To identify the drought severity assessment including drought classification system for tea estates.

1.4 Thesis Chapter Design, Layout and Cognitive summary

The thesis attempted to explain its content in the chapter 1 to 5. The chapter 1 represented the overall introduction of the research illustrating the current research problems with regard to lower production as well as the importance of land suitability evaluation and drought stress assessment for sustainable tea production. The chapter 2 stated the basic concepts of geospatial modelling for land suitability evaluation emphasizing Analytical Hierarchy Process (AHP) as well as the geospatial technology for drought assessment in tea estates. The chapter 3 described the land suitability evaluation considering various climatic, edaphic, topographic, accessibility, and remote sensing parameters as well as yield estimation of tea using phenological and biophysical factors. The chapter 4 implied the assessment of drought stress in tea plantation areas emphasizing the drought classification systems. The chapter 5 described the overall conclusions with the recommendations for future research.

CHAPTER 2
Review of Literatures

2.1 Literatures Review

2.1.1 GIS-based Land-use Suitability Evaluation

The land suitability can be denoted as fitness of a specific type of land use for a given type of land (FAO 1976). The GIS-based land-use suitability evaluation is a computer-assisted weighted overlay spatial analysis technique, which enables to keep the models in the numerical form. Among different methods used, the Analytical Hierarchy Process (AHP) is popular due to its simplicity in operation in the ArcGIS environment. The framework for land suitability evaluation can clarify how the sustainability functions. This method is used in the present research to evaluate the appropriateness of land for tea cultivation considering different suitability levels. Land suitability evaluation provides information on the constraints and potentials of a land in terms of the outputs as affected by the physical environment, for a given land use type. Various climatic, edaphic, topographic, and remote sensing parameters are usually considered for land suitability evaluation. According to the guideline of FAO land suitability classification, land is predominantly classified into suitable (S), and not suitable (N) category.

Table 2.1 FAO Land suitability evaluation framework

Order	Suitability classes	Details
Suitable (S)	Highly Suitable (S1)	Land having no substantial restrictions for specific land use activities
	Moderately Suitable (S2)	Land with slight restrictions for specific land use activities
	Marginally Suitable (S3)	Land with extreme restrictions for specific land use activities
Not Suitable (N)	Currently Not Suitable (N1)	Land with restrictions can be resolved in time rather than fixing with knowledge at reasonable cost
	Permanently Not Suitable (N2)	Land having serious restrictions that cannot be prevented using any possible solution.

Then, the suitable class (S) can be further classified into three classes according to the degree of suitability: S1, S2, S3 termed as highly suitable, moderately suitable, and marginally suitable classes, respectively. There are two classes in the not suitable category: N1 and N2 termed as currently not suitable and permanently not suitable. The land suitability evaluation consists of determining and classifying the lands in order according to the degree of suitability (**Table 2.1**).

2.1.2 Analytical Hierarchy Process (AHP)

The AHP is a multi-criteria decision-making process developed by (**Saaty, 1990**). The AHP is a robust tool for decision support system, which is able to solve complex problems in decision making process. The AHP has the potential to analyze a problem in a systemic way and to evaluate the problem comprehensively. There are four main phases in the AHP. In the first phase, the elements of the decisions are elaborated into a hierarchy, which includes the top class (goal), middle class (criteria) and bottom class (alternatives) **(Figure 2.1)**. In the second phase, the relative importance between each pair of criteria is measured. The priorities of each criteria involved in the AHP are calculated based on the experts' opinions using the preference scale proposed by Saaty. The third phase involves to synthesize all the prioritized alternatives. The sensitivity analysis is performed in the last phase measuring the consistency ratio. The basic concepts in solving problems with the AHP includes elaboration, comparison of criteria, and priority synthesize and the sensitivity analysis.

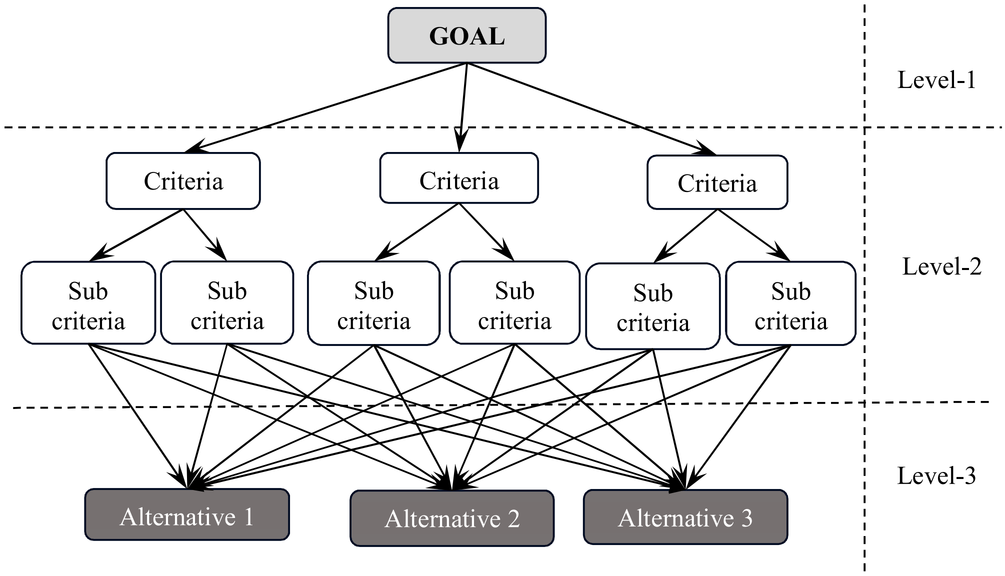


Figure 2.1 Multi-criteria hierarchy structure of the AHP

2.1.2.1 Elaborating the Decision Elements

The decision elements are elaborated into a hierarchy in the first phase. The hierarchy makes it easier to evaluate the problem. The structure of the elaborated hierarchy includes goal, criteria, and alternatives. The top class is involved in selecting the goal. The middle class considers the rules or the criteria, and the bottom class of the hierarchy considers the alternatives.

2.1.2.2 Comparison of Criteria

The AHP utilizes a bascic scale of preference expressed in numbers for the judgment. Questionnaires are used to gather expert' opinions to measure the relative importance of the criteria. Comparison for each pair of factors is described as integer values of 1 (for equal importance) to 9 (for extreme difference), where the higher number indicates the chosen factor is more important than others.

2.1.2.3 Priority Synthetize

Assessing the relative importance to the elements at each stage of the hierarchy can measure the criteria, sub-criteria, and alternatives, where the overall priorities for the alternatives are synthesized. The score in differential scoring infers the row criterion is of equal or higher importance than that column criterion. The reciprocal values (1/3, 1/5, 1/7, 1/9) are considered when the row criterion is less important than the column criterion(b_{ij}). The total priority for each alternative is measured with the sum of local priorities that are weighted with the elements of higher levels ($\overline{w}$).

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2.1}$$

$$\overline{w} = \frac{\sum_{j=1}^{n} b_{ij}}{n} \tag{2.2}$$

2.1.2.4 Sensitivity Analysis

Dividing the synthetized priority by the weights ($\overline{w}$) is called the consistency measure (CM). The total of consistency refers to the principal eigen value ($\lambda_{\max}$).

$$CM = \frac{\overline{w}}{\sum_{i=1}^{n} \overline{w}} \tag{2.3}$$

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{CM_i}{n} \tag{2.4}$$

Where, CI denotes the consistency index is calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{2.5}$$

The AHP offers a measurement to determine the consistency in the judgement of decisions to ensure the integrity of the relative significance of criteria. The Consistency ratio (CR) can be measured using the eigenvalues in the comparison matrix.

$$CR = \frac{CI}{RI}$$

RI is Random consistency index and its value is considered from the Random consistency index table proposed by Saaty (1989.

Table 2.2 Random consistency index

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

If CR<0.1, the consistency level in the pair-wise comparison is acceptable (Saaty, 1980).

2.1.3 Geospatial Technology for the Assessment of Drought

The geospatial technology is a combination of advanced tools, which contributes to the geographic mapping and analysis for the welfare of human societies. With the advancement of geospatial technologies through times, computers are able to store and transfer images together with the development of digital software, maps, and data sets on socio-economic and environmental phenomena, known as Geographic Information Systems (GIS). An essential feature of the GIS is its capacity to organize the range of geospatial data into a layered series of maps that enable specific topics to be analyzed and conveyed to broader audiences. Variety of geospatial technologies such as Remote Sensing (RS), Geographic Information Systems (GIS), Global Positioning System (GPS) and Internet Mapping Technologies could be used for environmental impact assessment. Drought is a detrimental and unpredictable climatic event, which could be assessed using various climatic and remote sensing indicators utilizing geospatial technologies. Among different remote sensing techniques, combined utilization of optical and thermal remote sensing is efficient for the assessment of drought stress and yield losses in tea estates.

2.1.3.1 Combined Utilization of Optical and Thermal Remote Sensing

The combined utilization of the optical and thermal infrared remote sensing technique from Landsat 8 OLI/TIRS and Sentinel-2 is useful to measure the land surface temperature. The thermal infrared sensors and the optical sensors from Landsat 8 could be used to measure the land surface temperature, and soil moisture content. On the other hand, the optical remote sensing technique could be adopted to quantify the NDMI, measuring the reflectance of near-infrared (narrow), and short-wave infrared bands from Sentinel-2. Thus, both the optical and thermal infrared sensors could contribute to assess the relationship between soil and plant canopy moisture during the drought season.

2.1.3.2 Yield Loss Assessment Using Remote Sensing Technique

Similarly, the optical sensors from Sentinel-2, which are considered robust tools for providing high resolution remote sensing data, could be used for assessing yield losses for the validation of drought. The optical remote sensing technique could be utilized to quantify the NDVI, and LAI measuring the reflectance of visible (red), and near-infrared bands from Sentinel-2. In previous studies, yield loss assessment for tea was performed using econometric approaches, however, remote sensing techniques could also be utilized successfully for yield loss assessment in tea.

CHAPTER 3

Integrating an Expert System, GIS, and Satellite Remote Sensing to Evaluate Land Suitability for Sustainable Tea Production in Bangladesh

3.1 Background

Land suitability evaluation is important for sustainable land resource planning and management (Jayasinghe et al. 2019). A range of parameters, e.g., soil conditions, topography, state of the climate, and vegetation indices are considered to evaluate land suitability (Ahamed et al. 2020; Wang et al. 1990). Such evaluation provides information about specific land use potentials and constraints. Effective management along with proper land use decisions results in higher productivity of land as well as a sustained environment (McDowell et al. 2018). For sustainable land resource management, the Food and Agricultural Organization (FAO) proposed guidelines for land evaluation (FAO 1976). According to the guidelines, land is classified into four categories: highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N) (Purnamasari et al. 2019; Habibie et al. 2019). The rapidly growing population as well as global warming exerts considerable pressure on scarce land resources all over the world (Vitousek et al. 1994). The yield of plantation crops such as tea is decreasing due to the effects of drought and land degradation caused by climate change, especially changes in rainfall and temperature (Gunathilaka et al. 2017). Therefore, determining suitable lands and climate for tea to obtain maximum yield and production is urgent. In addition, it is imperative to utilize fallow lands, hilly areas, and islands for sustainable land management for tea production.

Tea (*Camellia sinensis* L. (O.) Kuntze) is a valuable cash crop as well as a popular beverage crop and is renowned for its nutritional, medicinal, antimicrobial, and anticancer properties throughout the world (Lambert et al. 2003; Cooper et al. 2005; Bhattacharya et al. 2014). Bangladesh is one of the world's major tea-producing countries. Tea cultivation in Bangladesh began in the British colonial period in 1854. Most of Bangladesh's tea is produced in the Sylhet Division, and approximately 96% is cultivated in three districts of the Sylhet Division. Among these districts, Moulvibazar produces 63% of the tea and Sylhet and Habiganj combinedly produce 33% (Islam et al. 2019). At present, the country has 167 tea estates that produce approximately 96.07 million kilograms of tea annually with an average yield of 1768.52 kg/ha (BTB 2020). The tea industry of Bangladesh annually earns roughly BDT 1.775 billion (0.81% of GDP) in foreign currency, exporting nearly 18 million kilograms of tea (1.37% of the export of the global tea trade) (Kamruzzaman et al. 2015). According to world rankings, China ranked first, producing 2350 million kg of tea, followed by India (1267 million kg), Kenya (473 million kg), Sri Lanka (293 million kg), Turkey

(253 million kg), Vietnam (180 million kg), Indonesia (125 million kg), Argentina (84 million kg), and Bangladesh (83 million kg). Thus, Bangladesh ranked 9th in tea production (ITC 2017). The global production of tea has increased tremendously over the last 50 years. In addition, the average yield per hectare of tea in Bangladesh is apparently lower than that in other major tea-producing countries. The drawback to the higher tea yield in Bangladesh is the existence of marginally suitable lands with unfavorable climates (BTB 2020). For this reason, the selection of suitable lands is crucial in making proper use of available lands for tea production. Tea growers establish estates based on conventional knowledge and experience without utilizing scientific information or methods of validation. They consider site suitability rather than using appropriate information. This also affects production in the long term, exacerbating environmental problems in tea-growing areas (Jayasinghe et al. 2019).

With advances in information and communication technology, land suitability evaluation has been performed using geographical information system (GIS) and satellite remote sensing techniques (Bandyopadhyay et al. 2009). In addition, important criteria for sustainable tea production must be considered in the analytical hierarchy process (AHP) for prioritizing experts' opinions in accordance with the weight obtained from consistent GIS results (Habibie et al. 2019). Satellite remote sensing with a GIS-based AHP is a robust tool for spatial decision-making processes for land suitability analysis (Purnamasari et al. 2019). The results of land suitability evaluation should be validated with obtained yield data. Research on yield estimation of agricultural crops indicates that remote sensing techniques alone are not capable of accurate yield estimation (Clevers et al. 1994). To improve accuracy, the actual yield of individual tea estates should be incorporated with remote sensing data.

Multiple studies have been undertaken to evaluate land suitability for tea. Land suitability evaluation was performed in Sri Lanka using a GIS-based multicriteria approach (Jayasinghe et al. 2019). A land suitability assessment was performed for tea and orange in the Nghe An Province of Vietnam using land suitability evaluation (LSE) software by considering several ecological criteria (Nguyen et al. 2020). A comprehensive suitability evaluation for tea was carried out in Zhejiang Province of China using a Geographic Information System (GIS), and a modified land ecological suitability evaluation model showed the scientific basis for land suitability and the planting distribution of tea crops (Li et al. 2012). A GIS-based land use suitability assessment for forests and tea crops was performed by Chanhda et al. (2010) along the Laos–China border, while Gahlod et al. (2017) carried out research to assess the suitability of land for cardamom, rubber, and tea using geospatial techniques in Kerala, India by considering various physicochemical parameters. Those studies provided information regarding the constraints of land use for tea and opportunities for decision making as well as optimal utilization of land resources (Collette et al. 1983).

Suitability analysis facilitates the recognition of marginally suitable lands with limiting factors that aid decision makers in developing appropriate crop management systems for increasing the productivity of land (Gahlod et al. 2017). Upon consideration of suitability analysis results, it is urgent to implement further initiatives for turning unproductive tea estates into productive estates by adopting better management practices. This will also allow tea planters on new plantations to work in highly suitable and moderately suitable fallow lands (Jayasinghe et al. 2019). Therefore, it has been necessary to perform land suitability evaluation by considering other crop requirements. Accordingly, no studies regarding land suitability evaluation for tea in Bangladesh to increase production have been performed. In addition, further research initiative is required to utilize bio-physical and vegetative parameters for yield estimation of tea estates in relation to land suitability analysis. Therefore, a comprehensive study utilizing physical, climatic, and vegetative parameters for sustainable land use and higher productivity of tea was undertaken.

3.2 Objectives

This study has attempted to evaluate land suitability, considering multiple criteria to ensure long-term progress in the tea industry. This land suitability evaluation could improve land use policy for the sustainable management of lands in tea-growing areas in order to increase tea production in Bangladesh. The objectives of this study were to develop a land suitability model for increasing tea production in Bangladesh as well as to perform yield estimation using phenological and bio-physical parameters.

3.3 Materials and Methods

Sentinel-2 multispectral instrument (MSI) satellite images were utilized as the remote sensing dataset, and certain vector-layered edaphic and climatic geodata were processed to develop the map for suitability analysis. The criteria were categorized into four types for land selection of tea according to FAO guidelines. Primary data as well as ground reference information were obtained through fieldwork using a global positioning system (GPS) receiver to locate the tea estates in the study area.

3.3.1 Study Area

The study area is the Sylhet Division, located in the northeastern part of Bangladesh, and consists of four districts—Habiganj, Moulvibazar, Sunamganj, and Sylhet, which include 38 subdistricts **(Figure 3.1)**.

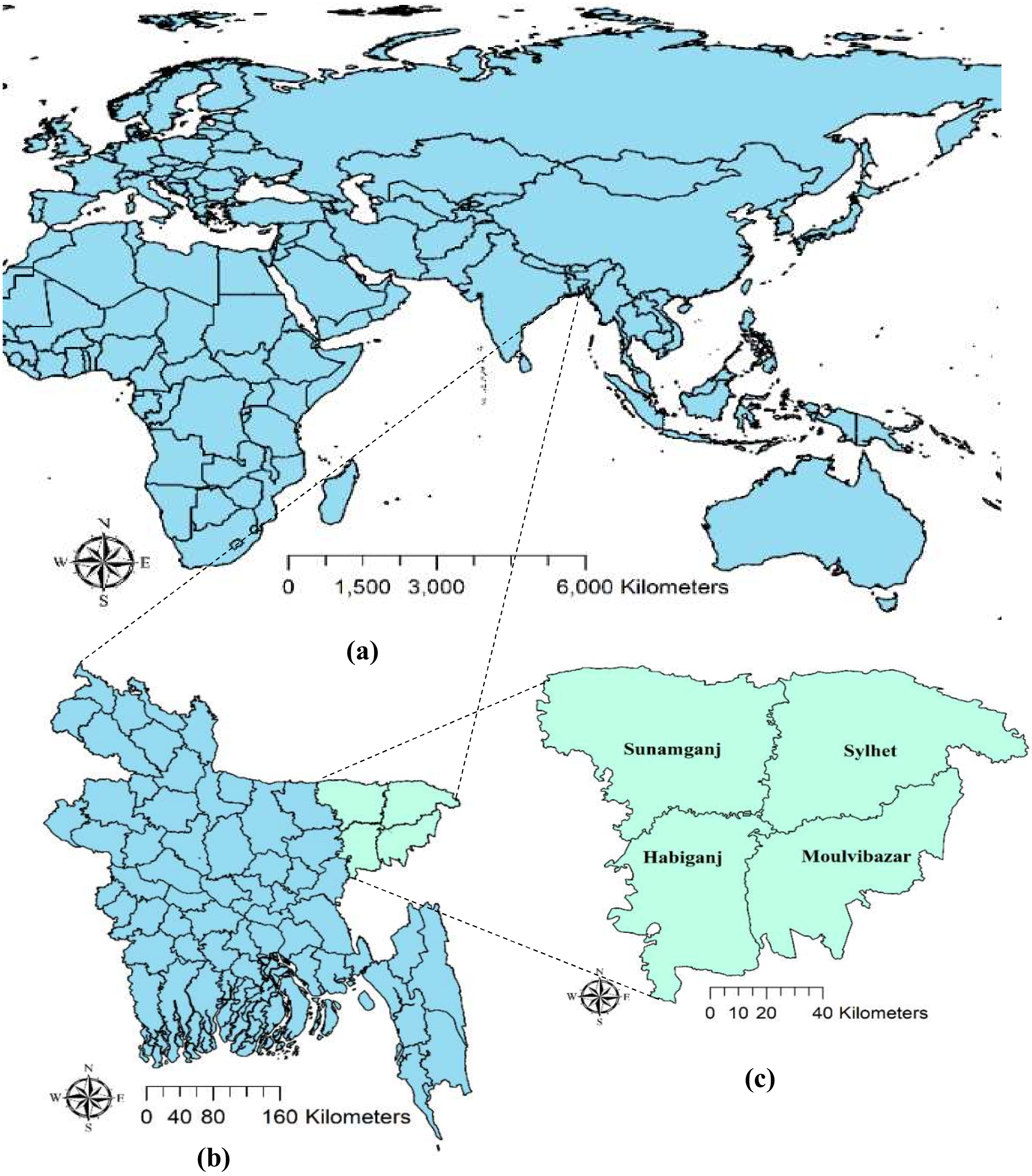


Figure 3.1 Geographical extent of the study area: (a) Bangladesh on the world map, (b) Bangladesh, and (c) Sylhet Division

The population size of this locality is approximately 10 million, which is less than 7% of the total population of Bangladesh. The study area lies between the latitudes of 23°58′ and 25°12′ north and the longitudes of 90°56′ and 92°30′ east. The area is surrounded by the Indian states of Meghalaya, Assam, and Tripura to the north, east, and south, respectively, and divisions of Chattogram to the southwest and, Dhaka and Mymensingh to the west. The area of land within the study area is 1,229,840 hectares and the elevation is less than 335 m. The study area receives an adequate amount of rainfall in the monsoon season that is favorable for tea cultivation.

3.3.2 Criteria for Suitability Analysis

Twelve criteria—land use and land cover (LULC), the normalized difference vegetation index (NDVI), elevation, precipitation, temperature, slope, soil texture, pH, drainage, soil type, distance from roads, and distance from rivers—were considered to determine suitable land for tea cultivation **(Table 3.1, Figure 3.2, and Appendix A)**.

Table 3.1 Generated map and sources of original data for the land suitability evaluation of tea

No.	Data	Description	Source
1	Map of LULC	20 m resolution	Sentinel-2, European Space Agency (ESA), 2019
2	Map of NDVI	20 m resolution	Sentinel-2, European Space Agency (ESA), 2019
3	Map of elevation	30 m resolution	Shuttle Radar Topography Mission (SRTM), NASA, 2019
4	Map of precipitation	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
5	Map of temperature	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
6	Map of slope	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
7	Map of soil texture	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
8	Map of soil pH	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019

9	Map of drainage	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
10	Map of soil type	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
11	Map of distance from Roads	Scale 1:50,000	Bangladesh Agricultural Research Council (BARC), 2019
12	Map of distance from Rivers	Scale 1:50,000	Bangladesh Country Almanac (BCA), 2019
13	Location of tea estates	GPS data	Field survey, 2019
14	Tea production	Statistical data	Bangladesh Tea Board (BTB), 2017–2019

3.3.2.1 Land Use and Land Cover

Land use and land cover (LULC) data were utilized to evaluate the lands for forests, tea estates, high agricultural lands, settlements, water bodies, rivers, and wetlands. According to land use and land cover, the majority of the study area was occupied by forests, tea estates, high agricultural lands, and wetlands for rice cultivation. LULC was built from Sentinel-2 datasets with 20 m resolution and processed using the maximum supervised likelihood classification in ArcGIS®. The raster layer for LULC was categorized into seven classes: forests, tea estates, high agricultural lands, settlements, water bodies, rivers, and wetlands **(Table 3.2).** The forest class consisted mostly of national reserve forests; the settlements consisted of households, public offices, and other infrastructures; and the water bodies consisted of areas of water such as beels, ponds, and lakes; a larger portion of the Sylhet Division is a low-lying area occupied by haor, a wetland ecosystem (Kamruzzaman et al. 2018).

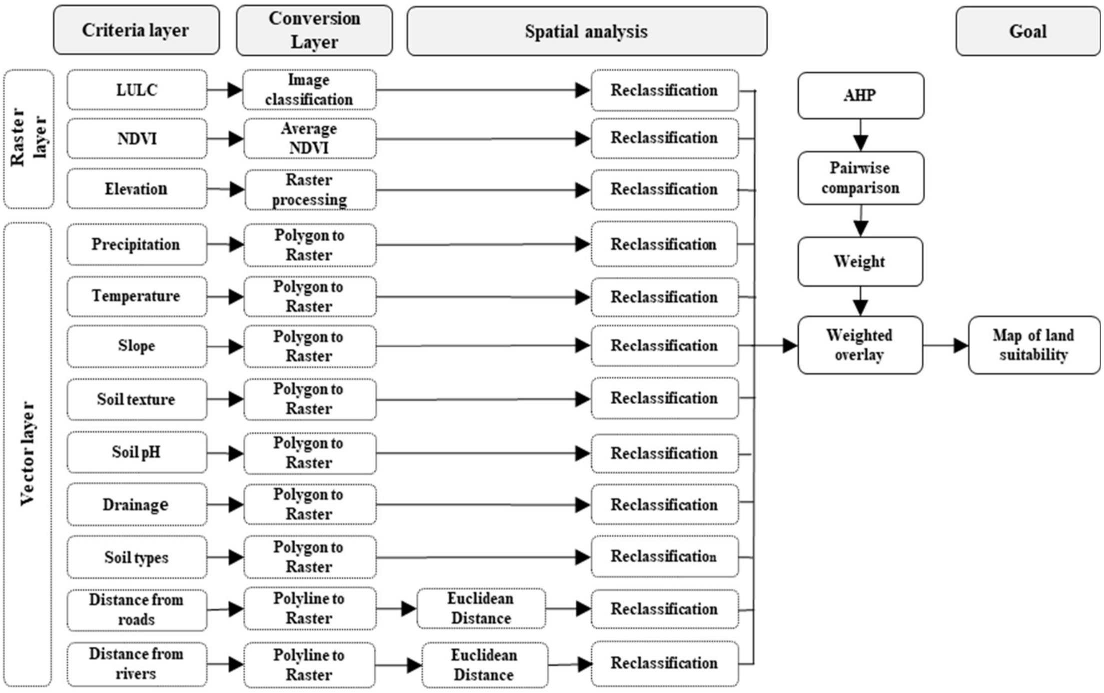


Figure 3.2 Conceptual framework for the land suitability evaluation of tea estates

Table 3.2 Reclassification of the criteria for the land suitability evaluation of tea

Criteria	Suitability Classes	Values/Sub-Criteria	Area (%)	Area (ha)
LULC	S1	Tea estates	16.41	201,818
	S2	Forest	10	123,008
	S3	High agricultural land	11.87	145,964
	N	Settlements, water bodies, rivers, and wetlands	61.72	759,050
NDVI	S1	>0.6	2.31	28,362
	S2	0.4–0.6	26.51	325,998
	S3	0–0.4	67.77	833,430
	N	<0	3.42	42,051

Elevation	S1	>15 m	35.05	431,045
	S2	10–15 m	28.75	353,533
	S3	7–10 m	22.28	274,016
	N	<7 m	13.92	171,246
Precipitation	S1	>1800 mm	38.18	469,553
	S2	1600–1800	46.54	572,386
	S3	1000 + 1600	15.28	187,901
Temperature	S1	18–25 °C	100	1,229,840
Slope	S1	5–25°	14.73	181,103
	S2	<5°	85.12	1046,828
	S3	>25°	0.16	1909
Soil texture	S1	scl, l, cl, sl	71.36	877,555
	S2	c, sicl, sic	27.22	334,729
	S3	c(ss), ls, s	1.43	17,556
Soil pH	S1	4.5–5.5	13.99	172,008
	S2	5.5–7.3	81.05	996,795
	S3	7.3–8.4	4.96	61,037
Drainage	S1	Moderately well drained to well drained	13.36	164,353
	S2	Imperfectly drained	9.60	118,083
	S3	Poorly drained	66.30	815,421
	N	Very poorly drained	10.73	131,983
Soil type	S1	Brown hill soils	13.24	162,782
	S2	Gray piedmont soils	11.84	145,659
	S3	Non-calcareous alluvium, Brown flood plain soils,	73.72	906,642

		Dark gray flood plain soils, Gray flood plain soils, Acid basin clays, Deep-red brown terrace soils		
	N	Peat, Water bodies, Urban	1.20	14,757
Distance from roads	S1	0–1.0 Km	13.97	171,759
	S2	1.0–2.0 Km	14.51	148,404
	S3	2.0–4.0 Km	21.81	268,246
	N	>4.0 Km	49.72	611,431
Distance from rivers	S1	0–0.5 Km	6.23	76,601
	S2	0.5–1.0 Km	11.68	143,618
	S3	1.0–2.0 Km	18.03	221,779
	N	>2.0 Km	64.06	787,842

An accuracy assessment was performed to calculate the accuracy of the LULC classification. According to the accuracy assessment for LULC, user accuracy (UA), producer accuracy (PA), and overall accuracy (OA) were determined. UA was calculated from the total correct samples in rows divided by the total reference samples in each row. PA was determined from the total correct samples in a column divided by the total reference samples in each column. OA was calculated from the total samples along the matrix diagonal from the reference divided by the total samples.

$$\mathrm{UA} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category (the row total)}} \times 100 \tag{3.1}$$

$$\mathrm{PA} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in that category (the column total)}} \times 100 \tag{3.2}$$

$$\mathrm{OA} = \frac{\text{Total number of correctly classified pixels (Diagonal)}}{\text{Total number of reference pixels}} \times 100 \tag{3.3}$$

3.3.2.2 Normalized Difference Vegetation Index (NDVI)

The NDVI is a vegetation index correlated with various biophysical parameters and different crop indices (Rouse et al. 1973; Romano et al. 2020; Phan et al. 2020). The proportion of green biomass sensed or captured in satellites is important for vegetation monitoring. Apart from this, the NDVI is used to measure the phenological variations in vegetation. Tea is a perennial crop that exhibits active vegetative growth in the monsoon season from March to November, and harvesting occurs within this time. In this study, the NDVI was calculated for tea plantations using Sentinel-2 satellite images. The map for the NDVI was developed using extraction by masking from Sentinel-2 images to distinguish the vegetation status of this area.

3.3.2.3 Elevation

Tea grows in a wide range of elevations from sea level to approximately 2200 m (Jayasinghe et al. 2019; Hajiboland et al. 2017). Tea is planted in the flat valleys of Assam, India at an elevation ranging from a few meters to approximately 200 m above sea level, while on the hill slopes of Darjeeling, it is cultivated up to an altitude of 2000 m. The elevation in the Sylhet Division ranges from −55 to 335 m. Most of the highland area is free from water logging and suitable for tea cultivation, despite the higher topographic elevation (Bozdağ et al. 2016). The elevation data were extracted using the Shuttle Radar Topography Mission (SRTM), 2019, NASA, with a 30 m resolution.

3.3.2.4 Precipitation

Moderate temperatures with high precipitation are favorable for tea cultivation, although tea is susceptible to water stress. Tea plants require an average minimum rainfall of 1000 mm per year, but 1800–2000 mm is optimal (Gahlod et al. 2017). The study area is characterized by higher rainfall of between 1000 and 2300 mm/year. Rainfall data were collected from the Bangladesh Agricultural Research Council and converted to a raster file. The raster file was processed according to the mean monthly rainfall data from March to November, when tea plants grow vigorously (Ahmed et al. 2014).

3.3.2.5 Temperature

The growth of tea plants is highly influenced by temperature. The yield of tea is also affected by increased average monthly temperature as well as constant higher temperature for longer periods. Temperature regimes below 13 °C and above 30 °C have been observed as detrimental for the shoot growth of tea plants (Jayasinghe et al. 2019). In the growing season, plants grow satisfactorily at temperatures ranging between 18 °C and 25 °C, which matched the temperatures of the study area (Gahlod et al. 2017).

3.3.2.6 Slope

Land slope affects erosion and surface runoff due to its microclimate variation. Slope also affects other soil properties, such as the soil moisture percentage, the proportion of clay materials, and the availability of other nutrients, such as nitrogen, calcium, and magnesium (Khormali et al. 2012). Land slopes ranging between 5° and 25° are optimal for tea cultivation. A slope gradient greater than 35° is considered unsuitable because it encourages soil erosion and landslides. Moreover, flattened slopes are also unsuitable for tea cultivation, as they may cause waterlogged conditions (Jayasinghe et al. 2019). Slope data were obtained from the Bangladesh Agricultural Research Council (BARC), 2019.

3.3.3.7 Soil Texture

Soil texture is considered an important criterion, as it influences other soil properties such as bulk density, hydraulic conductivity, and the water holding capacity. Tea plants gown in loamy soils produce leaves containing higher proportions of polyphenols, caffeine, and amino acids that are related to an adequate supply of soil nutrients, increased microbial activity, and effectiveness of nitrogenous fertilizer. Soils with higher clay and sand contents are worse than loamy soil in terms of moisture and nutrient holding capacity along with favorable microbial activities (Zhang et al. 2017). Textural classes designed for potential tea soils were considered according to Gahlod et al. (2017).

3.3.2.8 Soil pH

Tea usually grows well in soils with lower pH levels ranging from 4.5 to 5.5 (Natesan et al. 1999). Soil pH may further decline with the use of nitrogenous fertilizers such as ammonium sulfate and urea for higher yields. Moreover, tea plants take up larger quantities of A1 ions from soil and thus require an adequate supply of exchangeable Al and Fe ions in the soil (Foy et al. 1978). On the other hand, the growth of tea plants in soils is stunted and the mortality rate due to a higher pH level and lower amounts of exchangeable

Al, Fe, and Zn (Sultana et al. 2014). Classification with respect to soil pH was performed according to the guidelines of the Bangladesh Agricultural Research Council (Hussain et al. 2012).

3.3.2.9 Drainage

Tea plants are sensitive to stagnant water and cannot survive in areas with persistent waterlogging (Parthasarathy et al. 2006; Mukhopadhyay et al. 2017). Under waterlogged conditions, tea bushes are thinner with retarded growth and strive to survive in the presence of water-tolerant weeds (Rama Rao et al. 2007). Importantly, it has been reported that adequate drainage in tea soils can increase the yield by 30–35% (Parthasarathy et al. 2006). Tea plants are affected by excess water due to heavy precipitation in the Brahmaputra valley of Assam during the summer monsoons, causing a problem of surplus water disposal (Bhagat et al. 2010). Improved drainage is essential to provide adequate aeration in the root zone of tea plants for proper plant growth as well as to increase production. Drainage also prevents surface runoff to limit soil loss and maintain optimal soil moisture. Therefore, according to Nguyen et al. (2020), soil drainage was considered an important criterion for evaluating land suitability for tea.

3.3.2.10 Soil Type

Tea grows well in the hilly regions of the northeastern part of Bangladesh, which consists of brown hill soils (Egashira et al. 2007). Piedmont soils are formed within the transition between hills and lowland plains due to the accumulation of sediments from hills. Gray piedmont soils are moderately suitable for tea with respect to their moderate drainage and acidic to almost neutral pH levels (Prokop & Płoskonka 2014; Akhtaruzzaman et al. 2014). Non-calcareous alluvium and brown, dark gray, and gray flood plain soils were formed due to sedimentation in the flood plains, and are thus vulnerable with respect to drainage facilities and nutrient availability for tea plant growth (Egashira et al. 1998; Bhuiya 1987). Acidic basin clay soils are mostly observed in the Sylhet basin, but they are not important for agricultural production. Deep red brown terrace soil is the core component of barren lands covered with grasses (Egashira et al. 2007). Peat soils are not suitable for tea production, as they are found in low-lying areas and wetland ecosystems in Bangladesh, where flooding and waterlogging are common features (Islam et al. 2017).

3.3.2.11 Distance from Roads

There are three types of roads in the Sylhet division: highways, district roads, and local roads, including rural and urban roads. Distance from roads was considered because of the need to minimize the transportation costs associated with the tea cultivation input supply as well as export of tea in the country and abroad using highways, districts, and local roads. Minimum distances between fields and roads facilitate the transport of inputs and collected tea leaves**.** Data for distance from roads were retrieved in polyline vector form and then converted into a raster. Spatial analysis was performed to measure the distances using the Euclidean distance. Reclassification of the distances from roads was performed according to Pramanik (2016).

3.3.2.12 Distance from Rivers

The Sylhet division is crossed by the Surma, Kushiyara, Khowai, and Manu river as well as a large number of small rivers, which are part of the watershed in this area. Distances from rivers may also facilitate transport of input materials as well as processed tea leaves. In addition, it may be the source of irrigation water during the drought season. The data for distances from rivers were retrieved as a polyline vector and then converted into raster data. Once the vector data were converted to raster form, they were analyzed using Euclidean distance to calculate the distance from rivers. The study area with respect to distance from rivers was extracted by masking followed by reclassification according to the shortest distances.

3.3.3 Digital Image Processing

Geospatial data, including both image and feature datasets, were used in this research. Sentinel-2 images with a 20 m resolution were processed to generate the LULC and NDVI maps. Elevation data with a 30 m resolution from the Shuttle Radar Topography Mission (SRTM), NASA, were processed to form an elevation map. Vector data with a 1:50,000 scale for precipitation, temperature, slope, soil texture, soil pH, drainage, soil type, and distance from roads and distance from rivers were processed to form raster layers, followed by reclassification and weighted overlaying.

3.3.3.1 NDVI Computation

The NDVI is generated from two important wave bands—near-infrared and red bands—and is measured as follows,

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \tag{3.4}$$

Where, R_{NIR} is the reflectance of near-infrared, and R_{RED} is the reflectance of red. In this research, cloud-free Sentinel-2 image data were collected and utilized to measure the *NDVI* from band combinations of the *NIR* and red reflections utilizing band 8 and band 4. The *NDVI* values were extracted according to the ground reference information. The ground reference information for tea estates were collected in 2019 during its active vegetative growth stage starting in March and ending in November.

3.3.3.2 LAI Computation

The leaf area index (LAI) measured from remotely sensed data is an important parameter that can be effectively used for tea yield prediction. According to the correlation of the *LAI* with the *NDVI* observed in previous studies, the *LAI* was determined using the least square method and, could be expressed as follows (Tewari et al. 2003; Tuvshinbayar et al. 2017).

$$LAI = 0.57 \times \exp(2.33 \times NDVI) \tag{3.5}$$

3.3.4 Reclassification of Criteria

Reclassification was performed for interpretation of data in raster form by substituting a new single value or by categorizing the ranges of values into a single value. The raster map for each criterion was reclassified into four categories: highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N).

3.3.5 Analytical Hierarchy Process (AHP)

The AHP is a multicriteria decision-making process developed by Saaty (1990). In the first stage, the decision elements are expanded into a hierarchy, which includes three classes consisting of the top class (goals), the middle class (criteria), and the bottom class (alternatives). The top class of the hierarchy is involved in the selection of goals. The middle class defines the criteria, and the bottom class defines alternative decisions. A survey questionnaire was utilized to obtain expert's opinions on the relative significance of the criteria and factors. Comparisons for each factor pair were depicted as integer values of 1 (equal importance) to 9 (extreme difference), where a higher number denoted the alternative factor being more important than another (**Table 3.3**).

Table 3.3 Scale of preference for the analytical hierarchy process (AHP) pairwise comparison by Saaty (1989)

Scale	Degree of preference	Description
1	Equal Importance	Two factors contribute equally
3	Moderate importance of one factor over other factor	Experience and judgment slightly favor one over another
5	Strong importance	Experience and judgment strongly favor one over another
7	Very strong importance	Experience and judgment very strongly favor one over another
9	Extreme importance	The evidence favoring one over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between two adjacent scales	When compromise is required
Reciprocals	Opposite of the above	Used for inverse comparisons

For instance, in the comparison between LULC and the NDVI, a score of 1 denoted that both factors were equally important for suitability evaluation, and a score of 9 indicated that LULC was more important than the NDVI. All the scores were collected in a pair-wise comparison matrix, with the diagonal and reciprocal scores presented in a lower left-hand triangle. Reciprocal scores (1/3, 1/5, 1/7, and 1/9) were used in the row criterion that was observed as less important over the column criterion. In the second stage, the scoring of the criteria was performed via pair-wise comparison followed by scoring the scales of relative importance **(Table 3.4)**.

The third stage involved the calculation of the matrix, ensuring consistency among the criteria in the pair-wise comparison matrix. The AHP was also used to measure the normalized values for each criterion and alternative to determine the normalized principal eigen vectors and priority vectors. The pair-wise comparison matrix was calculated according to the following expression.

$$\begin{bmatrix} C_{11} C_{12} C_{13} & \cdots & C_{1n} \\ C_{21} C_{22} C_{23} & \cdots & C_{2n} \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ C_{m1} C_{m2} C_{m3} & \cdots & C_{mn} \end{bmatrix} \tag{3.6}$$

The sum of each column of the pair-wise matrix was expressed as follows.

$$C_{ij} \;=\; \textstyle\sum_{i=1}^{n} C_{ij} \tag{3.7}$$

Each element of the matrix was divided by the column total to generate a normalized matrix:

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^{n} C_{ij}} = \begin{bmatrix} X_{11} X_{12} X_{13} & \cdots & X_{1n} \\ X_{21} X_{22} X_{23} & \cdots & X_{2n} \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ X_{m1} X_{m2} X_{m3} & \cdots & X_{mn} \end{bmatrix} \tag{3.8}$$

The sum of the normalized matrix column was divided by the number of criteria (n) to calculate the weighted matrix of the priority criteria:

$$W_{ij} = \frac{\sum_{j=1}^{n} X_{ij}}{n} \begin{bmatrix} W_{11} \\ W_{12} \\ \vdots \\ W_{1n} \end{bmatrix} \tag{3.9}$$

The initial consistency vectors were generated by multiplying the pair-wise matrix by the vector of weights.

$$\begin{bmatrix} C_{11} C_{12} C_{13} & \cdots & C_{1n} \\ C_{21} C_{22} C_{23} & \cdots & C_{2n} \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ \vdots \;\; \vdots \;\; \vdots & \cdots & \vdots \\ C_{m1} C_{m2} C_{m3} & \cdots & C_{mn} \end{bmatrix} x \begin{bmatrix} W_{11} \\ W_{12} \\ \vdots \\ W_{1n} \end{bmatrix} = \begin{bmatrix} C_{11} W_{11} & C_{12} W_{12} & \ldots & C_{1n} W_{1n} \\ C_{21} W_{21} & C_{22} W_{22} & \ldots & C_{2n} W_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ C_{m1} W_{m1} & C_{m2} W_{m2} & \ldots & C_{mn} W_{mn} \end{bmatrix} = \begin{bmatrix} V_{11} \\ V_{12} \\ \vdots \\ V_{1n} \end{bmatrix} \tag{3.10}$$

The principal eigenvector (λ_{max}) was calculated by averaging the values for the consistency vectors:

$$\lambda_{max} = \sum_i^n CV_{ij} \tag{3.11}$$

Eigenvalues were measured to determine the relative weights by averaging the rows of each matrix. The largest value for the eigenvector was equal to the number of criteria, and when λ_{max} = n, the judgments were consistent. The normalized eigenvalues were calculated to determine the weights of the priority criteria. The principle value suggested that all criteria were consistent in the pair-wise comparison matrix **(Table 3.5).**

Table 3.4 Pair-wise comparison for scoring the criteria for tea cultivation

Criteria	LULC	NDVI	Elevation	Precipitation	Temperature	Slope	Soil Texture	Soil pH	Drainage	Soil Type	Distance from Roads	Distance from Rivers
LULC	1	1	0.33	0.14	0.20	0.20	0.33	0.20	0.14	0.33	0.33	0.33
NDVI	1	1	0.33	0.11	0.14	0.20	0.33	0.20	0.14	0.33	0.33	0.33
Elevation	3	3	1	0.20	0.33	0.33	1	0.33	0.20	1	1	1
Precipitation	7	9	5	1	3.00	5.00	5	3	1	5	7	7
Temperature	5	7	3	0.33	1	3.00	5	5	0.20	5	5	5
Slope	5	5	3	0.20	0.33	1	3	1	0.33	3	3	3
Soil texture	3	3	1	0.20	0.20	0.33	1	0.33	0.20	1	3	3
Soil pH	5	5	3	0.33	0.20	3.00	1	1	0.33	3	5	5
Drainage	7	7	5	1	5.00	3.00	5	3.00	1	5	7	7
Soil type	3	3	1	0.20	0.20	0.33	1	0.33	0.20	1	1	1
Distance from roads	3	3	1	0.14	0.20	0.33	0.33	0.20	0.14	1	1	1
Distance from rivers	3	3	1	0.14	0.20	0.33	0.33	0.20	0.14	1	1	1

Table 3.5 Normalized matrix of the criteria for tea cultivation

Criteria	LULC	NDVI	Elevation	Precipitation	Temperature	Slope	Soil Texture	Soil pH	Drainage	Soil Type	Distance from Roads	Distance from Rivers
LULC	0.022	0.020	0.014	0.036	0.018	0.012	0.014	0.014	0.035	0.013	0.010	0.010
NDVI	0.022	0.020	0.014	0.028	0.013	0.012	0.014	0.014	0.035	0.013	0.010	0.010
Elevation	0.065	0.060	0.041	0.050	0.030	0.020	0.043	0.023	0.050	0.038	0.029	0.029
Precipitation	0.152	0.180	0.203	0.250	0.272	0.293	0.214	0.203	0.248	0.188	0.202	0.202
Temperature	0.109	0.140	0.122	0.083	0.091	0.176	0.214	0.338	0.050	0.188	0.144	0.144
Slope	0.109	0.100	0.122	0.050	0.030	0.059	0.129	0.068	0.083	0.113	0.087	0.087
Soil texture	0.065	0.060	0.041	0.050	0.018	0.020	0.043	0.023	0.050	0.038	0.087	0.087
Soil pH	0.109	0.100	0.122	0.083	0.018	0.176	0.043	0.068	0.083	0.113	0.144	0.144
Drainage	0.152	0.140	0.203	0.250	0.454	0.176	0.214	0.203	0.248	0.188	0.202	0.202
Soil type	0.065	0.060	0.041	0.050	0.018	0.020	0.043	0.023	0.050	0.038	0.029	0.029
Distance from roads	0.065	0.060	0.041	0.036	0.018	0.020	0.014	0.014	0.035	0.038	0.029	0.029
Distance from rivers	0.065	0.060	0.041	0.036	0.018	0.020	0.014	0.014	0.035	0.038	0.029	0.029

The judgments were also verified to measure the consistency index (*CI*) that was calculated as follows.

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (3.12)$$

Here, *n* is the total number of criteria. Saaty (1989) also suggested that the consistency ratio (*CR*), which was compared with the consistency index as well as the random index (*RI*) **(Table 3.6)** (Aldababseh et al. 2018).

Table 3.6 Consistency random index (RI)

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

The consistency ratio was calculated as follows.

$$CR = \frac{CI}{RI} \quad (3.1)$$

3.3.6 Land Suitability Evaluation

The land suitability evaluation for tea was conducted according to the classification guidelines proposed by the FAO. The guidelines for suitability classification were utilized to assess the suitability of each land unit for a particular use. According to the FAO's guidelines for land evaluation, it was initially determined whether the land was suitable (S) or not suitable (N). The suitable class (S) was further divided as required. In practice, there are three categories—S1, S2, and S3—were used to evaluate the lands for tea cultivation. Thus, the land suitability evaluation was performed for the prioritized criteria that were reclassified into four categories. Eventually, the suitability classes for tea were determined using the weighted overlay based on the fraction weights obtained from expert opinions,

$$Weighted\ Overlay = \sum_{i=1}^{n} C_i * W_n \quad (3.14)$$

where, C_i denotes the criterion (*i*) that was reclassified and W_n denotes the number of criteria (*n*) that were weighted.

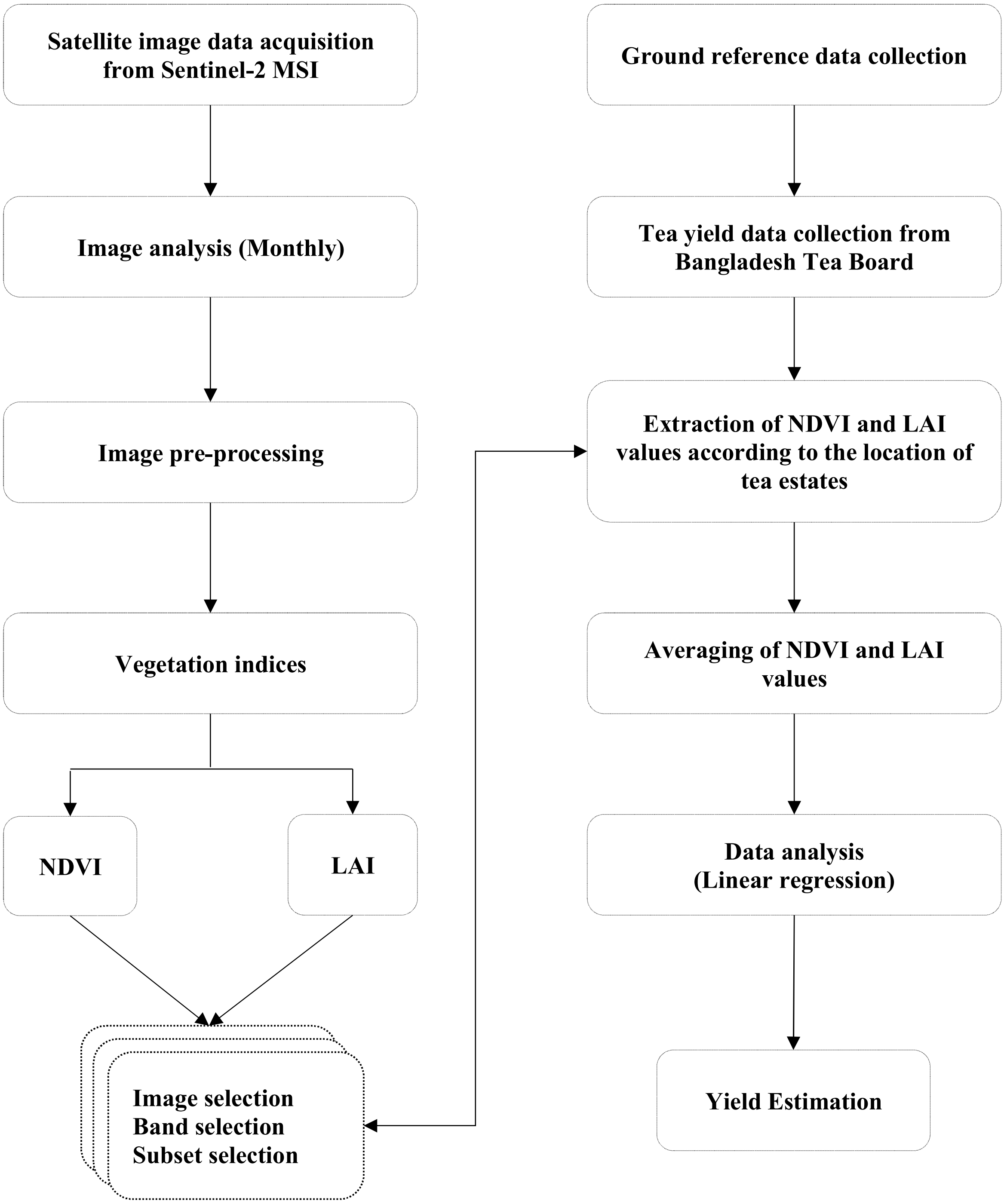


Figure 3.3 Yield estimation procedure from phenological datasets extracted from Sentinel 2 MSI

3.3.7 Ground Reference Information and Field Survey

Primary data were gathered during the 2019 field survey. The GPS waypoints for tea estate locations were collected around the Sylhet Division using a hand-held GPS locator (eTrex 10, Garmin, Olathe, KS, USA). These waypoints were utilized as reference to determine the location of each tea estate. According to the statistical references, among the 135 estates in the study area, 91 were located in Moulvibazar, 25 in Habiganj, and 19 in Sylhet district.

3.3.8 Validation of Yield

Yield data for three consecutive years (from 2017 to 2019) were gathered from the Bangladesh Tea Board (BTB). The NDVI values were also extracted from Sentinel-2 satellite imagery for the years 2017 to 2019. The monthly average NDVI values were extracted for the active growing season (March to November) over the tea estates located in the study areas. The NDVI values were obtained according to the ground reference points recorded during the field survey. The monthly average LAI values were derived from the values of NDVI utilizing geospatial techniques **(Figure 3.3).** The yield data were compared in a scatter plot through regression analysis using both the NDVI and the LAI.

3.4 Results

3.4.1 Reclassification

The raster layers of criteria were reclassified in accordance with the suitability levels into highly suitable, moderately suitable, marginally suitable and not suitable categories (**Figure 3.4 &3.5**). In the classification of LULC, the user accuracy (UA) was 100% for forests, tea estates, high agricultural lands and wetlands; 85.71% for water bodies and settlements; and 71.43% for rivers. On the other hand, producer accuracy (PA) was 100% for tea estates, water bodies, settlements, high agricultural lands and rivers and 87.5% and 72.73% for forests and wetlands, respectively (**Table 3.7**). In the accuracy assessment for LULC, the overall accuracy (OA) was 92%.

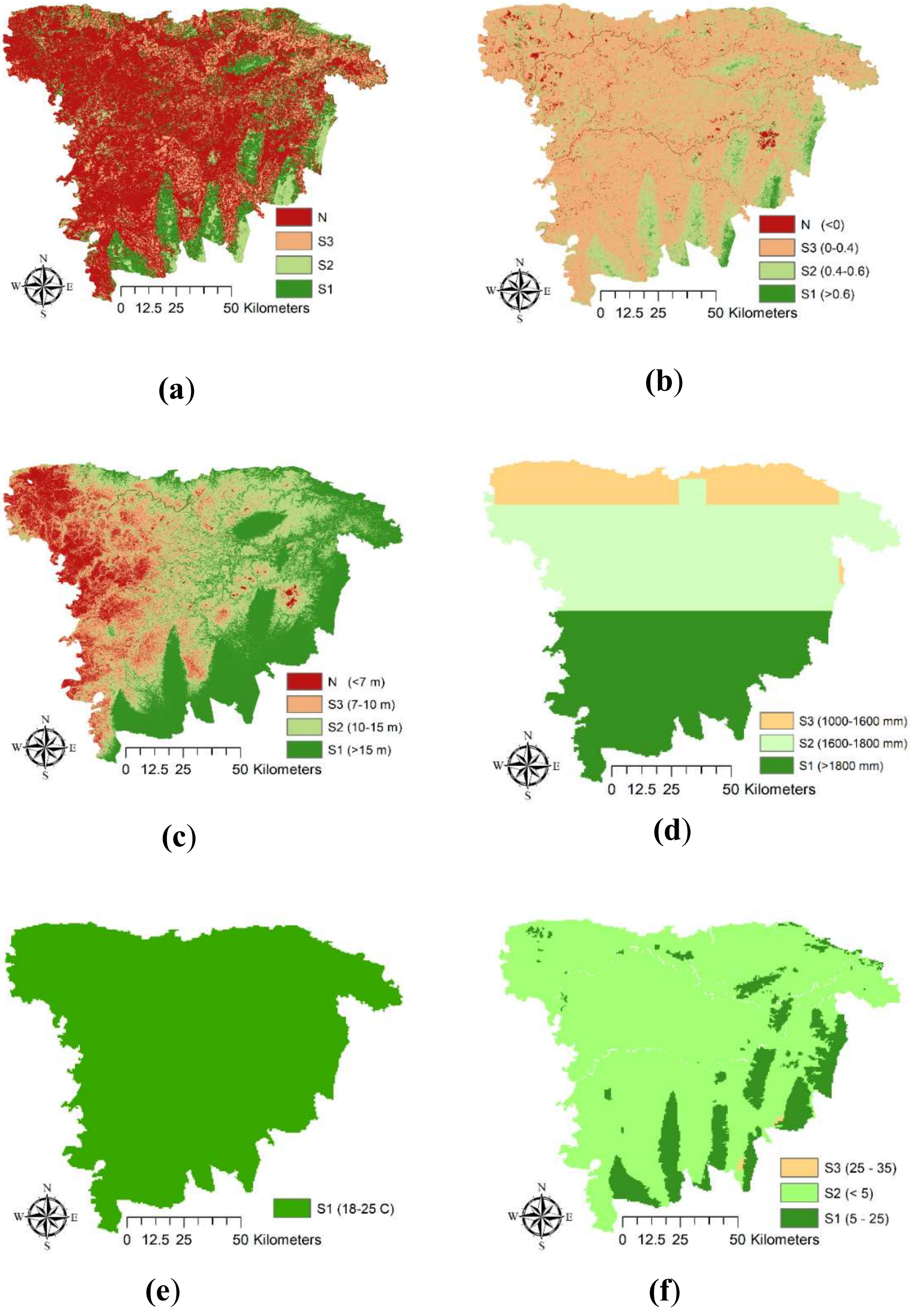


Figure 3.4 Reclassification of criteria: (a) LULC, (b) NDVI, (c) Elevation, (d) Precipitation, (e) Temperature, and (f) Slope

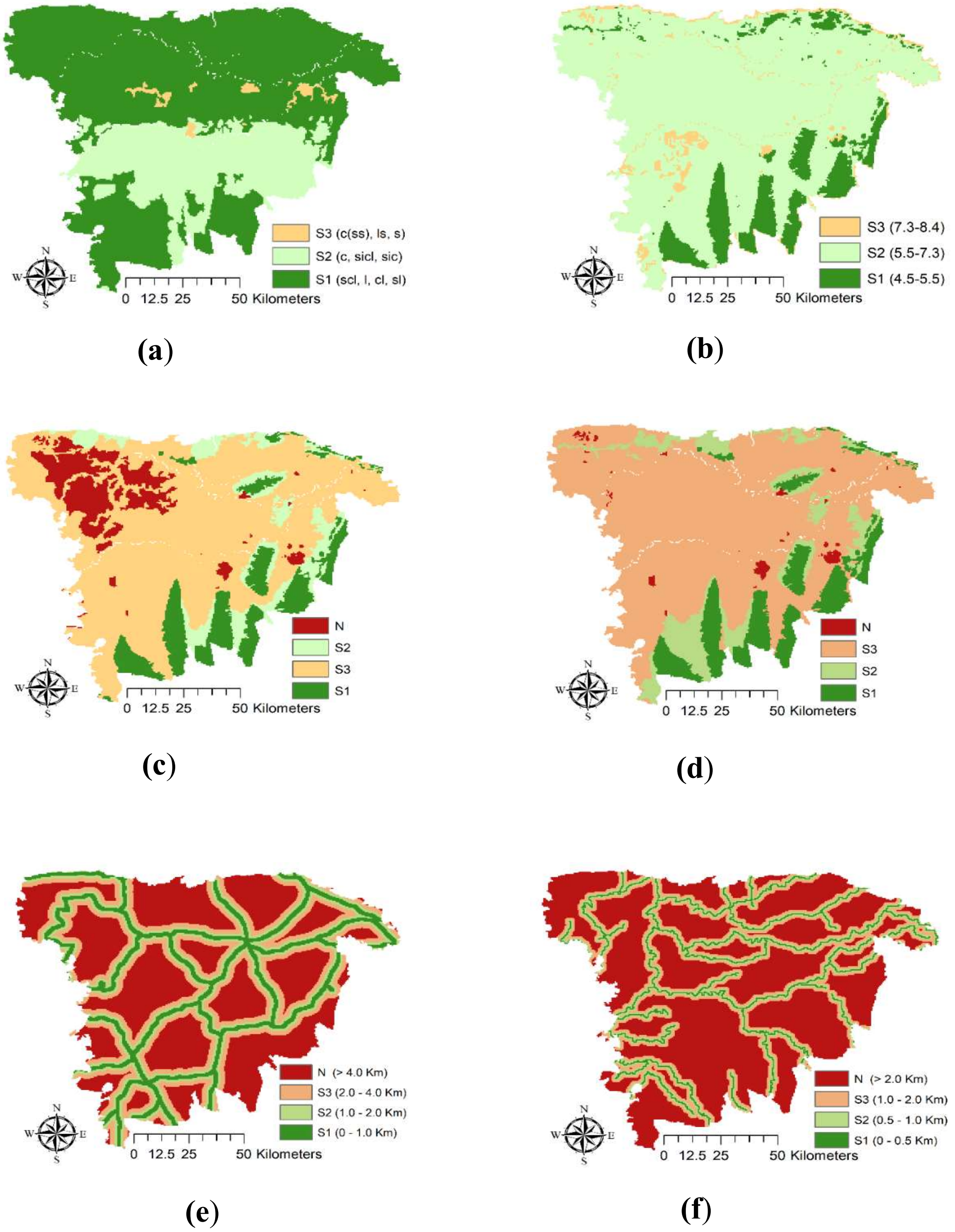


Figure 3.5 Reclassification of criteria: (a) Soil texture, (b) Soil pH, (c) Drainage, (d) Soil type, (e) Distance from roads, and (f) Distance from rivers

Table 3.7 Accuracy assessment for land use and land cover (LULC)

Components	Forests	Tea Estates	Water Bodies	Settlements	High Agril. Land	Rivers	Wet Lands	Total (User)	% Accuracy
Forests	7	0	0	0	0	0	0	7	100
Tea Estates	0	7	0	0	0	0	0	7	100
Water Bodies	0	0	6	0	0	0	1	7	85.71
Settlements	1	0	0	6	0	0	0	7	85.71
High Agril. Land	0	0	0	0	7	0	0	7	100
Rivers	0	0	0	0	0	5	2	7	71.43
Wetlands	0	0	0	0	0	0	8	8	100
Total (Producer)	8	7	6	6	7	5	11	50	
% Accuracy	87.5	100	100	100	100	100	100		

In the reclassification of multicriteria, for LULC 16.41% of lands (201,818 ha) were highly suitable, 10% (123,008 ha) were moderately suitable, 11.87% (145,964 ha) were marginally suitable, and 61.72% (759,050 ha) were not suitable. Considering the NDVI, 2.31% of the lands (28,362 ha) were highly suitable, 26.51% (325,998 ha) were moderately suitable, 67.77% (833,430 ha) were marginally suitable, and 3.42% (42,051 ha) were not suitable.

According to elevation, 35.05% of the areas (431,045 ha) were highly suitable, 28.75% (353,533 ha) were moderately suitable, 22.28% (274,016 ha) were marginally suitable, and 13.92% (171,246 ha) were not suitable. In the reclassification of precipitation, 38.18% of lands (469,553 ha) were in the highly suitable category, 46.54% (572,386 ha) were moderately suitable, and 15.28% (187,901 ha) were marginally suitable. In the reclassification of temperature, it was noted that 100% (1,229,840 ha) of lands were in the highly suitable category. In the case of slope, 14.73% of lands (181,103 ha) were highly suitable, 85.12% (1,046,828 ha) of lands (the majority of the area) were moderately suitable, and only 0.16% (1909 ha) of lands were marginally suitable. In the reclassification of soil texture, 71.36% (877,555 ha) of lands were highly suitable, 27.22% (334,729 ha) of lands were moderately suitable, and 1.43% (17,556 ha) of lands were marginally suitable. In the reclassification of soil pH, 13.99% (172,008 ha) of lands were highly suitable, 81.05% (996,795 ha) were moderately suitable, and 4.96% (61,037 ha) were marginally suitable.

According to the classification of drainage, moderately well-drained to well-drained lands, which accounted for 13.36% (164,353 ha), were highly suitable; imperfectly drained lands, which accounted for 9.60% (118,083 ha), were moderately suitable; poorly drained lands, which accounted for 66.30% (815,421 ha), were marginally suitable; and very poorly drained lands, estimated as 10.73% (131,983 ha), were in the not suitable category. Brown hill soils belong to the highly suitable category, accounting for 13.24% (162,782 ha), whereas gray piedmont soils, accounting for 11.84% (145,659 ha), belonged to the moderately suitable category. Non-calcareous alluvium, brown flood plain soils, dark gray flood plain soils, gray flood plain soils, acid basin clays, and deep red-brown terrace soils belonged to the marginally suitable category, accounting for 73.72% (906,642 ha), and peat soils, water bodies and urban areas, accounting for 1.20% (14,757 ha), were in the not suitable category.

According to the reclassification of distance from roads, it was observed that 13.97% (171,759 ha) of lands were in the highly suitable category, 14.51% (148,404 ha) were moderately suitable, 21.81% (268,246 ha) were marginally suitable, and 49.72% (611,431 ha) were not suitable. The reclassification of distance from rivers showed that 6.23% (76,601 ha) of the total lands were highly suitable, 11.68% (143,618 ha) were moderately suitable, 18.03% (221,779 ha) were marginally suitable, and 64.06% (787,842 ha) were not suitable for tea cultivation in the Sylhet Division of Bangladesh **(Table 3.2)**.

3.4.2 AHP Weights

In the AHP analysis, the comparison of the criteria scale matrices was accomplished according to the experts' opinions, where judgments for ranking the criteria influenced the suitability classes of lands. Twelve criteria for the land suitability evaluation of tea were determined according to the baseline survey and a review of the literature. The AHP for the selected criteria was supported by a pairwise matrix, and the weights were determined from the normalized matrices based on expert's knowledge to prioritize the criterion layer in the weighted overlay (Rashid et al. 2019). The results of the AHP demonstrated that precipitation (23%) was highly influential, followed by drainage (19%), temperature (15%), soil pH (10%), and slope (8%). There were similar influences of elevation, soil texture and soil type (5%), LULC and distance from rivers (3%), with the least influence of the NDVI and distance from roads (2%) (**Table 3.8**).

Table 3.8 AHP weights for the assessment of the relative importance of the criteria

Criteria	Expert A (30 Years)	Expert B (10 Years)	Expert C (12 Years)	Expert D (12 Years)	Expert E (8 Years)	Expert F (10 Years)	Expert G (12 Years)	Expert H (15 Years)	Expert I (12 Years)	Expert J (8 Years)	Average	Weight
LULC	0.024	0.023	0.022	0.033	0.037	0.038	0.030	0.018	0.019	0.020	0.026	3
NDVI	0.024	0.018	0.022	0.021	0.020	0.017	0.034	0.017	0.019	0.021	0.021	2
Elevation	0.035	0.040	0.051	0.088	0.058	0.068	0.054	0.040	0.063	0.047	0.054	5
Precipitation	0.214	0.244	0.248	0.200	0.249	0.258	0.202	0.217	0.232	0.205	0.227	23
Temperature	0.133	0.177	0.133	0.145	0.135	0.181	0.155	0.150	0.142	0.129	0.148	15
Slope	0.095	0.082	0.090	0.078	0.077	0.066	0.076	0.086	0.071	0.100	0.082	8
Soil texture	0.066	0.045	0.048	0.048	0.049	0.038	0.055	0.048	0.052	0.048	0.050	5
Soil pH	0.104	0.105	0.085	0.091	0.108	0.095	0.114	0.100	0.093	0.089	0.098	10
Drainage	0.186	0.182	0.191	0.200	0.178	0.157	0.189	0.219	0.207	0.226	0.194	19
Soil type	0.071	0.046	0.065	0.053	0.051	0.041	0.050	0.039	0.062	0.050	0.053	5
Distance from roads	0.024	0.019	0.023	0.023	0.020	0.020	0.020	0.033	0.020	0.020	0.022	2
Distance from rivers	0.024	0.019	0.023	0.023	0.020	0.020	0.020	0.033	0.020	0.046	0.025	3

3.4.3 Land Suitability

The suitability map was developed utilizing the weighted overlay spatial analysis according to the AHP weights (**Figure 3.6**). The result of the weighted overlay showed that 3.37% of the total lands (41,460 ha) were highly suitable, 9.01% (110,767 ha) were moderately suitable, 49.87% (613,367 ha) were marginally suitable, and 37.75% (464,246 ha) were not suitable **(Table 3.9)**. It was also observed that among the 135 tea estates in the Sylhet Division, 31 were located in the highly suitable areas, 79 in the moderately suitable areas, 24 in the marginally suitable areas, and only one in a not suitable area (**Figure 3.7**).

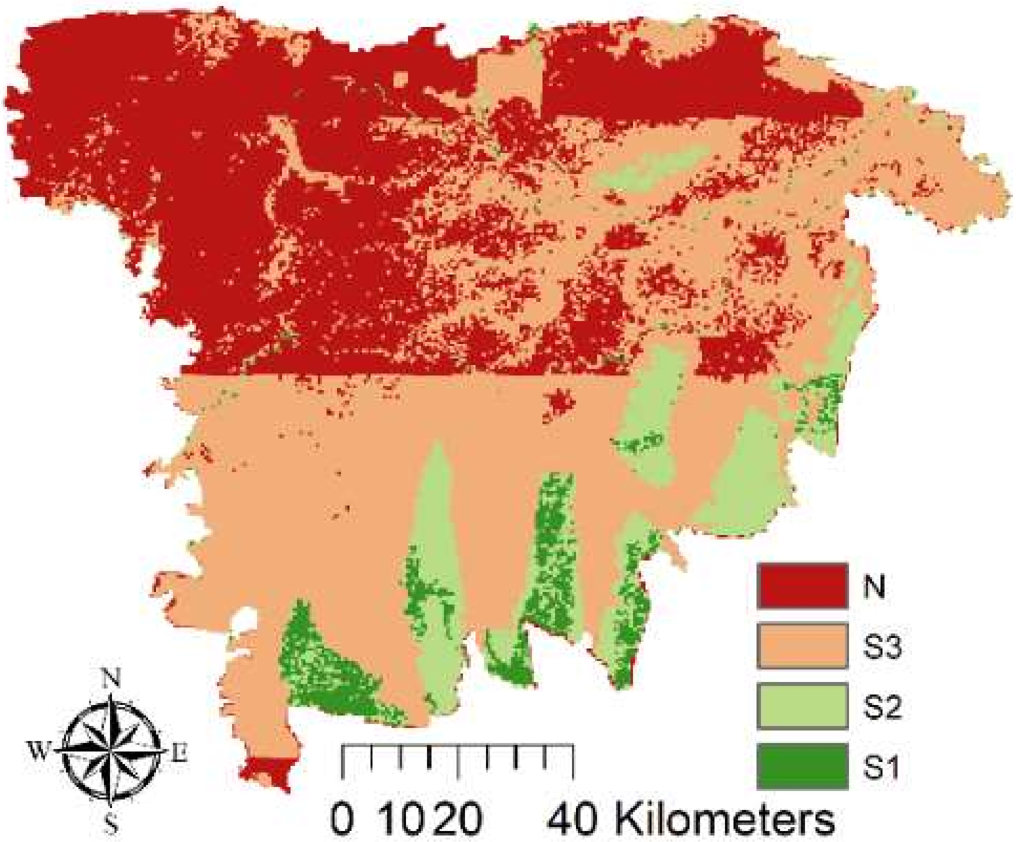


Figure 3.6 Suitability classes for tea estates

Table 3.9 Areas in the land suitability classes of tea

Suitability Level	Pixel Counts	Area (%)	Area (ha)
S1 (Highly suitable)	1535	3.37	41,460
S2 (Moderately suitable)	4101	9.01	110,767
S3 (Marginally suitable)	22,709	49.87	613,367
N (Not suitable)	17,188	37.75	464,246

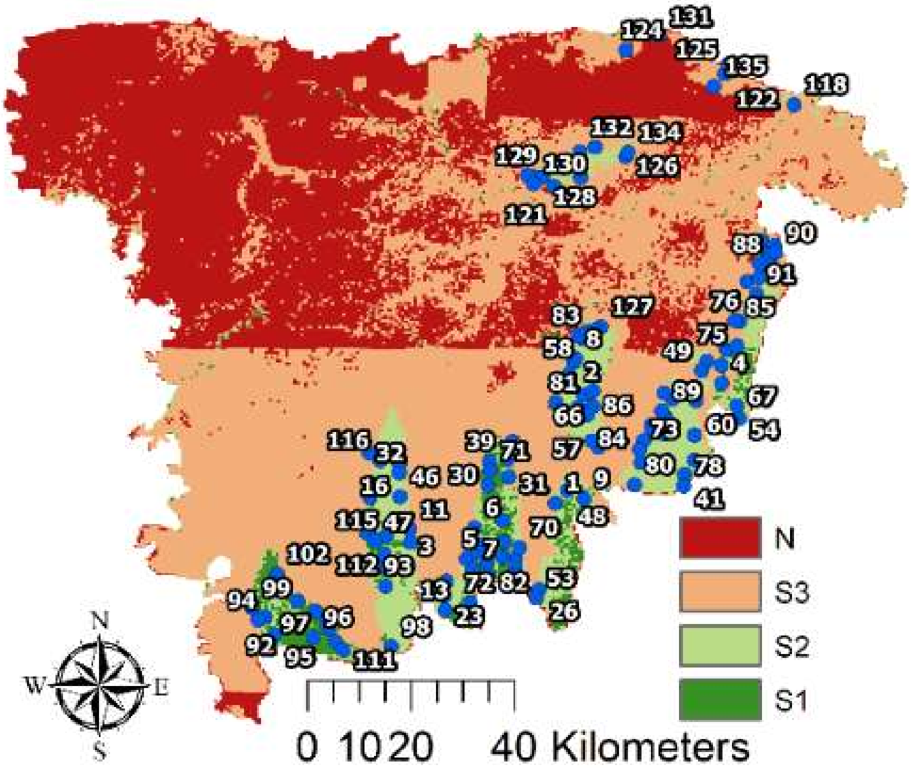


Figure 3.7 Validation of tea estates in different land suitability classes

3.4.4 Validation of Yield

Yield estimation and validation were performed using both NDVI and LAI values with the observed yield data. The trendline obtained from the scatter plot showed the effects of the NDVI and the LAI on yield. According to the regression analysis between the NDVI and yield, the coefficients of determination were 0.69, 0.66, and 0.67, and between the LAI and yield, they were 0.68, 0.65, and 0.63 for 2017, 2018, and 2019, respectively (**Figure 3.8**). The predicted yield maps were developed from the obtained linear equation using geospatial techniques. The red color in the map indicates the restricted area, and the light green to deep green color shows the tea-producing area (**Figure 3.9).**

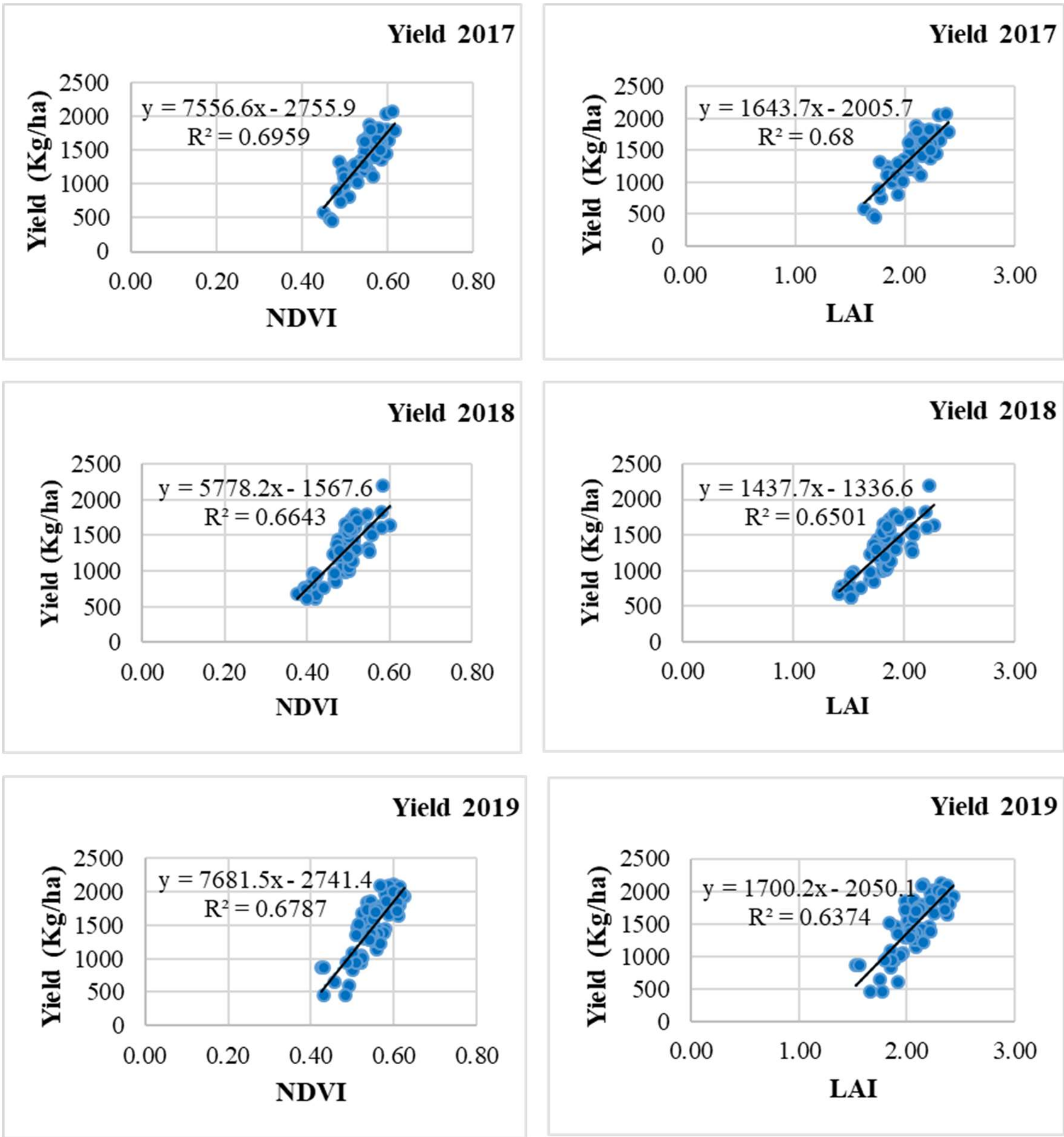


Figure 3.8 Regression analysis for yield prediction of tea using phenological indices and ground reference time series yield information

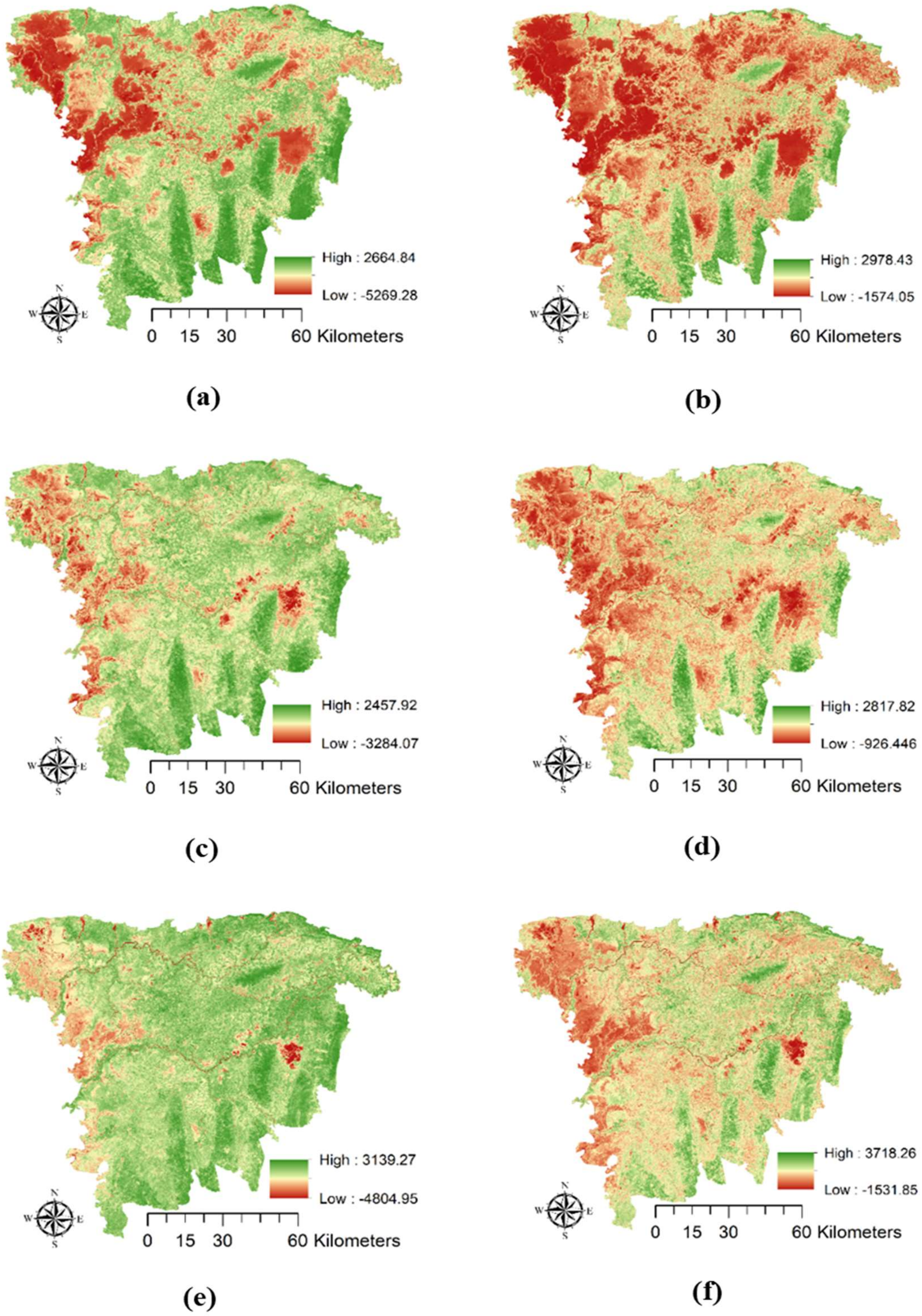


Figure 3.9 Yield maps of tea obtained from phenological indices: (a) NDVI 2017, (b) LAI 2017, (c) NDVI 2018, (d) LAI 2018, (e) NDVI 2019, and (f) LAI 2019

3.5 Discussion

Incorporation of Sentinel-2 MSI and geospatial datasets was significant in this study to assess environmental limitations as well as to evaluate land suitability for tea production (Hinton et al. 2007). LULC classification and NDVI measurements were performed from Sentinel-2 datasets that serves as a high-resolution remote sensing data. Edaphic, climatic, and topographic factors are critical and important for sustainable tea production (Amarathunga et al. 2008). The SRTM digital elevation datasets, prepared by NASA, used to generate the elevation layer of the study area, is significantly important in digital mapping of terrain due to its accessibility of high-quality elevation data. Edaphic and climatic parameters for this study were selected according to the reference of the previous studies. Distance from roads is an important criterion with respect to transportation, and distance from rivers, with the advantages of irrigation facilities and transportation, was considered another criterion in this research (**Appendix A**). An important step in the land suitability evaluation is to determine the weight of each criterion that affects suitability assessment (Jayasinghe et al. 2019). Multiple factors affect the land suitability evaluation because of the criteria are of unequal importance (Elsheikh et al. 2013). In this study, a multi-criteria decision-making process was used that integrates AHP with biophysical and remote sensing parameters. This study represents application of AHP along with the weighted overlay model for the land suitability evaluation of tea production resulting in a value of consistency ratio (CR) less than 0.1 (Purnamasari et al. 2019).

Most of the lands suitable for tea cultivation were located in the southern and eastern parts of the Sylhet Division. This result might be due to the suitable drainage system, slope, soil type, soil pH, and elevation in this area along with the most important factors, such as precipitation and temperature. On the other hand, around one-third portion of lands, mostly located in north-western part of the Sylhet Division, were not suitable due to the presence of wetlands that is not arable for tea cultivation along with other adverse edaphic factors. This research finds that drainage is an influencing factor after precipitation. One of the novel points of this research is the validation of yield using vegetative and biophysical indices based on time series NDVI and LAI datasets.

Previous research had the limitation of obtaining inappropriate validation results due to inadequate ground reference information. Validation of the results was accomplished in this research by physical verification with GPS identification of tea estate locations and corresponding time series yield data from tea estates. In previous studies on the land suitability evaluation of tea, only a few edaphic and climatic parameters were used to determine the areas in different suitability classes (Jayasinghe et al. 2019; Nguyen et al. 2020; Li et al. 2012; Chanhda et al. 2010; Gahlod et al. 2017). However, this research integrated the use of geospatial and remote sensing data with AHP to locate tea estates in different suitability classes. The limitation of this research was disregarding the influence of shade trees on tea estates. A new method needs to incorporate in future studies to remove the shade of trees from high-resolution remote sensing data.

3.6 Conclusions

This study launched a method of determining suitable lands for tea cultivation in Bangladesh utilizing GIS, satellite remote sensing, and AHP. Among the criteria used, precipitation had the greatest influence (23%), followed by drainage (19%), temperature (15%), and other factors. The weighted overlay using the AHP demonstrated that only 41,460 hectares (3.37%) of land were highly suitable, followed by 110,767 hectares (9.01%) of moderately suitable land. The majority of the area (613,367 hectares), which accounted for 49.87%, were marginally suitable, and a considerable portion of lands (464,246 hectares), estimated as 37.75%, were not suitable for tea cultivation. Among the 135 tea estates, 58% were in moderately suitable areas, 23% were in highly suitable areas, 18% were in marginally suitable areas, and less than 1% were in not suitable areas. The results of the land suitability evaluation for tea in Bangladesh would be useful in the decision-making process to boost production as well as for the sustainable management of agricultural lands. Thus, land suitability evaluation is essential for understanding the future land use and production trend of tea for the growth of the tea industry in Bangladesh.

CHAPTER 4

An Assessment of Drought Stress in Tea Estates Using Optical and Thermal Remote Sensing

4.1 Background

Drought is one of the most detrimental climatic factors, which influences plant growth and development, and ultimately it affects sustainable production of tea with regard to changing climate (Nalina et al. 2018; Ahmed et al. 2016). Drought influences more compared to other environmental factors to plant physiological processes altering the cellular mechanism and finally it affects crop growth, productivity, as well as quality of tea (Anjum et al. 2011; Shao et al. 2009). The duration and magnitude of drought affects the yield and quality of tea and the yield losses caused by drought stress is becoming frequent as well as unpredictable due to climate change effects such as increasing water stress in tea estates (Zhou et al. 2014). Tea (*Camellia sinensis* (L) O. Kuntze) is a perennial evergreen shrub cultivated in a wide range of soil and climatic conditions across the tropical, sub-tropical and Mediterranean region (Nalina et al. 2021; Hajiboland, 2017). Both the yield and quality of tea depends on several factors such as cultivars, cultural practices, and plant growth stages along with climate and season. Tea is a rain-fed plantation crop and its production depends mainly on climatic conditions for optimal growth. Therefore, changes in climate, especially, reduction in rainfall causes drought, which affects the production of tea (Wijeratne, 1996). Bangladesh is one of the major tea producing countries having the rank of 9^{th} producing 83 million kg of tea (International Tea Committee, 2017). The tea industry of Bangladesh annually earns roughly 20.90 million USD (0.81% of GDP) exporting around 18 million kilograms of tea (1.37% of the export of the global trade of tea) (Kamruzzaman et al. 2015). An important reason of lower production of tea is the adverse weather conditions like drought. The tea estates of Bangladesh predominantly experience drought during the winter season, from December to February (Das et al. 2020). It has been reported that the drought stress causes the yield losses in tea by 14-33% and the mortality rate of plants, especially the young plantations range between 6-19% (Nalina, 2021; Guo et al. 2017). Hence, it is important to find out the severity of drought in tea plantation areas for taking further steps to mitigate its adverse effects.

Droughts are primarily classified into four categories- meteorological drought indicates the deficit in precipitation, agricultural drought denotes the deficit in soil moisture, hydrological drought implies the reduction in surface runoff, groundwater, and storage of water, and the socioeconomic drought involves demand and supply of economic goods along with the elements of other kinds of droughts and the social responses. However, all kinds of droughts are associated with the sustained precipitation deficit (AghaKouchak et al. 2015; Wilhite, 2005). Several ground- and remote sensing-based indicators with their advantages and limitations, for the drought stress assessment are being used. The ground-based indicators consolidate the information of precipitation, status of soil moisture, and the supply of water rather than emphasizing many spatial details. Moreover, those drought indicators are used for the dispersed locations and thus, the limitation of those indicators is that they are relied on the collected data from the weather stations results in sparsely distributed drought that affects the authenticity of those drought indices (Brown et al. 2002). In contrast, the remote sensing-based drought indices are calculated using the surface reflectance of different bands derived from the satellite data over the entire area have been widely used for drought monitoring (Murad et al. 2011).

Historical drought indicators are used to represent the droughts in terms of their duration, severity, and areal extent (Mishra and Singh, 2010). Several drought indicators like the standardized precipitation index (SPI), the Palmer drought severity index (PDSI), the Standardized Precipitation Evapotranspiration Index (SPEI), as well as the Effective Drought Index (EDI) have been proposed to quantify the intensity and the pattern of droughts. Among those indicators, SPI is the widely used indicators with the advantage of its simplicity in use and the spatial consistency in interpretation that could be used in drought stress assessment and decision analysis. Thus, the SPI could be used efficiently for different time span from one month to several years in accordance with the user's interest (Kamruzzaman et al. 2019, Guttman, 1998).

With advances in remote sensing technology, the use of the ground-based drought indicators has been strengthened by the newly developed remote sensing-based indices with an opportunity for real time monitoring. Thus, the remote sensing technology is increasingly being considered a robust tool for drought detection. In climatological context, monitoring of precipitation, soil moisture, ground and terrestrial water storage, evapotranspiration, and snow are considered for both the ground- and satellite-based drought monitoring, while in ecological context, the magnitude of drought could be assessed observing vegetation health condition and land cover utilizing remote sensing data (AghaKouchak et al. 2015; Nemani et al. 2009). Different Satellite-based drought indices such as Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), Normalized Difference Moisture Index (NDMI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), Perpendicular Drought Index (PDI), Modified Perpendicular Drought Index (MPDI), Distance Drought Index (DDI), and Soil Moisture Index (SMI) are widely used indices for drought detection (AghaKouchak et al. 2015). According to the recent studies on drought stress assessment, it is evident that the vegetation water indices like NDMI is a powerful index, as it quantifies water content in the plant canopies of higher biomass ecosystems that is directly related to soil moisture status (Caccamo et al. 2011; Van Niel et al. 2003). On the other hand, drought stress could be assessed utilizing the surface brightness temperature derived from the thermal bands of different satellite instruments like MODIS, AVHRR, VIIRS, TM, ETM+, and TIRS. The land surface temperature (LST) quantified from the thermal infrared (TIR) channels has been observed to be a robust indicator for providing useful information on land surface moisture content that is an indispensable tool to assess the magnitude of the drought (Gutman, 1990).

Multiple studies have been carried out for assessing the drought severity utilizing the remote sensing technique. A study on NDVI-based agricultural drought stress assessment was performed to measure the magnitude of drought in Palar Basin of Tamil Nadu, India using IRS (Indian Remote Sensing Satellites)-1C & 1D (Krishna et al. 2009). Another study was performed in the western tracts of Tamil Nadu utilizing the satellite data of the National Oceanic & Atmospheric Administration (NOAA) (Muthumanickam et al. 2011). Drought stress assessment was carried out for the Hickory plantation in the western Zhejiang of China adopting a change detection approach, and using the data from multitemporal Landsat 8 imagery (Xi et al. 2016). A study was performed to investigate vegetation droughts for natural forests, rubber, and oil palm plantations in the peninsular Malaysia utilizing MODIS datasets (Razali et al. 2016). Another study was carried out in South Africa to assess the effects of drought on forest plantations using MODIS datasets with climate data, suggests that the NDMI (Normalized Difference Moisture Index) is a robust index to measure the interactions among precipitation, soil moisture, and water content in plant canopies (Xulu et al. 2018). A comprehensive study on the effects of drought and other disturbance on forest landscape in North Carolina, USA was carried out utilizing MODIS and Landsat datasets (Yang et al. 2020). Apart from those, several studies have been carried out in small scale for drought monitoring in tea plantation areas using Wireless Sensor Networks (WSNs) (Gupta et al. 2014; Jiang, 2011; Sun et al. 2010). The WSN-based drought stress assessment is not applicable for large and remote areas in many developing countries like Bangladesh due to the disruption in power supply and internet networks that are the major impediments in the sensor network systems. Those studies provide information regarding the research gap to measure drought stress in tea plantation areas in greater extent utilizing satellite remote sensing technique.

To the best of our knowledge, no studies regarding drought stress assessment for tea plantations in large scale has been carried out so far to measure the drought severity in tea estates using satellite remote sensing technology. Furthermore, no standard drought index method has been developed to asses drought severity as well. Therefore, a comprehensive study utilizing ground-based precipitation datasets as well as multi-satellite remote sensing datasets to develop a drought classification system was undertaken.

4.2 Objectives

The objectives of the present study were to assess the drought severity in tea plantation with a drought classification system using Standardized Precipitation Index and remote sensing technique as well as to characterize the spatiotemporal pattern of drought in tea plantation with a view to ensuring early warning for risk mitigation as well as sustainable tea production in Bangladesh.

4.3 Materials and Methods

Precipitation data gathered from the Bangladesh Meteorological Department (BMD) were used to calculate the SPI and drought frequency. Both the Landsat 8 OLI/TIRS and Sentinel-2 MSI satellite images were used as the remote sensing datasets. Ground reference Geographic Positioning System (GPS) information was recorded during the field survey to extract the points over tea plantation areas for quantifying the SMI, NDMI, LAI, as well as the predicted yields.

4.3.1 Study Area

The study area is considered the tea growing zone, lies between the latitudes of 23°58′40" and 25°11′25" north and the longitudes of 91°16′09" and 92°30′17" east, is located in the northeastern part of Bangladesh and consists of 21 sub-districts of the Sylhet Division **(Figure 4.1)**. The sub-districts are Moulvibazar, Kamalganj, Kulaura, Rajnagar, Sreemangal, Barlekha and, Juri from Moulvibazar district; Habiganj Bahubal, Chunarughat, Madhabpur and, Nabiganj from Habiganj district; and Sylhet, Balaganj, Beanibazar, Fenchuganj, Golapganj, Gowainghat, Jaintiapur, Kanaighat and, Zakiganj from Sylhet district. The area is bordered by the Indian Province of Meghalaya, Assam, and Tripura to the north, east, and south, respectively, and sub-district of Companiganj, Chatak, Jagannathpur, Baniachung and, Lakhai to the west and Divisions of Chattogram to the southwest. There are 135 tea estates in the study area with 98,413 hectares of land, contribute approximately 85% of total tea production of the country (Bangladesh Tea Board, 2020). This area is characterized by adequate amount of rainfall and favorable temperatures during the monsoon season that are congenial for tea production, however, experiences drought stress during winter season **(Figure 4.2)**.

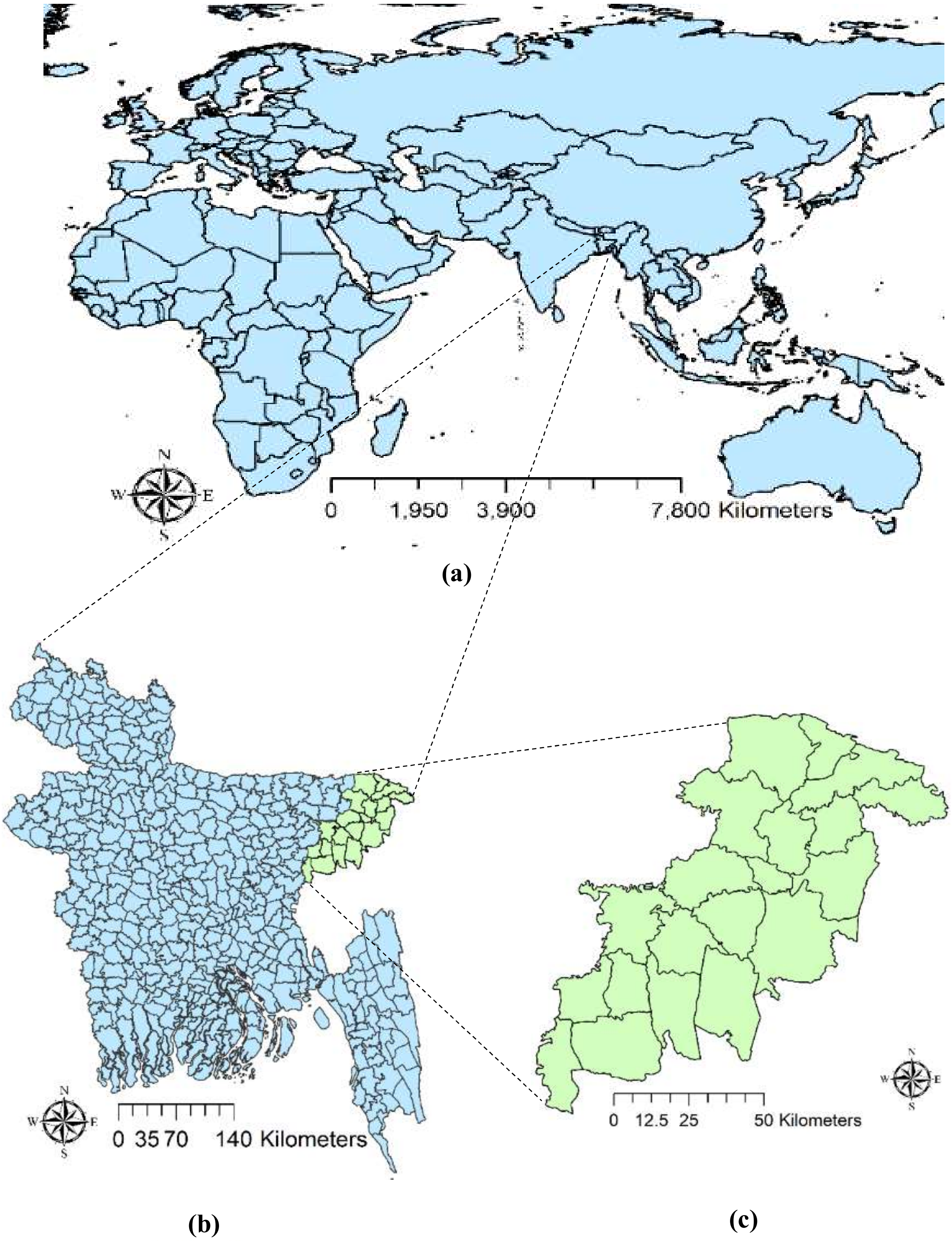


Figure 4.1 Geographical location of the study area: (a) Bangladesh on the world map, (b) Bangladesh, (c) Tea cultivation area in the Sylhet Division

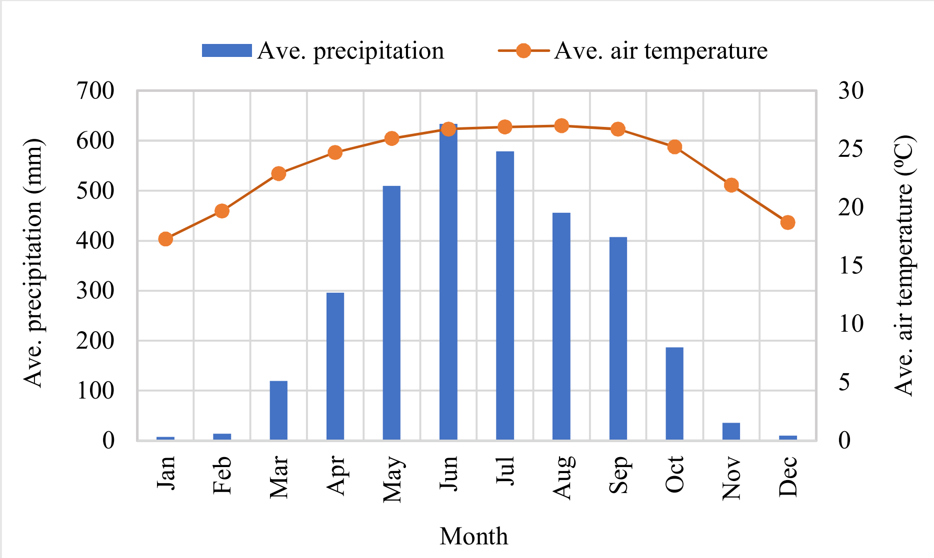


Figure 4.2 Climatogram showing the temporal distribution of precipitation and air temperature in the study area

4.3.2 Precipitation Data and the SPI Calculation

The daily precipitation data for the local weather stations, Sylhet and Sreemangal, which represent the rainfall scenario of the study area, were gathered from the Bangladesh Meteorological Department to obtain the monthly precipitation sums. Drought monitoring was carried out employing the monthly precipitation sums to calculate the standardized precipitation index (SPI) for the period from January 2018 to March 2021. The positive SPI values denote wet conditions, and the negative values indicate the drought period with less precipitation than normal (Habibie et al. 2020). The precipitation data collected from the local weather stations were utilized to classify wet and dry conditions (Paulo et al. 2012). The drought characterization was performed utilizing the SPI to measure the severity, duration, and monthly coverage of drought for each category (Paulo and Pereira, 2006). The accumulated SPI values were utilized to classify the drought. The SPI value, ≤ -1 refers to SPI-1, SPI-3, SPI-6, and SPI-12. Thus, the negative SPI values denote the corresponding drought severity for quantitative assessment of drought (World Meteorological Organization, 2012; Peterson and Vose, 1997; McKee et al. 1993). The SPI-1 computation was carried out for the year 2018-2019, 2019-2020, and 2020-2021 using the monthly precipitation data to investigate the future drought events. Drought classification was performed according to Razali et al. 2016.

The SPI in a cumulative distribution was expressed using the gamma function. The gamma distribution is used to define the probability density or the function of frequency (McKee et al. 1993). The gamma distribution can be denoted as follows:

$$G(x_i) = \int_0^{x_i} g(x_i)dx_i = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_0^{x_i} t^{\alpha-1}e^{-x_i/\beta}dx_i \qquad (4.1)$$

Here, $\alpha > 0$ and $\beta > 0$ denote the shape parameter and scale parameter, respectively (Alam et al. 2013).

x refers to the precipitation in millimeters in the consecutive months i, and $\Gamma(\alpha)$ is the gamma function. When, x_i=0, the cumulative gamma distribution is unknown, and the cumulative probability is encountered. The SPI estimation also involves a matching density function of the gamma likelihood to the precipitation frequency distribution.

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad (4.2)$$

$$\beta = \frac{x}{\alpha} \qquad (4.3)$$

$$A = \ln(x) - \frac{\sum \ln(x)}{n} \qquad (4.4)$$

For undefined gamma function, when x_i= 0, the value of G (x_i) can be expressed as follows:

$$H(x_i) = q + (1-q)G(x_i) \qquad (4.5)$$

Where, q is the probability of zero, the cumulative probability $H(x_i)$ is transformed to the standard normal distribution to the SPI values (McKee et al. 1993). To calculate the SPI, the cumulative probability distribution is transformed into a normal distribution, which can be expressed as follows:

$$z = SPI = -\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right),\ t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad (4.6)$$

When, 0 < H(x) <0.5, the following expression is true.

$$z = SPI = +\left(t - \frac{c_0+c_1t+c_2t^2}{1+d_1t+d_2t^2+d_3t^3}\right),\ t = \sqrt{\ln\left(\frac{1}{1-(H(x))^2}\right)} \quad (4.7)$$

The drought frequency was calculated according to the following formula:

$$\text{Drought frequency (\%)} = \frac{\text{Number of months affected by drought}}{\text{Total number of months}} \times 100 \quad (4.8)$$

4.3.3 Field Survey and Ground Reference Information

Ground reference information was collected during the field survey-2019. GPS locations of tea estates were recorded around the study area using a hand-held GPS locator (eTrex, Garmin, USA). Further, this GPS information was utilized to extract point values from the remote sensing data employing the Spatial Analyst Tools in ArcGIS **(Figure 4.3)**. According to the field survey, it was observed that among the 135 estates in the study area, 91 were located in Moulvibazar, 25 in Habiganj and 19 in Sylhet district (**Figure 4.4**).

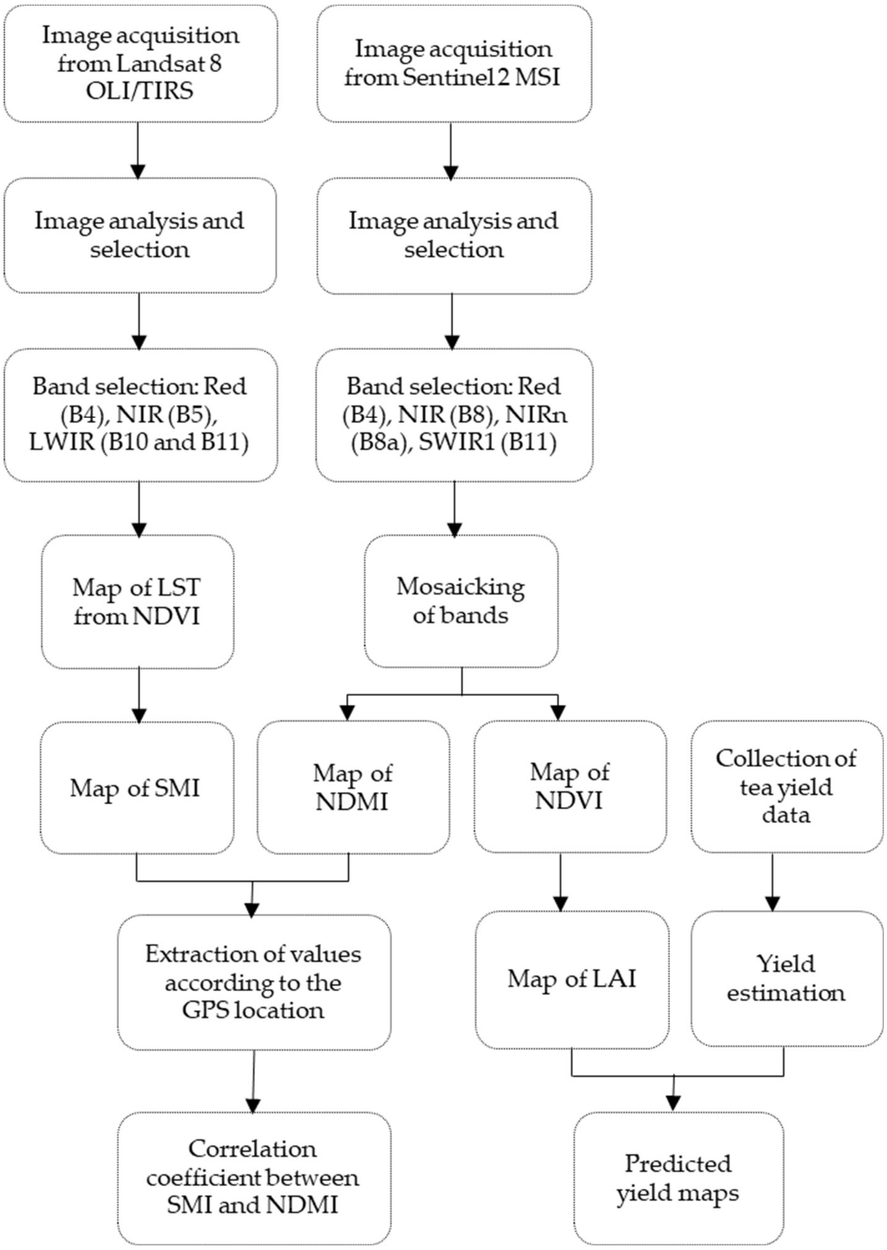


Figure 4.3 Flowchart for drought stress assessment in tea estates from remote sensing data

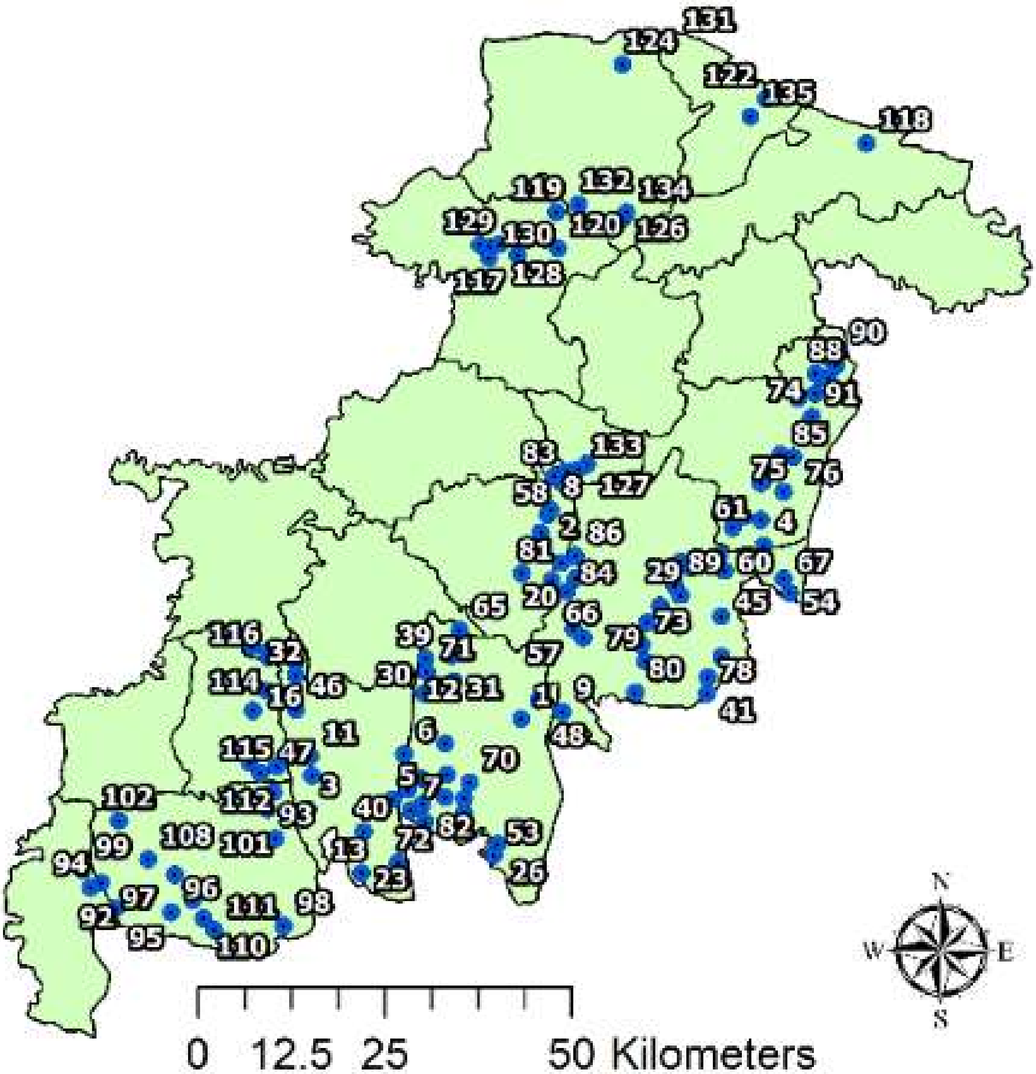


Figure 4.4 GPS location of tea estates according to the field survey

4.3.4 Remote Sensing Data

Multi-satellite image data from the Landsat-8 OLI/TIRS and Sentinel-2 MSI were gathered for drought estimation from December to February for the year 2018-2019, 2019-2020 and 2020-2021 **(Figure 4.3)**. The Landsat-8 is equipped with OLI (Operational Land Imager) and TIRS (Thermal Infrared Sensor) instruments. The OLI sensor provides image data in the coastal aerosol, visible (blue, green and red), NIR (near infrared), and SWIR (shortwave infrared) spectrum with a spatial resolution of 30m and in a panchromatic band with a spatial resolution of 15m. The TIRS sensor provides image data in two thermal infrared bands with a spatial resolution of 100m. The TIRS dataset, registered to the OLI data, is geometrically, radiometrically, and terrain-corrected 12-bit products. Landsat 8 C1 level 1 images with a path 136 and row 43 were processed to develop the maps of LST and SMI. The collected Landsat 8 image data were processed at a resolution of 30m using the resampling technique in ArcGIS followed by subsequent mosaicking and masking. All the selected bands from Landsat 8 were resampled to a 30 m resolution for the uniformity in cell size and data. Further, an algebraic operation, radiometric calibration, atmospheric and geometric corrections were performed for the raster images. The average reflectance for the raster images were calculated using the raster calculator tool to minimize the spatial variability. All the selected bands from Sentinel-2 image data resampled to a 20m resolution were used to develop the maps of NDMI, NDVI, NDVI, as well as yield maps. To quantify the LST, the NDVI was retrieved measuring the reflectance of near-infrared, and red bands from the data obtained from the optical sensors of Landsat-8 OLI, followed by the retrieval of the proportion vegetation (PV) and land surface emissivity (LSE). The spectral radiance was derived from the long-wave infrared (LWIR) bands obtained from the TIRS of Landsat-8, followed by quantifying the brightness temperature (BT); and finally, the LST maps were generated incorporating the values of PV and LSE with BT. On the other hand, the optical sensors from Sentinel-2 contributed to determining the NDMI, LAI, and predicted yields using the visible (red), near-infrared, and short-wave infrared (SWIR) bands. All the remote sensing indices were calculated from the satellite data with less than 2% cloud cover for three consecutive years were analyzed in the ArcGIS® environment.

4.3.4.1 Estimation of Land Surface Temperature (LST)

Land surface temperature is a controlling factor of canopy temperature and moisture content in vegetation that could be used efficiently to monitor soil moisture in vegetated land (Zhang et al. 2016). LST was quantified for the tea estates utilizing temporal information from Landsat-8 OLI / TIRS dataset with less cloud coverage (Binte Mostafiz et al. 2021; Habibie et al. 2019). There were two steps involved in the quantification of the LST. At first, the NDVI data were retrieved utilizing two wave bands: near-infrared (*B5*) and red (*B4*), according to the following expression:

$$NDVI = \frac{R_{NIR} - R_{RED}}{R_{NIR} + R_{RED}} \tag{4.9}$$

Proportion Vegetation (PV), measured from the NDVI that was calculated as follows:

$$PV = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDV_{\ min}}\right)^2 \qquad (4.10)$$

Here, $NDVI_{min}$ and $NDVI_{max}$, were obtained from the respective NDVI images. The land surface emissivity *(LSE)* was calculated from the *PV* according to the following formula (de Jesus and Santana, 2017):

$$LSE = 0.004 * PV + 0.986 \qquad (4.11)$$

In the second step, the thermal bands were transformed to the digital numbers for the quantification of the radiance. The spectral radiance was retrieved from the thermal bands (*B10* and *B11*), which can be expressed as follows:

$$L\lambda = ML + Q_{CAL} + AL \qquad (4.12)$$

$$L\lambda = 0.0003342 * Band10 + 0.1 \; and \; L\lambda = 0.0003342 * Band11 + 0.1$$

Where, $L\lambda$ expresses the spectral radiance of *TOA* (Top of Atmosphere) at the sensor's aperture, *ML* denotes the multiplicative rescaling factors of the corresponding bands that were derived from the metadata, Q_{CAL} denotes the pixel values (*DN*) of the quantized and calibrated standard products, and *AL* refers to the additive rescaling factor of the specific band. The brightness temperature (*BT*) was measured using the following expression:

$$BT = \frac{K2}{\ln\left[\left({K1}/{L\lambda}\right) + 1\right]} - 273.15 \qquad (4.13)$$

Where, *BT* refers to the satellite brightness temperature in Celsius. *K1* and *K2* denotes the calibration constants in Kelvin obtained from the metadata of thermal conversion constants of the respective bands. Finally, the LST was measured using the following formula:

$$LST = \frac{BT}{1 + \left(\frac{\lambda * BT}{PV}\right) * \ln LSE} \qquad (4.14)$$

4.3.4.2 Estimation of Soil Moisture Index (SMI)

Soil moisture is a potential indicator to understand drought severity, is primarily driven by the precipitation through the process of infiltration and evapotranspiration (Fang et al. 2021; Yin et al. 2019). Soil moisture is variable both spatially and temporally due to the difference in soil properties as well as drainage (Wang and Qu, 2009). Among different indices, LST-based SMI is a widely used index for monitoring soil moisture in the vegetated land. The SMI is the proportion of the difference between the current soil moisture as well as the permanent wilting point to the field capacity along with the residual soil moisture (Saha et al. 2019). The value of SMI ranges between 0 and 1; where, 0 denotes very dry condition and 1 refers to the extreme wet condition. The SMI is associated with the LST of a particular area that can be measured using the following expression:

$$SMI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \qquad (4.15)$$

Where, LST_{max} and LST_{min} refers to the maximum and minimum surface temperature of the study area.

4.3.4.3 Estimation of Normalized Difference Moisture Index (NDMI)

Normalized Difference Moisture Index determines the liquid water molecules in vegetation canopies that interact with solar radiation and thus, water deficit results in a reduction in photosynthesis affecting the growth and development of vegetation (Enquist and Ebersole, 1994). The NDMI is a measure of water content in the spongy mesophyll tissues of plant canopies, which acts as a functioning indicator of soil 案 dclimatic properties regulating water availability. The NDMI responds to variation in both the water content (absorption of *B8A*) and spongy mesophyll tissues of vegetation canopies (reflectance of *B11*) (Serrano et al. 2019; Gao, 1996). The NDMI was measured from Sentinel-2 satellite images using the following formula (Korhonen et al. 2017).

$$NDMI = \frac{NIR_n - SWI \quad _1}{NIR_n + S \qquad _1} = \frac{B8a - B1}{B8a + B11} \qquad (4.16)$$

Where, NIR_n is the near infrared (narrow) reflectance of band *8A* with the wavelength ranges from 855-875 nm and $SWIR_1$ is the shortwave infrared reflectance of band *11* with the wavelength of 1565-1655 nm.

4.3.5 Statistical Analysis

Mean values per-pixel of individual estates were used for drought monitoring in tea estates. Pearson correlation analyses were performed for assessing the relationship between soil and plant canopy moisture. Simple Linear Regression analyses were also performed to show the association of the LAI and time-series observed yield information for the prediction of yield in the drought period.

4.3.6 Validation of Yield in the Drought Period

Yield data for 2018, 2019, and 2020 were obtained from the Bangladesh Tea Board. The Normalized Difference Vegetation Index (NDVI) for the drought period was measured from the reflectance of band 4 *(Red)* and band 8 *(Near infrared)* from Sentinel-2 satellite imagery using the following formula.

$$NDVI = \frac{NIR-R}{NIR+R} = \frac{B8-B4}{B8+B4} \tag{4.17}$$

The Leaf Area Index (LAI) is an important determinant of tea yield that was also retrieved from the NDVI utilizing geospatial techniques. LAI was quantified according to the equation used in the previous studies based on the correlation between LAI and NDVI using the least square method (Tewari et al. 2003; Tuvshinbayar, 2017).

$$LAI = 0.57 \times exp(2.33 \times NDVI) \tag{4.18}$$

Yield data were compared with the corresponding LAI values in the scatter plot using simple linear regression analysis. The maps for predicted yields in the drought period were generated using the linear regression equation in ArcGIS environment. Finally, the extracted values obtained from the yield maps were compared with the observed yields in the drought period to measure the yield losses in tea.

4.4 Results

4.4.1 Standardized Precipitation Index (SPI) and Drought Classification

The results of the drought frequency observed in 39 months period for the Sylhet station showed that 15 months belonged to near-normal, 14 months normal, and 10 months moderately dry classes, which accounted for 38.46%, 35.90%, and 25.64%, respectively. In contrast, the Sreemangal station demonstrated the frequency for near-normal, normal, and moderately dry consditions were 28.21%, 41.02%, and 30.77%, respectively **((Figure 4.5 and Table 4.1)**.

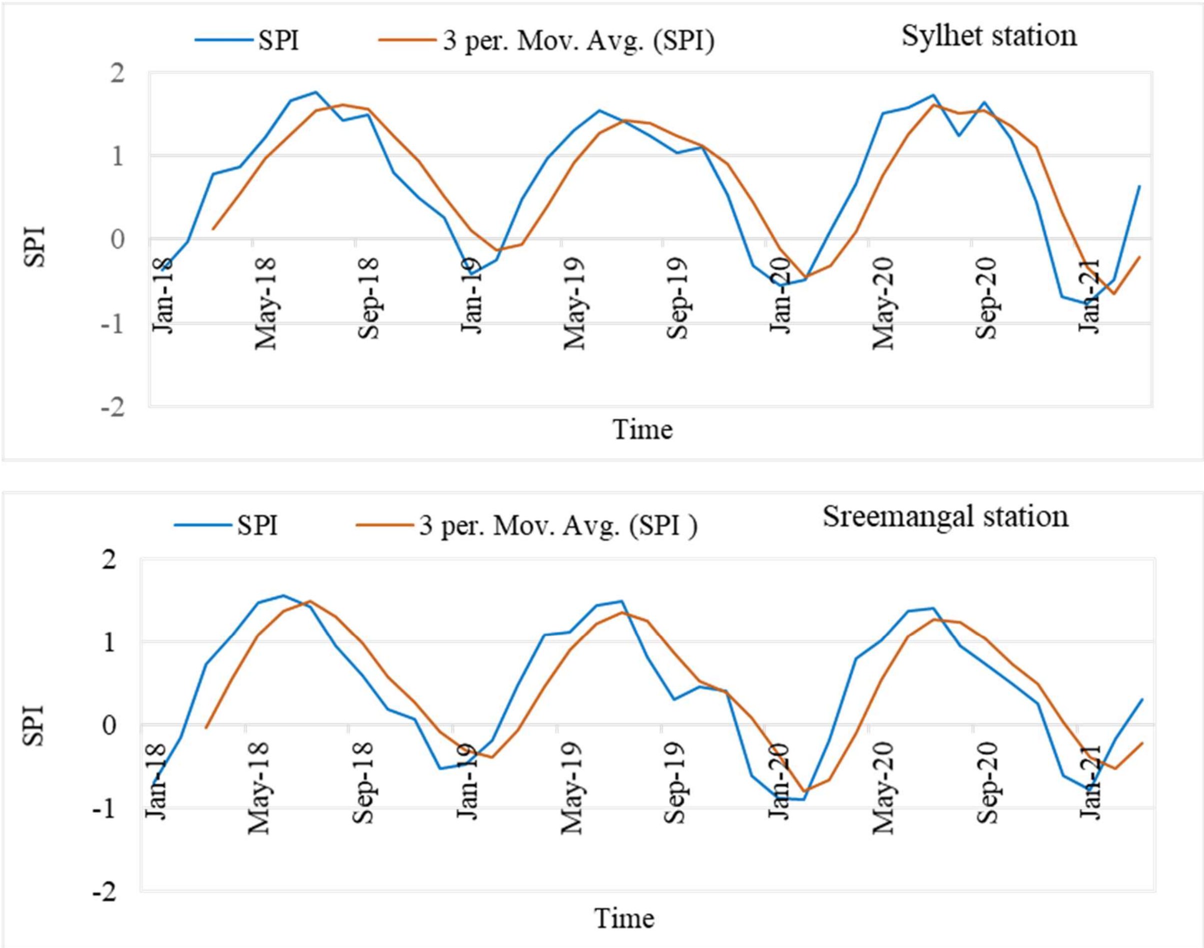


Figure 4.5 SPI trajectories for drought stress assessment

Table 4.1 Drought frequency in different categories

Drought Classes	SPI level	No. of months affected		Frequency (%)	
		Sylhet	Sreemangal	Sylhet	Sreemangal
Extremely wet	>3.0 to 3.0	-	-	-	-
Moderately wet	3.0 to 2.0	-	-	-	-
Near normal	2.0 to 1.0	15	11	38.46	28.21
Normal	1.0 to 0	14	16	35.90	41.02
Moderately dry	0 to -1.0	10	12	25.64	30.77
Severely dry	-1.0 to -2.0	-	-	-	-
Extremely dry	-2.0 to -3.0	-	-	-	-

4.4.2 Land Surface Temperature (LST)

The average LST in the drought period (December to February) for three consecutive years retrieved from the Landsat-8 remote sensing data demonstrated that the land surface temperature ranged between 14.25 and 27.68, 9.95 and 26.51, and 16.31 and 29.53, respectively **(Figure 4.6)**.

4.4.3 Soil Moisture Index (SMI)

The SMI in the drought season showed the status of soil moisture ranged between 0.02 and 1, 0.01 and 0.99, and 0.04 and 0.99, respectively for 2018-2019, 2019-2020, and 2020-2021, respectively **(Figure 4.7)**.

4.4.4 Normalized Difference Moisture Index (NDMI)

The average NDMI in plant canopies observed in the drought season ranged between -0.522 – 0.811, -0.365 – 0.824, and -0.360 – 0.853 in 2018-2019, 2019-2020, and 2020-2021, respectively **(Figure 4.8)**. The red color in the NDMI maps denotes the plant biomass with lower moisture content and the green color indicates the high moisture level in canopies.

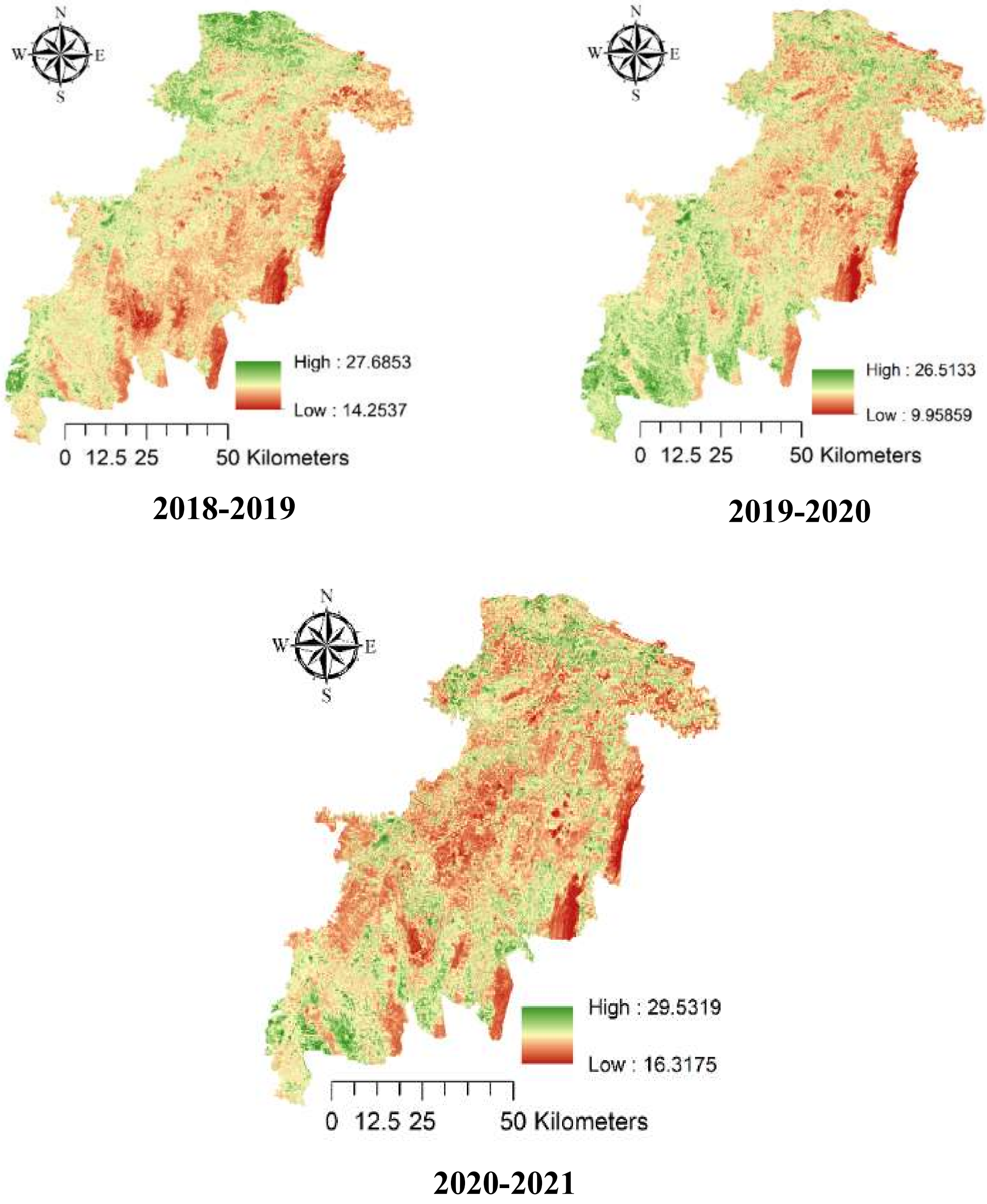


Figure 4.6 Land Surface Temperature (LST) in the drought period

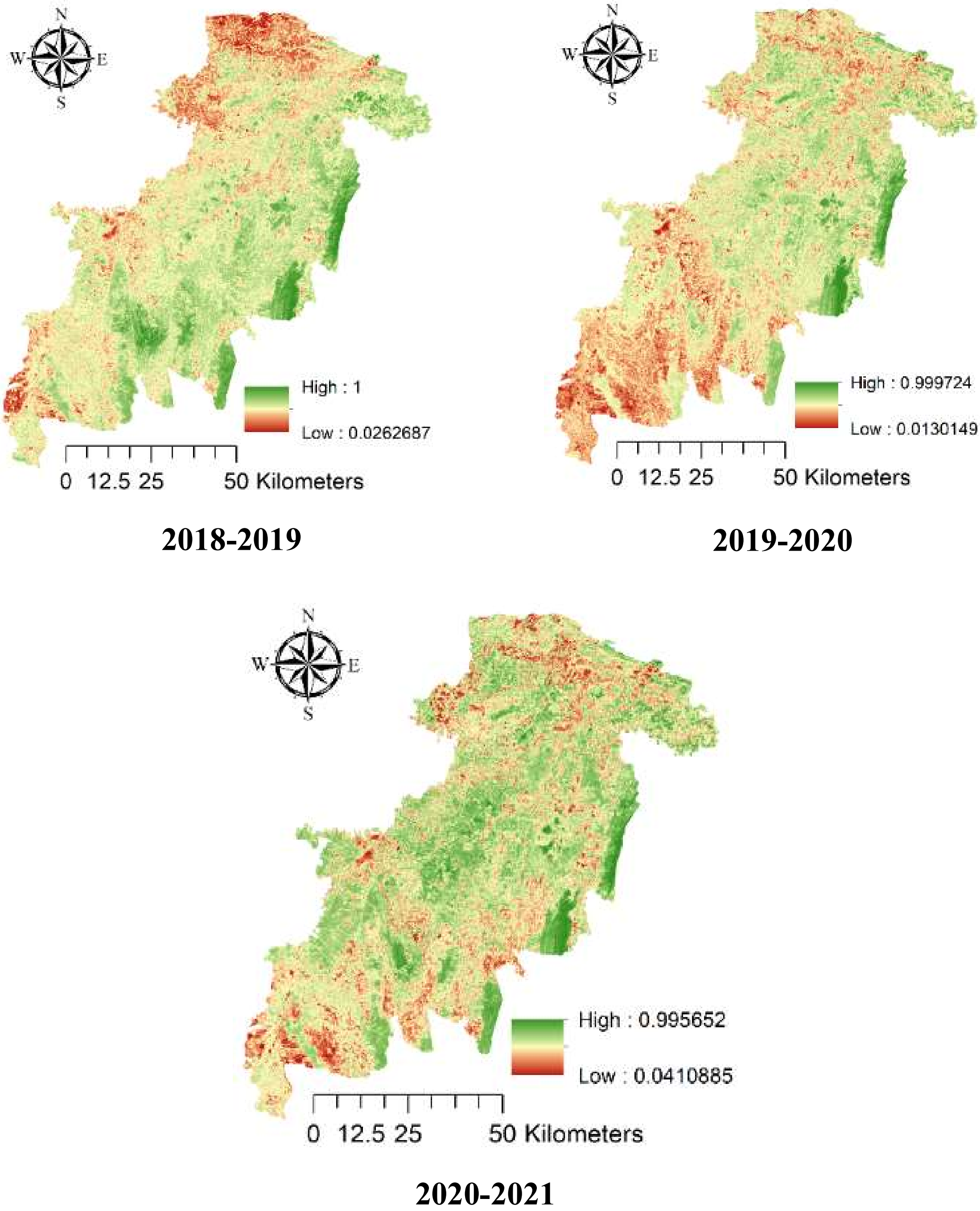


Figure 4.7 Soil Moisture Index (SMI) in the drought period

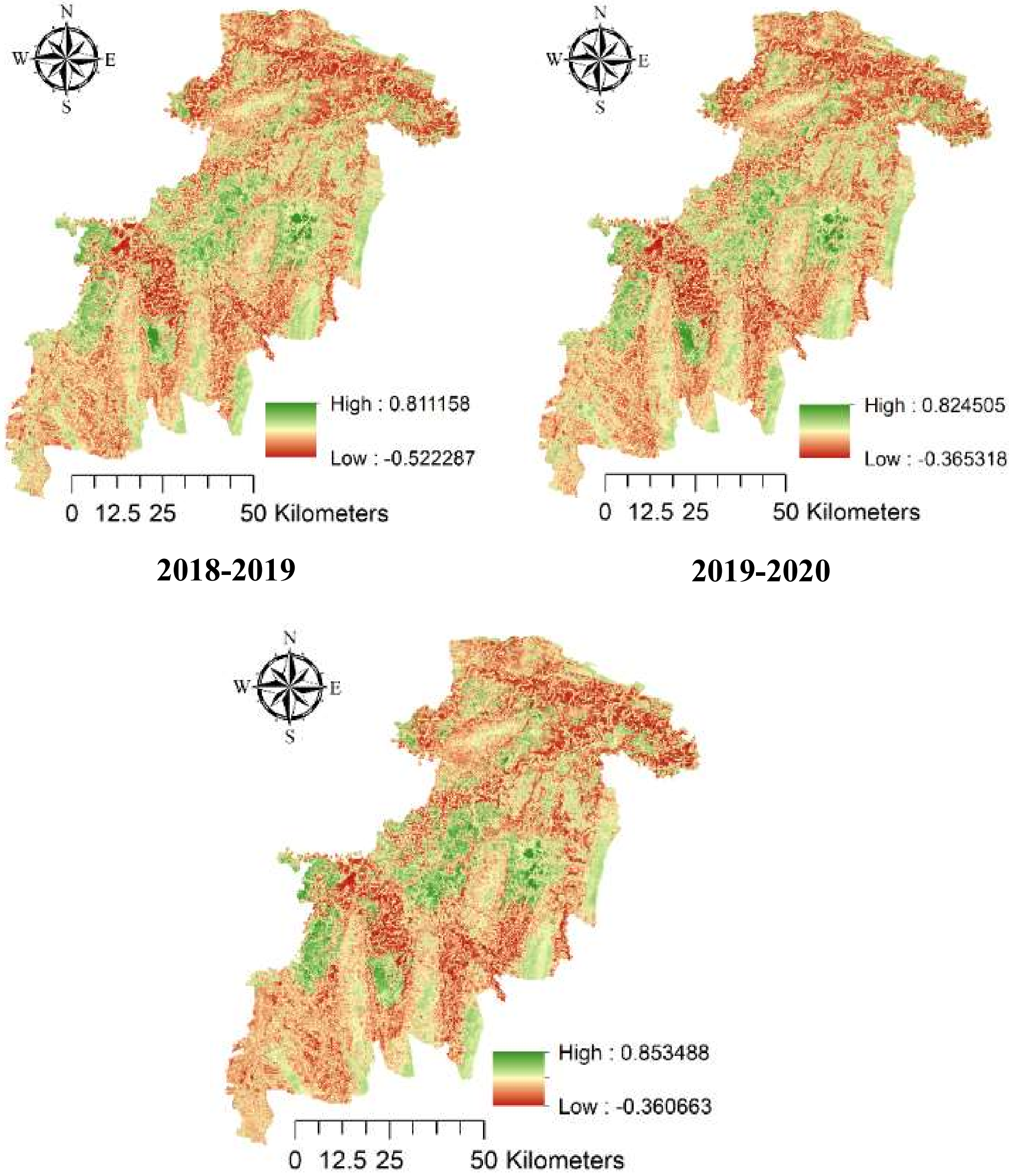


Figure 4.8 Normalized Difference Moisture Index (NDMI) in the drought period

4.4.5 Spatial Correlation between SMI and NDMI

The spatial correlation coefficients between the SMI and NDMI were 0.84, 0.77, and 0.79 in three consecutive years, respectively. This correlation provides the evidence that there is a strong interrelationship between water content in soil and plant biomass during the drought season **(Figure 4.9)**.

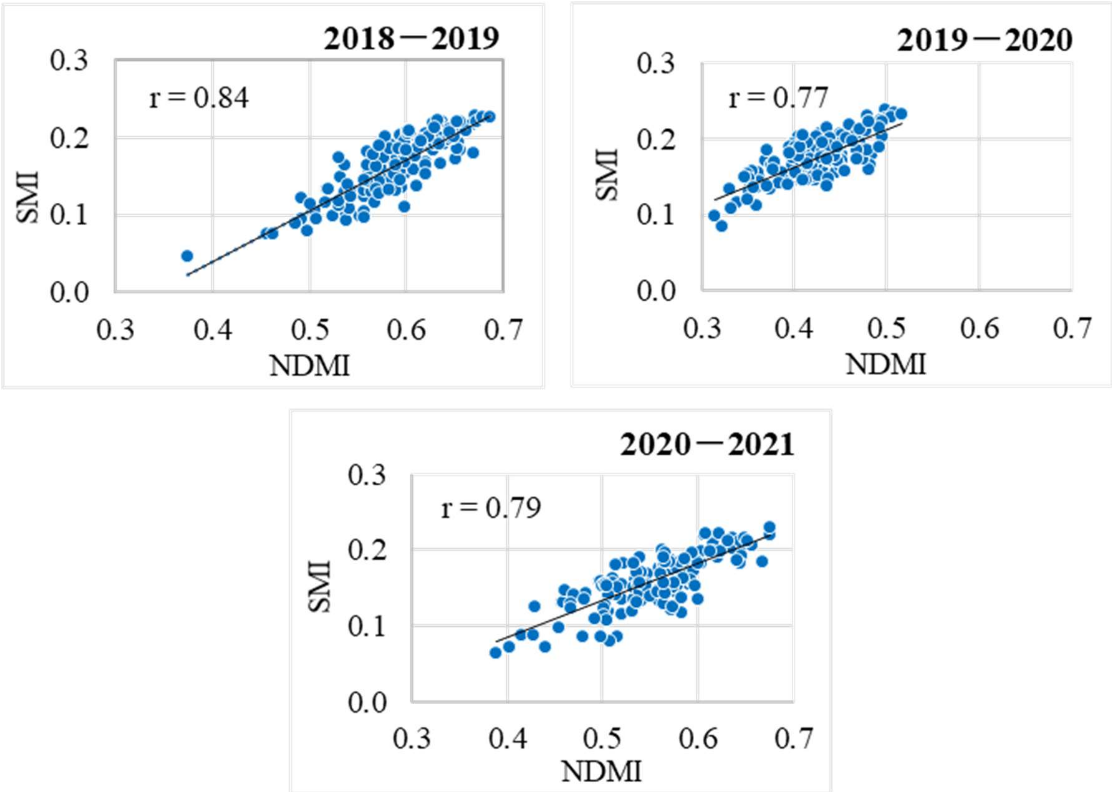


Figure 4.9 Correlation coefficients between SMI and NDMI in three consecutive years

4.4.6 Validation of Tea Yield in the Drought Period

The validation of yield in tea was performed using the NDVI and LAI-based yield prediction technique. **(Figure 4.10 – 4.14).**

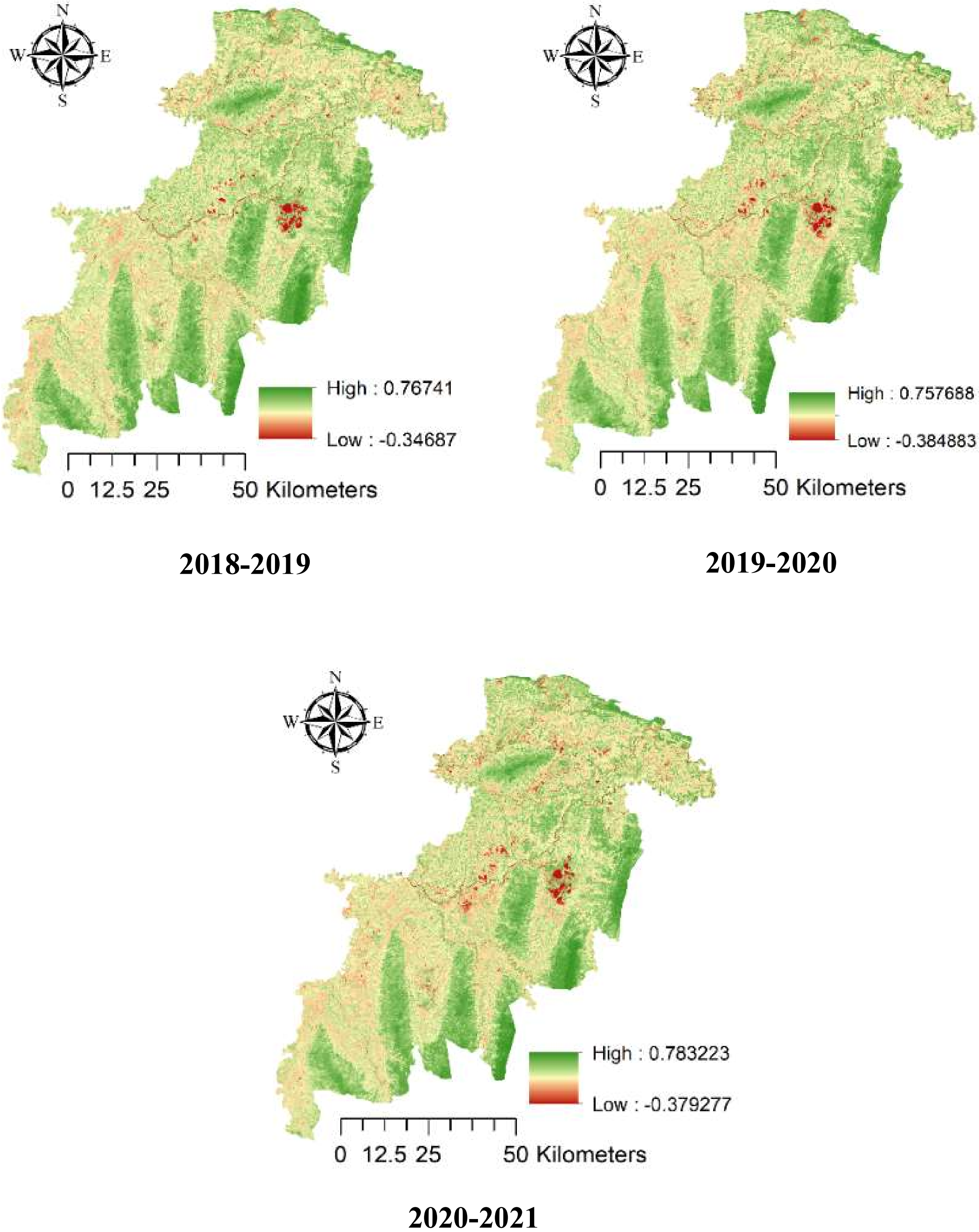
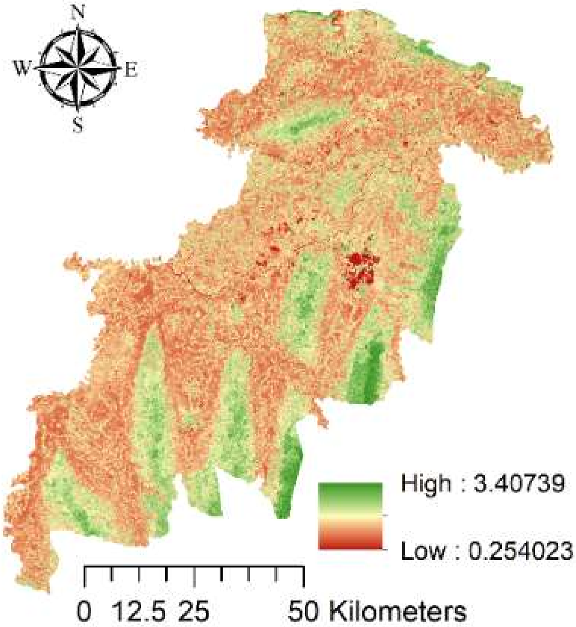
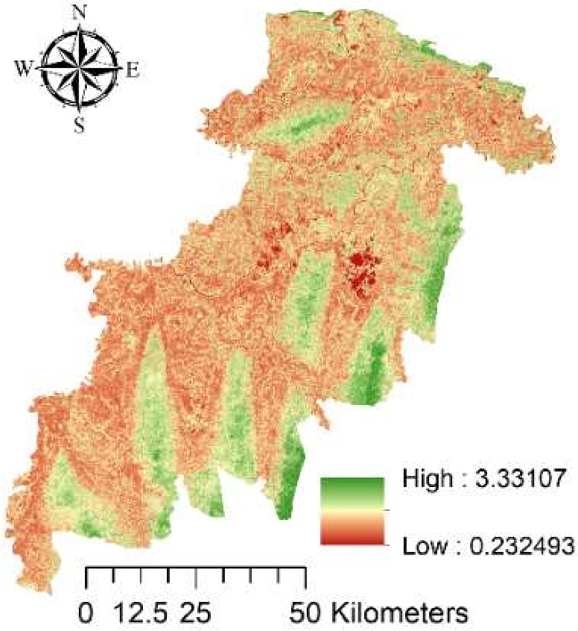


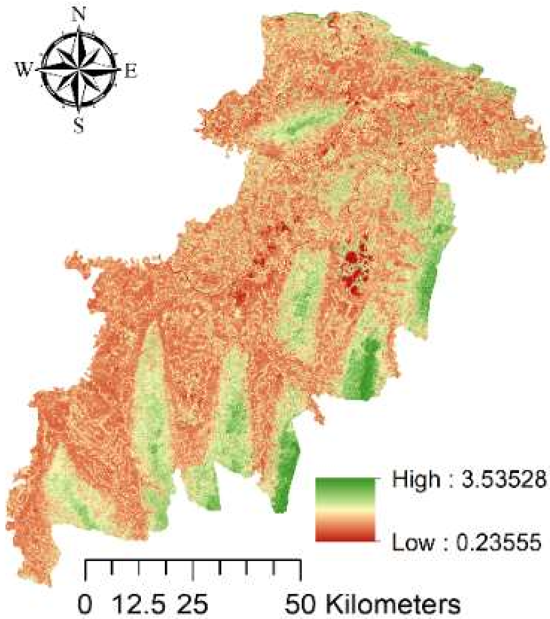
Figure 4.10 Normalized Difference Vegetation Index (NDVI) in the drought period



2018-2019



2019-2020



2020-2021

Figure 4.11 Leaf Area Index (LAI) in the drought period

The trendline obtained from the simple linear regression analysis between the observed LAI and time-series yield information during drought season in tea estates demonstrated a strong relationship with R^2 value 0.66, 0.71, and 0.68, for three consecutive years, respectively **(Figure 4.12)**. The regression analysis between LAI and the corresponding yield in the drought season of consecutive three years showed a strong relationship between LAI and tea yield. According to the trajectories of predicted yields during drought season, a lower yield was observed than actual yield for 83 estates in 2018, whereas the number of responsible estates were 81 each in 2019 and 2020. According to the predicted yield, it was also evident that the tea estates in the study area demonstrated yield losses of 7.72%, 11.92%, and 12.52% in three consecutive years, respectively **(Figure 4.14)**.

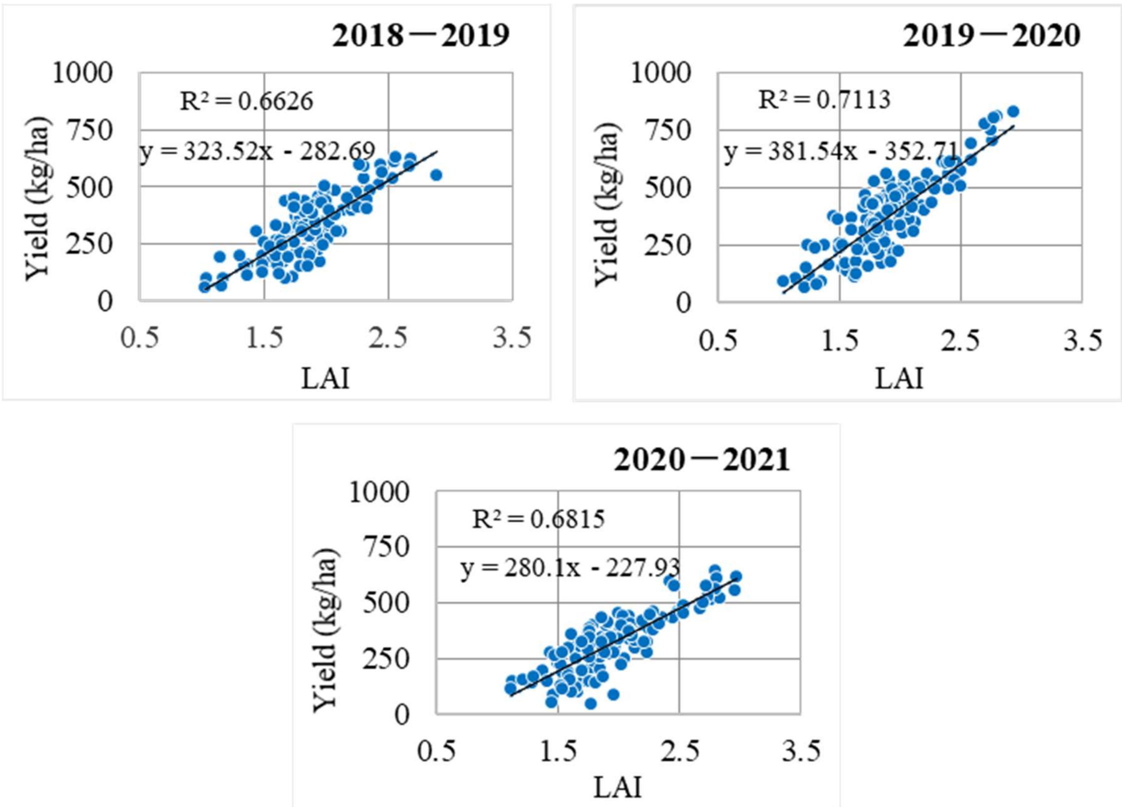
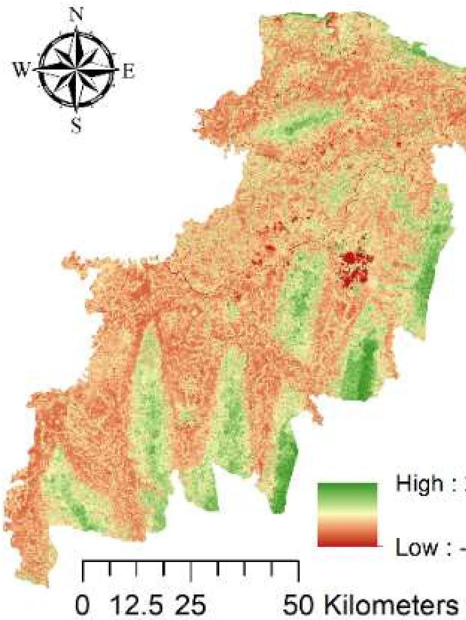
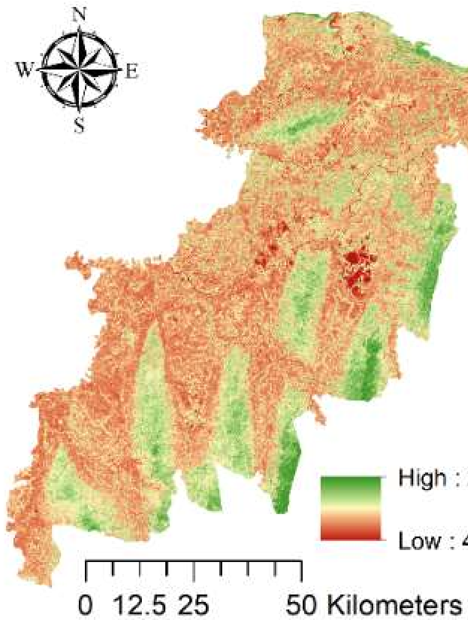


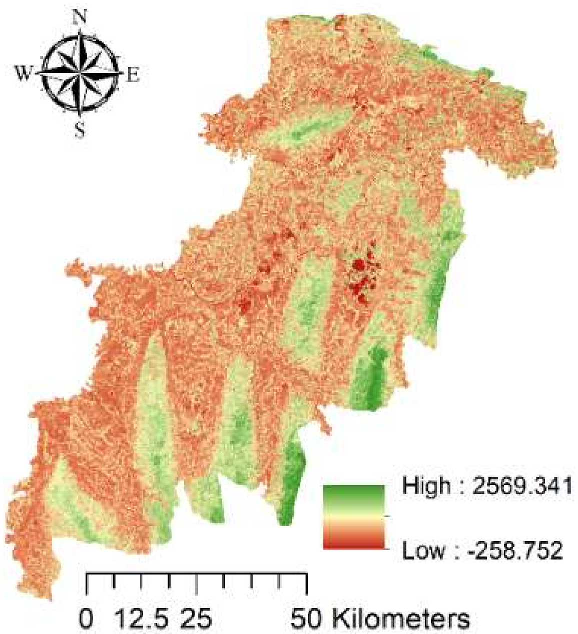
Figure 4.12 Regression analysis for yield prediction of tea during drought period



2018-2019



2019-2020



2020-2021

Figure 4.13 Yield maps of tea for the drought period

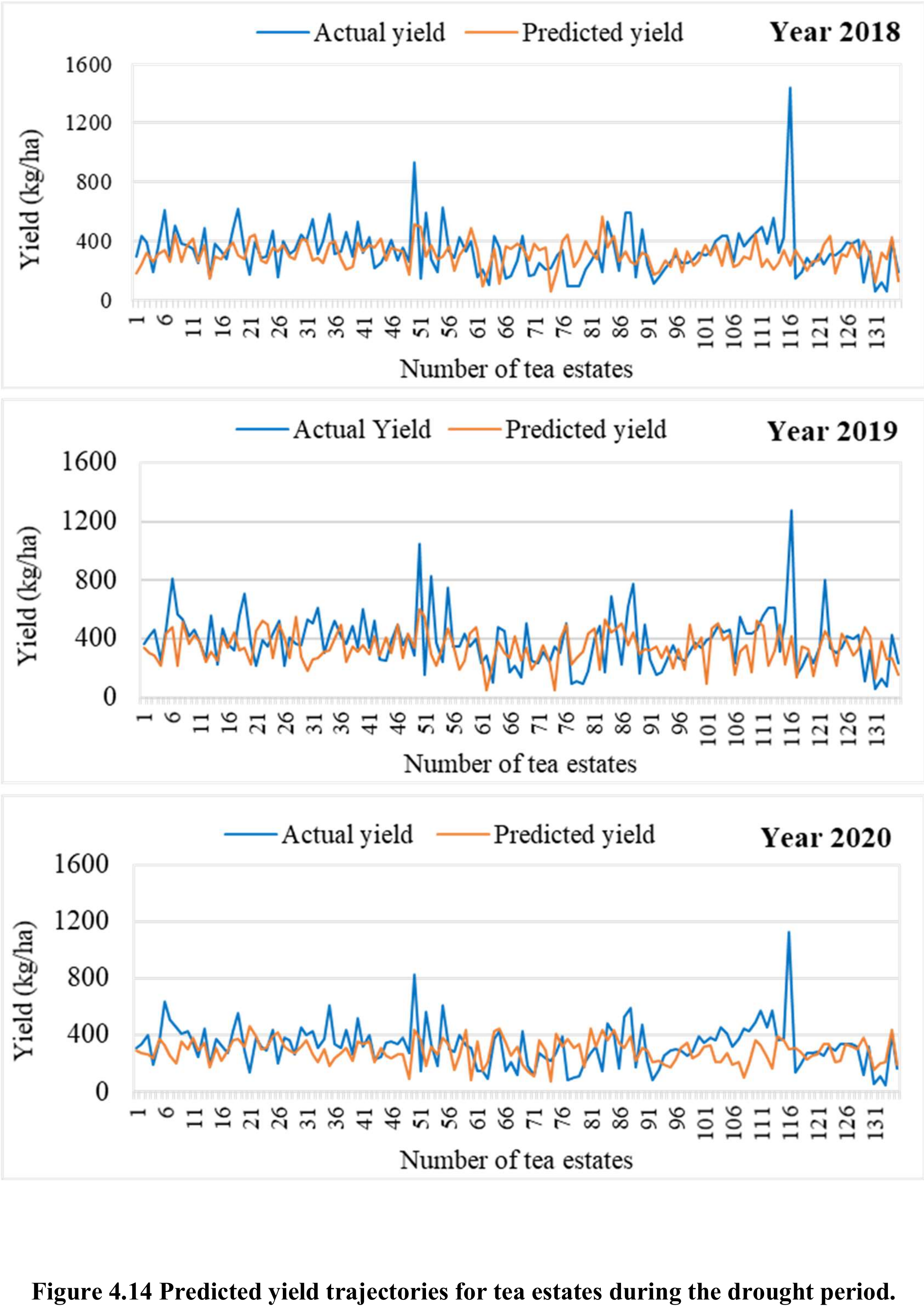


Figure 4.14 Predicted yield trajectories for tea estates during the drought period.

4.5 Discussion

The utilization of the standardized precipitation index (SPI) with the remote sensing datasets for drought monitoring was significant for this study (West et al. 2019). The optical and thermal infrared bands of remote sensing data are predominantly used to monitor soil moisture, despite their susceptibility to the effects of cloud (Chen et al. 2020). In contrast, the microwave satellite remote sensing data with their higher temporal resolution can be utilized to measure soil moisture recognizing the changes in dielectric properties of surface soil moisture, however, they are not reliable due to their lower spatial resolution (Sabaghy et al. 2018). For this reason, the optical and thermal remote sensing bands of Landsat-8 OLI/TIRS, considered robust tools to determine the land surface temperature and soil moisture content, were used to monitor drought for the tea plantation areas during cloud free winter period. The land surface temperature (LST) and vegetation indices like NDMI are robust indicators to measure soil moisture (Rahimzadeh-Bajgiran et al. 2012). The use of Sentinel-2 datasets for NDMI measurements was important because of its higher spatial resolution for monitoring vegetation water content by measuring the reflectance that served the aim of this research.

It is noticeable that the study area receives sufficient amount of rainfall in the active growing season during the monsoon, however, it faces drought after the monsoon season and thus, it hampers the productivity in tea during the drought season in the winter months. According to the classification of drought frequencies, the study area is characterized by normal and near-normal condition for 8 to 9 months, and the moderate dry conditions for 3 to 4 months in a year. As tea is sensitive to soil moisture deficit, the drought for 3 to 4 months causes yield losses affecting both the productivity and quality (Nalina et al. 2021; Nalina et al. 2018). The LAI-based yield prediction model was adopted to validate the drought period utilizing remote sensing techniques. The growth and development of tea leaves are reduced in the drought period due to the deficit in soil moisture. Another responsible reason for the reduction in leaf area of tea is that the tea bushes are heavily pruned at this time. These might be the reasons for the large differences between the observed yield and the predicted yields in tea.

The SMI-NDMI model based on optical and thermal infrared remote sensing is efficient and easy to calculate, however, it is sensitive to adverse weather conditions and cannot provide valid data in the presence of clouds (Wang et al. 2020). Therefore, it was not possible to obtain year-round cloud free data that was an impediment to prepare the year-round trajectories. To overcome this situation, an integrated optical and thermal infrared remote sensing, with microwave remote sensing technique, should be utilized to obtain year-round land surface soil moisture and vegetation water content that would be an inevitable tool for drought monitoring in tea plantation. This study utilized precipitation based-SPI, as well as remote sensing-based SMI and NDMI, to understand the water relationships under drought conditions rather than considering evapotranspiration losses of water from vegetated land as surface soil moisture distribution depends on soil-vegetation-atmosphere of drought condition. Those issues should be addressed in future studies for precise monitoring of drought in tea plantations.

4.6 Conclusions

This study suggests a method of drought monitoring and classification system for tea estates in Bangladesh utilizing standardized precipitation index with optical and thermal infrared remote sensing techniques. According to the results of drought frequencies, the ratio of near-normal, normal, and moderately dry months for the Sylhet station were 38.46%, 35.90%, and 25.64%, respectively. In contrast, the Sreemangal station showed the frequency 28.21%, 41.02%, and 30.77%, for near-normal, normal, and moderately dry condition, respectively. The spatial correlation between the SMI and NDMI were observed as 0.84, 0.77, and 0.79 in three consecutive years, referring that there is a strong interrelationship between soil and plant canopy moisture during the drought season. This study also predicts that 83, 81, and 81 estates among 135 tea estates demonstrated the lower yields than the observed yield during the drought season, and thus, they incurred yield losses, which accounted for 7.72%, 11.92%, and 12.52% in 2018, 2019, and 2020, respectively. The results of the drought stress assessment as well as the classification of droughts for tea plantations in Bangladesh would be important for policy makers, land use planners and scientists in the decision-making process in ensuring the early warning of the drought and thus, it would help tea growers to understand the future drought events for taking necessary initiatives to increase production.

CHAPTER 5
Overall Conclusion

5.1 Overall Conclusion

To emphasize the aim of climate smart agriculture, this study on tea was performed to mitigate the effects of land degradation and climate change. The study on land suitability evaluation for tea was carried out with a view to assessing the existing land resources as well as to finding new lands. This research attempted to consider all important environmental factors includes climatic, edaphic, topographic, accessibility, and remote sensing parameters for land evaluation. The application of AHP could increase the robustness of land suitability evaluation model. The Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) were considered vegetative and biophysical determinants of remote sensing aspect due to their importance in yield estimation of tea. The results of this study indicate that 3.37 % land of the study area was highly suitable, followed by 9.01% moderately suitable and around half of the total land was marginally suitable for tea cultivation. Therefore, the outcome of this research recommends the amelioration of this marginally suitable lands for tea cultivation. This research also suggests that the utilization of fallow lands for tea cultivation rather than encouraging deforestation and engulfing the agricultural lands. The developed model could be used in country- and regional level for land suitability evaluation as well as yield estimation of tea.

The drought stress assessment for tea plantation areas was a noble research initiative as it is incurred with the yield losses in tea. In addition to this, it has been an emerging need to develop a cost-effective model for drought monitoring in large scale. Therefore, the use of multi-satellite optical and thermal remote sensing technology was significant for this study. Considering a major objective of climate smart agriculture, monitoring and classification of drought in tea estates was undertaken to mitigate the risk of drought and to enhance resilience to the environment. The results of this study demonstrate that the study area experienced drought for 3 to 4 months in the winter season that is an important reason for yield losses in tea. The drought classification model for tea would also help land policy makers and tea growers to take necessary steps in advance for sustainable tea production.

The developed land suitability evaluation and drought assessment model for tea plantation areas would be valuable tools for land use planners and land policy makers for increasing tea production. The performed study also explored the importance of geospatial technology for land evaluation and drought monitoring in tea estates utilizing various environmental parameters. Finally, it could be stated that satellite remote sensing-based multi-criteria decision support system could be used efficiently in future studies on land suitability evaluation and drought detection of agricultural crops.

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Appendix A

Table A1. Criteria for land suitability evaluation of tea

Criteria	Suitability class	Sub-criteria	Reference
LULC	S1	Tea estates	Su et al. 2016; Su et al. 2017
	S2	Forest	Su et al. 2016; Su et al. 2017 Hajiboland 2017
	S3	High agricultural land	Su et al. 2017
	N	Settlements, water bodies, rivers and wetlands	Pezeshki 2001; Purnamasari et al. 2019
NDVI	S1	> 0.6	Choudhary et al. 2019
	S2	0.4 – 0.6	Choudhary et al. 2019
	S3	0.4	Choudhary et al. 2019
	N	< 0	Choudhary et al. 2019
Elevation	S1	> 15 m	Hajiboland 2017; Jayasinghe et al. 2019
	S2	10 – 15 m	Hajiboland 2017; Jayasinghe et al. 2019
	S3	7 – 10 m	Hajiboland 2017; Jayasinghe et al. 2019
	N	<7 m	Hajiboland 2017; Jayasinghe et al. 2019
Precipitation	S1	> 1800 mm	Gahlod et al. 2017
	S2	1600 – 1800 mm	Gahlod et al. 2017
	S3	1000 - 1600 mm	Gahlod et al. 2017
Temperature	S1	18 – 25 °C	Gahlod et al. 2017
Slope	S1	5 -25°	Jayasinghe et al. 2019
	S2	< 5°	Jayasinghe et al. 2019
	S3	> 25°	Jayasinghe et al. 2019
Soil texture	S1	scl, l, cl, sl	Gahlod et al. 2017
	S2	c, sicl, sic	Gahlod et al. 2017
	S3	c(ss), ls, s	Gahlod et al. 2017

Soil pH	S1	4.5 - 5.5	Jayasinghe et al. 2019; Sultana et al. 2014; Hussain et al. 2012; Natesan 1999
	S2	5.5 – 7.3	Jayasinghe et al. 2019; Sultana et al. 2014; Hussain et al. 2012; Natesan 1999
	S3	7.3 – 8.4	Jayasinghe et al. 2019; Sultana et al. 2014; Hussain et al. 2012; Natesan 1999
Drainage	S1	Moderately well drained to well drained	Nguyen et al. 2020; Sys et al. 1993
	S2	Imperfectly drained	Nguyen et al. 2020; Sys et al. 1993
	S3	Poorly drained	Nguyen et al. 2020; Sys et al. 1993
	N	Very poorly drained	Sys et al. 1993
Soil types	S1	Brown hill soils	Egashira et al. 2007
	S2	Grey piedmont soils	Prokop & Płoskonka 2014; Akhtaruzzaman et al. 2014
	S3	Non-calcareous alluvium, Brown flood plain soils, Dark grey flood plain soils, Grey flood plain soils, Acid basin clays, Deep-red brown terrace soils	Islam et al. 2017; Egashira et al. 2007; Egashira et al. 1998; Bhuiya 1987
	N	Peat, Water bodies, Urban	Islam et al. 2017
Distance from roads	S1	0 – 1.0 Km	Pramanik 2016
	S2	1.0 – 2.0 Km	Pramanik 2016
	S3	2.0 – 4.0 Km	Pramanik 2016
	N	> 4.0 Km	Pramanik 2016
Distance from rivers	S1	0 – 0.5 Km	Pramanik 2016
	S2	0.5 – 1.0 Km	Pramanik 2016
	S3	1.0 – 2.0 Km	Pramanik 2016
	N	> 2.0 Km	Pramanik 2016