DROUGHT SUSCEPTIBILITY ASSESSMENT FOR BARIND TRACT IN BANGLADESH USING MULTIVARIATE STATISTICAL ANALYSIS AND GEOSPATIAL TECHNIQUES

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ABSTRACT

Drought is considered an unpredictable disaster globally, which is usually caused by a prolonged absence and significant lack of precipitation. Thus, drought should be accurately and properly monitored and assessed for effective management of water resources and adaptive planning of agricultural practices. The National Water Management Plan (NWMP) of Bangladesh has identified drought as a significant water scarcity problem for the agriculturally dependent Barind Tract in northwestern Bangladesh. Drought is a growing problem in the Barind Tract because of uneven precipitation and heavy dependence on groundwater. Mapping drought-prone areas is, therefore, vital for early warning and mitigation planning for drought disasters. Therefore, the current study is aimed at evaluating the predictive performance of GIS and multivariate statistical analysis in drought susceptibility assessment in the Barind Tract of the northwestern region in Bangladesh. The widely used logistic regression was adopted as the multivariate statistical method in the current study. The drought inventory map, comprising 150 drought locations, was derived from prehistoric data and literature reviews. The drought inventory map based on meteorological data and remote sensing data was divided randomly into a test dataset, with two-thirds of the data allocated for the model training and the remaining one-third for the model validation purposes. The fifteen drought conditioning factors included in the spatial database were Temperature, Precipitation, Humidity, Soil Moisture, Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Land Use and Land Cover (LULC), Normalized Burning Ratio (NBR), Land Surface Temperature (LST), Groundwater Level (GWL) and Digital Elevation Model (DEM). Logistic regression and geographically weighted regression models were implemented using historical drought data, comprising 150 occurrence points, with 70% allocated for training and 30% for validation. Empirically, an overall precision of 86.7% and R^2 of 0.91 were obtained by the logistic regression model. Rainfall, temperature, groundwater level, and soil moisture were stated by the principal outcomes to be the primary influencing factors. Based on the final drought susceptibility map produced in the current study, it can be concluded that about 19.35% of the Barind Tract was categorized as the extreme drought zone. This has a high implication on the overall water resources management and irrigation activities over the study area. The findings of the current study could be a handy tool for the water managers and decision-makers in developing policies for the Integrated Water Resources Management (IWRM) to refine the development of targeted drought hazard mitigation and adaptation strategies.

Keywords: *Drought, Logistic Regression, Geospatial, GIS, Barind Tract, Bangladesh*

1. INTRODUCTION

Drought is a rigorous and predictive disaster that greatly influences millions of people, ecosystems, and economies worldwide (Van Loon, 2015). A deficiency of precipitation is the primary factor of this natural disaster (Rafiuddin et al., 2011) which is divided into four major types. (Arabameri et al., 2022; Ding et al., 2021). One of them hydrological drought, is observed when surface and groundwater resources, including rivers, lakes, and reservoirs, experience a prolonged period of below-normal water levels (Ding et al., 2021; Lorenzo-Lacruz et al., 2013). Inside the boarder context of South Asia, persistent drought poses a crucial challenge, affecting millions of people across the territory. The regions reliance on seasonal monsoon precipitation depicts it remarkably susceptible to arid situations when monsoon patterns become irregular or diminished (Ullah et al., 2023; Chandrasekara et al., 2021). Viewed through a broader South Asian lens, drought is a periodic problem that impact millions of people across the region. South Asia’s reliance on monsoon precipitation demonstrate the territory highly vulnerable to drought when monsoon trends are erratic or weak (Ullah et al., 2023; Chandrasekara et al., 2021; Buckley et al., 2014).

Bangladesh, despite being a country known for its susceptibility to floods and cyclones, also experiences significant drought conditions, particularly in the northwestern and southwestern regions (Brammer, 2016; Masum, 2019a; Toufique & Islam, 2014). The country’s climate is primarily influenced by the monsoon, and any disruption in rainfall patterns can lead to severe droughts (Masum, 2019b; Toufique & Islam, 2014). The northwestern districts of Rajshahi, Noagaon, Bogura, and Chapai Nawabganj are drought vulnerable region in Bangladesh. These regions receive lower precipitation relative to other parts of the country, making them highly vulnerable to prolonged dry spells (Sarkar et al., 2024; Islam, 2019; Rahaman et al., 2016). The impacts of drought in Bangladesh are severe, particularly for agriculture, which is the backbone of the country’s economy and livelihood for a large portion of the population. Crop failures due to insufficient rainfall led to food shortages, reduced income for farmers, and increased rural poverty (Alam et al., 2021; Dey et al., 2011). Additionally, groundwater depletion in drought-prone regions has become a critical concern, as excessive irrigation and declining water tables threaten long-term agricultural sustainability (Rahman et al., 2017).

The three key principal of interconnected drought management: surveillance and forecasting, vulnerability and risk analysis, drought mitigation, preparedness and response (Wilhite & Pulwarty, 2017). Enhancement in Remote Sensing (RS) and Geographic Information System (GIS) have modified the management of drought, assisting the implementation of respective phase (Belal et al., 2014). Susceptibility assessment developed the zone most vulnerable and early preparations suggest that planned and carried out to mitigate the impact (Keen et al., 2022; Vikram et al., 2015; Naumann et al., 2014). Recent drought research utilizes various indices (e.g., PDSI (Palmer, 1965), SPI (McKee, 1995) and mapping methods, often integrating Remote Sensing (RS) and Geographic Information System (GIS) with models like Multi-Criteria Decision-Making (MCDM) (Mokarram et al., 2021). While Artificial Neural Networks (ANN) are popular for drought susceptibility mapping (Oyounalsoud et al., 2024), they are computationally demanding and complex to interpret (Maier & Dandy, 2000), a drawback addressed by more transparent Fuzzy Logic (Tilmant et al., 2002). Conversely, qualitative methods like AHP introduce bias and require expert knowledge (Palchaudhuri & Biswas, 2016). Statistical methods, particularly Logistic Regression (LR) under Multivariate Statistical Analysis (MSA), are favoured for natural hazard mapping due to their simplicity and speed compared to machine learning (Chen et al., 2017).

Therefore, the main objective of the current study was to generate the extent of drought prone areas in the Barind Tract in the northwestern region of Bangladesh, using the Logistic regression (LR) techniques, under the MSA statistical method. Attempts were made to analyse the impact of the classes of each variable on drought, and extract the correlations within variables, so that the user can perform swift analysis using comprehensible and effective methods.

2. METHODOLOGY

2.1 The Study Area and Data Used

The drought prone area is situated in the northwestern part of the Bangladesh where Sapahar, Porsha, Niamatpur upazila under the Noagaon district, Nachole upazila under the Chapa Nawabganj district, Tanor, Godagari, and Pada upazila including Rajshahi city under the Rajshahi District it bounded by latitude 88º15′0″E and 88º45′0″E, and longitude 24º15′0″N and 25º20′0″N. The study area extends over approximately 2378.23km^2 (Figure 1). The climate condition of the study area is categorized as subtropical monsoon. In accordance with the Bangladesh Meteorological Department (BMD), the maximum temperature at Rajshahi meteorological station from 1981 to 2024, is 43.8°C (April, 1985), and there is an average of 298 days a year with an average temperature of 27°C, and 238 days with an average temperature of 30°C. On the other hand, the periodic mean precipitation at Rajshahi meteorological station, from1981 to 2024, varied between 792mm (2010) to 2241mm (1998). Generally, annual frequency of precipitation is 96 days, and precipitation period from June to September contribute to vast majority (90%) of the annual precipitation. In June and September, the average monthly precipitation ranges from 226mm to 300mm. Also, the typical value of relative humidity at Rajshahi meteorological station is 78%.

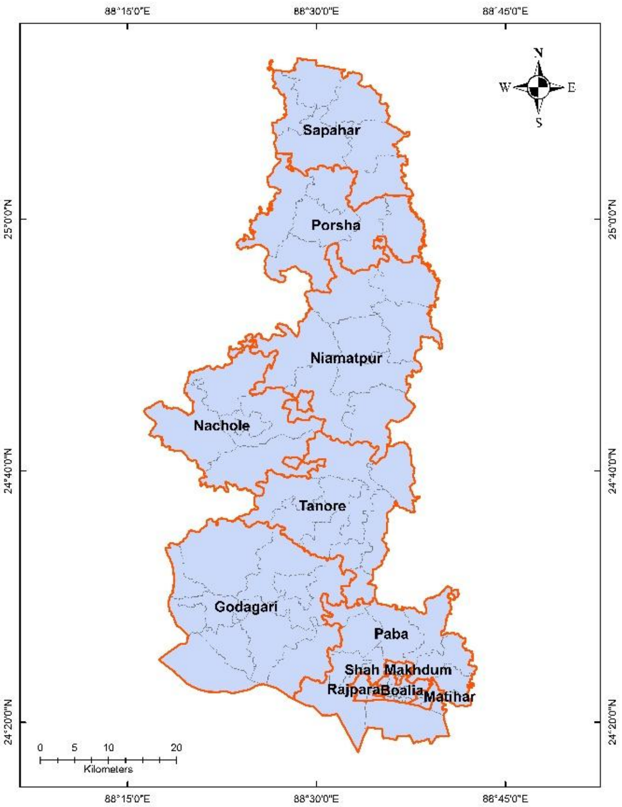

Figure 1. The Barind Tract (the study area) map in the northwest region of Bangladesh

2.2 Drought Inventory Mapping

Accuracy in recording the history of drought events impacts enormously on the accuracy of drought susceptibility mapping (Al-Abadi et al., 2024). One hundred fifty drought location points were selected for inclusion in the inventory map of the study area. Random points were used in the analysis, in that utilizing the polygon format of the inventory is problematic for the algorithm and exaggerates the results. In most of the alike natural hazard modelling recorded data was applied as a point format (Pradhan, 2010; Rahmati et al., 2016). The map was classified into a training set and validation set with a 70% and 30% split, respectively (Ohlmacher & Davis, 2003). Training points (105 points) were chosen at randomly for the generation of the dependent data, including of 0 and 1 weight, with 1 describing the existence, and 0 is the lack of drought. A corresponding of 137 points was identified as non-drought points and specified the 0 value, under the hypothesis that including of non-drought areas would improve the validity.

2.3 Drought Conditioning Factors

The variable preferred for specific study areas heterogeneous based on location characteristics. Although an individual conditioning factor could influence to a significant degree on drought in a specific region, it is possible that it has no impact in another region (Mokarram et al., 2021). These conditioning factors were originated based on field survey and literature sources (Sarkar et al., 2024). The twelve factors influencing drought susceptibility can be broadly grouped into climatic, hydrological, and remote sensing (RS) derived indices and parameters. Climatic factors include both the annual average maximum temperature and annual average rainfall, while hydrological conditions are represented by metrics such as annual average humidity, average annual soil moisture, and the groundwater level (GWL). Remote sensing provides crucial spatial data, with indices like the normalized difference water index (NDWI), normalized difference vegetation index (NDVI), and normalized difference moisture index (NDMI) reflecting surface wetness and vegetation health. Additionally, the land surface temperature (LST), the normalized burn ratio (NBR), the digital elevation model (DEM), and various land use and land cover (LULC) classes all serve as essential conditioning factors. These variables collectively capture the complex interplay of atmospheric, surface, subsurface, and land-use characteristics that govern a region's vulnerability to drought. Figure 2 explain the thematic maps of the variables.

2.4 Drought Susceptibility Modelling

2.4.1 Logistic Regression Model

For drought susceptibility study, logistic regression objective to achieve most appropriate model to describe the connection among the dependent and independent conditioning factors (Pradhan, 2010; Rahmati et al., 2016). In logistic regression, the more independent variables are integrated in the study, the more model is projected to reliable, however when the independent variables have a vital factors in determine the dependent variable (Ayalew et al., 2004). The logistic regression is used to predict the likelihood of a dependent variable outcome based on the value of the independent variable (Hosmer Jr et al., 2013). It is useful for prediction the occurrence of a drought based on several conditioning factors. The geospatial forecast of a drought in logistic regression is modelled weighing dependent and independent conditioning factors (Shirzadi et al., 2012). The factors possible to categorical or numerical or combination types. The occurrence of drought is symbolized by a binary variable (dependent variable). The logistic operations are valid for drought susceptibility analysis if the dependent conditioning factors are binary (Djeddaoui et al., 2017). Here, the dependent factors have coefficients of 0 (zero) and 1 (one), where zero represents no drought on other hand one represents a maximum probability of drought (Dai et al., 2004). The relationship among the drought occurrence and its response variables is described by Equation (1) as follows.

$$P = \frac{1}{1+e^{-z}} \tag{1}$$

where P is the possibility of a drought event, expressed as a value from 0 to 1. The value p is the predicted possibility of drought zone.

The logistic regression is the correlation between the dependent factor and independent factors, which can be depicted through a regression line as described by Equation (2). Where the coefficient β calculates the weight of each independent variable in the model.

$$Z = \beta_0 + \beta_1 X_1 + \dots\dots\dots\dots + \beta_n X_n \tag{2}$$

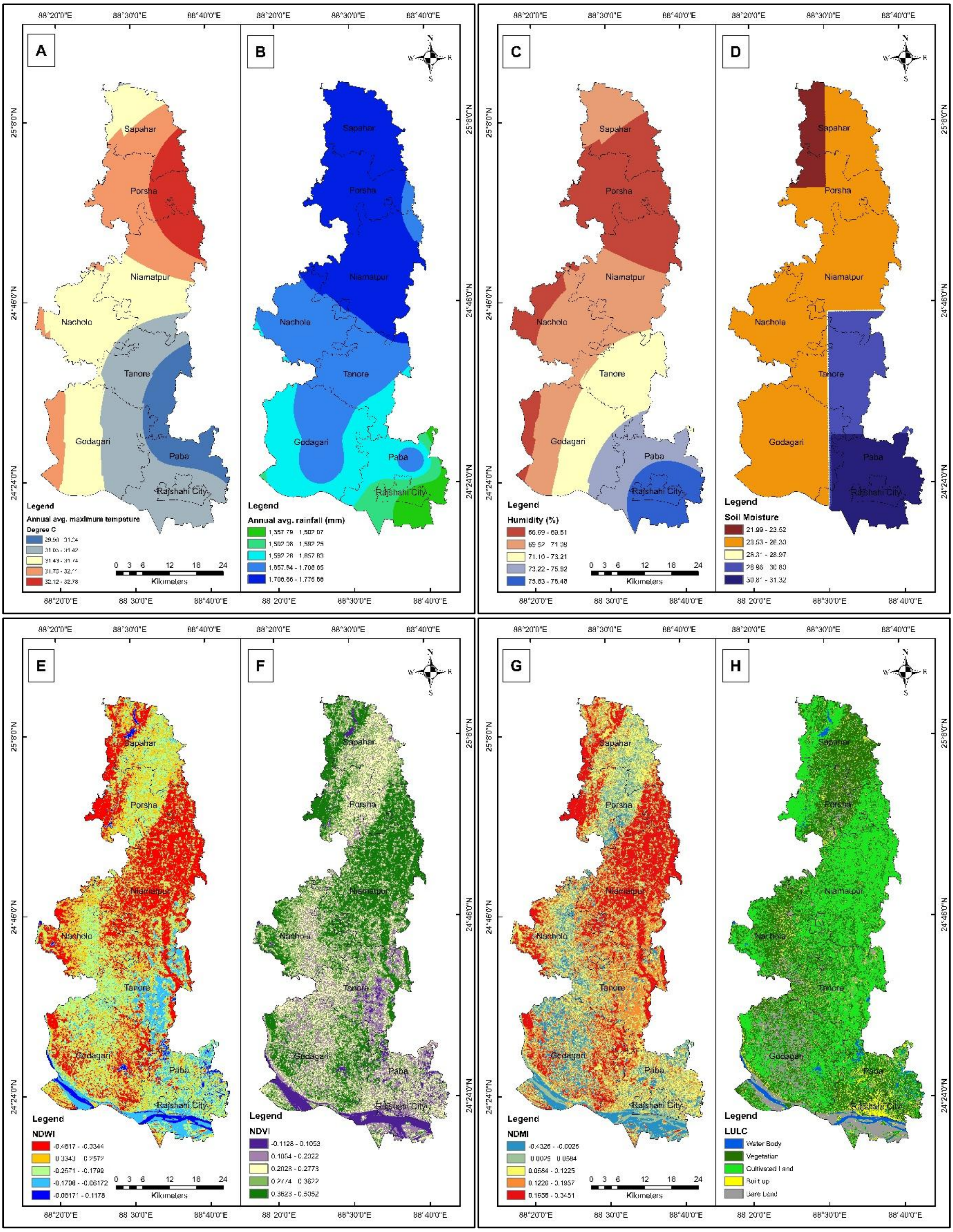

Figure 2: (a) Temperature, (b) Precipitation, (c) Humidity, (d) Soil Moisture, (e) Normalized Difference Water Index (NDWI), (f) Normalized Difference Vegetation Index (NDVI), (g) Normalized Difference Moisture Index (NDMI), (h) Land Use And Land Cover (LULC), (i) Normalized Burning Ratio (NBR), (j) Land Surface Temperature (LST) (k) Groundwater Level (GWL) and (l) Digital Elevation Model (DEM) (*Continued……*)

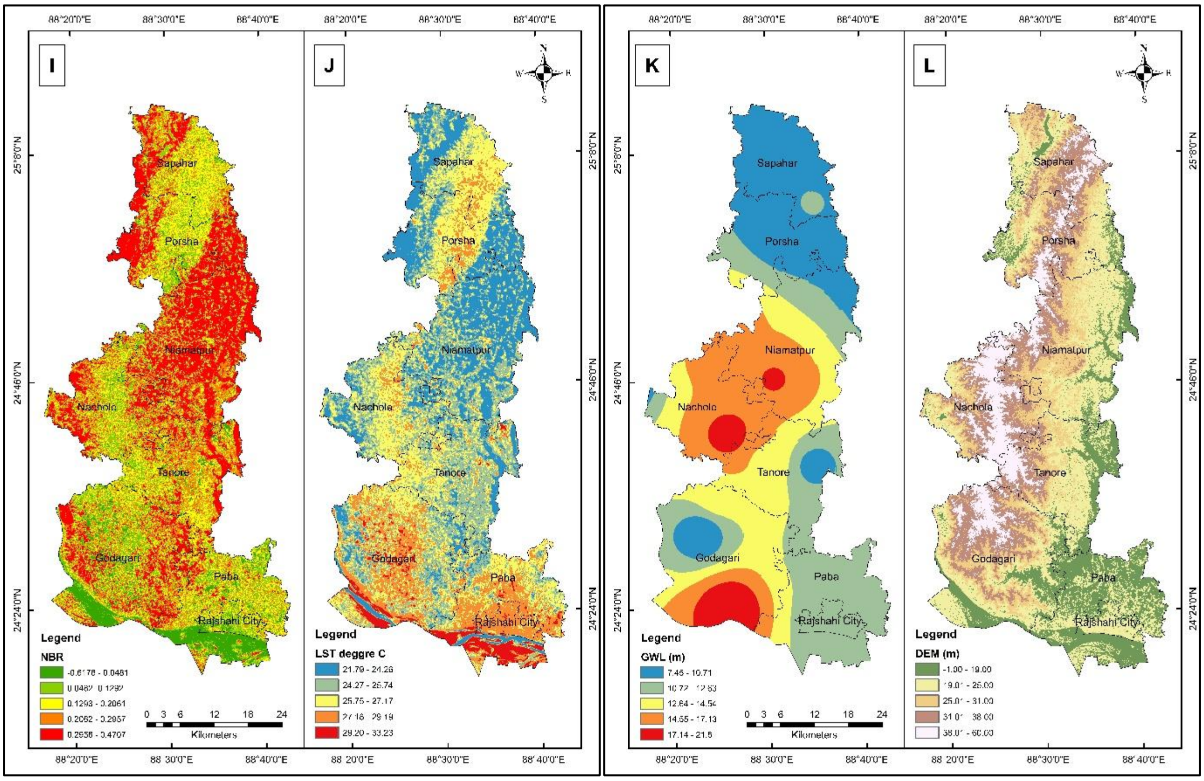

Figure 2: (a) Temperature, (b) Precipitation, (c) Humidity, (d) Soil Moisture, (e) Normalized Difference Water Index (NDWI), (f) Normalized Difference Vegetation Index (NDVI), (g) Normalized Difference Moisture Index (NDMI), (h) Land Use And Land Cover (LULC), (i) Normalized Burning Ratio (NBR), (j) Land Surface Temperature (LST) (k) Groundwater Level (GWL) and (l) Digital Elevation Model (DEM).

3. RESULTS AND DISCUSSION

3.1 Logistic Regression Results

A logistic regression model was formulated and executed using the ArcGIS 10.8 software to regulate the probability of drought. The coefficient of the related decision variable (temperature, rainfall, humidity, soil moisture, NDWI, NDVI, NDMI, LULC, NBR, LST, GWL, and DEM) is shown in Table 1 and Equation (3). As can be seen from the table, most of decisive variables are significantly related with the dependent variable with 5% significance level. Thus, these variables were used to derive the regression relationship between independent and decisive variables as given by Equation (3), which are then applied to predict the drought in GIS to achive the susceptibility map. The model findings were subsequently used to generate a drought susceptibility map in a GIS environment. The sign of a variable coefficient indicates its relationship with drought probability (Chung & Fabbri, 2003). A positive sign suggested the conditioning factors accelerates the probability of a drought, while a negative sign implies it decreases this probability.

$$z = -1.1525 + (0.0055 \times Temperature) + (0.0007 \times Rainfall) + (-0.0211 \times Humidity) + (0.0284 \times Soil\ moisture) + (1.6217 \times NDWI) + (3.0568 \times NDVI) + (0.8047 \times NDMI) + (-0.0170 \times LULC) + (-2.1646 \times NBR) + (-0.0330 \times LST) + (0.0854 \times GWL) + (0.0180 \times DEM) \quad (3)$$

The model achieved a coefficient of determination (R^2) of 0.91, indicating that the independent variables collectively account for 91% of the drought occurrence. As can be seen from Table 1, the significance level (Sig. *R*) for each independent variable was also measured from the model. According to Papadopoulou-Vrynioti et al. (2013) a variable with a Sig. *R*-value below 5% is considered to have a significant effect on drought. The results demonstrate that the rainfall, soil moisture, NBR, LST, GWL variables exhibit 5% level of significance with values of 0.000102, 0.000000, 0.000002, 0.000035, and 0.000000, respectively. Other independent variables, such as LULC, and humidity have less impact on drought occurrence as the others.

Table 1. Results on logistic regression coefficients and significance tests

Name of Variables	**Coefficient**	**t-Statistic**	**Sig. *R***	**VIF**
Intercept (C)	-1.1525	-1.5522	0.120778	-
Temperature	0.0055	0.7614	0.446479	1.1299
Rainfall	0.0007	3.9150	0.000102*	3.2997
Humidity	-0.0211	-3.1759	0.001530*	5.4274
Soil moisture	0.0284	6.6972	0.000000*	2.7347
NDWI	1.6217	1.8565	0.063521	130.5277
NDVI	3.0568	3.4873	0.000513*	171.5656
NDMI	0.8047	2.7502	0.006007*	14.0801
LULC	-0.0170	-1.0799	0.280308	5.2096
NBR	-2.1646	-4.9329	0.000002*	45.1874
LST	-0.0330	-4.1861	0.000035*	3.7568
GWL	0.0854	28.5226	0.000000*	1.1106
DEM	0.0180	16.0877	0.000000*	1.6482
White (standard error of regression)		0.169		
Probability (F-statistic)		0.000		
R^2		0.91		

Note: Level of significance are defined as $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$, respectively.

3.2 Drought Susceptibility Assessment and Mapping

The results of drought susceptibility mapping, which was created using an integrated model and employed the natural breaks (Jenks) classification method to delineate foure distinct risk categories. The map, Figure 3, visually portrays the spatial arrangement of these drought classes across the study area. The severity is classified into mild drought, moderate drought, severe drought, and extreme drought. The quantification in Table 2 indicates that the largest single zone of vulnerability is the moderate drought category, which covers the greatest percentage of the entire study area. Following this, the severe drought zone represents the second largest extent, while the mild drought area covers a comparable, slightly smaller proportion of the region. The smallest, yet most critical, zone in terms of intensity is the extreme drought category, which still accounts for a vital part of the total area mapped. The map reveals a highly complex spatial pattern of drought vulnerability rather than a simple gradient, offering a detailed understanding of the regional hazard distribution.

Table 2. Outline of the drought susceptibility zones

Drought Category	**Area Covered (%)**
Mild Drought	19.84
Moderate Drought	37.15
Severe Drought	23.66
Extreme Drought	19.35

3.3 Model Validation and Accuracy Assessment

The validation of a drought susceptibility map is essential for determined zone vulnerable to future drought. This process applies past known drought area that were deliberately excluded from the models training to ensure an unbiassed assessment. For this validation, the Receiver Operating Characteristics (ROC) method was worked with the Area Under the Curve (AUC) providing as the key metrics to assess the accuracy of the map, among was formulated using logistics regression (Pradhan, 2010). The validation of the drought susceptibility map of the study area is shown in Figure 4. As can be seen from the figure, the ROC model showed two individual rates: the success rate, which applies the training datasets and the prediction rate which operate the testing datasets. An overall precision of 86.7% was obtained by the logistic regression model, which demonstrates the the validity of the model for drought susceptibility assessment with reasonable accuracy.

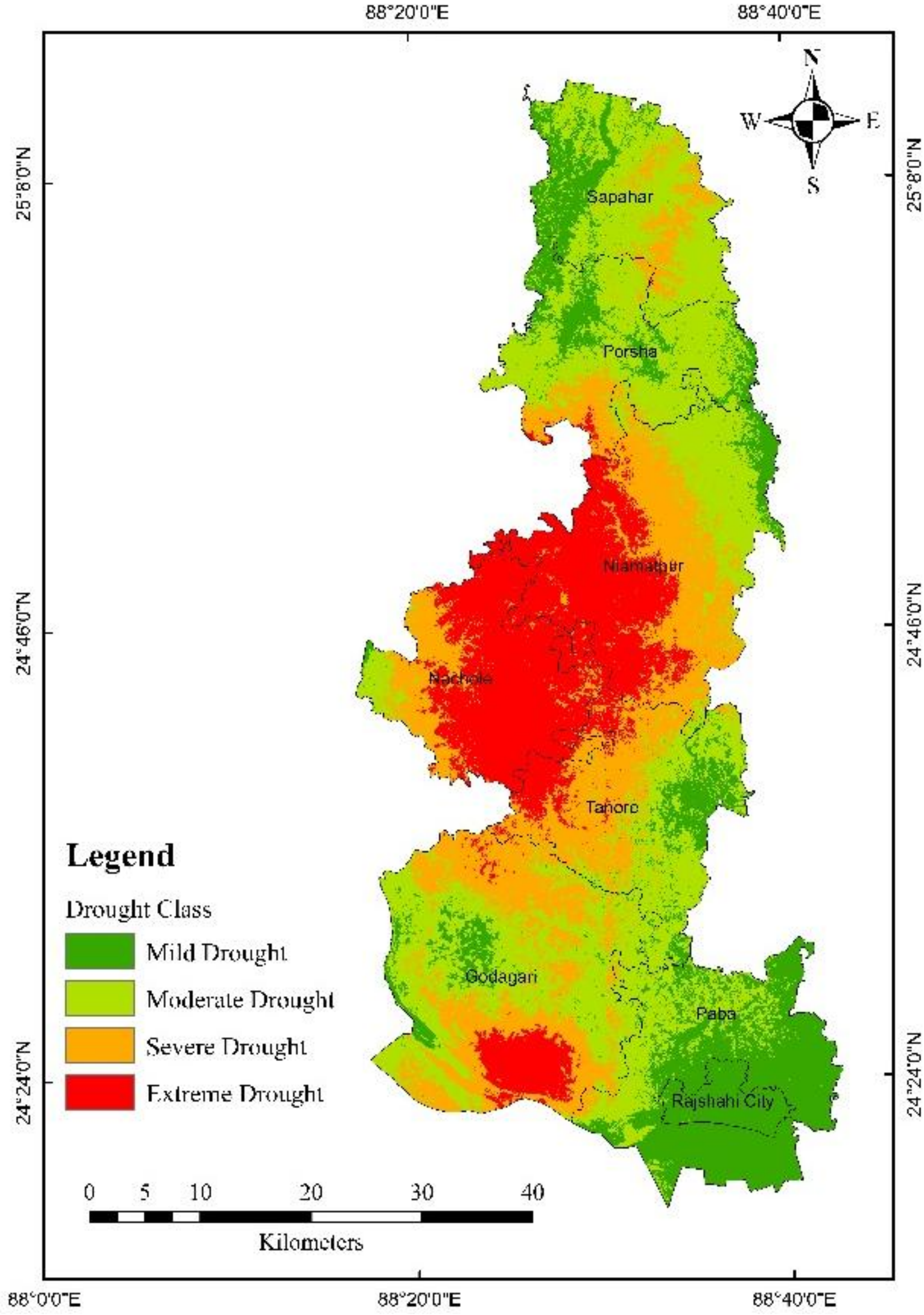

Figure 3. Drought susceptibility map of the study area

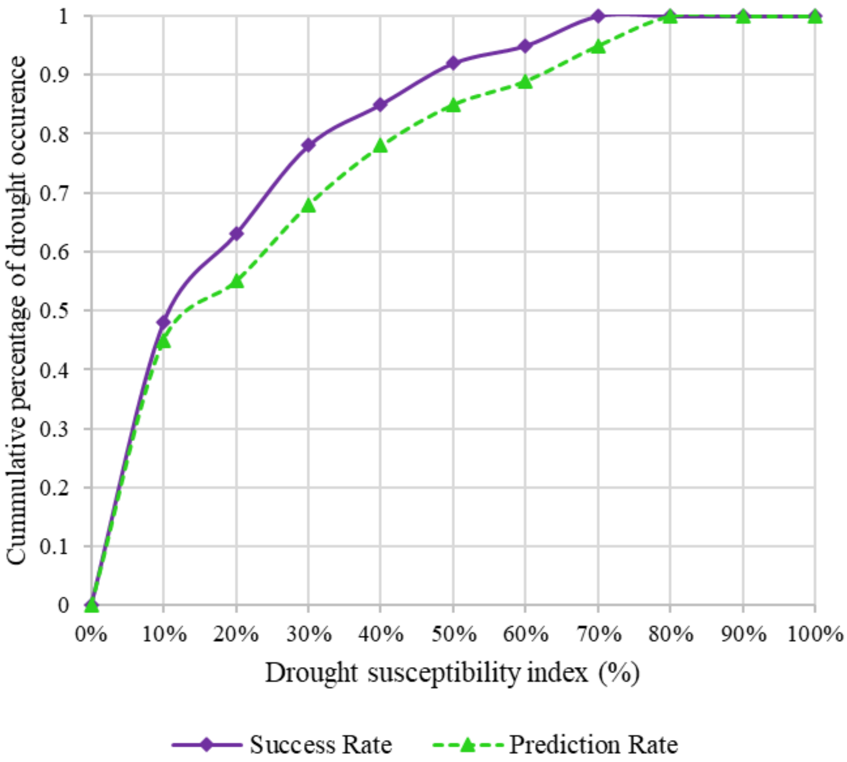

Figure 4. Validation of the drought susceptibility map of the study area

4. CONCLUSIONS

The research presents a robust drought susceptibility assessment for northwestern Bangladesh through the integration of geospatial analysis and Logistic Regression (LR) techniques. The overall model showed statistical significance, but diagnostics revealed challenges, including multicollinearity among remote sensing factors (NBR, NDVI, NDWI) and non-normal residuals (Jarque-Bera Statistic), while the adjusted R^2 value reached 0.91. Key climatic and hydrological factors, such as Temperature, Rainfall, Groundwater Level (GWL), and Soil Moisture, along with remote sensing indices like LST and NBR, emerged as dominant determinants of drought vulnerability, while the correlation and influence of these conditioning factors were thoroughly analysed. Approximately 37.15% of the region was classified as Moderate Drought, with the severe and extreme categories accounting for significant portions, collectively underscoring the urgency for targeted drought mitigation and adaptation strategies. The findings provide critical spatial evidence to inform disaster risk management and sustainable agricultural planning in the region. Future research should incorporate advanced machine learning or geo-statistical methods (beyond OLS/LR) to better handle complex factor relationships and non-stationarity, aiming to produce more accurate and robust susceptibility maps.

DECLARATION OF USE OF AI

We declare that AI was used in this paper only for language refinement, grammar correction, and improving clarity in cases where it was deemed necessary. However, no AI tools were used for research design, methodological framework development, data analysis, interpretation of results, and/or writing discussion. We also declare that all relevant research design ideas, software operation, generation of results and its presentation in Tables and Figures in the current paper are the authors' own work.

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