Applied Water Science (2025) 15:224
https://doi.org/10.1007/s13201-025-02584-1

ORIGINAL ARTICLE

Groundwater sustainability assessment and desertification susceptibility mapping in semi arid Bangladesh using integrated remote sensing and logistic regression modeling

Ragib Mahmood Shuvo[1] · Radwan Rahman Chowdhury[1] · Sanchoy Chakroborty[1] · Anutosh Das[1,2] · Abdulla Al Kafy[3] · Hamad Ahmed Altuwaijri[4] · Tekalign Ketema Bahiru[5]

Received: 23 January 2025 / Accepted: 10 July 2025

Abstract

Groundwater depletion poses a serious threat to water security in arid regions worldwide, risking sustainable water resources and agricultural stability. This study examines groundwater dynamics and water resource sustainability in the arid Barind Tract of Northwest Bangladesh using integrated remote sensing techniques and logistic regression modeling. It employed three key indices to assess water resource vulnerability: Normalized Difference Vegetation Index, Topsoil Grain Size Index, and Aridity Index, integrating them through logistic regression to evaluate desertification susceptibility and water sustainability. The regression model boasts an ROC value of 96.22% and R^2 of 0.3893, indicating good classification performance with acceptable class variance. Results show that 82.66% of the area faces significant water resource challenges, with 6.27% (103.26 km^2) at very high risk, 10.80% (177.89 km^2) at high risk, and 28.17% (464.05 km^2) at moderate risk. The northern regions, especially Porsha, Gomastapur, and Nachole Upazillas, are the most vulnerable to water depletion. The study recommends sustainable water management strategies, including surface water use through floating pontoons and rubber dams, emphasizing the urgent need for integrated water resource management to ensure long-term water security. Additionally, the research analyzed soil-vegetation feedback using rain use efficiency and found a negative loop in highly desertification-prone areas like Porsha and Nachole, indicating the need for regulation-based cropping practices and improved water governance in zones at risk of desertification to reduce crop-water redundancy. This research offers valuable insights for water resource planning and management in arid regions, supporting sustainable water governance and locally-led adaptation strategies for water-stressed environments.

Keywords Groundwater management · Remote sensing · Arid region hydrology · Desertification susceptibility · Logistic regression modelling

✉ Abdulla Al Kafy
abdullaalkafy@utexas.edu;
abdulla-al.kafy@localpathways.org

✉ Tekalign Ketema Bahiru
tekalign.ketema@obu.edu.et

Ragib Mahmood Shuvo
rmshuvo2507@gmail.com

Radwan Rahman Chowdhury
radwanrahman25.RR@gmail.com

Sanchoy Chakroborty
sanchoy.bitto@gmail.com

Anutosh Das
anutosh@urp.ruet.ac.bd

Hamad Ahmed Altuwaijri
haaltuwaijri@ksu.edu.sa

1 Department of Urban and Regional Planning, RUET, Rajshahi 6204, Bangladesh

2 Fire and Emergency Management Program, Division of Engineering Technology, Oklahoma State University, Stillwater, OK 74078, USA

3 Department of Geography and the Environment, The University of Texas at Austin, Austin, TX 78712, USA

4 Department of Geography, College of Humanities and Social Sciences, King Saud University, 11451 Riyadh, Saudi Arabia

5 Department of Geographic Information Science, Oda Bultum University, Chiro, Ethiopia

Introduction

Desertification is a challenging environmental problem with significant social and environmental implications that has generated debate in a number of areas (Thomas 1997). Desertification has usually been seen as a gradual change in the amount of life in dry, semi-dry, and semi-humid ecosystems. Groundwater is one of the biggest factor that dictates the possibility of future desertification (Santos et al. 2022). Loss of groundwater resources can include changes like a loss of agricultural productivity or, more dramatically, the replacement of one plant species with another that may be just as productive or helpful, or even a decrease in the density of the existing plant cover (Hare 1984). Drought, deforestation, climate change, human activity, or improper agriculture can all contribute to desertification, the deteriorating phase in which once-productive land changes into a desert by losing its flora and wildlife.

There are numerous instances of desertification possibilities which have been studied globally. Drought-prone regions of different countries from Asia and Africa exhibit similar desertification trends which eventually pose threat towards livability within those regions (Martínez-Valderrama et al. 2018; Mihi et al. 2022a; Eskandari Dameneh et al. 2021; Al-Obaidi et al. 2022; Kalyan et al. 2021; Zhao et al. 2006; Wijitkosum 2021). Semiarid regions of north Mediterranean, southern Africa, north and south America, which are most likely to be expanded are facing tremendous risk of desertification (Jain et al. 2024). Alongside, the Asian regions, with possibilities of dryland shrinkage are in huge risk of reduction in ecosystem services compounded by desertification, water shortage and hydroclimatic abnormalities (Jain et al. 2024).

Initiatives to map and monitor desertification processes using remote sensing (RS) commenced over thirty years ago in various climate-vulnerable locations. The ability to generate precise, specific, and extensive assessments of several underlying elements of desertification by remote sensing has been appreciated globally. RS-led outputs can be compartmentalized into multi-decision analysis, assisting in long-term decision making (Zhao et al. 2006; Lamqadem et al. 2018; Wei et al. 2018; Djeddaoui et al. 2017). Initially, assessment of vegetation index was used by most researchers to identify desertification susceptibility. Gradually, more underlying factors like, soil particle composition, aridity, surface albedo, soil and water salinity, were included in desertification analysis based on differential contexts of the semi-arid and arid regions (Wijitkosum 2021; Lamqadem et al. 2018; Wei et al. 2018; Djeddaoui et al. 2017; Mihi et al. 2022b; Hadid and Ahmed 2024; Kairis et al. 2014).

The Barind tract (BT) in northwest Bangladesh has a heterogenic characteristic in terms of landform, topography, hydrology and climatic perspectives, making one of the climate and resource vulnerable regions of Bangladesh. It is a hard red-soil region with an elevated topography, having higher temperatures and evaporation than the rest of the country. This area's surface water availability is likewise limited due to its geographical position. This dry terrain receives the least amount of precipitation each year in Bangladesh, averaging around 1500 to 2000 mm annually (Imon and Ahmed 2013). It is commonly assumed that the Tract formed as a result of tectonic uplift and/or existing as an erosional geomorphic feature (Rashid et al. 2015). The firm red Pleistocene clay soil of this region contributes significantly to periodic droughts and subsequent desertification possibilities, pushing 5.6 million people towards risk of food insecurity.

Despite numerous studies on groundwater fluctuations in the region (Rahman et al. 2017; Hossain et al. 2020; Das et al. 2021; Shuvo et al. 2024), there remains a substantial gap in understanding how these fluctuations directly impact the risk of desertification, particularly in the BT. This study aims to address this gap by identifying groundwater fluctuations and predicting potential desertification areas. This study will assess the temporal groundwater fluctuation and vegetation, soil particle properties, and climatic components of desertification by remote sensing approaches, combined with logistic regression modelling to forecast desertification susceptibility of the selected study area. Alongside, a number of viable strategies will be proposed to safeguard effective decision-making in the BT.

This study advances groundwater hydrology by integrating remote sensing techniques with logistic regression modeling, offering a comprehensive understanding of groundwater fluctuations and new methodologies for similar studies. The findings have significant implications for sustainable water management and policymaking in the BT, informing targeted interventions to mitigate ecological crises and ensure food security. This research highlights the urgent need for sustainable groundwater management, crucial for achieving the Sustainable Development Goals (SDGs) in vulnerable regions and serves as a model for other areas facing similar challenges.

Materials and methods

Study area

BT is a geographical designation for a portion of Bangladesh's larger Rajshahi, Nawabganj, Dinajpur, Rangpur, Joypurhat, Gaibandha, and Bogra districts, as well as West Bengal's Indian territorial Maldah district. It is situated at a higher elevation than the surrounding floodplains. There are two terrace levels, one at 40 m and the other between 19.8

and 22.9 m, according to the Tract's layout. Consequently, even when the monsoon floodplains are flooded, BT remains dry and is drained by a few tiny streams. BMDA has categorized BT into three groups based on its elevation and the availability of groundwater (Das et al. 2021). The high BT (HBT) lands are chosen as the study location because they are expected to bear the brunt of the groundwater's negative effects.

The study area was thoughtfully selected to encompass various administrative units, including the HBT and the Upazillas (sub-districts) of Nachole, Gomastapur from Nawabganj District, Porsha of Naogaon District, and Godagari, Tanore within the and Rajshahi districts in Bangladesh (Fig. 1). Despite their close geographical proximity, the deliberate inclusion of these multiple administrative units allows for a nuanced examination of potential variations in environmental and socio-economic factors. This strategic selection enhances the study's ability to draw meaningful conclusions about the factors under investigation by considering the broader context of the region (Ahmeduzzaman et al. 2012).

Channel migration, in especially the movement of the Tista and the Atrai and their distributaries over the past few centuries, has had a profound impact on the local climate. Temperatures and humidity have risen because to geological changes. In the warmest season, the average temperature is between 25 and 35 °C, and in the coolest season, it is between 9 and 15 °C. Some of the hottest days of summer

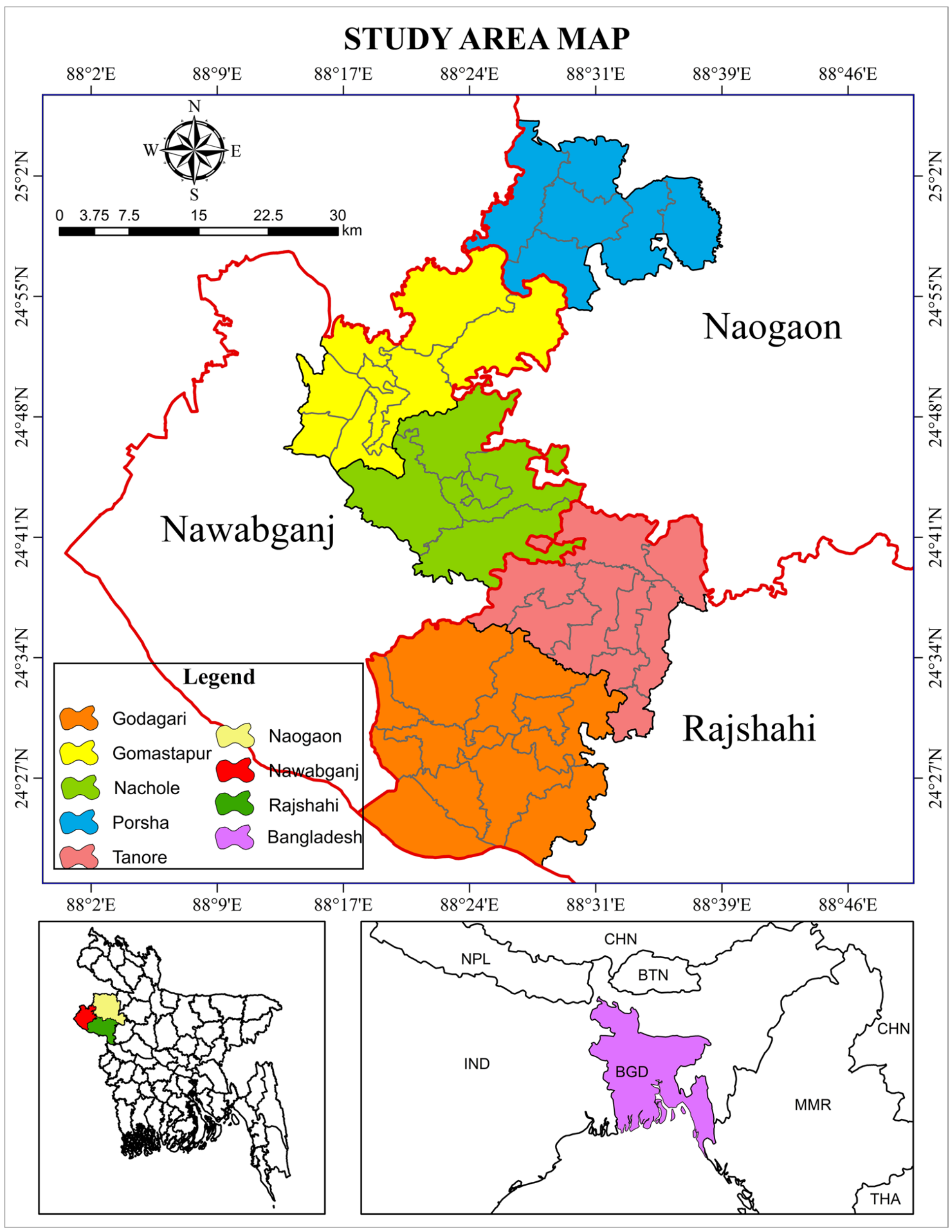


Fig. 1 Study area map

have temperatures of 45 °C or even higher (Hossain et al. 2020, 2019).

Research methodology

Desertification, as defined by the international community, is "land degradation in arid, semiarid, and dry sub-humid areas, which is primarily caused by human activities and to climate variations". Multiple interacting factors have an impact on the desertification process. The primary causes of desertification are human activity, soil degradation, climate change and vegetation loss. It is difficult to map the risk of desertification because of the complexity of the factors to be considered and the lack of available information. Based on prior study methodologies, three theme levels were used to map the desertification susceptibility. These are the normalized Difference Vegetation Index (NDVI), Topsoil Grain Size Index (TGSI) and Aridity Index (AI) (Kalyan et al. 2021; Wijitkosum 2021; Becerril-Piña et al. 2015; Hereher and El-Kenawy 2022; Ozgul and Dindaroglu 2021). The BT, with its unique tendency of agriculture-dependency within water-scarce region, specifically degrades available groundwater (GW) resources, along with erosion in soil properties (Rahman et al. 2017; Hossain et al. 2020; Aziz et al. Jan. 2015). The BT has a very low GW recharge potential, with almost 85% of the HBT has low recharge potential (Adham et al. 2010). Alongside, merely 8.6% of total precipitation recharges into GW table annually with 3 m of table declination (Adham et al. 2010). The same region has 54% of the total land area utilized for double cropping, while 34% is allocated for triple cropping (Hossain et al. 2019). The above-mentioned statements indicate the severe GW and soil degradation over the years, highlighting the justification of selecting NDVI and TGSI within the study. Additionally, the BT receives a very low annual rainfall and high evapotranspiration due to its topographical characteristics. Such a circumstance of combined climatic and human-induced attributes justified the selection of AI as one of the factors for desertification susceptibility (Aftabuzzaman et al. 2013; Rahman et al. Feb. 2016; Rahman and Mahbub 2012). The data sources and types required for mapping the selected indicators are briefed in Table 1.

In dry and semi-arid regions, one of the primary contributors to desertification is the absence of natural vegetation (also known as deforestation) (Martínez-Valderrama et al. 2018). The NDVI allows researchers to distinguish ecosystem functional categories or biozones, estimate annual net primary production (ANPP) at various global scales, and differentiate land cover at the regional and global levels (Paruelo et al. 2001; Running 1990). In the field of ecosystem monitoring, the NDVI, also known as the normalized reflectance difference between the near-infrared (NIR) and visible red bands, is being used rather frequently (Eq. 1) (Rouse et al. 1974).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

Various degrees of desertification lead to the formation of distinct topsoil textures. The severity of desertification increases as the surface soil particle composition becomes coarser (Wang et al. 2006). As a result, Topsoil Grain Size Index (TGSI) is suggested as an assessment tool for soil degradation (Liu et al. 2018). Xiao et al. (2006) developed the Topsoil Grain Size Index to evaluate top soil texture and soil erosion in Asia's semi-arid regions. TGSI is calculated as follows:

$$TGSI = \frac{RED - BLUE}{RED + BLUE + GREEN} \quad (2)$$

where, blue, red, and green are the bands of remote sensing data. The TGSI was found to compensate for the NDVI's shortcoming in capturing soil moisture variability, suggesting that it might be used to identify prospective vegetation establishment regions (Kim et al. 2020). Even though the majority of the studies implemented NDVI, the Bare Soil Index (BSI), or the proportion of total grass cover to assess desertification by identifying changes in vegetation or bare soil cover, these indices are heavily reliant on rainfall which has high temporal and spatial variability as well as uncertainty in arid regions.

Table 1 Accrued data and source

Analysis	Required data	Data source	Band usage	Timeline
NDVI	Landsat 9 Satellite image	US Geological Survey (https://earthexplorer.usgs.gov)	4, 5	2022
TGSI	Landsat 9 Satellite image	US Geological Survey (https://earthexplorer.usgs.gov)	2, 3, 4	2022
AI	Monthly rainfall data	Bangladesh Water Development Board (BWDB)	N/A	2017–2021
	Monthly temperature data	Data Access Viewer (https://power.larc.nasa.gov/data-access-viewer/)	N/A	2017–2021
GW fluctuation	Ground water table level	Barind Multipurpose Development Authority (BMDA)	N/A	2017–2021

AI is calculated by dividing the amount of projected evaporation by the amount of expected precipitation (Eq. 3) (Greve et al. 2019). AI categorizes climate conditions in respect to water accessibility. Calculating AI exhibits the impact of climatic factors on the local hydrological cycle, water resource management, and environment, highlighting the main reason behind selecting AI as one of the three indicators of desertification analysis (Liu et al. 2013).

$$AI_U = P/PET \tag{3}$$

where PET stands for potential evapotranspiration and P represents average annual precipitation (Middleton and Thomas 1992). Evapotranspiration data in this study were computed using the 'R' software with the SPET package, which uses the Penman–Monteith equation.

The outputs of the three above-mentioned indices were overlayed and amalgamated by logistic regression modelling to produce the desertification susceptibility map, showing the ranking of the vulnerable areas having a greater probability of future desertification. The goal of LRM is to choose the best model to characterize the connection between the occurrence of desertification and its risk in the context of risk mapping (dependent variable) and several indicators, including NDVI, TGSI, AI, and APSE (independent variables). For this model to work, all indices must be standardized to a byte-level range. Model validation was conducted using a 70–30 split approach, where 70% of the data was used for training and 30% for testing. Additionally, k-fold cross-validation (k = 5) was performed to assess model stability. The high ROC value of 96.22% was consistently achieved across all validation folds, confirming model robustness. The ROC and R^2 values for the logistic regression model are 96.22% and 0.3893, respectively. Good results are shown by an R^2 value of 1, whereas the absence of any correlation is indicated by an R^2 value of 0. For a very good fit, R^2 greater than 0.20 is required (Clark and Hosking 1986). These data suggest that the method of logistic regression gives adequate results. Finally, the logistic regression equation is established (Eq. 4). Equal intervals were utilized in order to properly categorize the final synthetic map of desertification risk (Mihi et al. 2022a). Due to inconsistency in spatial data availability on anthropogenic interactions on arid regions and low reliability of locally available database, APSE was finally excluded from this research. Nevertheless, the established regression equation can be of a greater potential if there is availability of authentic data regarding APSE.

$$\begin{aligned}\mathrm{Logit(Desertification)} = &-237.7689 + (0.355944 \times \mathrm{Topsoil\ Grain\ Size\ Index}) \\ &+ (0.014675 \times \mathrm{Normalized\ Difference\ Vegetation\ Index}) \\ &+ (0.570812 \times \mathrm{Aridity\ Index}) - (0.003177 \times \mathrm{Anthropic\ Pressure\ on\ the\ Steppe\ Environment})\end{aligned} \tag{4}$$

The results from desertification susceptibility assessment can be validated and supplemented with the help of soil-vegetation feedback theory which exhibits positive or negative feedback for crop-water use efficiency in the study area. Numerous studies applied remote sensing database to obtain soil-vegetation feedback where degradation in vegetation pattern is heavily correlated with subsequent losses in water and soil potential within semi-arid and arid regions (Mayor et al. 2013; Lejeune et al. 2002; Caylor et al. 2006; Couteron and Lejeune 2001; Casper et al. 2003). To study the soil-vegetation feedback, global researchers implemented a number of methods like HORAS model (Quevedo and Francés 2008), rainfall gradient and soil moisture component analysis (D'Odorico et al. 2007), PI model (Couteron and Lejeune 2001), Rain-Use Efficiency (RUE) assessment (Houérou 1984; Liu et al. 2024) and several approaches aided by remote sensing data. Based on the available data for this study and its applicability related with global studies, the RUE approach seemed appropriate as it studies the gradual declination of vegetation based on annual average or seasonal rainfall, the factor which severely affects the BT, and has been applied in similar conditions like this in different studies (Houérou 1984; Liu et al. 2024; Higginbottom and Symeonakis 2014; Ruppert et al. 2012). The RUE is calculated by the following equation:

$$RUE = \frac{Mean\ NDVI(Growing\ Season\ or\ Kharif)}{Annual\ or\ Seasonal\ Rainfall(mm)} \tag{5}$$

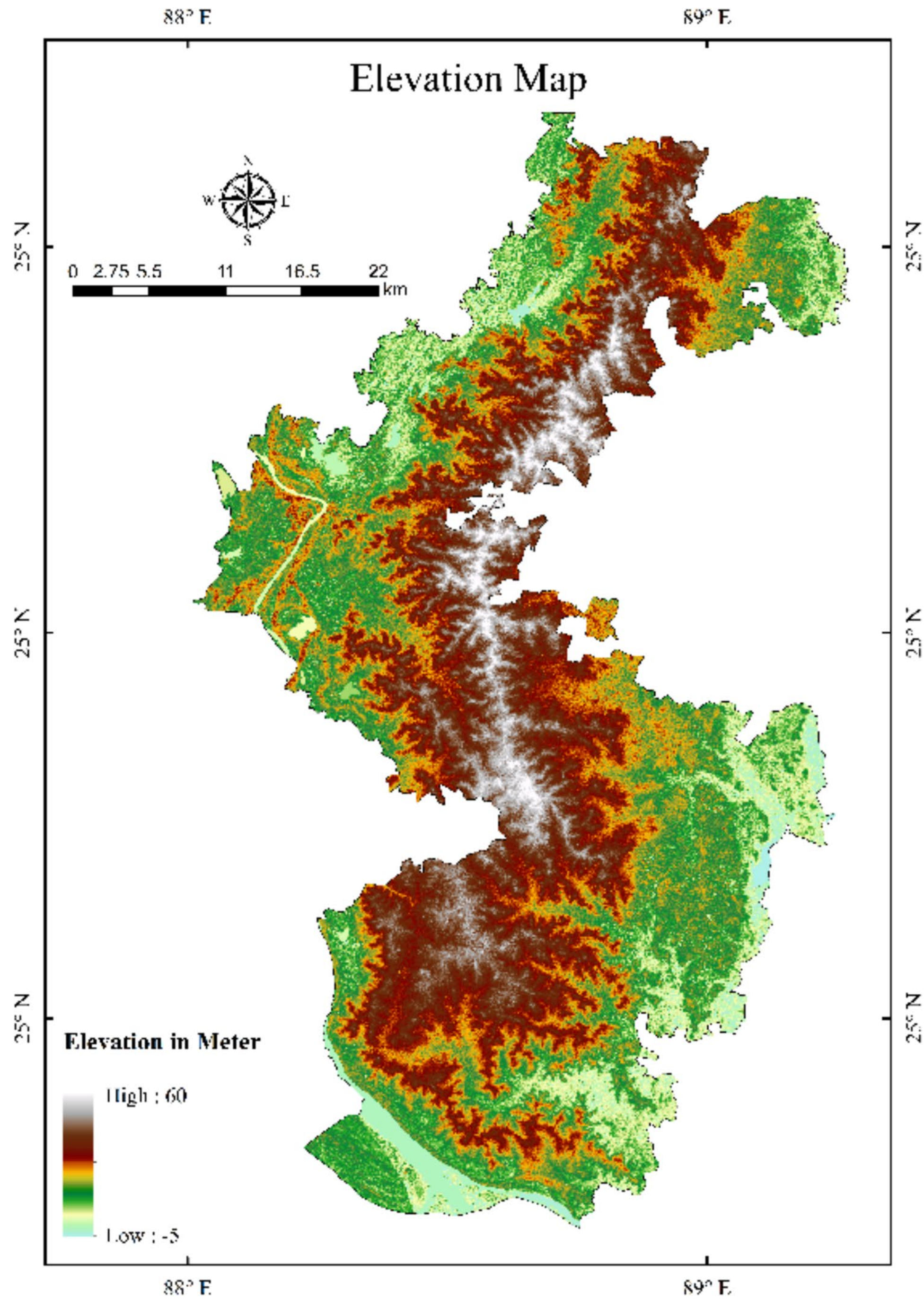
Results

Analysis of the land and water dynamics of BT

BT is situated in a zone free from flooding because of its high elevation, making it more susceptible to drought (Rahman et al. 2017). The elevation map (Fig. 2) highlights the natural undulation and unusual land dynamics of BT, which rise up to 60 m above sea level. These results in high exposure to heat, evaporation, and challenges in groundwater recharge. The resulting effect of the land dynamics is justified by the irregular fluctuation of groundwater in the study region.

The groundwater fluctuation map (Fig. 3) shows a brief about the pre-monsoon water level fluctuation throughout the study area. Only Godagari Upazilla is within the availability of surface water and hence has a range of groundwater

Fig. 2 Elevation map of the study area



level rise (Table 2). Other than this, the elevation goes higher along Tanore–Nachole–Gomastapur–Porsha. The recent 5-year analysis shows a glimpse of how these changes in exacerbate over the decades (Table 2).

The findings reveal an enormous difference in groundwater behavior. Porsha had the highest average fluctuation (5.56 m) and maximum value (6.52 m), as well as the largest standard deviation, indicating severe volatility in groundwater levels. Gomostapur and Nachole have relatively high fluctuation values, indicating persistent extraction pressure. In contrast, Godagari and Tanore, both near the Padma River, had significantly lower fluctuation magnitudes, with Godagari having the lowest mean (0.22 m) and standard deviation (0.33 m), indicating more stable groundwater conditions supported by surface water sources. Such variations highlight the importance of specialized water management techniques that are customized to each region's hydrological context.

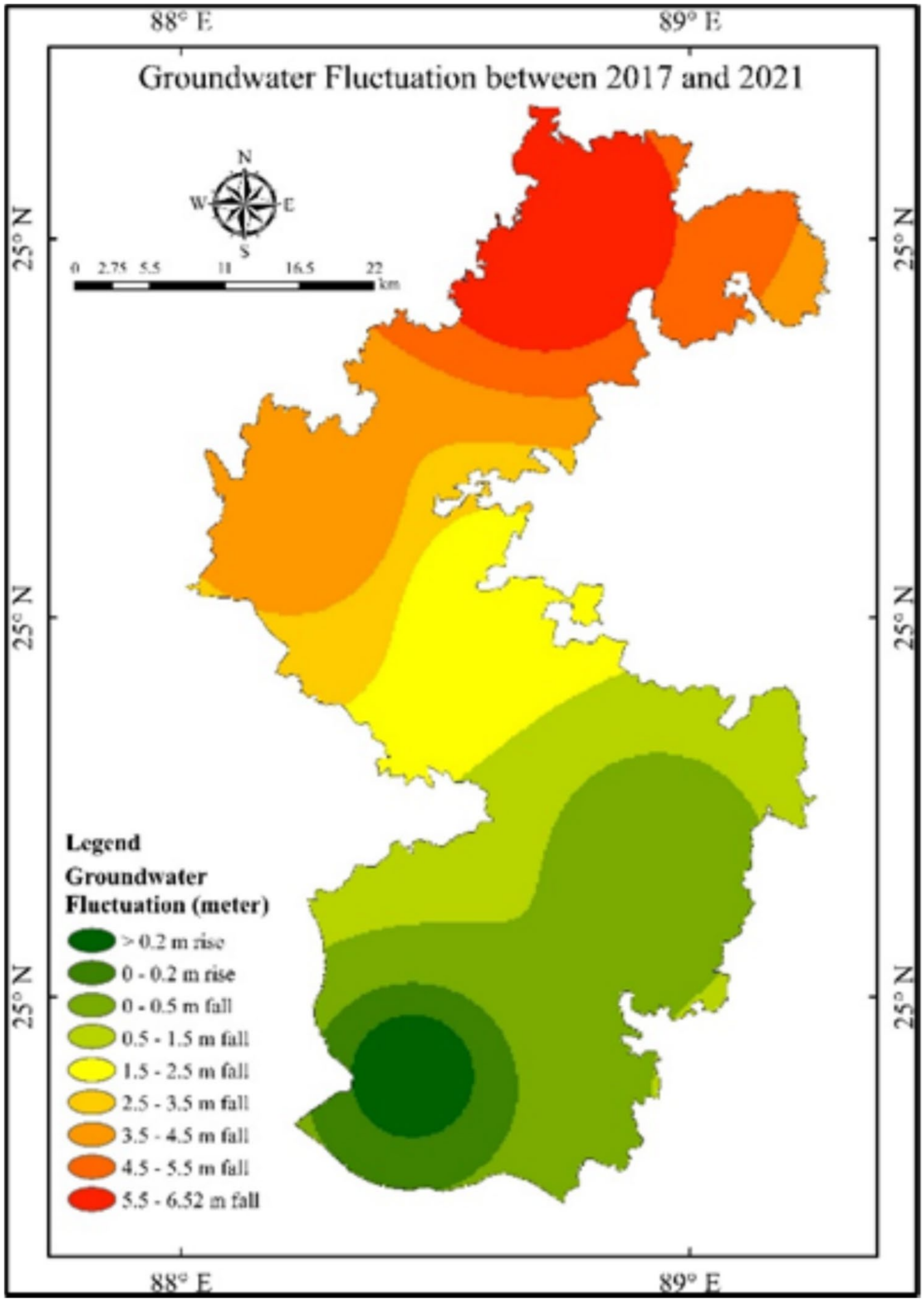


Fig. 3 Groundwater fluctuation map of the study area

Table 2 Groundwater fluctuation statistics of the study area

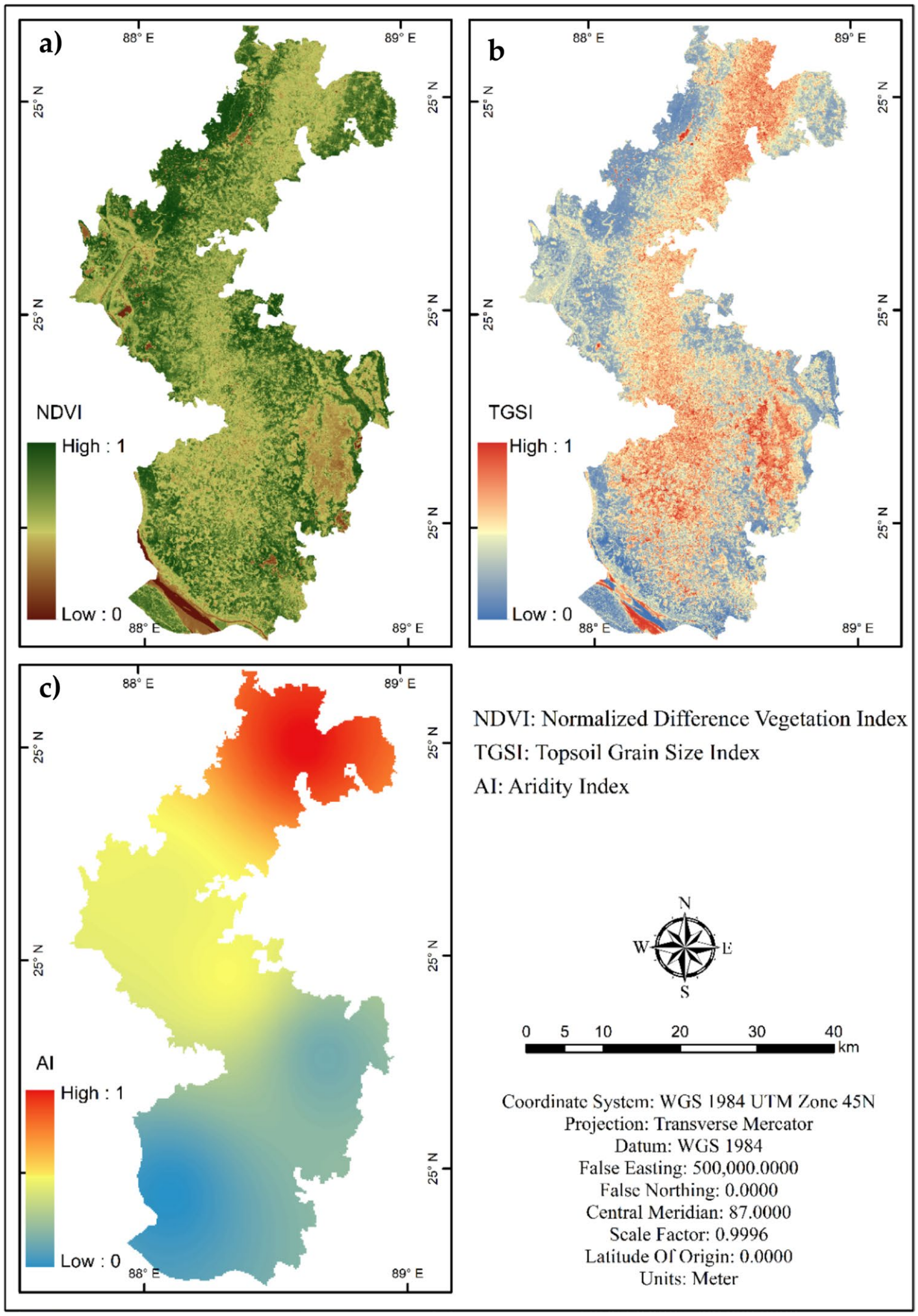
Upazila	Mean fluctuation (m)	Maximum fluctuation (m)	Standard deviation (m)
Godagari	0.215	1.261	0.333
Gomostapur	4.063	6.249	0.601
Nachole	2.148	4.089	0.575
Porsha	5.562	6.52	0.66
Tanore	0.549	1.601	0.361

Desertification susceptibility risk analysis

Analysis from the three indicators of desertification susceptibility

According to the NDVI data, steppe type vegetation represents for 48.68% of all vegetation types in the research region. Depending on the season and latitude, a steppe may be semi-arid or covered in grass, shrubs, or both (Fig. 4). The climate found in areas that are too dry to support a

Fig. 4 **a** NDVI, **b** TGSI, and **c** AI analysis of the study area



forest but not as arid as a desert is referred to as a "steppe climate." Then, dense vegetation, which was represented by the forest steppe, covered 44.19% of the entire region, with the majority of it being spread in the north-west and south-east (Table 3). The two almost straight flows of thick vegetation are separated by steppe vegetation. The desert steppe vegetation is sparsely distributed in the north of the study area and densely concentrated in a tiny portion of the south-east corner, which makes up 6.29% of the study area, as well as in a small portion of the south along the Padma River (mainly char area). To sum it all up, 1% of the area is taken up by water, which comprises a tiny stretch of the Padma River in the south and a few scattered ponds. Here, NDVI is associated with the level of photosynthetic activity of green vegetation; the vast desert steppe is characterized by low NDVI values, which correspond to a low level of photosynthetic activity. On the other hand, the forest steppe is defined by high NDVI values, which correspond to a high level of photosynthetic activity (high NDVI value).

Table 3 Summary of analysis from NDVI, TGSI and AI

Index	Description	Area (km^2)	Percentage (%)
NDVI	Water body	13.65	0.82
	Desert steppe	104.44	6.29
	Steppe	807.85	48.69
	Forest steppe	733.30	44.20
TGSI	Soil covered by vegetation or water bodies	655.66	39.49
	Medium contents of fine sand	663.17	39.94
	High contents of fine sand	307.00	18.49
	Soil is fully covered by fine sand (desert)	34.59	2.08
AI	Arid	41.16	2.48
	Semi-arid	639.59	38.53
	Sub humid	641.21	38.63
	Humid	337.97	20.36

Over half of the region is covered with water or plants and medium contents of fine sand, according to TGSI (Fig. 4). They're 39.49% and 39.94% of the land respectively. The Padma River causes a large concentration of vegetation or water in the south. It is common to have good-quality soil for vegetation near the river in the context of the Bengal Delta. High contents of fine sand are mainly diffused in the north and southwest with a mixture of medium contents of fine sand. It covers almost 18.49% of total land (Fig. 4).

This type of soil can turn into a desert area in the future with the help of a dry climate. Fully covered by fine sand dominates the Padma River char and a small amount of the southeast. Poorly dispersed in the north, which represents 2.8% of the area. In Porsha, Naogaon, the number of high contents of fine sand and entirely covered land is higher than in other areas.

In short, the aridity increases in the north and slowly reduces in the south part of the area (Fig. 4). The arid part covers 2.48% of the total area, mostly in the center of Porsha Upazilla, Naogaon. The amount of rainfall is significantly low, which factor make the area more arid. The semi-arid and subhumid areas cover almost the same amount of area (respectively 38.53% and 38.63%). A small portion of the subhumid area is laid between the humid area near the Godagari and Tanore Upazilla boundary lines. The humid area occupies 20.36%, mainly situated near the Padma River and the north portion of Tanore Upazilla, Rajshahi, resulting low aridity.

Desertification susceptibility risk analysis of the study area

The desertification risk map depicts the potential for desertification in the research area, the creation of which required the combining of data on soil, vegetation, and weather (Fig. 5). The potential for desertification to spread varies across the research region, as expected, depending on the relative strength of the three main components known to control this phenomenon risk gradients. To supplement the descriptive interpretation of NDVI, TGSI and AI in relation to desertification susceptibility, a quantitative study was performed. Specifically, the mean values of each indicator were determined for the five classes: No Risk, Moderate, High, and Very High (Table 4).

A Pearson correlation analysis was used to determine the strength of link between each index and the risk classifications (1 = No Risk, 5 = Very High Risk). The NDVI score had a negative link with desertification risk ($r = -0.465$), showing that places with less plant cover area are more vulnerable. In contrast, the TGSI and AI both showed high positive correlations ($r = 0.786$ and $r = 0.988$, respectively), indicating that coarser soils and drier climatic conditions significantly contribute to the risk gradient.

The data show that the northern half of the study area has the majority of the very high-risk zones. A 6.27% portion of the area is made up of these type zones (Table 4). A total of 10.8% of the land is classified as high risk, mostly in the Northern portion and is situated around the very high-risk zone, marked in red. This was the outcome of a number of contributing factors that encourage potential desertification, including harsh climatic conditions with less rainfall (1100–1300 mm), degraded soil structure, human activities such as groundwater overexploitation, water waste, an insufficient pricing and monitoring system for groundwater extraction, and degradation of natural vegetation brought on by the built environment, deforestation, and loss of soil moisture due to a lack of groundwater availability. The central and central-northern portions, comprising 28.17% of the total land, are moderately at risk. Rest of the area (17.33%) is at totally no risk of desertification. Which fully placed in the Godagari Upazilla. Availability of surface water especially the existence of the Padma River, make the area less vulnerable than the rest of the study area.

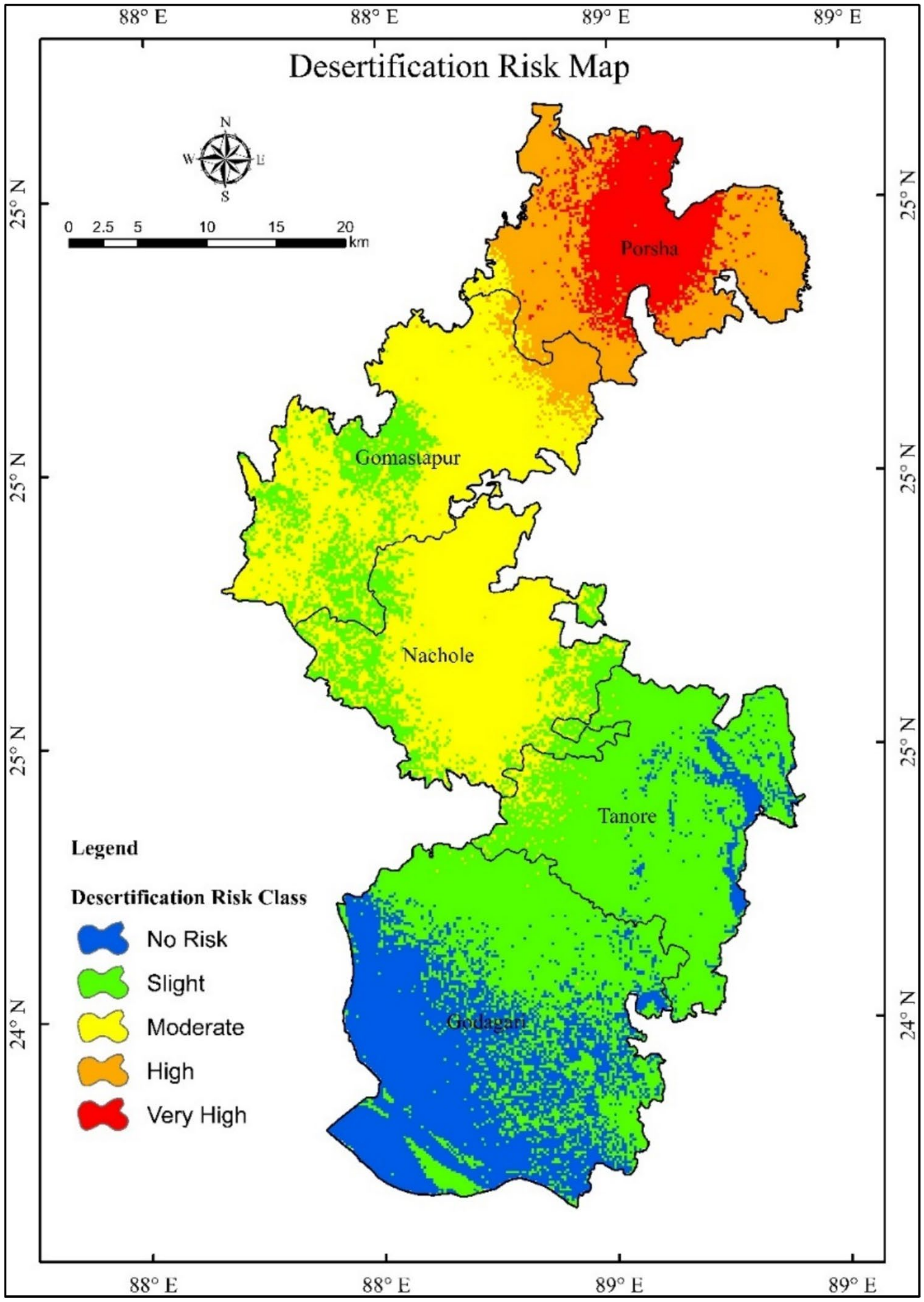


Fig. 5 Desertification susceptibility risk map of the study area

Table 4 Classes of desertification risk

Desertification risk class	Area (km^2)	Percentage (%)
No risk	285.46	17.33
Slight	616.40	37.42
Moderate	464.05	28.17
High	177.89	10.80
Very high	103.26	6.27

Outlining soil-vegetation feedback for validating desertification susceptibility analysis

In drylands, a decrease in RUE is frequently associated with land degradation, RUE serves as a useful measure of how effectively vegetation consumes available moisture. The results from RUE assessment of the study area exhibit Porsha have the lowest RUE (0.025), showing possible symptoms of degradation despite moderate NDVI, whereas Godagari has the highest RUE (0.031), indicating a more responsive vegetation cover in relation to rainfall and proximity to surface water regions. These results are consistent with the soil vegetation feedback theory, highlighting that a decrease in vegetation weakens plant productivity by reducing soil penetration and moisture retention (Rietkerk and Koppel 1997). Furthermore, surface drying can be accelerated and groundwater recharge reduced by slight vegetation loss, according to dryland hydrology models (Rodríguez-Iturbe and Porporato 2005). Hence, regions with consistently low RUE in spite of sufficient rainfall may fall victim to early desertification, where vegetative function is compromised (Table 5).

Discussion

Flooding and monsoon rains in Bangladesh are the main sources of groundwater recharge. The BT is situated in a zone free from flooding because of its high elevation, making it susceptible to drought. The region's thick, mushy clay surface acts as an aquitard, preventing groundwater recharge and boosting surface runoff (Rahman et al. 2017). As a result, with rising water use for irrigation, the groundwater level in this area is gradually declining over years. In the study region, rain infiltration, stream and channel flow, and pond and low-lying area percolation recharge groundwater. A small amount of recharge comes from neighboring higher elevations and irrigated farms, resulting water table declination up to 6 m during the last five years which is very alarming.

Water levels typically fluctuate in a seasonal rhythm. A cycle of water discharge and recharge is maintained throughout the year, which keeps the sustainability of groundwater within a region. The arid regions gradually break the cycle while climatic conditions change and the balance between extraction and preservation stumbles. Regional elements that contribute to the fluctuations, like proximity to rivers, the duration of the rainy season, the frequency of dry seasons, and the intensity of pump operation, are highlighted in the study region as well. Results from such irregularities in water resource management are causing high expenditure in agricultural production, overexploitation of groundwater, and challenges in conducting livelihood practices in the study region.

Table 5 Soil-vegetation feedback analysis of the study area

Upazila	Rainfall (mm)	NDVI	RUE	Feedback loop
Godagari	117.11	3.67	0.031	Positive
Gomostapur	101.50	3.02	0.030	Neutral
Porsha	104.36	2.57	0.025	Strong negative
Tanore	109.27	3.44	0.031	Positive
Nachole	108.84	2.99	0.027	Relatively negative

The results also depict that the regions with better groundwater discharge are situated at a location with less elevation and more proximity of the surface water reservoirs. Godagari has already brought surface water from Padma River by pressure pump for travelling about 3.5 km. But this can easily be extended to the whole BT by lifting technology. The canal networking channel of BT is absolutely feasible for surface water channelization (Hossain et al. 2022). BMDA constructed floating pontoons onto which centrifugal pumps were mounted using rubber-made flexible armed hope pipes so that the water from those sources could be used for agriculture (Fig. 6). The implementation of floating pontoons and rubber dams has shown success in similar semi-arid regions. For instance, Hossain et al. (2022) demonstrated that double lifting methods reduced irrigation costs by 30–40% in the BT (Hossain et al. 2022). Initial investment costs are estimated at $50–75 per hectare, with payback periods of 3–5 years based on reduced groundwater extraction expenses.

Alongside, results from RUE analysis depict that a negative feedback loop will eventually influence land and subsurface water degradation, causing severe desertification. A high risk of desertification will ultimately cripple the livelihood opportunities of the communities, forcing them to migrate in other regions for survival. According to IPCC, the two main causes driving the progress of desertification are climatic changes and insufficient human activities, which calls for the management of the non-renewable resources, inclusive of the community people (IPCC 2024). Therefore, in order to commence reducing the desertification stress, regulations upon controlling the intensive cropping culture and introduction of high-yielding and less-irrigation crops have to be initiated within the study area.

Regions with climatic challenges have to be dealt with sensitive approaches so that the sustainability of livelihood and resources do not collide with each other. The people in BT are forced to discharge groundwater to serve their livelihood purpose despite of knowing the unsustainability of this resource. The desertification susceptibility analysis highlighted regions where the intensive agricultural process has to be managed to conserve water resource for future generations. Through this research, the plausible solutions can be implemented in terms of policy and governance, to regulate the controlled usage of groundwater in order to establish sustainable agriculture, water resource management and adaptation to climatic hazards.

Limitations of the study

This study has several methodological and data-related limitations that should be acknowledged. First, the exclusion of the Anthropic Pressure on Steppe Environment

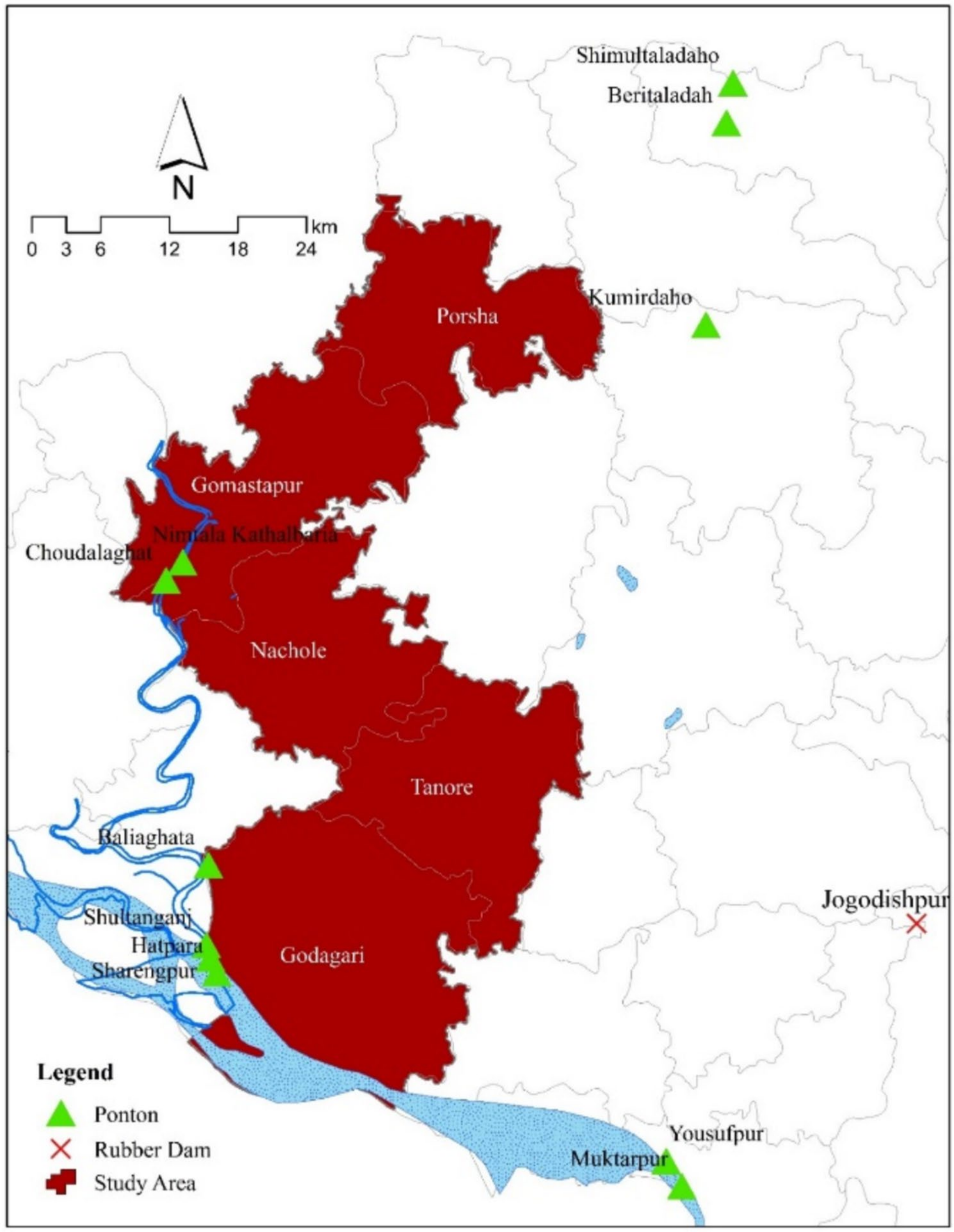


Fig. 6 Location of surface water irrigation by pontoons and rubber dams in the Northwest Bangladesh

(APSE) variable represents a significant limitation. APSE was initially designed to capture human influences including population density, agricultural intensity, and infrastructure development patterns across the study area. However, the variable was omitted due to inconsistent spatial data availability and reliability concerns regarding government survey datasets, which posed risks of introducing systematic errors into the regression analysis. Second, the study relies on a single year (2022) of satellite imagery for vegetation and soil analysis, which may not capture seasonal or interannual variability in desertification indicators. This temporal limitation could affect the representativeness of the findings, particularly in a region known for significant climatic fluctuations. Third, the logistic regression model, while achieving high ROC values, was validated using available ground-truth data that may not comprehensively represent all micro-climatic conditions within the heterogeneous BT landscape. The model's performance in areas with unique topographical or hydrological characteristics remains uncertain. Finally, the study does not incorporate socio-economic factors such as farming practices, crop selection patterns, or local water management policies, which significantly influence desertification processes in agricultural regions. These human dimensions are critical for comprehensive desertification assessment but were beyond the scope of the current remote sensing-based approach. Future research should address these limitations by integrating multi-temporal satellite data, incorporating reliable socio-economic datasets, and developing hybrid models that combine remote sensing observations with field-based measurements to enhance the accuracy and applicability of desertification susceptibility mapping.

Conclusions

This research provides a comprehensive framework for assessing groundwater dynamics and desertification susceptibility in arid regions through integrated remote sensing and logistic regression modeling. The study demonstrates that 82.66% of the BT faces significant water resource challenges, with elevation gradients from south to north correlating strongly with increasing desertification risk. The northern regions, particularly Porsha, Gomastapur, and Nachole Upazillas, exhibit the highest vulnerability due to combined effects of low precipitation (1100–1300 mm annually), elevated topography (up to 60 m above sea level), and intensive groundwater extraction for agriculture.

The methodological contribution of this study lies in the successful integration of vegetation, soil texture, and climatic indices through logistic regression modeling, achieving 96.22% ROC accuracy. The incorporation of RUE analysis validates the desertification assessment through soil-vegetation feedback theory, revealing negative feedback loops in high-risk areas that accelerate land degradation processes. This multi-indicator approach provides a robust, transferable methodology for similar semi-arid regions globally.

From a policy and governance perspective, this study offers critical insights for regional water resource management and sustainable development planning. The spatially explicit risk mapping enables policymakers to: (1) prioritize water conservation investments in very high-risk zones covering 6.27% of the study area, (2) implement targeted agricultural regulations in moderate to high-risk areas encompassing 45.24% of the region, and (3) develop early warning systems for desertification monitoring. The identification of surface water utilization potential through floating pontoons and rubber dams provides actionable adaptation strategies that can reduce groundwater dependency while maintaining agricultural productivity.

The findings directly support SDG achievement in vulnerable regions, particularly SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action), and SDG 15 (Life on Land). The study demonstrates that immediate intervention is required to prevent irreversible ecosystem degradation and ensure long-term water security for 5.6 million inhabitants dependent on BT resources.

Future research directions should focus on: (1) integrating socio-economic variables including farming practices, water pricing mechanisms, and community adaptation strategies to enhance human–environment interaction understanding, (2) incorporating machine learning algorithms such as Random Forest or Support Vector Machines for improved susceptibility classification accuracy and temporal prediction capabilities, (3) developing time-series analysis using multi-temporal satellite data to monitor desertification progression and validate model predictions, and (4) conducting comprehensive cost–benefit analyses of proposed mitigation technologies including feasibility assessments and implementation timelines for scaling across similar arid regions.

This research establishes a scientific foundation for evidence-based water governance and climate adaptation strategies, providing a replicable framework for addressing water security challenges in arid regions experiencing rapid environmental change.

Acknowledgements The authors extend their appreciation to the Ongoing Research Funding program (ORF-2025-848), King Saud University, Riyadh, Saudi Arabia

Author contributions “Conceptualization, R.M.S, R.R.C and S.C; methodology, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; software, R.M.S, R.R.C and S.C; validation, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; formal analysis, R.M.S, R.R.C and S.C; investigation, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; resources, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; data curation, R.M.S, R.R.C, S.C, A.D, A.A.K and H.A.A; writing—original draft preparation, R.M.S, R.R.C, S.C, A.D and A.A.K; writing—review and editing, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; visualization, R.M.S, R.R.C, S.C, A.D, A.A.K, H.A.A and T.K.B; supervision, A.D, A.A.K, H.A.A and T.K.B; project administration, A.D, A.A.K, H.A.A and T.K.B; funding acquisition, H.A.A. All authors have read and agreed to the published version of the manuscript.

Funding This research work was supported by the Ongoing Research Funding program (ORF-2025-848), King Saud University, Riyadh, Saudi Arabia.

Data availability Data sources along with analytical insights are available and provided in the article.

Declarations

Conflicts of interest The authors declare no conflicts of interest.

References

Adham MI, Jahan CS, Mazumder QH, Hossain MMA, Haque A-M (2010) Study on groundwater recharge potentiality of Barind Tract, Rajshahi District, Bangladesh using GIS and remote sensing technique. J Geol Soc India 75:432–438

Aftabuzzaman M, Kabir S, Islam MK, Alam MS (2013) Clay mineralogy of the pleistocene soil horizon in Barind Tract, Bangladesh. J Geol Soc India 81:677–684

Ahmeduzzaman M, Kar S, Asad A (2012) A study on ground water fluctuation at Barind Area, Rajshahi. Int. J. Eng. Res. Appl. IJERA 2248–9622

Al-Obaidi JR et al (2022) The environmental, economic, and social development impact of desertification in Iraq: a review on desertification control measures and mitigation strategies. Environ Monit Assess 194(6):440. https://doi.org/10.1007/s10661-022-10102-y

Aziz MdA et al (2015) Groundwater depletion with expansion of irrigation in Barind Tract: a case study of Rajshahi District of Bangladesh. Int J Geol Agric Environ Sci 3:32–38

Becerril-Piña R, Mastachi-Loza CA, González-Sosa E, Díaz-Delgado C, Bâ KM (2015) Assessing desertification risk in the semi-arid highlands of central Mexico. J Arid Environ 120:4–13. https://doi.org/10.1016/j.jaridenv.2015.04.006

Casper BB, Schenk HJ, Jackson RB (2003) Defining a plant's belowground zone of influence. Ecology 84(9):2313–2321. https://doi.org/10.1890/02-0287

Caylor KK, D'Odorico P, Rodriguez-Iturbe I (2006) On the ecohydrology of structurally heterogeneous semiarid landscapes. Water Resour Res. https://doi.org/10.1029/2005WR004683

Clark WAV, Hosking PL (1986) Statistical methods for geographers. Wiley, New York

Couteron P, Lejeune O (2001) Periodic spotted patterns in semi-arid vegetation explained by a propagation-inhibition model. J Ecol 89(4):616–628. https://doi.org/10.1046/j.0022-0477.2001.00588.x

Das A, Kashem S, Hasan M (2021) Using market mechanism to stimulate sustainable use of the non-renewable environmental resource (Groundwater) in barind tract of Bangladesh. HKIE Trans Hong Kong Inst Eng 28(1):39–48. https://doi.org/10.33430/V28N1THIE-2020-0036

Djeddaoui F, Chadli M, Gloaguen R (2017) Desertification susceptibility mapping using logistic regression analysis in the Djelfa area, Algeria. Remote Sens 9(10):10. https://doi.org/10.3390/rs9101031

D'Odorico P, Caylor K, Okin GS, Scanlon TM (2007) On soil moisture–vegetation feedbacks and their possible effects on the dynamics of dryland ecosystems. J Geophys Res Biogeosci. https://doi.org/10.1029/2006JG000379

dos Santos JC et al (2022) Aridity indices to assess desertification susceptibility: a methodological approach using gridded climate data and cartographic modeling. Nat Hazards 111(3):2531–2558. https://doi.org/10.1007/s11069-021-05147-0

Eskandari Dameneh H, Gholami H, Telfer MW, Comino JR, Collins AL, Jansen JD (2021) Desertification of Iran in the early twenty-first century: assessment using climate and vegetation indices. Sci Rep 11(1):20548. https://doi.org/10.1038/s41598-021-99636-8

Greve P, Roderick ML, Ukkola AM, Wada Y (2019) The aridity index under global warming 14(12): 124006

Hadid RS, Ahmed BA (2024) Determining the agricultural drought and desertification intensity in Diyala Province/Iraq using Sentinel-2 images. Iraqi J Sci. https://doi.org/10.24996/ijs.2024.65.5.45

Hare FK (1984) Changing climate and human response: the impact of recent events on climatology. Geoforum 15(3):383–394. https://doi.org/10.1016/0016-7185(84)90046-0

Hereher M, El-Kenawy A (2022) Assessment of land degradation in Northern Oman using geospatial techniques. Earth Syst Environ 6(2):469–482. https://doi.org/10.1007/s41748-021-00216-7

Higginbottom TP, Symeonakis E (2014) Assessing land degradation and desertification using vegetation index data: current frameworks and future directions. Remote Sens 6(10):10. https://doi.org/10.3390/rs6109552

Hossain MI, Bari MN, Kafy A-A, Rahaman ZA, Rahman MT (2022) Application of double lifting method for river water irrigation in the water stressed Barind Tract of northwest Bangladesh. Groundw Sustain Dev 18:100787

Hossain MI, Bari N, Miah SU, Jahan CS, Rahaman MF (2019) MAR technique to reverse the declining trend of groundwater level in Barind Area, NW, Bangladesh. J Water Resour Prot 11(6):6. https://doi.org/10.4236/jwarp.2019.116045

Hossain MI, Bari MN, Miah SU (2020) Opportunities and challenges of managed aquifer recharge (MAR) at drought prone water stressed Barind Area, Bangladesh. In: Proceedings of the 5th international conference on civil engineering for sustainable development (ICCESD 2020), pp 7–9

Le Houérou HN (1984) Rain use efficiency: a unifying concept in arid-land ecology. J Arid Environ 7(3):213–247. https://doi.org/10.1016/S0140-1963(18)31362-4

IPCC (2024) Chapter 3 : Desertification—special report on climate change and land. Accessed: 08 Sep 2024. Available: https://www.ipcc.ch/srccl/chapter/chapter-3/

Imon A, Ahmed M (2013) Water level trend in the barind area (7): 1–15

Jain S, Srivastava A, Khadke L, Chatterjee U, Elbeltagi A (2024) Global-scale water security and desertification management amidst climate change. Environ Sci Pollut Res Int 31(49):58720–58744. https://doi.org/10.1007/s11356-024-34916-0

Kairis O et al (2014) Evaluation and selection of indicators for land degradation and desertification monitoring: types of degradation, causes, and implications for management. Environ Manage 54(5):971–982. https://doi.org/10.1007/s00267-013-0110-0

Kalyan S, Sharma D, Sharma A (2021) Spatio-temporal variation in desert vulnerability using desertification index over the Banas River Basin in Rajasthan, India. Arab J Geosci 14(1):54. https://doi.org/10.1007/s12517-020-06417-0

Kim J et al. (2020) Identifying potential vegetation establishment areas on the dried Aral Sea floor using satellite images 31(18): 2749–2762, https://doi.org/10.1002/ldr.3642

Lamqadem AA, Saber H, Pradhan B (2018) Quantitative assessment of desertification in an arid oasis using remote sensing data and spectral index techniques". Remote Sens 10(12):12. https://doi.org/10.3390/rs10121862

Lejeune O, Tlidi M, Couteron P (2002) Localized vegetation patches: a self-organized response to resource scarcity. Phys Rev E 66(1):010901. https://doi.org/10.1103/PhysRevE.66.010901

Liu Q, Liu G, Huang C (2018) Monitoring desertification processes in Mongolian Plateau using MODIS tasseled cap transformation and TGSI time series. J Arid Land 10(1):12–26. https://doi.org/10.1007/s40333-017-0109-0

Liu Z, Skrzypek G, Batelaan O, Guan H (2024) Rain use efficiency gradients across Australian ecosystems. Sci Total Environ 933:173101. https://doi.org/10.1016/j.scitotenv.2024.173101

Liu X, Zhang D, Luo Y, Liu C (2013) Spatial and temporal changes in aridity index in northwest China: 1960 to 2010. Theor Appl Climatol 112(1):307–316. https://doi.org/10.1007/s00704-012-0734-7

Martínez-Valderrama J et al (2018) Doomed to collapse: why Algerian steppe rangelands are overgrazed and some lessons to help land-use transitions. Sci Total Environ 613–614:1489–1497. https://doi.org/10.1016/j.scitotenv.2017.07.058

Mayor ÁG, Kéfi S, Bautista S, Rodríguez F, Cartení F, Rietkerk M (2013) Feedbacks between vegetation pattern and resource loss dramatically decrease ecosystem resilience and restoration

potential in a simple dryland model. Landsc Ecol 28(5):931–942. https://doi.org/10.1007/s10980-013-9870-4
Middleton N, Thomas D (1992) World atlas of desertification. UNEP, London, Edward Arnold
Mihi A, Ghazela R, Wissal D (2022a) Mapping potential desertification-prone areas in North-Eastern Algeria using logistic regression model, GIS, and remote sensing techniques. Environ Earth Sci 81(15):385. https://doi.org/10.1007/s12665-022-10513-7
Mihi A, Ghazela R, Wissal D (2022b) Mapping potential desertification-prone areas in North-Eastern Algeria using logistic regression model, GIS, and remote sensing techniques. Environ Earth Sci 81(15):385. https://doi.org/10.1007/s12665-022-10513-7
Ozgul M, Dindaroglu T (2021) Multi-criteria analysis for mapping of environmentally sensitive areas in a karst ecosystem. Environ Dev Sustain 23(11):16529–16559. https://doi.org/10.1007/s10668-021-01363-7
Paruelo JM, Jobbágy EG, Sala OE (2001) Current distribution of ecosystem functional types in temperate South America. Ecosystems 4(7):683–698. https://doi.org/10.1007/s10021-001-0037-9
Quevedo DI, Francés F (2008) A conceptual dynamic vegetation-soil model for arid and semiarid zones. Hydrol Earth Syst Sci 12(5):1175–1187. https://doi.org/10.5194/hess-12-1175-2008
Rahman ATM, Jahan C, Mazumder Q, Kamruzzaman M, Hosono T (2017) Drought analysis and its implication in sustainable water resource management in Barind Area, Bangladesh. J Geol Soc India 89:47–56. https://doi.org/10.1007/s12594-017-0557-3
Rahman AS, Kamruzzaman Md, Jahan CS, Mazumder QH (2016) Long-term trend analysis of water table using 'MAKESENS' model and sustainability of groundwater resources in drought prone Barind Area, NW Bangladesh. J Geol Soc India 87(2):179–193. https://doi.org/10.1007/s12594-016-0386-9
Rahman MM, Mahbub AQM (2012) Groundwater depletion with expansion of irrigation in Barind Tract: a case study of Tanore Upazila. J Water Resour Prot 4(08):567
Rashid MB, Islam PDMS, Islam M (2015) River morphology and evolution of the Barind Tract, Bangladesh. J Nepal Geol Soc 49:65–76
Rietkerk M, van de Koppel J (1997) Alternate stable states and threshold effects in semi-arid grazing systems. Oikos 79(1):69–76. https://doi.org/10.2307/3546091
Rodríguez-Iturbe I, Porporato A (2005) Ecohydrology of water-controlled ecosystems: soil moisture and plant dynamics. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511535727
Rouse Jr JW, Haas RH, Deering DW, Schell JA, Harlan JC (1994) Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation
Running SW (1990) Estimating terrestrial primary productivity by combining remote sensing and ecosystem simulation. In: Remote sensing of biosphere functioning. Springer, pp 65–86
Ruppert JC et al (2012) Meta-analysis of ANPP and rain-use efficiency confirms indicative value for degradation and supports non-linear response along precipitation gradients in drylands. J Veg Sci 23(6):1035–1050. https://doi.org/10.1111/j.1654-1103.2012.01420.x
Shuvo RM et al (2024) Geospatially informed water pricing for sustainability: a mixed methods approach to the increasing block tariff model for groundwater management in arid regions of Northwest Bangladesh. Water 16(22):22. https://doi.org/10.3390/w16223298
Thomas DSG (1997) Science and the desertification debate. J Arid Environ 37(4):599–608. https://doi.org/10.1006/jare.1997.0293
Wang X-P, Li X-R, Xiao H-L, Pan Y-X (2006) Evolutionary characteristics of the artificially revegetated shrub ecosystem in the Tengger Desert, northern China. Ecol Res 21(3):415–424. https://doi.org/10.1007/s11284-005-0135-9
Wei H et al (2018) Desertification information extraction based on feature space combinations on the Mongolian Plateau. Remote Sens 10(10):10. https://doi.org/10.3390/rs10101614
Wijitkosum S (2021) Factor influencing land degradation sensitivity and desertification in a drought prone watershed in Thailand. Int Soil Water Conserv Res 9(2):217–228. https://doi.org/10.1016/j.iswcr.2020.10.005
Xiao J, Shen Y, Tateishi R, Bayaer W (2006) Development of topsoil grain size index for monitoring desertification in arid land using remote sensing. Int J Remote Sens. https://doi.org/10.1080/01431160600554363
Zhao H-L, Zhou R-L, Zhang T-H, Zhao X-Y (2006) Effects of desertification on soil and crop growth properties in Horqin sandy cropland of Inner Mongolia, North China. Soil Tillage Res 87(2):175–185. https://doi.org/10.1016/j.still.2005.03.009