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Meteorological drought assessment in northern Bangladesh: A machine learning-based approach considering remote sensing indices

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ABSTRACT

Meteorological drought, driven by inadequate precipitation, has significant repercussions for water resources, agriculture, and human well-being. This study conducted an extensive assessment of meteorological drought in northern Bangladesh, employing remote sensing indices and machine learning techniques. The main aim was to evaluate meteorological drought occurrences in northern Bangladesh from 2010 to 2019, utilizing seven drought parameters and a machine learning model. Utilizing a Random Forest (RF) model, this study employed the Standardized Precipitation Index (SPI) as the dependent variable and seven remote sensing indices as independent variables. Through this methodology, the study assessed the significance of these indices generated by the model and integrated them, culminating in the creation of a meteorological drought distribution map spanning 2010 to 2019. This approach offers novel insights by probing the interplay and collective impacts of these indices, shedding light on previously unexplored aspects of regional drought patterns of northern Bangladesh. The major findings showed that precipitation strongly influenced both short-term and long-term meteorological drought episodes. Moreover, land surface-related indices, such as Evapotranspiration (ET) and Normalized Difference Water Index (NDWI), exhibited a more pronounced impact on short-term drought occurrences, while vegetation-related indices like Normalized Multi-band Drought Index (NMDI) and Normalized Difference Vegetation Index (NDVI) demonstrated greater influence over long-term drought events. During this timeframe, the Rajshahi division experienced frequent extreme and severe drought events. Moderate droughts and abnormally dry conditions were widespread. The Barind tract area consistently faced moderate to extreme droughts, with exceptions in 2011, 2014, and 2019. On average, over 5% of the region had extreme droughts, while more than 12% experienced severe droughts during this decade. Long-term drought indicators (SPI 6 and SPI 9) consistently showed higher frequencies of extreme and severe droughts compared to short-term indicators (SPI 1 and SPI 3), emphasizing the influence of prolonged rainfall deficits on extreme droughts and the relevance of longer time frames for severe drought dynamics. The RF model demonstrated strong performance with accuracy ranging from 81% to 95%. Low prediction errors (RMSE 6% to 31%) and high out-of-bag (OOB) accuracy ranging from 76% to 98% highlighted its accuracy. The F1 score consistently exceeded 76%, indicating high precision and recall. Cross-validation values ranged from 78% to 94%, affirming reliable generalization to new data. Incorporating the main findings, this study contributes valuable insights for the formulation of targeted drought mitigation strategies in northern Bangladesh. It is imperative to note that the scope of this study is confined to the northern region of Bangladesh, and generalizing these findings to other regions should be exercised with caution. Nevertheless, the research methodology and approach can serve as a model for future studies in related fields, advancing knowledge of how to assess droughts using remote sensing and machine learning methods.

1. Introduction

Drought, one of the biggest hazards in the world, results in water shortages, which not only make economic losses more susceptible but also seriously endanger human life (Park et al., 2016; Quiring and Papakryiakou, 2003; Wu et al., 2001). The onset of drought is a gradual and intricate phenomenon that often commences with inadequate levels of precipitation (Gao et al., 2023). Almost every year, drought-related

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agricultural failure and water shortage issues plague many nations (Park et al., 2016). According to a study, drought causes $6 billion to $8 billion in worldwide economic loss annually, considerably exceeding other natural disasters (He et al., 2021). Bangladesh is one of the nations that are susceptible to natural disasters, and drought is a significant disaster there, as are floods, cyclones, coastal erosion, sea level rise, salinity intrusion, and storm surges (Akash et al., 2023; Rahman and Lateh, 2016; Rudra and Sarkar, 2023; Sarkar et al., 2023, Sarkar et al., 2021). In the past five decades, Bangladesh has suffered about twenty severe droughts (Chakraborty et al., 2022; Islam et al., 2022; Rahman and Lateh, 2016). Drought has a disproportionately negative impact on the northern regions of the country, including the Barind tract and the Teesta floodplain areas, due to high rates of poverty, reliance on agriculture, a lack of adaptive capacity, and a high degree of seasonal and annual rainfall variability (Habiba et al., 2011; Shahid and Behrawan, 2008). According to many studies, Bangladesh's northern region is a hotspot for drought and frequently experiences drought events (Haque et al., 2000; Islam et al., 2022; Rahman and Lateh, 2016). In the past few decades, several drought phenomena have affected the 16 administrative regions that make up northern Bangladesh (Islam et al., 2022).

Drought is a relative term that can mean many things depending on the specifics of the observations, the operational metrics, and the prevailing weather patterns (Dracup et al., 1980; Islam et al., 2022) and there are several ways in which drought can manifest (Park et al., 2016; Wilhite et al., 2007). Based on widely used classification techniques, drought can be categorized into four distinct types: meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought (Heim, 2002; Młyński et al., 2021; Shi et al., 2022; Yin et al., 2021). A lack of precipitation leads to meteorological drought, alternatively, in instances where dry climatic conditions prevail in a certain region (Młyński et al., 2021), and prolonged meteorological dryness leads to agricultural drought through reducing soil moisture levels (Park et al., 2016; Sandeep et al., 2021). Drought causes and effects are interlinked through feedback mechanisms and couplings in land–atmosphere dynamics (Rhee et al., 2014). To accurately anticipate and evaluate drought, as well as to keep tabs on the current drought situation, knowledge of these aspects is essential (Park et al., 2016; Tadesse et al., 2005). Assessment and monitoring of drought can play an important part in comprehending regional drought traits and aiding in the creation of an effective drought management plan for northern Bangladesh, and so governments, scientists, and environmentalists are all involved in the development of effective management policies to lessen the issue triggered by drought (Rahman and Lateh, 2016).

There are a number of drought indices that can be used to track the severity of drought and the state of the water supply, both of which can be crucial in forming effective plans to deal with the effects of drought in the future (Alley, 1984; Quiring and Papakryiakou, 2003; Yang et al., 2023). Several drought indices have been created with the use of real-time precipitation data, including the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), Palmer Drought Severity Index (PDSI) and Moisture Anomaly Index (Palmer, 1965), and the China-Z index (Wu et al., 2001), to mention a few. At the 2009 World Meteorological Organization meeting, the SPI was recommended as a standard global meteorological drought indicator (Park et al., 2016; Wardlow et al., 2012). On the contrary, with satellite data's extensive geographic coverage and high temporal resolution, drought assessment and tracking can be done effectively (Swain et al., 2011). It is possible to analyze drought using satellite-based drought factors since satellite remote sensing has been used to develop products linked to drought (Anderson et al., 2011). The complexity and diversity of drought cannot be completely explained by a single indicator because there are many different factors that contribute to it (Park et al., 2016). Therefore, mixing different drought indices is useful for assessing drought (Hayes et al., 2005; Mizzell, 2008; Wardlow et al., 2012) and this mixing indices approach started in the 1990s (Heim, 2002). Therefore, it is feasible to properly assess and monitor drought situations for various climatic zones by combining satellite derived drought variables and metrics (Park et al., 2016). A lot of studies showed that, there are some remote sensing indices that are widely used to assess and predict meteorological drought such as, Normalized Difference Vegetation Index (NDVI) (Das and Sarkar, 2023; Fathi-Taperasht et al., 2022; Gu et al., 2007; Han et al., 2019), Normalized Difference Water Index (NDWI) (Gao, 1996; Gu et al., 2007), Normalized Difference Drought Index (NDDI) (Gu et al., 2007; Park et al., 2016), Normalized Multi-band Drought Index (NMDI) (Aksoy et al., 2019; Wang and Qu, 2007), Normalized Difference Moisture Index (NDMI) (Das et al., 2023), Evapotranspiration (ET) (Jiang et al., 2021; Lambert et al., 2013; Zhan et al., 2021), and satellite derived Precipitation index (Jiang et al., 2021; Park et al., 2016). Long-term drought is strongly correlated with vegetation indices like NDVI and NMDI, whereas short-term drought is strongly correlated with surface related indices like ET (Park et al., 2016). To assess meteorological drought, it is important to consider what weighting scheme to use when blending these types of indices together because different factors have different effects on drought according to the region, and the type of drought (Park et al., 2016). Here's where various machine learning models come in. Machine learning models can effectively rank the significance of different drought indices such as NDVI, NDWI, ET, etc. given their corresponding drought indicators such as SPI, SPEI, PDSI, etc. (Han et al., 2019; Park et al., 2016) and those weights are widely used as the weights of the indices for the blending approach (Park et al., 2016). There are a lot of models available and used for assessing droughts and identifying the relative importance of remote sensing indices such as, Random Forest (RF) (Feng et al., 2019; Mokhtari and Akhoondzadeh, 2020; Park et al., 2016), Artificial Neural Network (ANN) (Belayneh et al., 2014; Citakoglu and Coşkun, 2022; Saha et al., 2021), Support Vector Regression (SVR) (Belayneh et al., 2014), Adaptive Neuro Fuzzy Inference System (ANFIS) (Citakoglu and Coşkun, 2022), Markov Chain (Rezaeianzadeh et al., 2016) and so on. Among them, RF is one of the most effective models for drought assessment (Park et al., 2016) and quantifying the importance of drought indices by reducing errors such as overestimation and sensitivity to the training data configuration (Breiman, 2001; Yang et al., 2023).

Several studies like, drought hotspot analysis using local indicators (SPI and VCI) (Islam et al., 2022), modeling of climate induced drought using rainfall and relative humidity (Rahaman et al., 2016), evaluating the spatiotemporal characteristics of drought using Effective Drought Index (EDI) (Kamruzzaman et al., 2019), observing meteorological drought trends using the EDI (Mondol et al., 2021), drought risk assessment using SPI and some socio-economic factors (Shahid and Behrawan, 2008) have been done in the northern region over the years. But most of them have often focused on individual factors without thoroughly considering their combined effects in the context of a meteorological drought indicator, different remote sensing indices and a machine learning approach (Das et al., 2023; Sultana et al., 2021). The above cited studies did not analyze how satellite-derived drought indicators affect meteorological drought severity in northern Bangladesh. However, drought indicators' intricate relationships, relative importance, and effects on meteorological drought in this region have yet to be fully investigated and there is a lack of adequate research on the spatiotemporal distribution of drought concerning frequency, intensity in the northern region (Islam et al., 2022; Kamruzzaman et al., 2019; Mondol et al., 2021). While various drought indices have been developed using real-time precipitation data, the integration of diverse remote sensing indices with a machine learning model has been less extensively investigated (Anderson et al., 2011; Vicente-Serrano et al., 2010). This study seeks to bridge these gaps by providing a systematic analysis of meteorological drought patterns in the northern region of Bangladesh using remote sensing indices and a machine learning model. By integrating seven satellite-derived drought indices (i.e., NDVI, NDWI, NDMI, NDDI, NMDI, ET and Precipitation) while using SPIs at varying time scales (i.e., 1-month, 3-month, 6-month and 9-month) as meteorological drought indicators and employing a robust machine learning model, the Random Forest (RF), this study seeks to quantify the individual and combined impacts of these indices on meteorological drought severity. This study blended drought indices using the RF model to assess their value and use them as weights for each index for each drought indicator (SPI) from 2010 to 2019 in northern Bangladesh. Through this approach, this study aims to uncover the nuanced interactions between various remote sensing indices and the meteorological drought indicator (SPI), offering insights that have been previously unexplored in this specific region. This study holistically evaluates several drought indices and uses the RF model to quantify these parameters to better understand meteorological drought dynamics in northern Bangladesh, unlike previous studies that focused on specific drought indices or did not examine their combined influence through machine learning.

Overall, the aim of this study is to examine several drought indicators derived from satellite imagery to determine how well they are connected to identify meteorological drought and which indicators are most responsible for drought events in northern Bangladesh. The objectives of this research were 1) to comprehensively assess drought conditions based on satellite-derived drought factors from 2010 to 2019 with a focus on identifying nuanced and region-specific patterns and 2) to conduct an in-depth investigation of meteorological drought by examining influential drought factors and employing a random forest model, aiming to provide a more detailed and context-specific understanding of drought dynamics during the study period. Ultimately, the findings of this study will provide a crucial basis for the development of specific measures to mitigate drought and improve resilience in the northern region, which experiences recurrent drought occurrences. This research is pivotal for fostering sustainable solutions in the face of changing climatic conditions.

2. Methods and materials

2.1. Description of the study area

The northern region of Bangladesh, which includes the Rajshahi and Rangpur divisions of administration and sixteen districts of Bangladesh, has been selected as the study area (Fig. 1). The study area is located between 88°10 and 89° East longitudes and 23°48 and 26°38 North latitudes, with a total area of 34,359 sq. km, including 2824 sq. km of aquatic bodies, and a mean elevation of approximately thirty meters beyond mean sea level (Islam et al., 2022; Sarkar et al., 2022). The Padma River forms the southern boundary, the Jamuna River the eastern, and the Indian border the western (Islam et al., 2022). This region is inhabited by 38 million people approximately (Rajshahi division: 20,353,119 and Rangpur division: 17,610,956) (Daily Sun, 2022).

The northern region has substantial anomalies in temperature and precipitation because to its location over the tropic of cancer and because of this, it typically has a monsoon climate with a significant quantity of precipitation falling between May and September (1583 mm) (Das et al., 2023). While monsoon humidity is consistently high throughout the year, it drops dramatically as the dry season winds down (Rashid, 2019; Shahid, 2010). In this region, there are three seasons: a dry winter (December to February), a pre-monsoon hot summer (March to May), and a rainy monsoon (June to October) (Das et al., 2023). The area experiences a yearly average rainfall ranging from 1400 to 1550 mm, depending on the season. The region's mean temperature is 24.5 °C, with the summer months experiencing temperatures exceeding 40 °C and the winter months experiencing temperatures below 10 °C (Shahid and Khairulmaini, 2009).

The northern region can be geographically classified into four distinct regions, namely the Barind tract, Himalayan piedmont plains, alluvial lowland along the Jamuna river, and alluvial lowland along the Padma (Ganges) river (Sumiko, 1993). Nearly 80 % of the land in this region is used for agriculture, making it agriculturally dominant (Murphy et al., 2017). Approximately 59 % of the agricultural land in the region is encompassed by irrigation land, with surface water accounting for approximately 75 % of the irrigation water utilized (Das et al., 2023). Notably, the exclusive means of irrigation available in this particular area throughout the arid season is groundwater (Shahid and Hazarika, 2010). The aridity of the soils in this area is a result of restricted and erratic rainfall patterns, compounded by impediments to the natural course of the river (Brammer, 1996; Rashid, 2019).

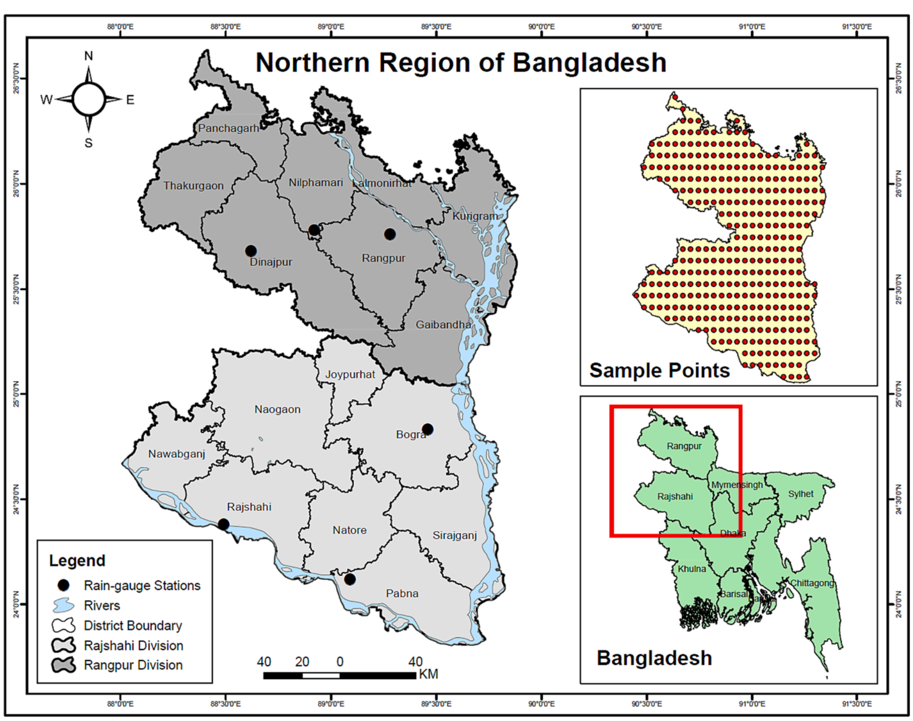


Fig. 1. Study area.

2.2. Description of data

2.2.1. Remote sensing data

A total of six drought factors were obtained from two types of MODIS satellite imagery on the Terra platform by using some formula (Table 1). MOD09A1 surface reflectance with 500-meter spatial resolution was used to calculate the NDVI, NDWI, NDMI, NDDI, and NMDI indices from 2010 to 2019. On the other hand, MOD16A2 with 500-meter spatial resolution was used to calculate the ET index for the ten years, where the values were calculated as the average annual evapotranspiration rate in kg/m2 for each year. The seventh drought factor, precipitation, was obtained from NASA's IMERG satellite image. It provides rainfall data with a 0.1 by 0.1-degree (or roughly 10 km by 10 km) resolution. In this study, the average annual rainfall data from IMERG was used to generate this index from 2010 to 2019, where all the precipitation index was expressed in units of mm/day. The selection of the seven factors for meteorological drought assessment in this study was guided by their established roles in influencing drought conditions. The chosen drought factors collectively offer comprehensive insights into vegetation health, moisture content, and the overall water balance of the study area. The inclusion of these factors was also influenced by data availability for the study area, reliability, and compatibility with the employed machine learning approach. While acknowledging the significance of temperature as a drought-related parameter, it is important to note that the focus of this study was specifically on land surface and vegetation-related indicators, which have demonstrated strong associations with drought dynamics in this region. In the context of employing ET as one of the factors, its interrelation with the temperature indirectly encompasses the temperature-related dimension of drought within this study. Multiple studies have demonstrated a strong correlation between ET and Land Surface Temperature (LST), highlighting their interdependence, wherein changes in land surface temperature have a notable impact on the rate of evapotranspiration (Danda et al., 2023; Jiang and Weng, 2017; Rocha et al., 2020; Wang et al., 2020). Nonetheless, the potential role of temperature as an influencing factor is duly acknowledged, and its exploration could be a valuable avenue for future research aimed at a more holistic understanding of meteorological drought dynamics. Ultimately, the construction of all seven variables was accomplished through utilization of the Google Earth Engine (GEE) platform. Following the completion of index construction for the ten-year study period, all of these indices were subsequently integrated into the Geographic Information Systems (GIS) platform, specifically ArcGIS, for the purpose of standardization (see to Table 1). The inclusion of this phase was deemed important due to the presence of indices with varying units, which could potentially impact the overall blending procedure. The utilization of the standardization approach facilitated the establishment of a uniform range of values between 0 and 1 for all indices, hence enabling their comparability and appropriateness for consolidation. Within this particular context, the assigned numerical values of 0 represent the state with the least amount of moisture, while the values of 1 are indicative of the most absorbed condition.

Table 1
Remote sensing-based drought factors with their formula and source.

Drought factors	Formula	Source
NDVI	$(Band2 - Band1)/(Band2 + Band1)$	(Breunig et al., 2012)
NDWI	$(Band4 - Band2)/(Band4 + Band2)$	(McFeeters, 1996)
NDDI	$(NDVI - NDWI)/(NDVI + NDWI)$	(Gu et al., 2007)
NDMI	$(Band2 - Band5)/(Band2 + Band5)$	(Zhou and Guo, 2007)
NMDI	$\frac{Band2 - (Band6 - Band7)}{Band2 - (Band6 + Band7)}$	(Wang and Qu, 2007)
Scaled NDVI	$(NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min})$	(Park et al., 2016)
Scaled NDWI	$(NDWI - NDWI_{min})/(NDWI_{max} - NDWI_{min})$	
Scaled NDDI	$(NDDI_{max} - NDDI)/(NDVI_{max} - NDVI_{min})$	
Scaled NDMI	$(NDMI - NDMI_{min})/(NDMI_{max} - NDMI_{min})$	
Scaled NMDI	$(NMDI - NMDI_{min})/(NMDI_{max} - NMDI_{min})$	
Scaled ET	$(ET - ET_{min})/(ET_{max} - ET_{min})$	
Scaled Precipitation	$\frac{Precipitation - Precipitation_{min}}{Precipitation_{max} - Precipitation_{min}}$	

2.2.2. Reference data

In this study, the SPI was utilized as a reference for monitoring meteorological drought. Data on monthly precipitation spanning a period of ten years (2010–2019) were procured from Bangladesh Agricultural Research Council (BARC) for six distinct stations (Fig. 1). Subsequently, the SPI values spanning from 2010 to 2019 were computed utilizing the cumulative monthly precipitation measurements obtained from each respective station. The selection of rainfall stations for measuring the SPI was a critical aspect of this study. Due to the spatial variability of rainfall patterns in the study area, careful consideration was given to station placement. The decision to utilize six strategically placed rainfall stations was based on several factors that collectively ensured the reliability of SPI calculations. The chosen stations, namely Bogra, Dinajpur, Ishurdi, Rajshahi, Rangpur, Sayedpur were selected to cover diverse geographical and topographical conditions within the study area (i.e., northern region – the Barind Tract, Teesta Floodplain). Each station had a robust historical dataset spanning the entire study period, contributing to the consistency and quality of the precipitation data. While it is recognized that a larger number of stations could potentially enhance SPI accuracy, it is worth noting that comparable studies have demonstrated successful outcomes with a limited number of stations. For instance, a study assessed meteorological drought using only four stations, achieving robust results (Mondol et al., 2021). Another research, in a manner akin to this study, utilized the same six meteorological stations for SPI-based drought assessment and attained commendable outcomes (Afrin et al., 2019). This suggests that even with a small number of stations, accurate meteorological drought assessment is achievable. Furthermore, the inclusion of additional stations located outside the study area was deemed problematic due to potential variations in climatic influences. To address this, spatial interpolation techniques, specifically Inverse Distance Weighting (IDW), were employed. This technique enabled the extension of SPI values across the study area, taking into account the spatial distribution of precipitation. While the use of six rainfall stations may appear limited, this approach was a deliberate trade-off that aimed to strike a balance between data accuracy and the complexities posed by the region's diverse rainfall patterns. The spatial interpolation techniques applied further contributed to capturing the overall meteorological drought dynamics within the study area. The present analysis was performed utilizing the SPEI package in RStudio. In this study, various time scales of the SPI were employed to account for the temporal delay between precipitation and drought conditions. There are various time scales of SPI are available, including accumulated 1-month (SPI1), accumulated 3-month (SPI3), accumulated 6-month (SPI6), and accumulated 9-month (SPI9). The SPI1 and SPI3 types typically denote short-term SPIs, while the SPI6 and SPI9 types are indicative of long-term SPIs (Kamruzzaman et al., 2019). Consequently, these four categories of SPIs were utilized in this study in order to employ SPI1 and SPI3 (short-term SPIs) as short-term drought indicators. On the other hand, SPI6 and SPI9 (long-term SPIs) were utilized as indicators of long-term drought.

2.3. Methods

2.3.1. Machine learning approach – Random Forest

Numerous statistical techniques, including simple and multiple linear regressions, are available for evaluating the association between the drought factors and conditions of drought (Narasimhan and Srinivasan, 2005; Rhee et al., 2010; Zhang and Jia, 2013). It is difficult to ascertain the correlations between multiple drought factors and drought conditions using linear regression models due to their complexity (Park et al., 2016). However, machine learning methods (i.e., RF) have shown to be robust and flexible when used to evaluate the connection between drought-related factors and drought conditions (i.e., SPI) and to determine the relative importance of the variables (Park et al., 2016). So, in this study the RF model was used to carry out the previously stated activities. Python's open-source cross-platform integrated development environment Spyder was used to implement this model. In this study, the process of trial-and-error was used to find the best parameters of RF model suitable for this study. In the context of machine learning studies, it is common to employ various ratios for the training-test split, including 80/20, 70/30, and 60/40. However, the 80/20 split, which designates 80 % of the data for training and 20 % for testing, is frequently utilized because this proportion ensures an adequate amount of training data for effective model training, while also providing sufficient testing data to estimate the model's performance in out-of-sample scenarios (Nay et al., 2018) and the rationale for this concept is derived from the widely recognized Pareto principle (Joseph, 2022). Ultimately, in the context of this study, this particular ratio demonstrated the highest level of accuracy, a conclusion drawn following a series of iterative trials involving distinct ratios. Notably, this ratio consistently yielded elevated percentages in terms of Out-of-Bag (OOB) accuracy and cross-validation accuracy across a majority of cases. Importantly, it is noteworthy that prior investigations have also applied this ratio to their analyses, consistently yielding the most precise outcomes (Nay et al., 2018; Park et al., 2016). The most optimal number of trees for this model was determined to be 1000 through systematic trial-and-error experimentation as well. Table 2 provides an overview of the RF model parameters employed in the analytical framework of this study.

The RF model was implemented for each year between 2010 and 2019, resulting in a total of 40 runs that produced the importance of the seven factors for each SPI type and year. To assess the performance of the model for each run, five accuracy methods were employed with their respective purposes in this study (Table 3).

Table 3
Description of the accuracy methods.

Name	Purpose in this study
Overall Accuracy	To evaluate the overall effectiveness of the model
RMSE	To evaluate the performance of the model in predicting values (Park et al., 2016)
OOB Accuracy	To provide an estimate of the accuracy of the model in data selection, training and testing process (Bhatia, 2019)
Cross Validation	To check if the model is overfitting its training data and offer an estimate of how well it can generalize to new data (Fox et al., 2017)
F1 Score	To provide a measure of the model's performance in correctly classifying data points into each class based on precision and recall metrics (Sinha et al., 2020)

2.3.2. Inverse Distance weighted (IDW) interpolation of SPI

The computation of various SPIs was accomplished through the utilization of six rain-gauge stations positioned across the northern expanse of Bangladesh. However, these computations merely provide insights into values specific to these designated sites. Consequently, to endow the SPIs with relevance and applicability across the entire research area, a sophisticated GIS interpolation technique known as IDW was adeptly employed. According to ESRI, the IDW interpolation approach computes the values of individual cells within the study region by synthesizing the values from representative sample data points situated in proximity to each processing cell. Moreover, the IDW method is particularly well-suited for interpolating data points situated on relatively flat terrain (Maleika, 2020). It is worth noting that nearly all of the land in Bangladesh falls within an elevation range of 10 m (Dewan et al., 2021) and in the northern region the variation is too small. So, there was no need to consider the substantial influence of elevation during interpolation (Islam et al., 2022). The selection of the power coefficient and the number of neighbors for the IDW interpolation method was a challenge. This study employed a trial-and-error approach to determine the optimal 'n' value. After conducting multiple testing, a value of '2′ was determined to be the most suitable fit and the number of neighbors were '12′. Furthermore, these settings were identified as optimal in a previous study focusing on drought within the northern region of Bangladesh (Islam et al., 2022).

From 2010 to 2019, all SPIs were mapped using this method in ArcGIS. The SPI values from all 358 locations and years 2010–2019 were extracted and entered into a dataset in which the SPIs served as dependent variables and the seven drought factors as independent variables. For the RF model, however, the dependent variables' values must be either 0 or 1, or wet, normal, mild, moderate, etc. So, after extracting the values of SPIs for the 358 points, those values were classified based on the classification (Shamsnia, 2014) represented in Table 4.

2.3.3. Analyses of the drought factors

The determination of the relative importance of the seven drought factors for the assessment of meteorological drought was accomplished through the application of the RF model. It is noteworthy that the model's optimal functionality hinges upon the availability of a substantial dataset. Therefore, approximately 358 random points were generated using GIS to adequately cover the northern region of Bangladesh (Fig. 1). In a sequential progression, the values corresponding to the seven indices were meticulously extracted for each of these 358 points, spanning the temporal expanse from 2010 to 2019. After that, the IDW tool in ArcGIS was harnessed for the spatial interpolation of precipitation indices. This decision was underpinned by the origin of these indices from NASA's IMERG satellite imagery, characterized by a resolution of approximately 10 km by 10 km. Given the larger pixel values and nuanced fluctuations intrinsic to the study area relative to the image resolution, the application of IDW was deemed instrumental. This measure was intended not only to improve the precision of the precipitation indices but also to improve the quality of the resulting data, thereby facilitating a more thorough understanding of the nuances in the precipitation indices' values. The IDW method was executed with the settings similar to IDW interpolation of SPI mentioned in the previous section. From the recalibrated precipitation index outputs, values were once again extracted from 358 points. Consequently, these updated precipitation index values demonstrated heightened accuracy and alignment with the prevailing conditions, surpassing the reliability of their predecessors. The outcome of this entire procedure yielded a dataset wherein the SPIs were considered as the dependent variables while the seven indices served as the independent variables.

Table 2
Parameters of RF model.

Criteria	Parameters
Model name	Random Forest Classifier (RFC)
Training data	80 % (Randomly selected)
Testing data	20 % (Randomly selected)
Data selection method	Out-of-Bag (OOB)
Number of trees (n_estimators)	1000
Other settings	Default
Platform	Spyder (Python 3.9)

Table 4
SPI classification.

SPI value	Class
2.00 and more	Extremely wet
0.50–1.99	Wet
−0.49 to 0.49	Normal
−0.99 to −0.50	Mild drought
−1.49 to −1.00	Moderate drought
−1.99 to −1.50	Severe drought
−2 and less	Extreme drought

The dataset, which was prepared and comprised of 358 randomly selected points, was inputted into the RF model, categorized by year and SPI type. Ultimately, the algorithm successfully produced an assessment of the relative importance of each index across various years and SPI categories.

2.3.4. Meteorological drought distribution map

The ultimate outcome of this study consists of a series of meteorological drought distribution maps spanning the period from 2010 to 2019, corresponding to each type of drought indicator, namely SPIs. Following the determination of the significance of each drought factor using the RF model, these factors were assigned specific weights. To generate the conclusive maps, these factors were amalgamated through the utilization of a GIS tool known as the "Raster Calculator." Each factor was then multiplied by its designated weight and subsequently combined with the other indices. This iterative process yielded the final drought distribution maps. Given that all the indices employed in this procedure were standardized (as indicated by Scaled NDVI, Scaled NDMI, etc. in Table 1), the resultant maps also adopted a standardized format with values encompassing the range from 0 to 1. In order to visualize the maps based on different drought classes all the maps were classified based on the classification (Park et al., 2016) represented in Table 5. To gain a more profound comprehension of drought occurrences and their spatiotemporal attributes, an in-depth investigation was conducted by quantifying the extent of each drought class on the meteorological drought distribution maps corresponding to each SPI type spanning the period 2010 to 2019. Employing GIS techniques, the spatial dimensions of meteorological drought events for each year were meticulously computed. The delineation of these processes is graphically depicted in Fig. 2, providing a clear overview of the study's methodologies.

3. Results

3.1. Drought factors

In this study, seven remote sensing indices were employed as meteorological drought factors. These factors were systematically constructed and analyzed to fulfill the study's objectives (Fig. 3). The findings of this factor analysis shed light on the spatial distribution of vegetation, water content, moisture content, evapotranspiration rate, precipitation rate, and the propensity for drought in northern Bangladesh.

The non-vegetation surfaces adjacent to the Padma and Jamuna rivers were identified by the use of NDVI indices (Fig. 3a). The Barind tract demonstrated a somewhat lower density of vegetation compared to other regions. In contrast, the Natore and Pabna districts consistently displayed dense vegetation over the duration of the study, as evidenced by the NDWI indices (Fig. 3b), which imply higher water content. The primary land cover in the northern region consists of barren and urban regions, with varying levels of moisture content recorded in the districts of Joypurhat, Bogura, and Natore. The NDMI indices (Fig. 3c) indicated increased moisture content in close proximity to significant river systems, but certain regions in Joypurhat, Bogura, and Natore districts displayed excessive amounts of moisture. In addition, the NDDI indicators (Fig. 3d) consistently illustrated the presence of moist conditions along significant river corridors, suggesting a diminished likelihood of drought events. From 2010 to 2019, a significant portion of the Rajshahi division encountered a notable increase in aridity, indicating an increased susceptibility to drought occurrences. The NMDI indices (Fig.re 3e) revealed the presence of dry conditions in certain areas of the Barind tract and Rangpur division, with a gradual decrease in intensity during the length of the study. Following that, ET indices (Fig. 3f) revealed moderate evapotranspiration rates in the majority of regions, occasionally interspersed with high or extremely high rates in specific areas and years. Finally, the precipitation indices (Fig. 3g) underscored a notable decrease in rainfall across the entire Rajshahi division, accompanied by drier climate conditions observed in various locations within the Rangpur region. Conversely, areas situated proximate to the Himalayan range, including specific segments of Panchagrah, Lalmonirhat, and Kurigram, experienced elevated levels of precipitation during the study period in northern Bangladesh.

Table 5
Meteorological drought classification.

Value	Drought class
0.5–1.0	No drought
0.4–0.5	Abnormally dry
0.3–0.4	Moderate drought
0.2–0.3	Severe drought
0.0–0.2	Extreme drought

3.2. SPI

This study employed diverse iterations of the SPI as robust indicators of meteorological drought. Specifically, it harnessed 1-month and 3-month SPI values to scrutinize short-term meteorological drought patterns, while 6-month and 9-month SPI values were instrumental in the examination of long-term meteorological drought dynamics. A meticulous exploration of SPIs, encompassing the extensive timeframe from 2010 to 2019, was methodically conducted. This rigorous analysis relied on precipitation data acquired with precision from a strategically curated network of six rain gauge stations positioned within the defined study area. Fig. 4 serves as an invaluable visual representation, offering a comprehensive illustration of the climatological drought patterns discerned through this extensive investigation.

The study employed various SPI indices, each of which covered a range from +2, representing significantly moist or non-drought circumstances, to −2, indicating extreme dryness or extreme drought. Significant variations in the frequency of drought events were observed within the geographical region during the period of investigation. A clear and noticeable pattern was observed, in which the severity of drought increased within each SPI category from the previous category in a certain year. In the year 2010, a considerable proportion of the northern part of Bangladesh experienced arid conditions or varying levels of drought, as evidenced by the SPIs. On the contrary, a decrease in the occurrence of drought episodes was documented in the region in 2015. Throughout the majority of years, there was a consistent pattern of drought occurrences, with the Rajshahi region consistently experiencing the most severe drought episodes, as indicated by the outcomes of the SPI.

3.3. Importance

This study employed a methodology entailing the allocation of weights to each drought factor, subsequently amalgamating them to generate comprehensive drought distribution maps. This approach facilitated the determination of the relative significance of each factor. This observation underscored the relative importance of various drought factors in the computation of SPI, particularly in the context of meteorological drought, across diverse temporal resolutions.

Table 6 provides a succinct overview of the comparative significance exhibited by seven distinct drought-related factors across varying temporal scales within the northern region of Bangladesh. It was discerned that throughout each year of the study period and across all SPI time scales, a substantial degree of importance was ascribed to Precipitation variables. This alignment was expected given that SPI calculations relied on rainfall data, signifying a robust correlation between Precipitation variables and SPIs. Conversely, the significance of the remaining six drought factors was established with minor variances, consistently maintaining close proximity to each other in terms of importance.

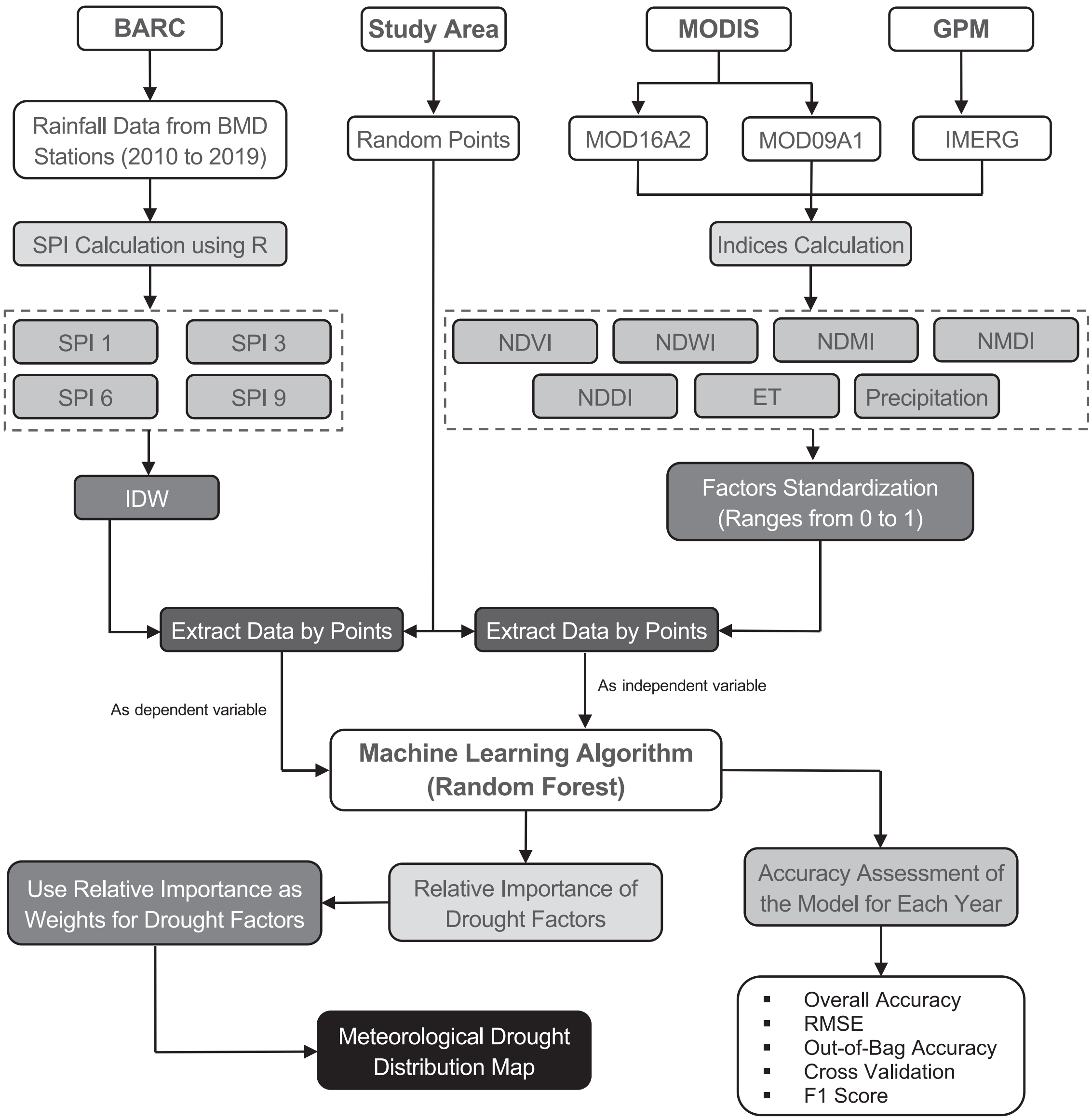


Fig. 2. Methodological framework of this study.

In this study, it was observed that NDVI, NDWI, NDMI, NDDI, and NMDI displayed diminishing relative importance as the time scales of SPI increased, while ET and Precipitation exhibited an augmented relative importance with longer time scales of SPI. Over the course of the study period, the significance of the NDVI index (Fig. 5.a) and NDDI index (Fig. 5.d) gradually declined as the time scales of SPI extended. In contrast, the NDWI index (Fig. 5.b) and NMDI index (Fig. 5.e) demonstrated their highest importance in SPI 1 and the lowest in SPI 3, with intermediate importance in SPI 6 and SPI 9. The relative importance of the NDMI index peaked in SPI 1, declined in SPI 3, increased in SPI 6, and reached its lowest point in SPI 9 (Fig. 5.c). Conversely, the ET index exhibited its highest importance in SPI 9 and the lowest in SPI 6 (Fig. 5.f), whereas the Precipitation index displayed the lowest importance in SPI 1 and the highest in SPI 9 (Fig. 5.g). This temporal lag between drought severity and the variations in land surface and vegetation variables, as illustrated in this manner, has been explored in various research endeavors (Gessner et al., 2013; Piao et al., 2003).

To ascertain the predominant meteorological drought factor in northern Bangladesh during the 2010–2019 period, data from Table 7 underwent summarization. This study computed average importance values for each drought factor, considering both short-term meteorological drought indicators (SPI 1 and SPI 3) and long-term ones (SPI 6 and SPI 9). These results are visually depicted in Fig. 6 within this study.

In this study, a notable observation was the strong correlation between the Precipitation factor and meteorological drought. Precipitation exhibited a significant influence, averaging 28.32 % on short-term drought events and 26.78 % on long-term drought events, surpassing other factors significantly. Short-term drought events were also influenced by ET and NDWI, averaging 13.57 % and 12.13 %, respectively. In contrast, long-term drought events were more affected by NMDI and NDVI, with an average importance of 14.27 % and 12.87 %, respectively. These findings highlight the varying roles of different factors in meteorological drought across temporal scales in northern Bangladesh from 2010 to 2019.

3.4. Meteorological drought

The meteorological drought distribution maps represent the conclusive outcomes of this study, effectively portraying the spatiotemporal attributes of meteorological drought in northern Bangladesh during the period spanning 2010 to 2019 (Fig. 7).

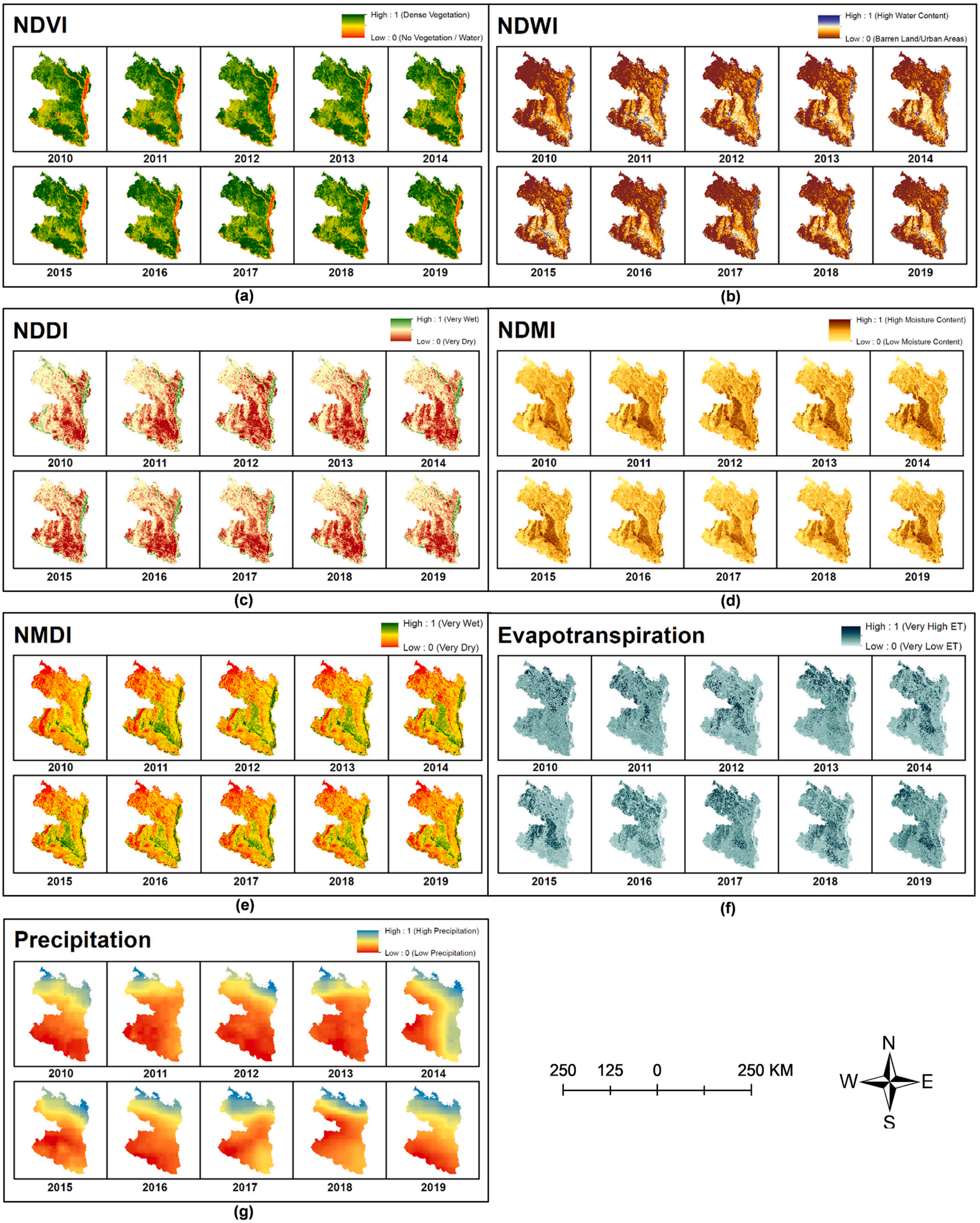


Fig. 3. Remote sensing indices: (a) NDVI, (b) NDWI, (c) NDMI, (d) NDDI, (e) NMDI, (f) ET, (g) Precipitation

In the study period spanning from 2010 to 2019, a detailed analysis of drought occurrences in the northern region of Bangladesh was conducted. Evidently, the Rajshahi division, specifically encompassing the districts of Rajshahi, Chapainawabganj, and Naogaon, consistently encountered recurrent occurrences of extreme and severe drought events, with near-annual frequency. This noteworthy pattern is further corroborated by the congruent observations in a number of studies, thereby reinforcing the robustness and validity of the identified drought dynamics in this region (Islam et al., 2022; Rahman and Lateh, 2016; Shahid and Behrawan, 2008). This trend underscores the vulnerability of these areas to drought impacts. Concurrently, moderate drought incidents and abnormally dry conditions were observed across various parts of northern Bangladesh. The Barind tract area in Bangladesh is widely acknowledged as being very susceptible to drought, with the

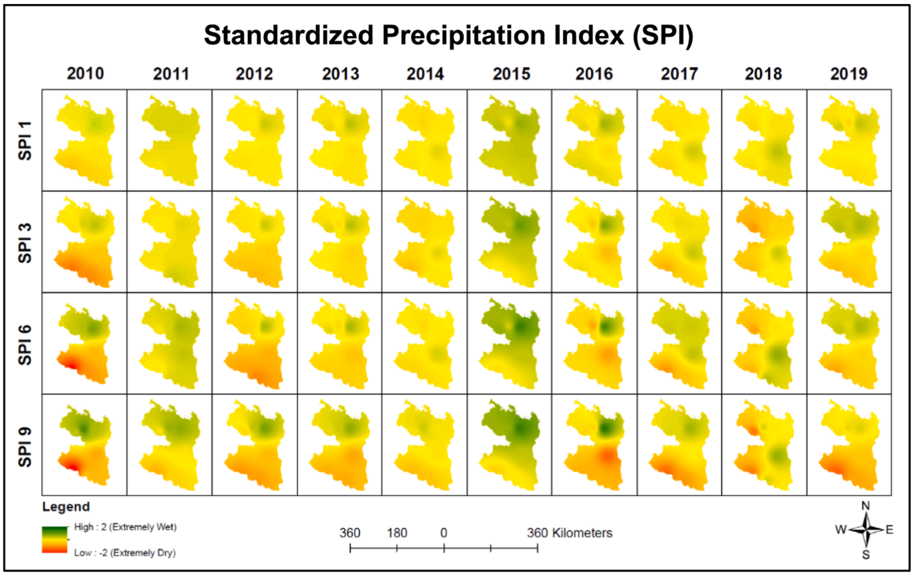


Fig. 4. Meteorological drought indicator of this study (SPI).

Table 6
The relative importance (%) of the drought factors for 1-, 3-, 6-, and 9-month SPI.

Year	Factor	Relative importance				Year	Factor	Relative importance			
		SPI 1	SPI 3	SPI 6	SPI 9			SPI 1	SPI 3	SPI 6	SPI 9
2010	NDVI	5.22	6.98	8.81	10.03	**2015**	NDVI	11.03	8.84	8.14	8.11
	NDMI	6.40	7.74	11.03	10.94		NDMI	10.85	9.60	9.79	9.61
	ET	5.47	5.98	8.36	9.42		ET	10.48	9.71	8.54	7.95
	NDWI	6.82	8.48	11.09	11.56		NDWI	12.82	9.44	9.19	10.02
	PRCP	63.14	55.01	39.42	35.90		PRCP	30.92	43.63	44.56	42.99
	NMDI	6.79	8.26	11.13	11.36		NMDI	11.33	9.69	10.52	11.30
	NDDI	6.16	7.55	10.16	10.79		NDDI	12.57	9.09	9.26	10.01
2011	NDVI	14.89	13.22	12.72	12.05	**2016**	NDVI	11.62	11.41	11.04	8.40
	NDMI	14.46	13.18	12.80	12.15		NDMI	11.49	11.77	10.37	8.53
	ET	14.84	14.93	12.35	11.29		ET	10.89	13.22	11.87	11.40
	NDWI	15.49	13.67	13.19	11.24		NDWI	11.40	11.40	10.36	9.24
	PRCP	8.49	18.18	21.31	29.35		PRCP	32.03	30.22	34.51	43.68
	NMDI	14.40	13.22	14.39	12.28		NMDI	11.31	11.05	11.41	9.23
	NDDI	17.43	13.60	13.24	11.65		NDDI	11.26	10.94	10.44	9.51
2012	NDVI	5.57	11.20	9.91	9.17	**2017**	NDVI	11.84	11.61	11.90	9.53
	NDMI	5.45	9.45	8.01	7.77		NDMI	12.15	9.71	10.61	11.44
	ET	7.72	8.80	8.90	10.94		ET	10.46	12.73	11.98	10.82
	NDWI	7.03	8.76	9.30	8.87		NDWI	13.36	9.34	8.87	10.64
	PRCP	60.18	43.99	45.27	46.20		PRCP	24.52	35.76	36.86	36.41
	NMDI	7.26	8.82	9.47	8.93		NMDI	13.39	11.18	11.17	10.97
	NDDI	6.78	8.99	9.13	8.12		NDDI	14.29	9.66	8.60	10.19
2013	NDVI	6.98	5.65	7.67	9.83	**2018**	NDVI	13.33	12.09	11.18	12.35
	NDMI	7.21	6.80	8.30	9.19		NDMI	11.06	11.44	10.73	11.74
	ET	11.45	11.36	10.63	10.97		ET	12.88	14.68	10.44	13.66
	NDWI	9.69	8.39	9.56	11.03		NDWI	13.30	12.47	11.31	12.70
	PRCP	48.17	53.14	45.08	39.05		PRCP	20.98	23.25	33.13	23.62
	NMDI	8.63	7.65	9.55	9.92		NMDI	15.95	14.51	12.22	13.75
	NDDI	7.86	7.02	9.20	10.00		NDDI	12.52	11.57	10.98	12.18
2014	NDVI	11.93	12.52	9.29	12.68	**2019**	NDVI	12.65	5.70	8.50	5.79
	NDMI	11.67	13.17	12.28	11.59		NDMI	14.14	5.63	8.87	6.79
	ET	9.73	14.77	10.36	9.58		ET	13.63	8.99	9.72	6.79
	NDWI	14.88	12.29	12.12	13.57		NDWI	12.65	6.20	8.54	8.18
	PRCP	24.88	22.84	32.31	27.17		PRCP	20.34	60.71	47.47	56.49
	NMDI	15.01	13.21	12.95	13.99		NMDI	13.74	6.74	7.90	8.41
	NDDI	11.90	11.21	10.70	11.42		NDDI	12.84	6.03	9.00	7.55

occurrence of moderate to severe droughts exhibiting a notable increase in terms of intensity, frequency, and severity (Mondol et al., 2021; Rahman and Lateh, 2016). The present analysis reveals that the Barind tract region had consistently experienced a prolonged period of drought conditions, ranging from moderate to extreme intensity, throughout the bulk of the previous decade. However, it is important to note that there were some exceptions to this tendency in the years 2011, 2014, and 2019. During the year 2010, the districts of Chapainawabganj and Naogaon had a notable increase in the occurrence of extreme and severe drought episodes. Likewise, the districts of Panchagrah, Thakurgaon, and certain areas of Nilphamari had repeated occurrences of both severe and mild drought conditions over the years 2011, 2012, 2014, 2015,

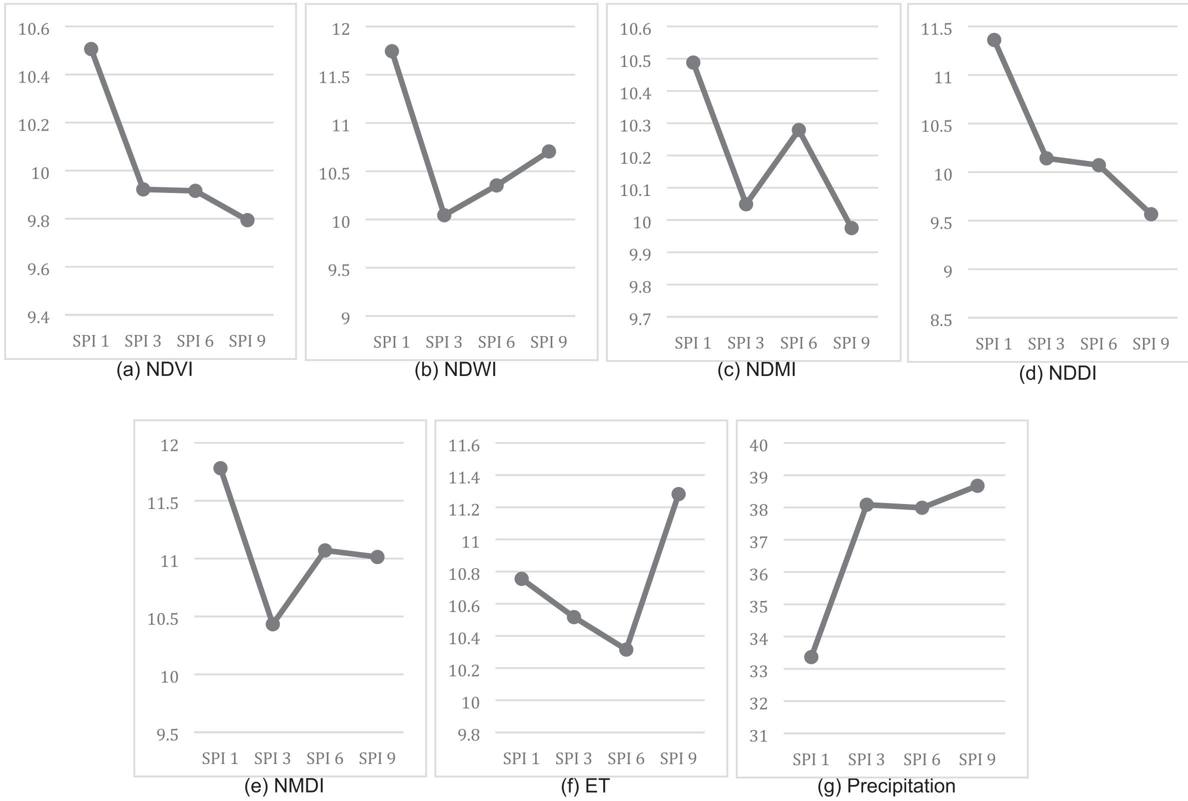


Fig. 5. Average importance of drought factors based on different SPI.

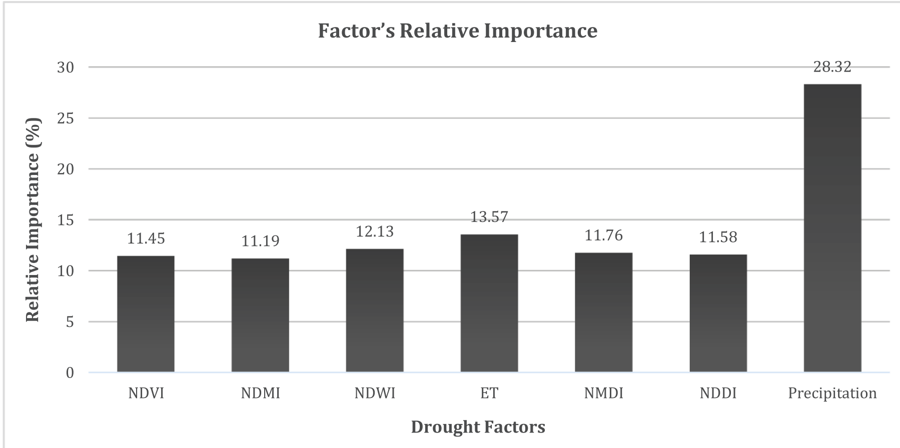
Table 7
Accuracy assessment of the RF model.

SPI	Accuracy Type (%)	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
SPI 1	Overall Accuracy	93.00	93.00	95.00	82.00	85.00	92.00	89.00	84.00	83.00	96.00
	RMSE	6.30	10.19	6.90	8.18	8.29	6.74	10.40	6.90	11.75	6.99
	Out of Bag Accuracy	93.00	98.00	90.00	84.00	84.00	88.00	85.00	86.00	83.00	94.00
	F1 Score	93.05	89.01	93.10	90.23	91.01	98.48	85.33	97.89	91.25	98.54
	Cross Validation	94.00	96.00	90.00	83.00	85.00	90.00	85.00	83.00	85.00	96.00
SPI 3	Overall Accuracy	92.00	90.00	85.00	92.00	86.00	89.00	85.00	82.00	82.00	89.00
	RMSE	12.62	21.57	11.19	10.20	9.69	15.13	17.77	17.22	22.43	10.71
	Out of Bag Accuracy	90.00	94.00	82.00	90.00	83.00	85.00	84.00	84.00	82.00	90.00
	F1 Score	86.59	85.94	86.11	90.26	89.35	98.48	78.98	95.85	91.25	97.92
	Cross Validation	87.00	93.00	81.00	91.00	81.00	84.00	80.00	83.00	85.00	84.00
SPI 6	Overall Accuracy	85.00	95.00	83.00	89.00	85.00	86.00	85.00	82.00	82.00	84.00
	RMSE	19.81	11.51	18.50	12.76	8.86	21.10	27.79	19.03	28.10	10.34
	Out of Bag Accuracy	91.00	93.00	87.00	82.00	80.00	82.00	82.00	80.00	76.00	89.00
	F1 Score	97.22	95.85	94.02	90.41	89.29	95.85	87.30	94.44	77.43	95.81
	Cross Validation	88.00	94.00	90.00	85.00	82.00	80.00	84.00	84.00	78.00	82.00
SPI 9	Overall Accuracy	83.00	85.00	82.00	84.00	86.00	82.00	81.00	85.00	83.00	90.00
	RMSE	30.67	28.14	21.66	22.08	21.46	25.16	30.82	25.07	28.64	11.75
	Out of Bag Accuracy	80.00	85.00	80.00	81.00	84.00	80.00	85.00	78.00	80.00	92.00
	F1 Score	98.61	80.01	90.48	95.82	80.69	86.75	94.41	81.08	91.20	95.84
	Cross Validation	81.00	83.00	79.00	82.00	85.00	80.00	82.00	86.00	89.00	91.00

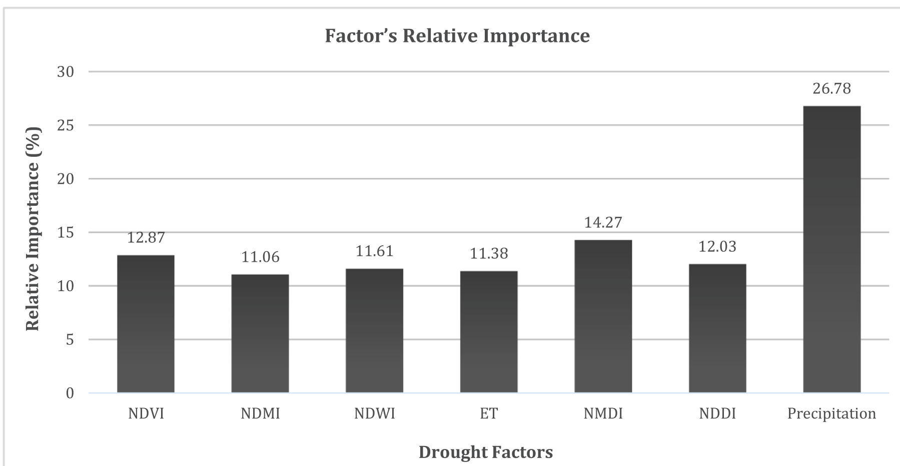
2016, and 2018. In contrast, the districts of Joypurhat and Bogura exhibited comparatively lower levels of impact, as they encountered notable instances of drought primarily during the years 2011, 2014, 2017, and 2019. The aforementioned data collectively emphasize the heterogeneous nature and differing levels of severity of drought events in different districts of northern Bangladesh from 2010 to 2019.

Furthermore, the meteorological drought distribution map provided a comprehensive depiction of drought's impact on northern Bangladesh from 2010 to 2019. The distribution and severity of drought across the region were effectively captured through this analysis. Quantification of affected areas in terms of each drought class was facilitated by calculating area percentages. Notably, the year 2010 recorded over 30 % of northern Bangladesh grappling with moderate drought events, marking it as the most affected class. Subsequent years demonstrated varying trends, with noteworthy changes in 2011 as the percentage of areas with no drought events reached.

its pinnacle, ranging from 35 % to 40 %. Transitioning into 2012, there was a notable shift in the percentage of areas impacted by moderate drought, reaching a peak ranging from 25 to 33 %. A separate study specifically identified that approximately 29 % of the region had been affected by moderate drought during that year in the northern region (Mamun et al., 2018). Notably, 2013 exhibited the highest occurrence of abnormally dry conditions, affecting 28 to 33 % of areas. Additionally, years like 2014, 2015, 2016, and 2017 displayed varying



(a) Influential factors of short-term meteorological drought



(b) Influential factors of long-term meteorological drought

Fig. 6. Influential factors of meteorological drought in northern Bangladesh.

distributions of drought classes, emphasizing the fluctuating nature of drought patterns across the study area. A study has determined that, on average, the increasing trend of drought in the northern region amounts to approximately 4.1 % every 10 years (Mamun et al., 2018). Significantly, the study underscored that throughout the period spanning from 2010 to 2019, a substantial segment of northern Bangladesh consistently confronted the impact of extreme and severe drought conditions. On average, over 5 % of the study area encountered extreme drought events, while the incidence of severe drought events affected more than 12 %. This trend signifies a notable escalation in the frequency of extreme drought events within this geographic expanse over time, further accentuating the region's ongoing struggle with persistent drought challenges.

The relationship between the measured area percentage and different types of SPI (Fig. 8) was also explored, revealing intriguing trends. Notably, long-term drought indicators (SPI 6 and SPI 9) consistently exhibited a higher frequency of area percentage in the extreme drought category compared to short-term indicators (SPI 1 and SPI 3), with a few exceptions. This suggests the cumulative impact of prolonged precipitation deficits in driving extreme drought occurrences. Similarly, in the category of severe drought, SPI 6 and SPI 9 also demonstrated higher frequency percentages, further reinforcing the relevance of longer time frames in understanding severe drought dynamics. Notably, variations were observed across different years and SPI types for other drought classes, underscoring the nuanced interplay between drought severity and SPI types.

3.5. Accuracy assessment of the RF model

Values for five accuracy metrics were reported in Table 7 to assess the performance of the random forest model. The values of the five categories of accuracy provided supporting evidence for the model's capacity to reliably predict or categorize data and gave insights into the model's ability to generalize to new, unknown data.

The current study employed accuracy assessment metrics to evaluate the overall efficacy and dependability of the RF model used to generate drought distribution maps in the northern region of Bangladesh. The overall accuracy metric, which measured the concordance between predicted and observed values, consistently demonstrated strong performance, with values exceeding 80 % in the majority of instances and ranged from 81 % to 95 %. This demonstrated the model's ability to capture the relative importance of the drought factors considered. The RMSE accuracy metric reflected the model's capacity to reliably predict values. In this study, RMSE values ranged from 6 % to 31 %, indicating that prediction errors were comparatively low in all cases. The Out-of-bag (OOB) accuracy metric was particularly crucial for machine learning classification models as it estimated the model's accuracy during the data selection, training, and testing processes. The OOB accuracy values in this study ranged from 76 % to 98 %, suggesting the RF model performed well in these crucial stages. The F1 score, a prominent metric used to assess the classification performance of the model by measuring the precision and recall of data point classification for each class, continuously exhibited elevated values in our investigation, with a range of 76 % to 99 % observed in the majority of instances. This

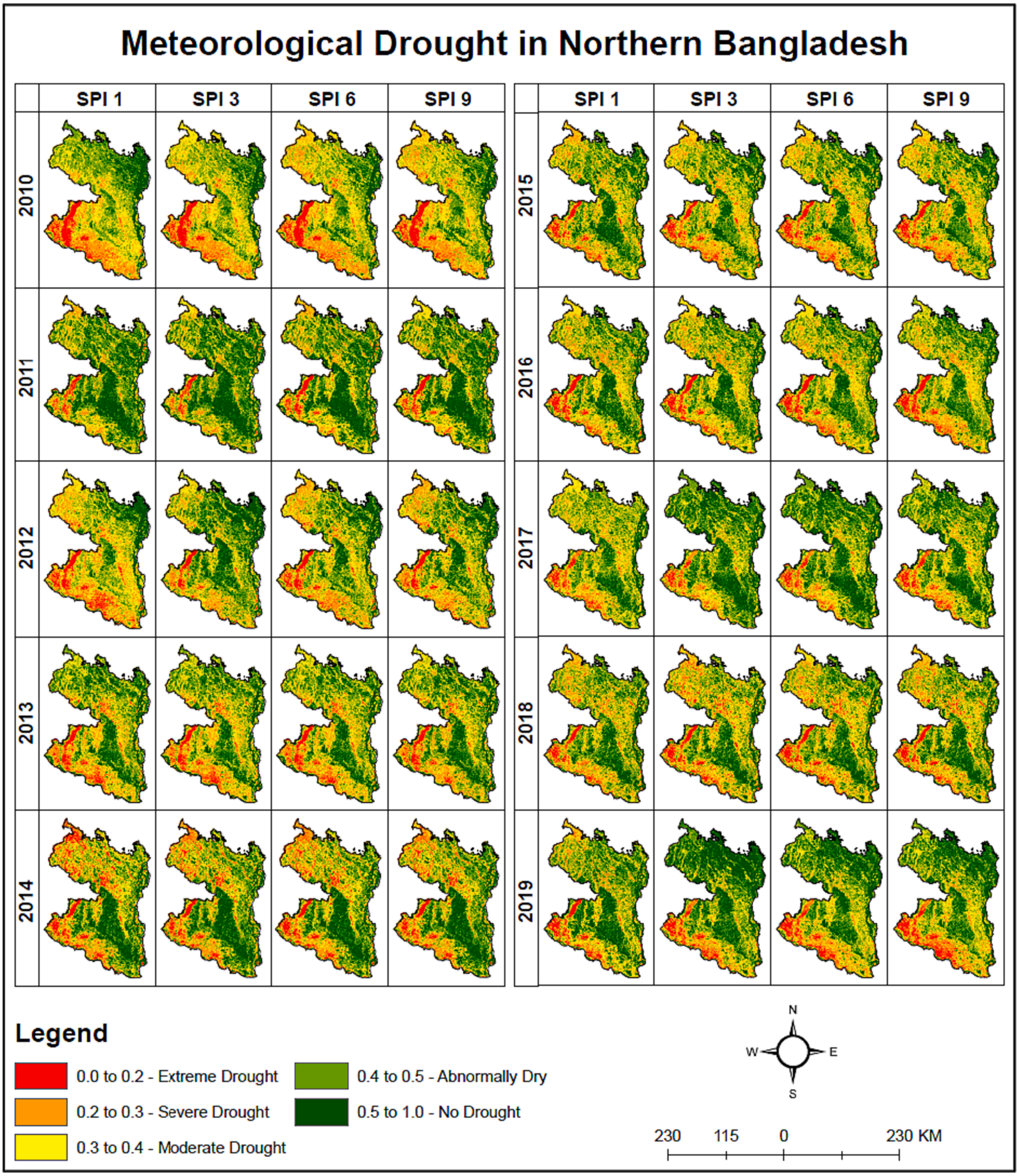


Fig. 7. Meteorological drought distribution map of northern Bangladesh.

observation suggests that the model possesses a high level of competence in effectively categorizing data points with precision. Furthermore, the utilization of cross-validation as a metric in this study allowed for an assessment of the RF model's ability to generalize to new and unseen data. This approach effectively mitigated the risk of overfitting to the training data. The obtained values for the cross-validation metric ranged from 78 % to 94 %. In summary, the evaluation of these accuracy measures highlights the strength and dependability of the RF model in capturing the relative importance of drought causes and producing accurate drought distribution maps for the northern region of Bangladesh.

4. Discussion

Bangladesh has been susceptible to drought, as evidenced by the occurrence of around twenty significant drought occurrences within the last five decades (Rahman & Lateh, 2016). The aforementioned occurrences have had a noteworthy influence on the northern region,

Fig. 8. Area percentage based on drought classes.

resulting in a substantial decrease in agricultural productivity, estimated to be between 25 and 30 % (Habiba et al., 2011; Islam et al., 2022). Assessing and monitoring drought occurrences is crucial for understanding regional drought features and such insights help create a drought management plan that addresses northern Bangladesh's unique challenges. The present study undertook a complete evaluation of meteorological drought in the northern part of Bangladesh, specifically concentrating on Rajshahi and Rangpur divisions, encompassing sixteen districts. This study sought to examine the dynamics of meteorological drought in the specified region between 2010 and 2019 by employing seven satellite-derived drought parameters and the Random Forest (RF) model. The performed study not only provides illumination on the changing patterns of drought, but also offers valuable insights into the complex interactions among many components that contribute to the severity of drought.

The study area's SPI production fluctuations over time illuminated climatic drought dynamics in northern Bangladesh. A consistent trend of increasing meteorological drought severity within each SPI class from the previous class in a given year indicated a decade-long escalation of drought conditions in the studied area. The SPI findings also showed that most of the Barind tract region and some districts have experienced various meteorological drought occurrences over the decade. Multiple satellite-derived indices revealed the geographical distribution of vegetation, water and moisture content, evapotranspiration rate,

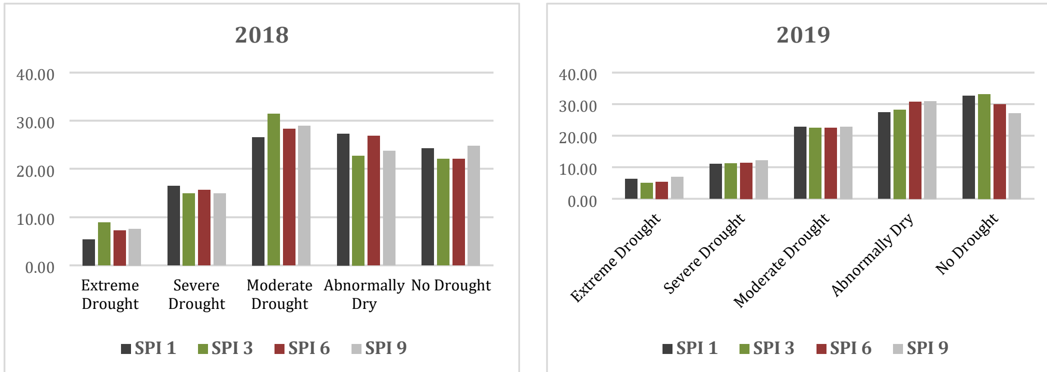


Fig. 8. (*continued*).

precipitation rate, and drought likelihood in northern Bangladesh. NDVI indices showed non-vegetation surfaces on the Padma and Jamuna rivers, indicating water bodies. The Natore and Pabna districts had lush vegetation, but the Barind tract had less. This showed the relevance of regional river networks and diverse vegetation. Also, NDWI indices showed substantial water content along river streamlines. Most of the north was cities and desolate land. The water content in Joypurhat, Bogura, and Natore districts varied from high near rivers to dry or urban regions. High moisture levels along major rivers indicated water presence, according to NDMI indices. In Joypurhat, Bogura, and Natore districts, moisture levels were higher than elsewhere in northern Bangladesh. These findings showed how river systems affect moisture patterns and spatial variability. Along major river streamlines, the NDDI indexes showed wet conditions, reducing drought risk. However, the Rangpur division and sections of the Barind tract were very dry and the severity of the condition was decreasing, according to the NMDI indices. The Rajshahi division was heavily drought-prone. The rates of evaporation varied across northern Bangladesh, with some places having moderate rates and others having high or very high rates in some years, according to ET indexes. This revealed geographical variability in evapotranspiration and water demand and availability across the research area. Rajshahi and several Rangpur districts were drier, according to precipitation indicators. Near the Himalayas, Panchagrah, Lalmonirhat, and Kurigram received more rain. The northern part of Bangladesh has geographical variation in vegetation, water content, moisture, and drought risk. Understanding these trends was essential for drought management and resource allocation.

This study determined which drought parameters were most important for assessing SPI (i.e., meteorological drought) at various time scales in the study area, which was critical to attaining the study's objectives. Precipitation significantly affected meteorological drought episodes in the study area, emphasizing the need of appropriate rainfall in drought mitigation. The study found that ET and NDWI were more influential in short-term meteorological drought and drought indicators like NMDI and NDVI were more influential in long-term meteorological drought in northern Bangladesh (Fig. 6). Multiple studies have established that ET and NDWI are factors associated with the land surface (Huizhi & Jianwu, 2012; Li et al., 2013), whereas NMDI and NDVI are factors associated with vegetation (Wang & Qu, 2007; Zhang and Jia, 2013). The findings of this study indicate that land surface-related indices exert a greater influence on short-term drought events, while vegetation-related indices exhibit a stronger impact on long-term drought events.

During the ten-year period from 2010 to 2019, the northern region of Bangladesh exhibited a recurring pattern of extreme and severe drought events, notably in the Rajshahi division, encompassing Rajshahi, Chapainawabganj, and Naogaon districts. The Barind tract is known for its susceptibility to drought, and this study's meteorological drought distribution map confirms this, as the majority of the Barind tract area has been affected by moderate to severe droughts of increasing intensity, frequency, and severity over the past decade. It's worth noting that while this trend was prominent over the decade, exceptions occurred in 2011, 2014, and 2019. In 2010, Chapainawabganj and Naogaon experienced a marked rise in extreme and severe drought occurrences. Similarly, districts like Panchagrah, Thakurgaon, and certain areas of Nilphamari witnessed recurring episodes of both severe and mild drought conditions between 2011 and 2018. In contrast, Joypurhat and Bogura districts faced comparatively lower drought impacts, with notable instances primarily in 2011, 2014, 2017, and 2019. An important understanding was gained from the examination of area percentages taken from the drought maps, revealing that longer time frames (SPI 6 and SPI 9) demonstrated an increase in the areas impacted by various drought classes. This finding suggested that prolonged periods of precipitation shortages resulted in more frequent occurrences of drought events. This comprehensive analysis underscores the heterogeneous nature of drought events in various districts of northern Bangladesh during the studied period. These findings closely resemble with some studies outcomes (Islam et al., 2022; Mondol et al., 2021; Rahaman et al., 2016; Rahman & Lateh, 2016) but they display more classes of variations of drought events over the past decade and upholding the influence of underlying factors as well as the relationship of the severity of droughts with time varying SPIs.

Numerous prior investigations have centered on drought assessments in northern Bangladesh. These studies have adopted various methodologies, including diverse drought typologies, seasonal examinations, and analyses based solely on rainfall data or SPI only. However, none of these studies have integrated remote sensing indices with a machine learning model to comprehensively assess the influence of these indices and establish correlations between time-varying scales of the SPI and the frequency as well as severity of drought events. The study's findings effectively bridge these research gaps in the context of northern Bangladesh, providing a comprehensive and unique contribution to the existing body of knowledge in the field of drought assessment in this region. Drought patterns and severity in northern Bangladesh were influenced by several internal factors. Variations in vegetation density and moisture content, particularly in the Barind tract, played a crucial role in drought vulnerability. Changes in precipitation patterns, including decreased rainfall and drier climates in specific regions, heightened drought susceptibility. Conversely, areas near the Himalayan range with elevated precipitation levels experienced lower drought risks. The study also highlighted a temporal lag between drought severity and variations in land surface and vegetation variables, contributing to nuanced interplays among factors. The consistent increase in drought severity within each SPI category indicates worsening drought conditions, particularly in the Rajshahi division. Different factors played varying roles in short-term and long-term drought events, with precipitation emerging as the most influential factor, followed by ET, NDWI, NMDI, and NDVI. These internal causes provide insights into the complex dynamics of meteorological drought in northern Bangladesh.

In light of these findings, this study carries significant implications for drought mitigation and resource allocation strategies. It is important to emphasize that the study's contributions extend beyond academic research and have practical relevance. The insights into the intricate dynamics of meteorological drought gained from this study hold the potential to significantly impact the region's resilience and preparedness. This includes more effective early warning systems that can be tailored to specific drought types, enabling timely responses. Moreover, the findings can inform resource allocation strategies for agriculture, optimize water resource management, and guide climate-resilient practices. Local communities can benefit from this research by implementing targeted environmental conservation efforts and enhancing their disaster preparedness. Overall, this study not only advances scientific knowledge but also offers actionable insights that can enhance the region's ability to cope with and mitigate the impacts of drought.

5. Conclusion

Bangladesh, which is situated in South Asia's delta region, is in fact considered to be highly susceptible to many climatic risks, such as meteorological drought. Northern Bangladesh is particularly susceptible to drought's devastating impacts. This study has illuminated the intricate dynamics of meteorological drought in northern Bangladesh during the period from 2010 to 2019. The comprehensive analysis underscores the pronounced impact of precipitation, evapotranspiration, and vegetation-related factors on the severity of drought, both in the short and long terms. During this period, Rajshahi division's Rajshahi, Chapainawabganj, and Naogaon districts consistently experienced severe drought, with the Barind tract facing prolonged drought. Panchagrah, Thakurgaon, and parts of Nilphamari observed intermittent severe and moderate droughts. The meteorological drought maps highlighted drought distribution, while area percentages analysis emphasized long-term SPIs' (SPI 6 and SPI 9) consistency in extreme and severe droughts, underlining the importance of longer time scales. Leveraging the capabilities of the random forest model and remote sensing indices, this research successfully assessed localized drought occurrences and highlighted the considerable regional diversity in drought characteristics across the study area. As the scope of investigation expands, this research not only advances the comprehension of meteorological drought but also paves the way for further inquiry. The empirical insights gleaned from this study have practical implications for devising effective drought management strategies in the vulnerable northern Bangladesh region. This study also emphasized the significance of applying machine learning techniques and remote sensing indices in drought assessment, offering insightful information for further research and monitoring projects.

However, it is essential to acknowledge certain limitations inherent in this study. The scope was confined to the northern region of Bangladesh, necessitating caution in extending the findings to other geographical contexts. Moreover, the choice of the machine learning model and associated parameters may yield disparate results in different regions. Future endeavors should encompass a broader geographic spectrum and consider alternative modeling approaches to enrich the understanding of meteorological drought dynamics. The synthesis of the findings with the future trajectory of research underscores the pertinence of this study within the broader framework of ecological indicators and climate resilience, advocating for informed decision-making and adaptive strategies in the face of meteorological drought challenges.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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