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Assessing Climate and Land-Use Change Scenarios on Future Desertification in Northeast Iran: A Data Mining and Google Earth Engine-Based Approach

Weibo Yin [1], Qingfeng Hu [2,*], Jinping Liu [2,3], Peipei He [2], Dantong Zhu [2] and Abdolhossein Boali [4]

1 School of Civil Engineeing and Transportation, North China University of Water Resources and Electric Power, Zhengzhou 450046, China; yinweib@ncwu.edu.cn
2 College of Surveying and Geo-Informatics, North China University of Water Resources and Electric Power, Zhengzhou 450046, China
3 Hydraulics and Geotechnics Section, KU Leuven, Kasteelpark Arenberg 40, BE-3001 Leuven, Belgium
4 Department of Arid Zone Management, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan 4913815739, Iran
* Correspondence: huqingfeng@ncwu.edu.cn

Abstract: Desertification poses a significant threat to dry and semi-arid regions worldwide, including Northeast Iran. This study investigates the impact of future climate and land-use changes on desertification in this region. Six remote sensing indices were selected to model desertification using four machine learning algorithms: Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting Machine (GBM), and Generalized Linear Models (GLM). To enhance the model's reliability, an ensemble model was employed. Future climate and land-use scenarios were projected using the CNRM-CM6 model and Markov chain analysis, respectively. Results indicate that the RF and SVM models performed best in mapping current desertification patterns. The ensemble model highlights a 2% increase in decertified areas by 2040, primarily in the northwestern regions. The study underscores the importance of land-use change and climate change in driving desertification and emphasizes the need for sustainable land management practices and climate change adaptation strategies to mitigate future impacts.

Keywords: land degradation; desertification; prediction; modelling; ensemble model

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1. Introduction

Desertification, a complex environmental issue, is accelerating globally, particularly in arid and semi-arid regions. This phenomenon, a process leading to land degradation and reduced productivity, poses a significant environmental challenge in arid and semi-arid regions worldwide [1]. Climate change and unsustainable land-use practices are major drivers of this phenomenon, leading to significant ecological, economic, and social consequences. Although various factors contribute to desertification, climate change and subsequent land-use changes are the primary drivers [2]. Climate change, characterized by long-term shifts in temperature, precipitation, wind patterns, and other climatic variables, is a major contributor to desertification [3]. This phenomenon has led to an expansion of desert areas, affecting over 250 million people directly and billions more indirectly [4]. Desertification can occur in all climates, accompanied by a decline in ecological and biological capacity [5]. Rising temperatures and altered precipitation patterns reduce agricultural and rangeland productivity, often prompting land-use changes such as the conversion of agricultural land to urban or industrial areas [6]. This interplay between climate change and land-use change creates a negative feedback loop, exacerbating desertification [7].

Land-use change, such as the conversion of forests and grasslands to agricultural or urban areas, exacerbates these effects by reducing vegetation cover, increasing soil erosion, and decreasing soil infiltration. These changes disrupt the local and regional water and energy balance, amplifying the impacts of climate change and accelerating desertification. For example, the reduction in vegetation cover caused by land-use change leads to increased surface temperatures and decreased soil moisture, further altering precipitation patterns and intensifying droughts. In essence, desertification, land-use change, and climate change are interconnected and mutually reinforcing processes. Addressing desertification requires a comprehensive and integrated approach that simultaneously addresses climate change mitigation, sustainable land management, and restoration of degraded ecosystems.

The Middle East, including Iran, is highly susceptible to desertification due to its naturally arid and semi-arid climate, rendering its ecosystems fragile and vulnerable to degradation [8]. Northeast Iran, with its particularly harsh climatic conditions, is especially vulnerable to this environmental threat. Human activities, such as unsustainable land use, have further intensified these pressures, accelerating the desertification process. In Iran, desertification is a pressing environmental issue with profound implications for the environment, economy, and society [9]. Therefore, assessing and predicting desertification in Iran is essential for developing effective mitigation and adaptation strategies to promote sustainable development in arid regions.

Numerous studies have been conducted globally to assess and map desertification, leading to the development of various models. However, desertification assessment models require extensive spatial and temporal data, and given that this phenomenon occurs in arid regions, extracting large-scale and long-term information is challenging [10]. Therefore, establishing a data extraction process based on remote sensing techniques for desertification assessment is essential [11]. Nonetheless, due to the complex nature of desertification, researchers believe that its assessment can be satisfactory only when reliable remote sensing indices are considered for this purpose [12]. To date, it has not been possible to determine such indices that can be used at various global, regional, national, and local scales. In most studies, three to five remote sensing indices have been used to assess the desertification hazard. However, given the multifaceted nature of this phenomenon, the obtained results may not be sufficiently accurate [8]. For instance, in many studies, the NDVI threshold is used to classify the degree of desertification [13,14]. Consequently, as this method considers only vegetation cover, the accuracy of classification results will decrease [15].

In this study, machine learning techniques were employed to model and project desertification. These methods are multi-index approaches that utilize remote sensing data to analyze changes in land cover, soil moisture, temperature, and other indicators that influence desertification. By applying advanced machine learning algorithms such as random forests, neural networks, and support vector machines, complex patterns of desertification can be identified, and highly accurate models can be developed to predict future trends [16]. The use of a single method may not yield satisfactory results. When models are correctly combined, they can produce more accurate results. Ensemble models, which combine multiple machine learning algorithms, have a significant advantage over individual models. These models can improve prediction accuracy by combining the results of different models. In the context of desertification assessment, the use of ensemble models can lead to more accurate predictions and better decision-making in natural resource management and mitigating the effects of desertification. In this study, an ensemble machine learning model in the SDM package in R software (R-4.4.1) was used to achieve a more accurate classification. Predicting future desertification is also of paramount importance as this phenomenon not only leads to a reduction in arable land and increased pressure on natural resources but also jeopardizes the food, economic, and social security of communities [17]. With climate change and increased human activities such as land-use change and unsustainable agriculture, the rate of desertification has accelerated [18]. Therefore, predicting desertification based on climate and land-use change scenarios is crucial as this approach allows for a more accurate analysis and evaluation of the interactions between these two key factors on desertification trends. Scenario modeling of these two factors can help identify high-hazard areas and develop effective management strategies to mitigate the impacts of desertification, as well as provide guidance for decision-makers in developing sustainable policies.

Golestan Province in northeastern Iran has faced land degradation, water and wind erosion, land-use change, and groundwater depletion over the past decade. Therefore, this study aimed to model and predict the risk of desertification based on climate and land-use changes in northeastern Iran. This research introduced the use of a combined model based on remote sensing indices as a suitable method for accurately assessing desertification. Additionally, producing future desertification maps for the study area based on climate and land-use change scenarios can contribute to better planning and management of natural resources, developing environmental protection policies, and adopting effective strategies to mitigate the negative impacts of desertification, thereby preventing environmental and human crises.

This study advances the field of desertification research by integrating advanced machine learning techniques with remote sensing data to accurately assess and predict future trends. By employing an ensemble modeling approach, we aim to improve the robustness and reliability of the results. Furthermore, the incorporation of climate and land-use change scenarios enables a comprehensive assessment of the potential impacts of these factors on desertification, facilitating the development of informed strategies for mitigation and adaptation. This research contributes to the existing body of knowledge by providing a comprehensive assessment of desertification in Northeast Iran and offering valuable insights into the potential impacts of future climate and land-use changes. The findings of this research can inform policymakers and decision-makers in developing effective strategies to mitigate the adverse effects of desertification and promote sustainable land management practices.

2. Materials and Methods

2.1. Study Area

The study area, spanning 20,367 square kilometers, is geographically located between 36°25′ and 38°08′ North latitude and 53°50′ and 56°18′ East longitude. This region is bordered by the Turkmen desert to the north, the Caspian Sea coastal plain to the west, and the Alborz mountain range to the south (Figure 1). The highest and lowest elevations in the region are approximately 3813 m above sea level (Shahkoh Mountain) and −32 m below sea level (Gomishoan Lagoon), respectively. The average annual precipitation, average evaporation, and average temperature of the region over a 30-year period (1993–2023) were estimated to be 530 mm, 1338 mm, and 17.3 °C, respectively. The De Martonne (1926) and Ivanov (1941) methods classified the region's climate as arid and steppe, respectively.

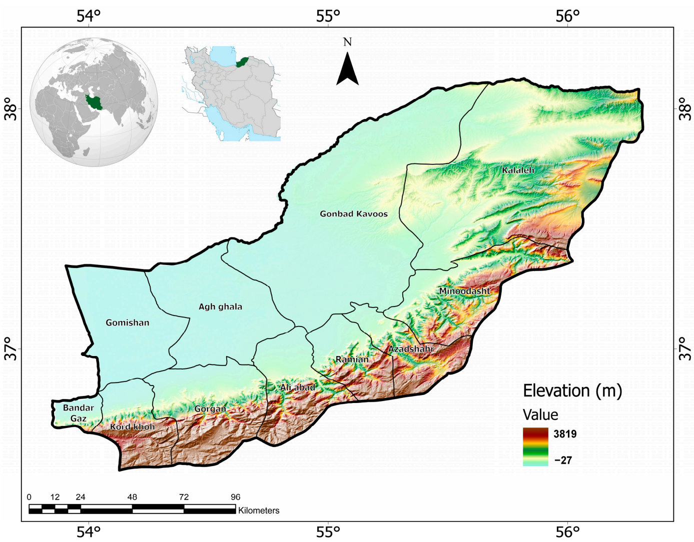

Figure 1. Geographical location of the study area in Iran and Golestan province.

2.2. Data Collection

In July 2021, 42 soil samples were collected from the study area to measure salinity and texture indices. To assess vegetation cover, one-meter square plots were systematically established along 100-m transects (3 transects per land use and 10 plots per transect) in the region. The percentage of vegetation cover in each plot was determined by expert opinion and extrapolated to the entire land use. Ten meteorological stations with a 30-year statistical period (1993–2023) were used to analyze climatic parameters such as temperature and precipitation. To evaluate groundwater depth, data from 75 wells (obtained from the Golestan Province Water Resources Organization) were used over a 30-year period (1993–2023). To investigate the impact of human factors on desertification, a land-use map was prepared. During field visits, training points were established in each land usage to prepare the land-use map.

This study employs two types of atmospheric data: observed and simulated. Observed data is sourced from Stations data, while simulated data was derived from the CNRM-CM6 global climate model. Developed by the Met Office Hadley Centre, this model was utilized for the CMIP6 climate simulations and is noteworthy for its integrated Earth system components. The research focuses on three future scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) simulated by CNRM-CM6 for the period of 2031–2050.

2.3. Remote Sensing Indices for Desertification Modeling

In this study, Google Earth Engine was utilized to generate remote sensing indices for modeling desertification in 2023. For this purpose, surface reflectance band 1 Landsat images were selected, which have undergone atmospheric and geometric corrections, as well as cross-calibration between different sensors to ensure the accuracy and consistency of the data used in the analysis. To develop the model, the most significant indices influencing desertification needed to be identified. Therefore, by taking inspiration from MEDALUS model indicators and reviewing comprehensive sources, the most important influencing indicators in the region's desertification were identified. In the next step, several remote sensing indicators were considered for each selected indicator. Subsequently, the index that exhibited the highest correlation with ground-truth data was selected for desertification modeling. The root mean square error (RMSE) and coefficient of determination (R^2) were used as criteria for selecting the best indices.

2.4. Desertification Modeling Using Machine Learning Algorithms

Selecting an Appropriate Number of Training Samples is the first step in implementing machine learning algorithms. Various approaches have been proposed for selecting the number of training samples, with no single method universally accepted. Therefore, to reduce spatial autocorrelation, 100 samples were randomly selected using visual interpretation of Google Earth images and field visits for implementing machine learning algorithms. Fifty samples were taken from areas where desertification had occurred, and 50 samples were taken from areas where desertification had not occurred. Ultimately, 70% of these samples were randomly selected as the training group, and the remaining 30% were selected as the testing group for modeling.

Four machine learning algorithms were employed to model desertification using the SDM package in R: Support Vector Machine (SVM) [1,2], Gradient Boosting Machine (GBM) [3,4], Generalized Linear Model (GLM) [5], and Random Forest (RF) [6,7]. Each algorithm was run randomly three times to ensure that the classification was not influenced by the sampling point distribution. To evaluate the accuracy of the machine learning models, three indices were used: Kappa coefficient, Receiver Operating Characteristic (ROC) curve, and True Skill Statistic (TSS). The Kappa coefficient is a measure of model accuracy, ranging from -1 (lowest accuracy) to 1 (highest accuracy) [8]. The ROC curve, plotted as the true positive rate against the false positive rate, is a graphical tool for evaluating model performance, and its area under the curve (AUC) is a measure of model accuracy, ranging from 0.5 (random) to 1 (perfect). Previous studies have categorized AUC values into several performance levels, including excellent (0.9–1), very good (0.8–0.9), good (0.7–0.8), moderate (0.6–0.7), and poor (0.5–0.6) [9,10]. The TSS also evaluates model accuracy by considering sensitivity and specificity at a specific threshold, ranging from 0 to 1, with higher values indicating better model accuracy. These indices, by providing complementary information, allow for a more comprehensive evaluation of the performance of machine learning models [11].

2.5. Ensemble Modeling for Desertification Prediction

Ensemble models, which combine the strengths of multiple base models, offer improved accuracy and reliability in predictions [12]. By aggregating results from various models and mitigating noise and biases, ensemble models enhance predictive accuracy and reduce error probabilities [13]. Moreover, ensemble methods provide greater flexibility in handling complex datasets, leading to more informed decision-making and effective management strategies in desertification and other environmental studies [14]. In this study, after evaluating the performance of four machine learning models, a weighted ensemble model was implemented using the SDM package in R to develop an optimal model for desertification modeling. Subsequently, to predict desertification in 2044 under static conditions, two scenarios were considered: land-use change and precipitation. Future land-use change was predicted using a Markov chain model, while precipitation was estimated using a LARS model.

2.6. CA–Markov Model

The CA–Markov model integrates cellular automata, Markov chains, and multi-objective land allocation (MOLA) to forecast future land-use changes [15]. Initially, a Markov chain model is employed to compute the probability of land-use class transitions, represented as a transition probability matrix, based on changes observed between time T0 and T1. While the Markov chain model provides temporal probabilities, it lacks spatial information regarding the geographic location of land uses. To address this limitation, a CA–Markov model is utilized, which incorporates spatial adjacency and user-defined spatial distribution of transition probabilities into the Markov chain framework [16]. In this study, land-use maps from 2004 to 2023 were used to predict the 2042 map. To assess the accuracy of the CA–Markov model, a 2023 map was predicted using the 2004 and 2014 maps, and the results were compared with a reference map created through supervised classification.

2.7. Statistical Downscaling

This study investigated the influence of climate change on desertification in the Golestan province. Three climate change scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) from the CNRM-CM6 model were used to predict scenarios for the period of 2031–2050. To apply these large-scale climate projections to the local watershed, the LARS-WG8 statistical model was employed for downscaling. A primary challenge in regional climate change impact studies is the mismatch between the large scale of climate models and the smaller scale of actual impact areas. This discrepancy, arising from variations in topography and climatic conditions, limits the direct application of model results to specific locations. To bridge this gap, downscaling techniques were employed [17]. This research utilized the statistical downscaling method, specifically the LARS-WG8 model, to generate regional climate scenarios.

3. Results

3.1. The Selection of Remote Sensing Indicators

For desertification modeling, six indicators based on remote sensing were selected (Table 1). The literature review revealed that the TGSI is the most appropriate index for evaluating soil surface texture. An increase in soil surface grain size is a clear indicator of land degradation [18,19]. When surface soil particles become coarser, this change is considered a warning sign of the onset or progression of destructive processes such as erosion and desertification. This indicates that the TGSI index can be an effective tool for monitoring and predicting soil degradation in desert and semi-desert areas. The NDSI, VSSI, and SI indices were used to assess soil salinity. The NDSI index, with a low root mean square error (RMSE = 5.21) and a suitable coefficient of determination (R^2 = 0.71), was selected for modeling. By analyzing data from the Chrips, PERSIANN, GPM, and TRMM satellites, it was determined that Chrips satellite data had the highest correlation with the synoptic station data in the region and, thus, was chosen for modeling (Table 1). Five indices NDVI, DVI, EVI, and SAVI were considered for evaluating vegetation cover. The NDVI index, with a root mean square error (RMSE = 2.41) and a suitable coefficient of determination (R^2 = 0.83), had the highest correlation with ground data (percentage of vegetation cover in plots). The land-use change map was used as a remote sensing indicator to examine the role of human factors in desertification. The accuracy of the land-use change map was validated using ground truth data collected during field visits and Google Earth imagery (Table 1). The WEHI model has three indicators; wind speed, soil moisture, and bare soil. The high correlation coefficients between the WEHI model, which is capable of remote sensing, and the ground evidence map show the high capability of this model in estimating wind erosion (Table 1 and Figure 2).

Table 1. Indicators based on the degree of correlation with ground surface data.

Numbers	Indicators	Remote Sensing Indicators	Ground Surface Data	Correlation Rate Between Satellite Indicators and Ground Surface Data R^2	RMSE	Reference
1	Soil texture	TGSI	Soil surface profile	0.82	0.87	[18,19]
2	EC	NDSI		0.71	5.21	
3	Rainfall	Chrips	synoptic stations	0.65	141.33	[20]
4	Groundwater depth	-	The water depth of the wells	0.79	4.01	[21]
5	Vegetation percent	NDVI	Vegetation percentage in plots	0.83	2.41	[22]
6	Wind erosion	WEHI model = /NDMI) wind speed * MBI(	Map of ground evidence	0.86	0.89	[23]
7	Land use	Land-use changes	Map of ground evidence	0.71	0.64	[24]

3.2. Desertification Modeling

After selecting the remote sensing indices, desertification modeling was conducted in 2023 using four machine learning models (Figure 3). The results of all four models indicated severe land degradation in the northern regions of the study area, with scattered patches of high degradation intensity also observed in the southern and northeastern areas. To evaluate the modeling results, statistical parameters including the Kappa coefficient, Receiver Operating Characteristic (ROC) curve, and True Skill Statistic (TSS) were used (Table 2). Based on the results, the RF and SVM models outperformed the GLM and GBM models. Overall, the RF model was identified as the best performer with AUC = 0.91, TSS = 0.88, and Kappa = 0.90, while the GLM model was the weakest with AUC = 0.79, TSS = 0.77, and Kappa = 0.65.

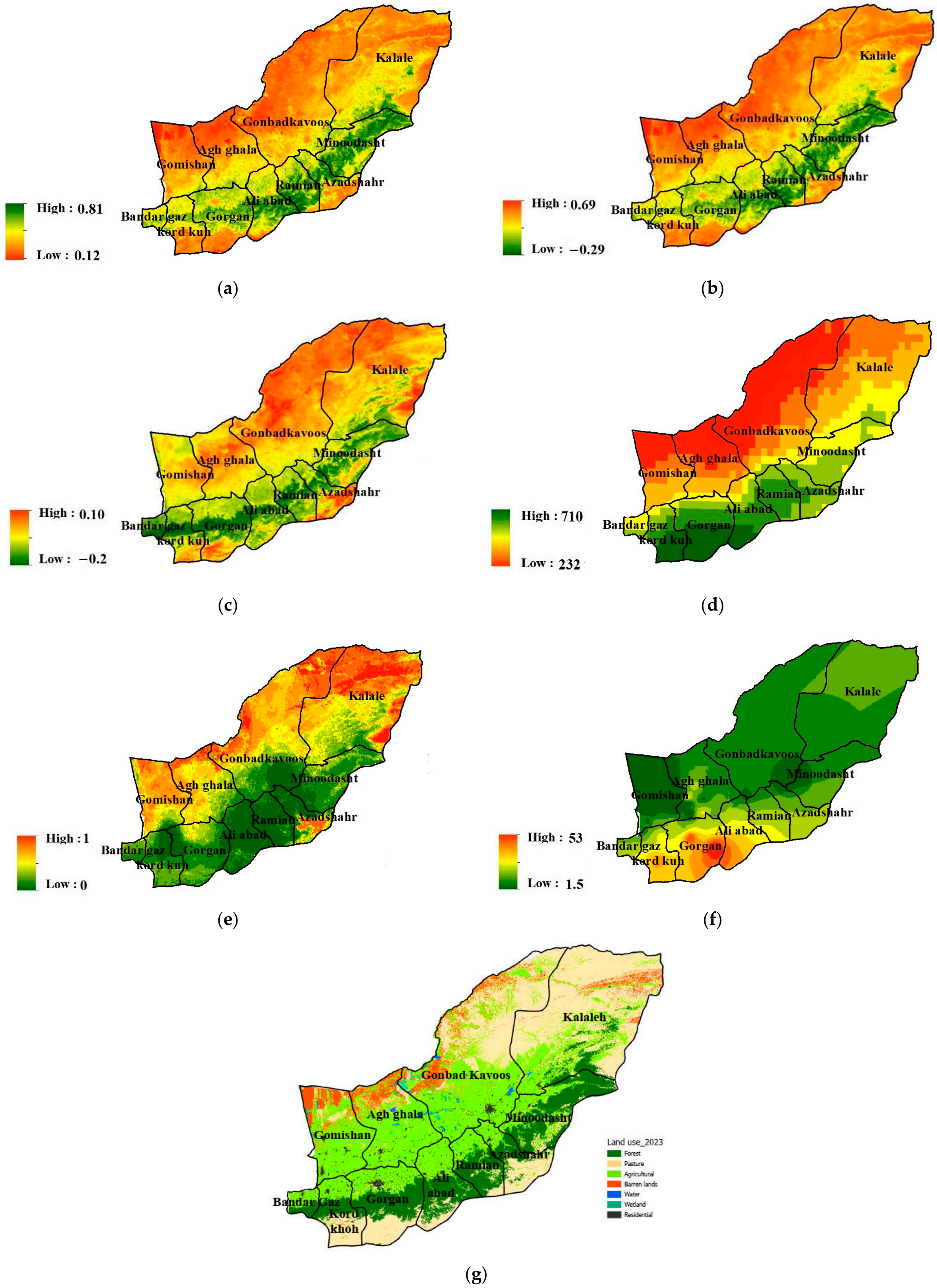

Figure 2. Remote sensing indicators for desertification modeling, (**a**): NDVI, (**b**): NDSI, (**c**): TGSI, (**d**): Chrips, (**e**): WEHI, (**f**): Groundwater and (**g**): Land use.

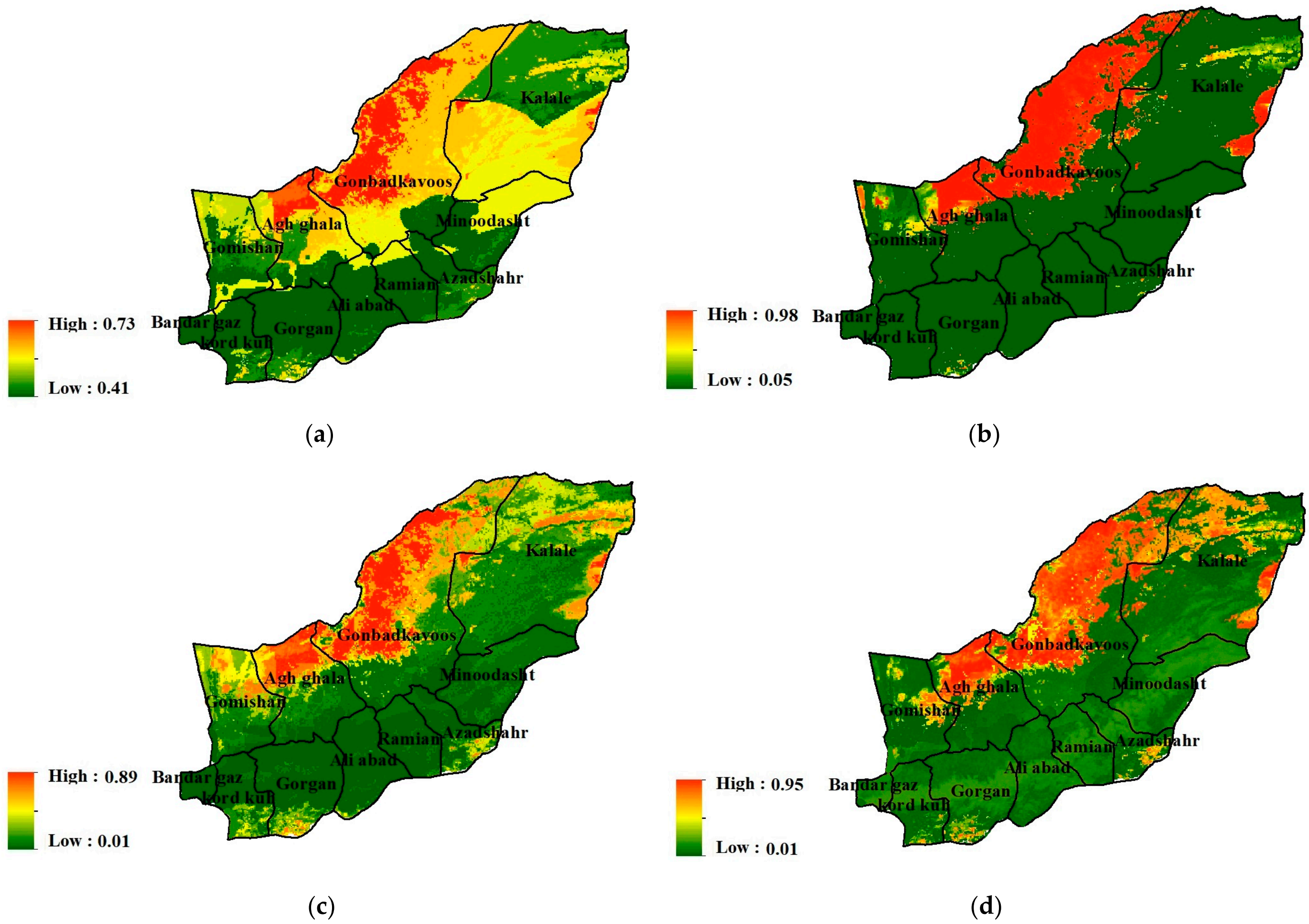

Figure 3. Desertification in northeastern Iran using different models in the SDM package. (**a**), (**b**), (**c**), and (**d**) are models GBM, GLM, RF, and SVM in 2023, respectively.

Table 2. Performance evaluation of models based on various indicators.

Methods	AUC	TSS	KAPPA
GLM	0.79	0.77	0.65
GBM	0.85	0.80	0.72
RF	0.91	0.88	0.90
SVM	0.89	0.86	0.88

The varying performance of the models indicates the presence of uncertainty in their results. Therefore, it is necessary to use ensemble models that leverage the strengths of multiple models. In this study, a weighted average of the four models RF, SVM, GBM, and GLM was used, with the RF model receiving the highest weight and the GLM model the lowest in the ensemble model (Figure 4). The results of the ensemble model also indicate severe desertification in the northern regions of the study area, though the intensity of desertification is shown to be lower compared to the individual models.

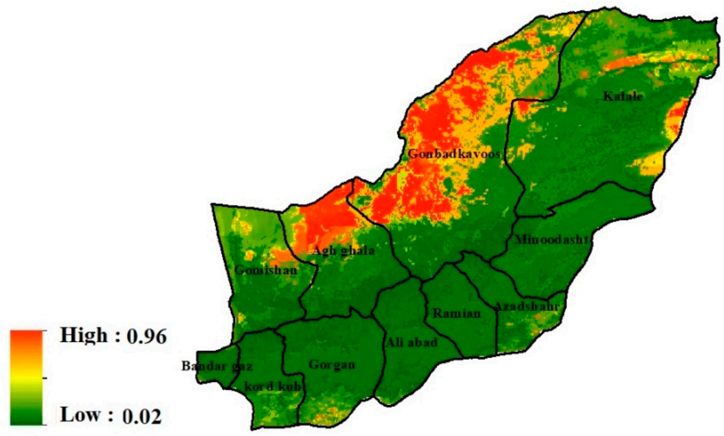

Figure 4. Ensemble model of desertification assessment.

3.3. Importance of Variables in Modeling

Identifying the factors influencing desertification is crucial for managing and preventing this phenomenon. A thorough analysis of these factors allows researchers and environmental managers to model desertification-prone areas more accurately. This, in turn, supports the development of effective strategies to combat desertification. Accordingly, the significance of the indicators used in desertification assessment was determined based on the ensemble model. The process of combining the models was based on the weighted averaging method, where the weight of each model was determined according to its prediction accuracy. Then, the importance of variables was calculated through the weighted combination of the base model results. This approach allowed us to more accurately identify the variables influencing desertification. The variable importance plots presented in the article demonstrate the impact of the key variables that were influential across all models. The results showed that, in order of importance, land-use change, groundwater depth, precipitation, WEHI, NDVI, NDSI, and TGSI are the most influential factors in the region's desertification (Figure 5). Based on these findings, utilizing scenarios such as land-use change and precipitation can be effective in identifying areas prone to desertification and formulating strategies for its control and prevention

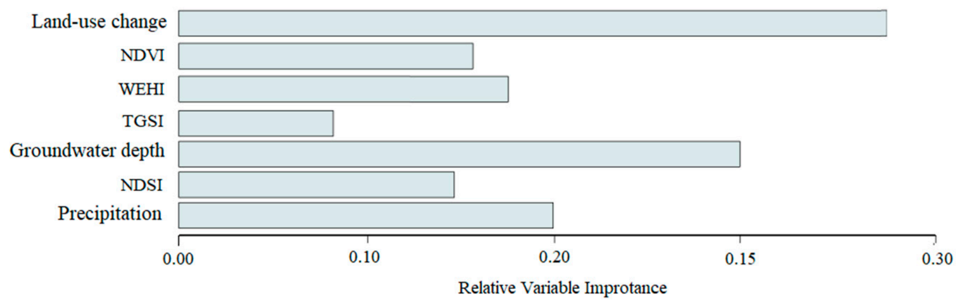

Figure 5. Importance of variables in the study area in 2023.

3.4. Prediction of Future Desertification

To predict desertification in 2040, assuming other parameters remain constant, the average changes in precipitation during the period of 2031–2051 and land use were simulated. Results from the CNRM-CM6 model indicate an increase in precipitation across Golestan Province in the future period. The findings showed that under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, annual precipitation at the synoptic station in Gorgan is expected to increase by 78.5, 58.11, and 109.78 mm, respectively, during the 2031–2050 period. At the Gonbad station, precipitation is predicted to increase by 59.99, 56.20, and 78.12 mm under these scenarios. Similarly, at the Kalaleh and Maraveh Tappeh stations, precipitation is expected to rise, with increases of 55.26, 50.55, and 57.99 mm at Kalaleh, and 33.55, 28.42, and 41.30 mm at Maraveh Tappeh, assuming the realization of the climate change scenarios (Figures 6 and 7).

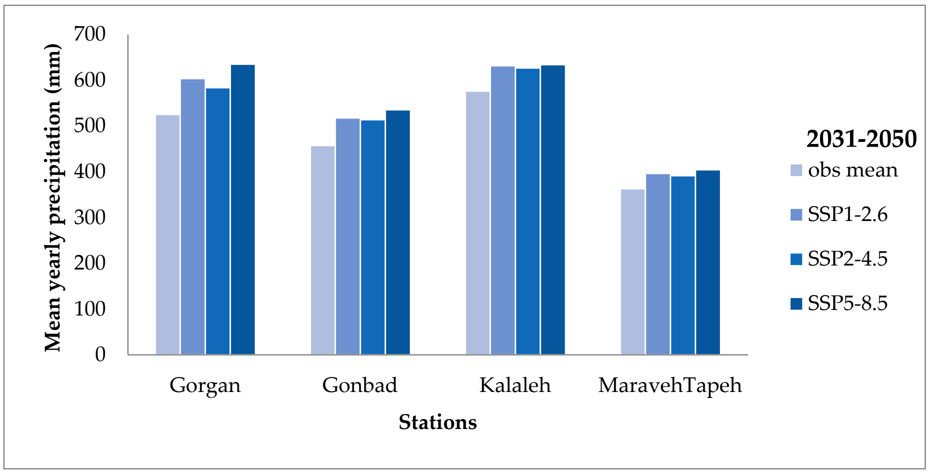

Figure 6. Precipitation prediction in regional stations using different scenarios for the period of 2031–2050.

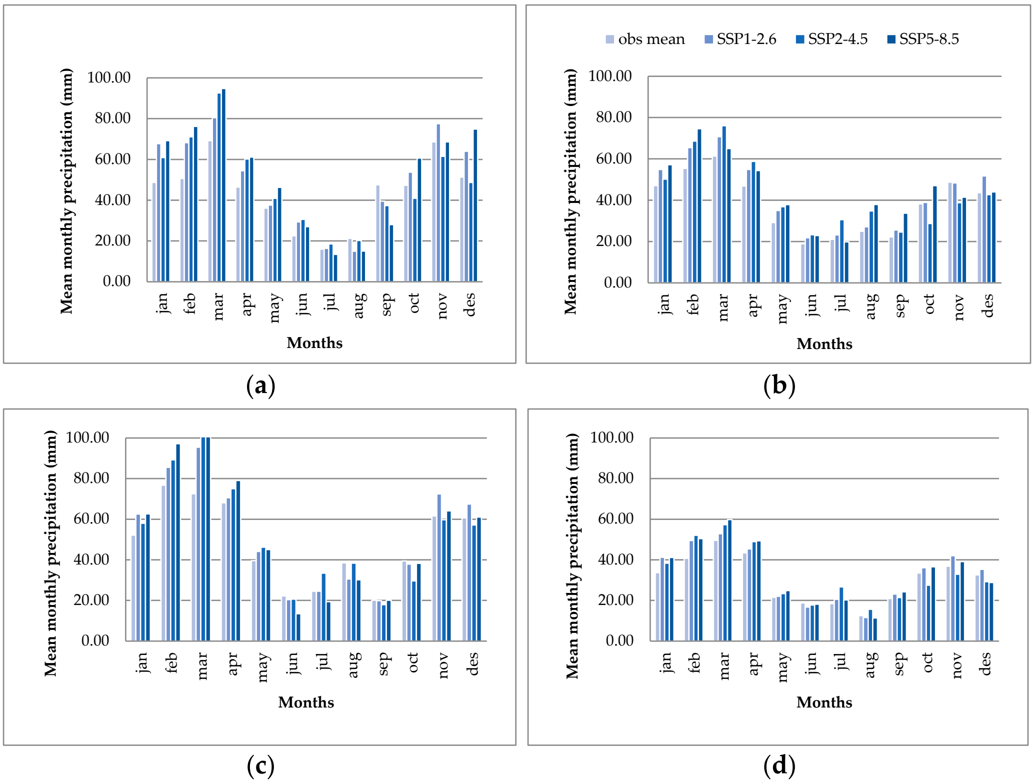

Figure 7. Monthly precipitation prediction using different scenarios for the period of 2031–2050 in (**a**) Gorgan station, (**b**) Gonbad station, (**c**) Kalaleh station and (**d**) Maraveh Tappeh station.

The land-use prediction in 2040, using the Markov Chain model and comparing it with current land use (2023), indicates a reduction in forest areas by 7093 hectares (0.35 percent), rangeland areas by 109,182 hectares (5.38 percent), and wetland areas by 840 hectares (0.04 percent), along with an increase in agricultural land by 4800 hectares (0.24 percent), barren land by 104,998 hectares (5.18 percent), water bodies by 1000 hectares (0.05 percent), and residential areas by 6317 hectares (0.31 percent) (Table 3 and Figure 8). Assuming constant indices for soil surface texture, soil salinity, groundwater depth, and vegetation cover density, and also considering the projected average precipitation for the 2031–2050 period and land use in 2040, desertification was projected using an ensemble model for 2040 (Figure 8). The 2040 desertification map indicates an expansion of this phenomenon in the northern regions of the area. The results showed that desertification in 2040 is expected to increase by approximately 2% (40,562 hectares), with the advance occurring in the Northwest regions adjacent to the Gorgan wetland and the Sangi Tappeh desert (Table 4 and Figure 9).

Table 3. Investigating the trend of land-use class changes.

Class	Land Use	2023 (Hectares)	2040 (Hectares)	Percent Changes
1	Forest	338,308	331,215	−0.35
2	Pasture	708,316	599,134	−5.38
3	Agricultural	804,025	808,825	0.24
4	Barren lands	124,644	229,642	5.18
5	Water	8201	9201	0.05
6	Wetland	8718	7878	−0.04
7	Residential	35,901	42,218	0.31
Total		2,028,113	2,028,113	

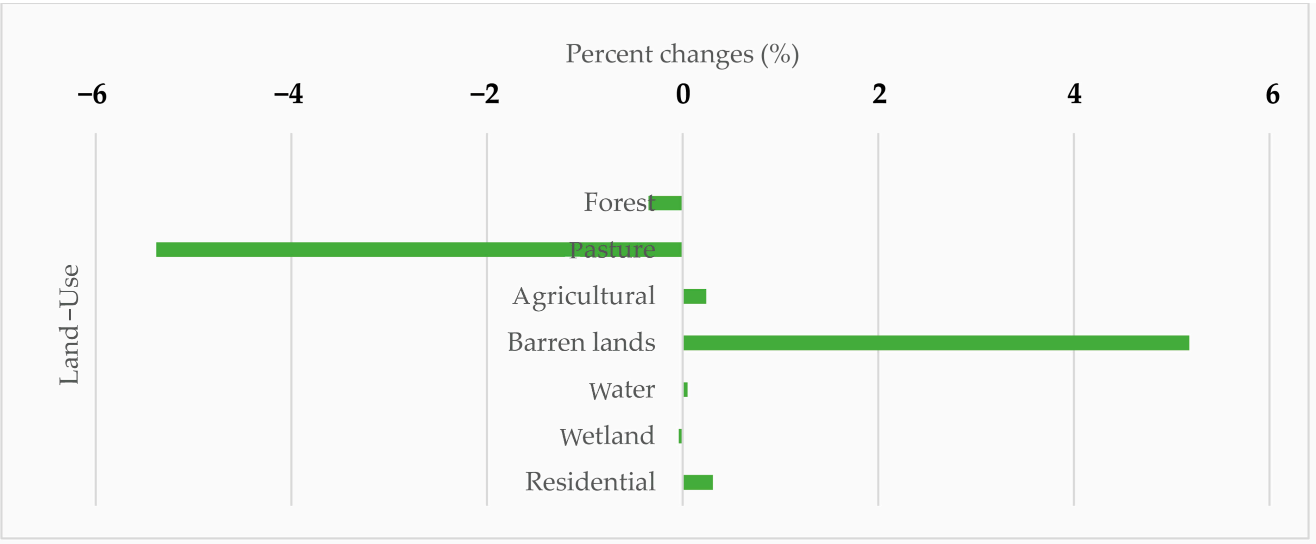

Figure 8. Predicted land-use change between 2023 and 2040.

Table 4. The trend of desertification class changes.

Class	Desertification	2023 (Hectares)	2040 (Hectares)	Percent Changes
1	Low	1,345,809	1,204,281	−6.97
2	Moderate	321,785.44	402,430.4	+3.97
3	Severe	165,359.77	185,680.8	+1
4	Very Severe	195,158.80	235,720.8	+2
Total		2,028,113	2,028,113	

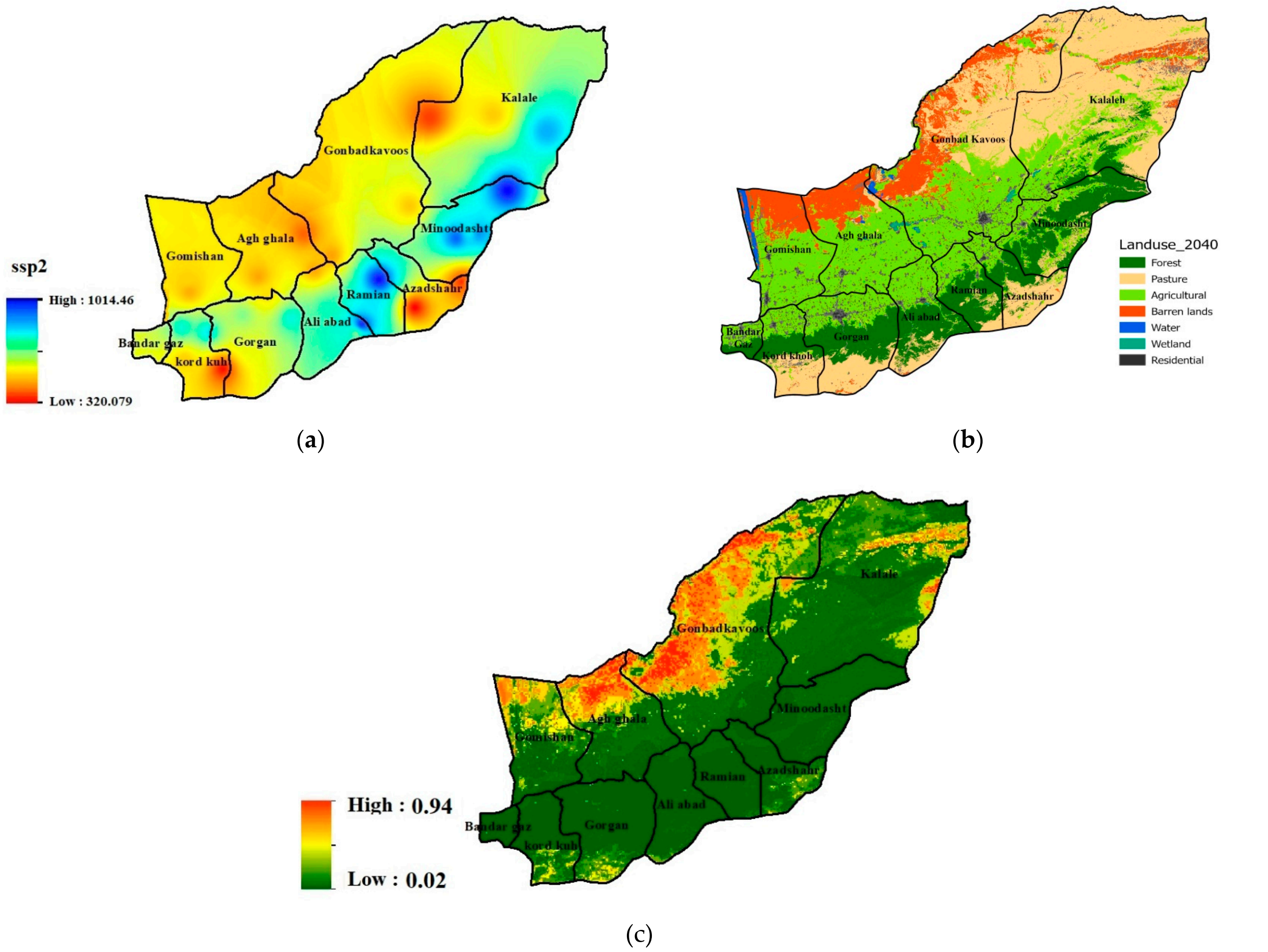

Figure 9. (**a**) Rainfall scenario in 2040, (**b**) Land-use scenario in 2040, and (**c**) Desertification in 2040.

4. Discussion

The novel combination of six distance-based indices with the SDM package in R provides a unique perspective on desertification modeling. This approach enables accurate projections of future desertification trends. Results indicate that the Random Forest (RF) and Support Vector Machine (SVM) models outperformed the Gradient Boosting Machine (GBM) and Generalized Linear Model (GLM) in terms of predictive accuracy. The superior performance of the RF model can be attributed to its ensemble nature, which involves combining multiple decision trees trained on different data samples to enhance diversity and mitigate overfitting.

Random Forest (RF) and Support Vector Machine (SVM) were employed in this study due to their proven effectiveness in handling complex classification problems. RF, with its ensemble nature, reduces variance and improves predictive accuracy by combining multiple decision trees. SVM, on the other hand, excels in high-dimensional space and can effectively separate data classes. While both models offer advantages, they also have limitations. RF can be computationally expensive for large datasets, and SVM can be sensitive to hyper-parameter tuning. To mitigate these limitations and enhance the overall robustness of the model, an ensemble approach was adopted, combining the strengths of both models [25–28].

The Random Forest model outperformed other models in the analyses conducted in this study for several reasons. By combining a large number of decision trees and random sampling, this model reduces data fluctuations and prevents overfitting. Consequently, this method utilizes uncertainty metrics for each tree and ultimately selects the prediction based on majority voting, resulting in higher prediction accuracy. Other studies have also demonstrated the effectiveness of this model. For example, recent research has shown that the Random Forest model, due to its noise-resistant structure, performs exceptionally well, particularly in complex problems and noisy datasets. The findings of this study align with these previous studies, demonstrating that, compared to models such as GLM and BRT, which are more sensitive to data fluctuations, the RF model exhibits greater stability in accuracy [14,29,30].

The ensemble approach, which combines the strengths of Random Forest and Support Vector Machine, proved to be particularly effective in modeling desertification. By mitigating the limitations of individual models, such as overfitting in RF or sensitivity to hyper parameters in SVM, the ensemble model provided a more robust and reliable prediction. The reduced uncertainty in the ensemble predictions allowed for more confident projections of future desertification trends. The results of this study underscore the benefits of ensemble modeling in complex environmental modeling tasks. By combining multiple diverse models, the ensemble approach not only improves predictive accuracy but also enhances the interpretability of results. The ensemble model's ability to identify the most influential factors contributing to desertification (e.g., climate change, land use) provides valuable insights for developing targeted mitigation strategies. Furthermore, the ensemble framework can be adapted to other environmental problems, making it a versatile tool for addressing complex challenges [13,14].

The ensemble model results indicate a higher intensity of desertification in the northern regions of the study area. The analysis reveals that changes in desertification in Golestan Province are influenced by a complex interplay of environmental and anthropogenic factors. Key drivers include land-use change, alterations in groundwater depth, and precipitation patterns. Land-use change, particularly the conversion of agricultural land and pastures to rainfed and fallow lands, significantly accelerates desertification. These changes often result in the loss of natural vegetation, which acts as a barrier against soil erosion. Reduced vegetation cover also leads to increased evaporation and decreased infiltration, disrupting soil moisture balance. Another critical factor is the decline in groundwater levels. Excessive groundwater extraction and climate change can induce soil dryness and reduced agricultural productivity. Additionally, changes in precipitation, a significant climatic factor, play a crucial role. Decreased precipitation in the arid and semi-arid regions of Golestan reduces soil moisture and hampers the regeneration of natural vegetation, exacerbating desertification. Conversely, sudden and intense rainfall events can cause soil erosion and degrade soil structure and biota. Overall, our findings indicate that desertification in Golestan Province is a result of complex interactions between human and natural factors, necessitating appropriate environmental policies and comprehensive conservation measures for effective management and control.

Climate and land-use change simulations reveal complex trends in the study area, with potentially significant environmental consequences. Climate modeling results indicate a general increase in precipitation in the Golestan province. This increase is observed across all synoptic stations but varies spatially, with higher increases observed from east to west. These variations may be attributed to factors such as station location, topography, and changes in large-scale atmospheric circulation patterns. While increased precipitation could have positive impacts like enhanced soil moisture, improved vegetation cover, and reduced drought risk, the increased intensity and frequency of extreme rainfall events may lead to flooding, soil erosion, and land degradation.

Land-use projections from 2023 to 2040 indicate substantial changes that directly influence desertification processes. The significant expansion of barren lands and the decline in pastureland can have detrimental effects on the region, including increased barren lands, resulting from reduced vegetation cover, soil erosion, decreased soil infiltration, and ultimately intensified desertification. Changes in precipitation and land use interact to influence desertification processes. While increased precipitation can improve vegetation cover and reduce soil erosion, it can also lead to flooding and soil degradation if not coupled with proper water and soil management.

The 2040 desertification map indicates an eastward expansion of desert areas from the northeastern regions. The findings suggest that without effective desertification control measures, a 2% increase (40,562 hectares) in desertified areas could occur by 2040. Unsustainable agricultural practices, coupled with land-use changes, are likely to exacerbate desertification in the future. To mitigate these impacts, strategies such as protecting environmentally sensitive areas, conserving natural resources, promoting sustainable agriculture, and optimizing land use are recommended.

While this study provides valuable insights into the spatial and temporal patterns of desertification in Northeast Iran, it is important to acknowledge certain limitations. The accuracy of the results is dependent on the quality and resolution of the input data, particularly remote sensing data. Additionally, the complexity of desertification processes and the influence of various socio-economic factors may not be fully captured by the models employed in this study. Future research could explore more advanced modeling techniques, such as machine learning algorithms that incorporate deep learning, to further improve the accuracy and robustness of the predictions. Furthermore, integrating socio-economic factors into the analysis can provide a more comprehensive understanding of the drivers of desertification and inform targeted interventions.

5. Conclusions

This study highlights the significant role of land-use change and climate variability in driving desertification in Northeast Iran. By integrating advanced machine learning techniques, such as Random Forest and Support Vector Machine, with remote sensing data, this research has enabled accurate mapping and prediction of future desertification trends. The ensemble modeling approach further enhances the robustness and reliability of the results.

The findings indicate that the northern regions of the study area are particularly vulnerable to desertification. The projected increase in desertification by 2040, driven by climate change and land-use change, underscores the urgent need for effective mitigation and adaptation strategies. To address this pressing issue, it is imperative to implement sustainable land management practices, such as afforestation, agroforestry, and soil conservation measures. Additionally, climate change mitigation strategies, including reducing greenhouse gas emissions and promoting renewable energy sources, are crucial to limit the adverse impacts of climate change on desertification.

While this study provides valuable insights, it is important to acknowledge the limitations inherent in the research, such as the reliance on data quality and model assumptions. Future research could explore more advanced modeling techniques, incorporate additional socio-economic factors, and refine the evaluation metrics to further enhance the understanding of desertification dynamics. By addressing the challenges posed by desertification, it is possible to protect ecosystems, safeguard livelihoods, and ensure the long-term sustainability of the region.

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