Journal of Geoscience and Earth Observation
http://dx.doi.org/10.62762/JGEO.2025.205415

RESEARCH ARTICLE

Spatiotemporal Assessment of Desertification Sensitivity in Ningxia, China, Using the MEDALUS Framework and Random Forest Classification (2001–2022)

Munaza Nawaz[1], **Wilson Kalisa**[1,*], **Zakria Zaheen**[1], **Moughal Tauqir**[1], **Jiahua Zhang**[1,*], **Adnan Abbas Shah**[2] and **Kalim Ullah**[3]

[1] Remote Sensing Information and Digital Earth Center, College of Computer Science and Technology, Qingdao University, Qingdao 266071, China
[2] Department of Meteorology, COMSATS University Islamabad, Islamabad 45550, Punjab, Pakistan
[3] Department of Electrical Engineering, University of Science and Technology, Bannu, Khyber Pakhtunkhwa, Pakistan

Abstract

In semi-arid regions, desertification is a critical environmental degradation factor. This study analyzes land degradation and desertification vulnerability dynamics in Ningxia, China (2001–2022) using the MEDALUS framework with a Random Forest classifier. Land-cover change was significant due to irrigation and agricultural expansion, with farmland increasing to 65.29% of the landscape while grassland shrank to 10.13%, intensifying ecological pressure. Bare land followed a U-shaped trend, reaching 9.17% in 2022, indicating increased soil exposure. Soil quality remained moderately stable, with 70–80% of land retaining integrity despite ongoing degradation. Vegetation quality fluctuated considerably, as poor vegetation quality decreased from 42.42% in 2001 to 36.6% in 2022, with scattered local recovery. Management quality improved due to irrigation modernization and policy implementation, while long-term aridity moderately constrained climatic conditions. The Desertification Sensitivity Index (DSI) varied over time: low-desertification areas accounted for 44.47% in 2001, while high-desertification areas comprised 29.06%. By 2011, conservation efforts increased stable areas to 48.26%. However, in 2022, high-desertification areas persisted across 9,552.49 km², primarily in northern and central regions characterized by poor soil and uneven rainfall. This research provides robust scientific evidence to inform land management, vegetation rehabilitation, and climate adaptation strategies in vulnerable drylands.

Keywords: desertification, MEDALUS, random forest, Ningxia, land degradation, remote sensing, dryland ecosystems, google earth engine (GEE).

Submitted: 05 December 2025
Accepted: 06 April 2026
Published: 16 April 2026

Vol. 1, **No.** 1, 2026.
10.62762/JGEO.2025.205415

***Corresponding authors:**
✉ Wilson Kalisa
2020020669@qdu.edu.cn
✉ Jiahua Zhang
zhangjh@radi.ac.cn

Citation
Nawaz, M., Kalisa, W., Zaheen, Z., Tauqir, M., Zhang, J., Shah, A. A., & Ullah, K. (2026). Spatiotemporal Assessment of Desertification Sensitivity in Ningxia, China, Using the MEDALUS Framework and Random Forest Classification (2001–2022). *Journal of Geoscience and Earth Observation*, 1(1), 39–54.

© 2026 by the Authors. Published by Institute of Central Computation and Knowledge. This is an open access article under the CC BY license (https://creativecommons.org/licenses/by/4.0/).

1 Introduction

Desertification has emerged as one of the most pressing global environmental challenges of the 21st century, particularly affecting arid, semi-arid, and dry sub-humid regions [1]. According to the United Nations Convention to Combat Desertification (UNCCD), desertification refers to the degradation of the arid, semi-arid, and dry sub-humid areas that can be explained by climatic changes and anthropogenic factors [2]. Unsustainable land management, climate change, and inappropriate water management are among the threats to continued degradation of dryland ecosystems that affect biodiversity, agricultural productivity, food security, and the livelihoods of millions of people, especially in already vulnerable ecosystems [3]. Poverty, migration, and competition over limited natural resources are the main triggers of social instability, conflict, and degradation of the ecosystem in semi-arid areas like Ningxia, China [43]. Evaluations and monitoring of desertification are a mandatory aspect of the development of successful land conservation policies, climate-resilience policies, and sustainable development policies [4]. The issue is multifaceted as it is the result of the interactions between the whole range of both natural and human-made factors, which is why it requires holistic evaluation frameworks encompassing both biophysical and socio-economic aspects of land degradation [5].

The Mediterranean Desertification and Land Use (MEDALUS) model has become a useful instrument in determining the threat of desertification; it has initially been developed as a part of the Mediterranean MEDALUS initiative that is financed by the European Union [6]. The model uses four main quality indices that are used to come up with a composite Desertification Sensitivity Index (DSI). Soil Quality Index (SQI) analyzes the characteristics of the soils including the texture, depth, slope gradient, and probability of erosion [7]. The Climate Quality Index (CQI) takes into consideration the variability of the precipitation, the indices of aridities, or even the degrees of drought. Vegetation Quality Index (VQI) is a measure of land-cover stability, vegetation density and productivity of the land-cover derived using the values of the Normalized Difference Vegetation Index (NDVI) [8]. Anthropogenic impact is assessed by the Management Quality Index (MQI) using land-use intensity, the level of population pressure, and infrastructure development [9]. The DSI is the result of the geometrical interpretation of the above-mentioned standardized indices, which subdivides land into discrete stratification of vulnerability [37]. The methodological flexibility of the model has helped it to be used in a variety of ecosystems, such as in the Mediterranean area and arid areas in Africa and Asia [10].

Effective desertification monitoring has been realized with the recent technological advancements. Satellite remote sensing provides time-adjustable and spatially comprehensive information on the land-surface changes [11]. To improve land-cover classification, machine-learning algorithms, specifically Random Forest (RF), an ensemble machine learning algorithm that consists of numerous decision trees, provides more predictive power and reduces overfitting. This ensemble method is specifically useful in the case of processing high-dimensional remote-sensing measurements [12, 13, 18]. Combining the MEDALUS framework with those sophisticated analytical techniques comprises an influential paradigm in the modern study of desertification, as it would allow assessing the land-degradation processes more strictly and dynamically [19].The current research aims to use the MEDALUS model that is integrated with remote sensing and machine learning to assess the shift in desertification sensitivity in Ningxia in 2001 and 2022. Analysis will be based on a comparison of the DSI results obtained using land-cover classifications produced by the RF. It will map and analyse land cover changes over the 21 years span by synthesizing satellite-derived environmental indices with socio-economic and climatic variables with the aim of: (1) mapping and comparing DSI values of 2001, 2011 and 2022 (2) evaluating trends in land sensitivity to desertification and (3) identifying hotspots areas that will need priority intervention.

The topicality of the given work is also supported by the fact that the issues of land degradation persist in Ningxia, where the anthropogenic impact on the terrestrial resources is aggravated by the population growth and the disappearance of the forests as well as irregular precipitation and unsustainable agricultural technologies. Spatial understanding of the dynamics of land degradation is an essential element in informing the effective policy efforts, community-based adaptation models and sustainable land use planning. The paper has a few interventions to modern desertification studies in arid and semi-arid ecosystems.

The combination of MEDALUS framework and the

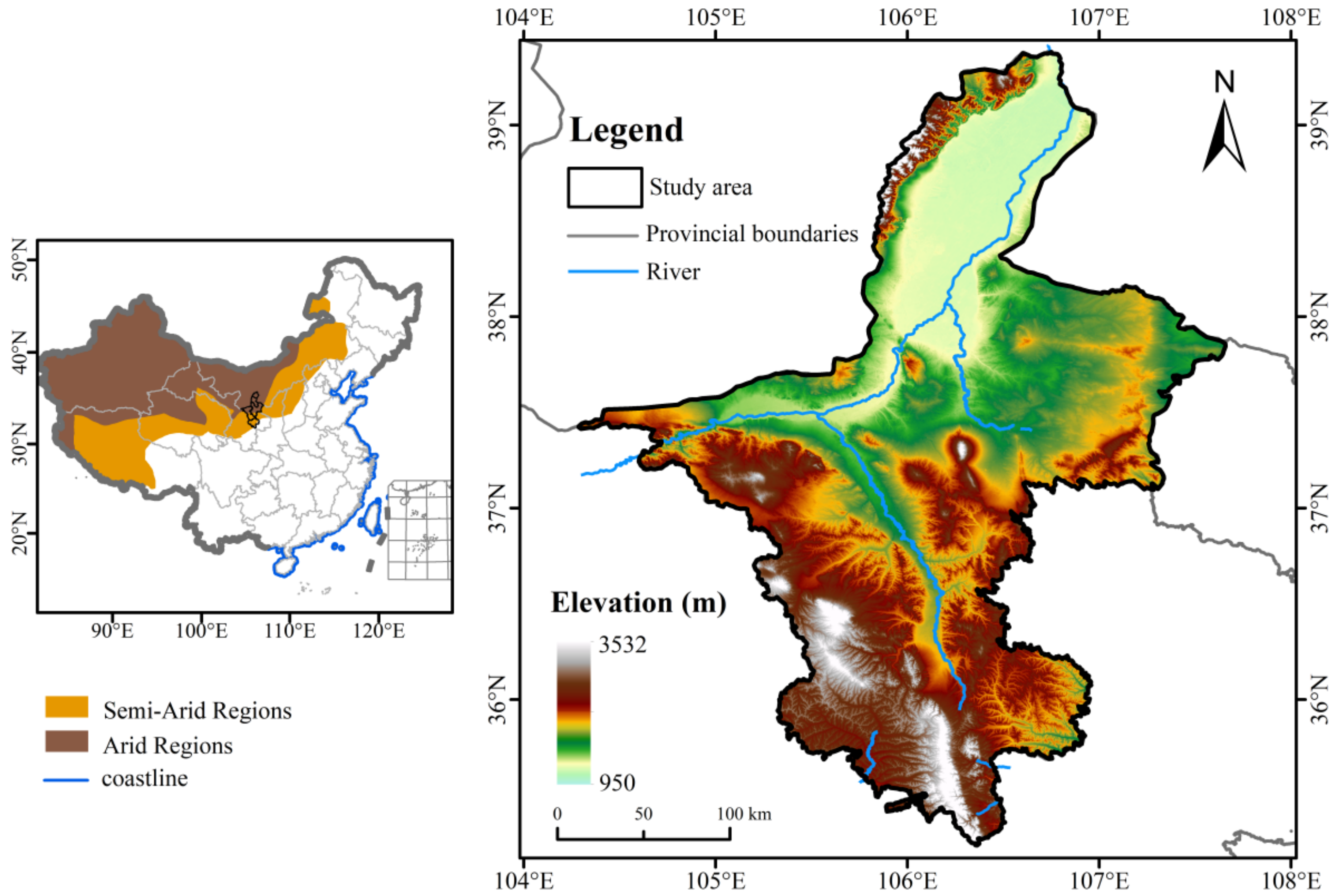

Figure 1. Location of Ningxia within China, showing its ecological transition from desert plains to mountain zones.

comparison of RF land-cover classification over three benchmark years (2001, 2011 and 2022) will result in the analysis going beyond the limits of single-temporal evaluation and more accurately present the long-term ecological changes in Ningxia. The findings showed that there is a strong ecological lag: the vegetation recovery is faster than the soil regeneration which, in its turn, represents a resilience pattern that has hardly been recorded in the area. The study outlines unique desertification processes by comparing time dynamics of DSI classes that include persistent hotspots, recuperating zones, stabilized plateau and re-pressurized sectors and thus outpacing traditional non-dynamics mapping techniques. Additionally, the paper provides empirical findings on whether national ecological programmes such as the Grain-for-Green, irrigation modernization, and grazing reforms lead to land-sensitivity results. Lastly, concurrent analysis of soil, vegetation, climate and management indices will provide a holistic outlook on the biophysical and socio-economic predictors of desertification processes hence informing land governance and climate-adaptation planning.

2 Study Area

The Ningxia Hui Autonomous Region is situated in the northwest of the People's Republic of China, encompassing latitudes 35.014°N to 39.23°N and longitudes 104.017°E to 107.39°E. It serves as a transition zone between the Tengger Desert on the northwest and the Loess Plateau on the south [20]. Such geographic arrangement creates a high ecological gradient, which is depicted in Figure 1, with the altitudinal extremes of about 1,100-3,500 m respectively in the lowlands and the Liupan Mountains in the south, making the region especially vulnerable to the process of desertification [21]. The climatic condition of Ningxia is a temperate continental climate of low and highly fluctuating annual precipitation that ranges between 150 and 400 mm, with the northwestern area getting less than 200 mm [22]. The rates of potential evaporation are also high, with the range between 1,800 and 2,200mm/yr, contributing to natural aridity. The temperature does vary considerably seasonally, with an annual average temperature around 5-10°C, winter reaching 0°C and summer exceeding 30°C, which puts a further strain on local biogeocenosis [23]. There are also frequent spring droughts and dust storms that also reduce the land degradation, especially in the prone desert-oasis transition zones [24].

Vegetation follows a distinct aridity gradient, shifting from sparse desert shrubs (e.g., Artemisia ordosica) in the northwest to steppe grasslands (Stipa bungeana) in central regions and forest-steppe in the Liupan Mountains [25]. Croplands in the Yellow River (irrigated) are a sharp contrast of degraded native grasslands, where overgrazing has reduced the coverage by about 40 per cent since 2000 [26]. The soil changes to salt and sand in the north and loessal soils in the south; erosion by winds is dominant in the desert periphery, and erosion by water is dominant in the Loess plateau [27]. Approximately 30% of the irrigated soils have become salinized due to unsustainable watering, and the rain-fed croplands must endure the loss of nutrients [28]. The reliance of irrigation by Yellow River, which irrigates 40 per cent of the arable land, underscores the susceptibility of agriculture to climatic variability [29].

Overgrazing (destroying 60% of grasslands), past deforestation, and excessive extraction of groundwater are the interrelated natural and man-made causes of desertification in Ningxia [30]. Climate change increases these stresses [31], and the increasing temperatures and prolonged droughts can exacerbate the impact of the Tengger Desert. Even though some of the degraded lands have been restored due to such policies as Grain for Green, the margins of the north-western desert continue to pose critical hotspots, which require integrated management [32].

3 Methods

To evaluate the sensitivity of desertification in Ningxia, the present research used the MEDALUS framework, which combines biophysical and anthropogenic indicators to derive a DSI. The methodology involved the computation of four main indices of quality including CQI, SQI, VQI and MQI which were done based on spatial data sets and ecological variables which are related to land degradation. These indices were calculated with the help of standardized formulas and then divided into the levels of sensitivity because of the expert-developed thresholds modified by Kosmas et al. [6] and Ogbue et al. [33]. The product is the geometric meaning of the four indices which gives the final DSI, thus classifying the land into discrete vulnerability classes. Figure 2 shows the methodology workflow.

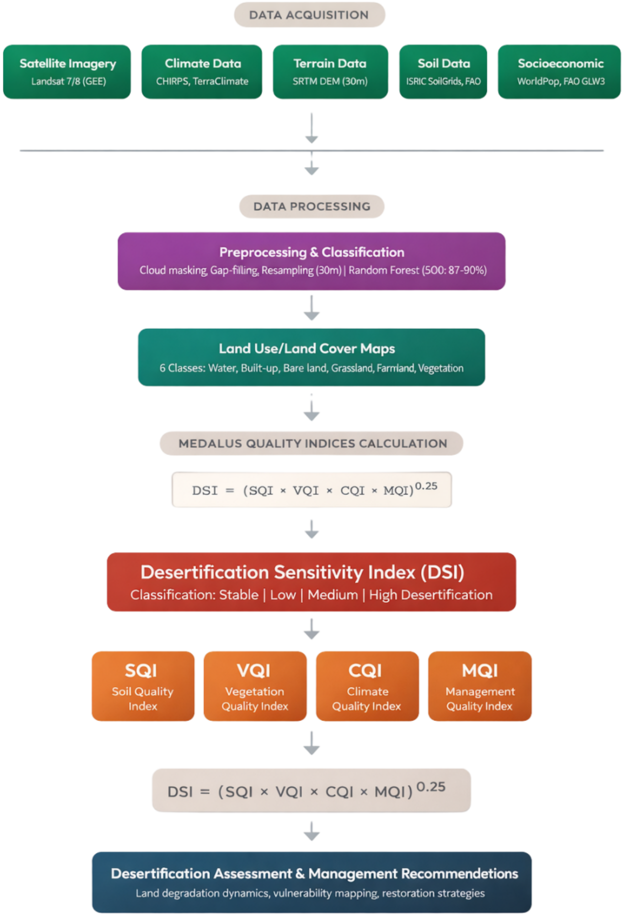

Figure 2. Methodological flowchart for deriving the DSI using the MEDALUS framework integrated with Random Forest classification.

3.1 Data Sources and Preprocessing

Multiple geospatial datasets were acquired and preprocessed to derive the quality indices (Table 1). All datasets were resampled to a common 30-meter resolution using bilinear interpolation for continuous variables and nearest-neighbor resampling for categorical data. Cloud masking was applied to Landsat imagery using the QA band, and gap-filling was performed for any remaining missing values using temporal compositing from adjacent dates within the same growing season. All analyses were conducted in Google Earth Engine (GEE) and ArcGIS Pro 3.0.

3.2 Random Forest Land Cover Classification

Land Use and Land Cover (LULC) maps for 2001, 2011, and 2022 were generated using RF classification implemented in GEE. RF is an ensemble machine learning algorithm that constructs multiple decision trees during training and outputs the mode of classes for classification tasks [14, 15]. The algorithm was selected for its robustness to noise, ability to handle high-dimensional data, and resistance to overfitting [16, 17].

Parameters of Classification and Training: The RF classifier was set to have 500 decision trees (ntree = 500), several decision trees that were decided using sensitivity analysis and showed that the level of accuracy did not increase after 500 decision trees. The square root of the number of input features was the number of variables sampled at each split (mtry) because this choice is consistent with traditional methodological tradition. These input features included the following categories: (1) surface reflectance bands: Blue, Green, Red, NIR, SWIR1, SWIR2, which were obtained by computing annual median composite Landsat imagery; (2) spectral indices: including the NDVI, Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), and Enhanced Vegetation Index (EVI); (3) topographic variables: elevation, slope, aspect, which were obtained by the use of the SRTM DEM were collected using stratified random sampling across six LULC classes: water, built-up, bare land, grassland, farmland, and vegetation (forest/shrubland). A minimum of 500 training pixels per class were collected for each time period, totaling approximately 3,000 samples per year. Sample locations were verified using high-resolution imagery from Google Earth Pro and available field survey data from published regional land cover studies.

Classification accuracy was evaluated using independent validation samples (30% of total samples withheld from training) through stratified k-fold cross-validation (k = 10). Overall accuracy (OA), Kappa coefficient, and per-class producer's and user's accuracies were computed (Table 2). The classification achieved overall accuracies of 87.3% (2001), 89.1% (2011), and 90.2% (2022), with Kappa coefficients ranging from 0.84 to 0.88, indicating substantial to almost perfect agreement [14, 15].

3.3 Climate Quality Index (CQI)

Climate is a critical factor in how an area is pre-disposed to degradation. In the MEDALUS context, CQI was obtained by means of combination of two major elements: annual precipitation, and frequency of droughts (or possible evapotranspiration). The CQI is calculated as a geometric means of the aridity index and the drought index as it is depicted in Equation (1). Climate zone classification is carried out based on the patterns of observed confluence of precipitation and drought stress (Table 3). The used threshold values are borrowed under the original MEDALUS framework [6], and are adjusted according to regional precipitation patterns; as a result, regions with an annual precipitation less than 200 mm are classified as highly sensitive, due to the high levels of moisture losses which are characteristic of desert-margin conditions [36].

$$\mathrm{CQI} = \sqrt{(\text{Aridity Index} \times \text{Drought Index})} \qquad (1)$$

3.4 Soil Quality Index (SQI)

The SQI measures the inherent degradation susceptibility of soils using dimensions like textural class, depth, parent material and slope. The SQI was calculated as in the following equation (2). Among various soils, the water holding and resistance to

Table 1. Data sources for deriving degradation sensitivity indices in the MEDALUS model.

Index	Parameter	Data Source	Resolution
CQI	Annual Rainfall	CHIRPS v2.0	0.05 deg (~5 km)
CQI	Aridity Index	TerraClimate / FAO	~1 km
SQI	Slope	SRTM DEM v3	30 m
SQI	Soil Depth	ISRIC SoilGrids 2.0	250 m
SQI	Parent Material	FAO Soil Map	Vector
SQI	Soil Texture	ISRIC SoilGrids 2.0	250 m
VQI	NDVI	Landsat 7/8 (GEE)	30 m
VQI	Plant Cover	MODIS MOD44B v6	250 m
VQI	Fire Risk	MODIS MCD64A1 v6	500 m
MQI	Land Use	Landsat 7/8 (RF)	30 m
MQI	Population	WorldPop v2	100 m
MQI	Grazing Pressure	FAO GLW3	~10 km

Table 2. Random Forest classification accuracy assessment.

Year	Overall Accuracy (%)	Kappa Coefficient	Avg. Producer Acc. (%)	Avg. User Acc. (%)
2001	87.3	0.84	85.6	86.2
2011	89.1	0.86	87.4	88.1
2022	90.2	0.88	88.9	89.5

Table 3. Climate sensitivity classification.

Annual Rainfall	Drought Level	Score	Justification
200 mm	High	1.0	Severe aridity, desert conditions
200-400 mm	Moderate	1.5	Semi-arid, seasonal stress
400 mm	Low	2.0	Adequate moisture, lower risk

Source: Adapted from [6] and [33]

Table 4. Soil sensitivity classification.

Soil Texture	Erosion Risk	Score	Justification
Sandy soils	High	1.0	Poor water retention, wind-prone
Loamy soils	Moderate	1.5	Balanced properties
Clayey soils	Low	2.0	Good structure, erosion-resistant

Source: Adapted from [6] and [33]

Table 5. Vegetation sensitivity classification (based on NDVI).

NDVI Range	Condition	Score	Justification
0.2	Sparse/Degraded	1.0	Minimal cover, high exposure
0.2 - 0.4	Moderate	1.5	Partial cover, seasonal greenness
0.4	Dense/Healthy	2.0	Full cover, strong protection

Source: Adapted from Kosmas et al. [6] and regional studies [25, 26]

erosion capacities vary and hence determines the classification of soils (Table 4). Sandy soils have the highest sensitivity score of 1.0, which is due to the fact that they have relatively low water-hold mechanisms, a high rate of infiltration, and a high vulnerability to wind erosion, which is particularly high in the northern desert edges of Ningxia [27].

$$\mathrm{SQI} = \sqrt[4]{\begin{aligned}&\text{Slope} \times \text{Soil Depth}\\ &\times \text{Parent Material} \times \text{Soil Texture}\end{aligned}} \tag{2}$$

3.5 Vegetation Quality Index (VQI)

Vegetation cover is necessary to stabilize the land surface and reduce the erosive forces. Besides ecological features such as fire risk, erosion protection and drought resistance, the VQI includes the NDVI as indicators of plant health and density. The thresholds of NDVI in Table 5 were calculated based on the local vegetation features and past studies in the semi-arid areas in China [25]. Values below 0.2 indicate sparse vegetation with minimal protective cover, typical of degraded lands and bare surfaces. Values between 0.2-0.4 represent moderate vegetation density common in grasslands and shrublands, while values exceeding 0.4 indicate dense vegetation with high erosion protection capacity [26]. VQI was calculated using Eq.(3).

$$\mathrm{VQI} = \sqrt[4]{\begin{aligned}&\text{Fire Risk} \times \text{Erosion Protection}\\ &\times \text{Drought Resistance} \times \text{Plant Cover}\end{aligned}} \tag{3}$$

3.6 Management Quality Index (MQI)

MQI incorporates indicators of anthropogenic stress, including land use intensity, population pressure, and grazing pressure. Areas subjected to deforestation and overgrazing are assigned to higher degradation sensitivity (lower scores), while those under sustainable land management receive lower sensitivity scores. It was calculated as shows in Eq. (4). Table 6 presents the classification criteria for management conditions, where scores of 1.0,

Table 6. Land management classification.

Management Condition	Description	Score
Overgrazing, Deforestation	Intensive degradation pressure	1.0
Some conservation efforts	Mixed practices, partial protection	1.5
Sustainable agriculture	Afforestation, controlled grazing	2.0

Source: Adapted from [6] and [33]

Table 7. Desertification sensitivity index classification.

DSI Range	Sensitivity Level	Interpretation
1.0	High Desertification	Critical degradation, priority intervention needed
1.0 - 1.25	Medium Desertification	Moderate risk, monitoring required
1.25 - 1.5	Low Desertification	Low sensitivity, stable conditions
1.5	Stable/Resilient	Non-sensitive, healthy ecosystem

Source: Adapted from [6] and [33]

Table 8. Land cover classification (2001, 2011, and 2022).

LULC Class	Area 2001 (km^2)	2001 (%)	Area 2011 (km^2)	2011 (%)	Area 2022 (km^2)	2022 (%)
Water	567.06	1.13	372.56	0.74	374.54	0.74
Built-up	1,000.82	1.99	1,812.36	3.60	1,940.57	3.85
Bare land	3,741.99	7.42	2,171.86	4.31	4,619.72	9.17
Grassland	15,889.98	31.53	11,763.55	23.34	5,107.09	10.13
Farmland	21,570.84	42.80	28,611.89	56.77	32,909.34	65.29
Vegetation	7,633.20	15.14	5,671.67	11.25	5,452.63	10.82

1.5, and 2.0 correspond to high, moderate, and low degradation sensitivity, respectively.

$$\mathrm{MQI} = \sqrt[3]{\begin{aligned}&\text{Land Use} \times \text{Population Pressure}\\ &\times \text{Grazing Pressure}\end{aligned}} \tag{4}$$

3.7 Desertification Sensitivity Index (DSI)

The result is the DSI which is a result of calculation of the geometric means of the four constitutive quality indices. Following categorisation of the DSI values follow established sensitivity limits as in Table 7. Interestingly, the Medium Desertification course (1.0-1.25) scored zero spatial coverage on all the temporal units under study implying that the degraded land cover to stable land cover is sudden and not gradual. This momentary shift coincides with the clear zonal division between the desert edges and irrigated lands of agriculture that was reported by Wang et al. [20]. Other arid areas with strong gradients of environmental conditions also report similar trends in binary distributions [9]. It was calculated using Eq. (5)

$$\mathrm{DSI} = \sqrt[4]{SQI \times VQI \times CQI \times MQI} \tag{5}$$

4 Results

4.1 Land Use/Land Cover Changes (2001-2022)

Table 8, Figures 3 and 4 illustrate the Land Use and Land Cover (LULC) change results of 2001, 2011, and 2022. Over the period from 2001 to 2022, there has been a significant change in the landscape, which is evident from the proportion increase in agricultural land from 42.8 % to 65.29 % and from 1.99 % to 3.85 % in built-up areas. This increase has largely been at the cost of grassland, which significantly reduced from 31.53 % to 10.13 %, and vegetation, which significantly reduced from 15.14 % to 10.82 %. Water features remained relatively stable, constituting less than 1 % of the area, while bare land, which initially reduced to 4.31 % in 2011, significantly increased to 9.17 % in 2022. The LULC changes in Ningxia from 2001 to 2022 are shown in Table 8 and Figures 4 and 5. The agricultural land increased greatly from 21,570.84 km^2 (42.8 %) to 32,909.34 km^2 (65.29 %), which is an increase of 52.5 % in two decades. This growth is attributed to more active cultivation following population increase following the population increase, the irrigation projects initiated by the government on the Yellow River, and the incentives of agricultural policies such as the Grain-for-Green project that initially converted the marginal lands into croplands and then back to the restoration causes reversed the trend in the Loess plateau. The grassland area reduced sharply from 31.53 % (15,889.98 km^2) in 2001 to 10.13 % (5,107.09 km^2) in 2022, which is due to overgrazing, pasture conversion, and drying up because of climate change, especially in the central and northern regions of Ningxia. Similarly, the vegetation area (forest and shrubland) reduced from 15.14 % to 10.82 %, which emphasizes the loss of biodiversity and the reduction in carbon sequestration capacity. The built-up area almost doubled from 1.99 % to 3.85 %, which confirms the rapid urbanization in the Yinchuan, Shizuishan, and Wuzhong corridors and matches the urban expansion trends in the country. The bare land area followed a U-shaped trend, which reduced to 4.31 % in 2011 due to reforestation and soil conservation efforts but again increased to 9.17 % in 2022, which may be due to deforestation, aridity, and soil exposure because of over-cultivation.

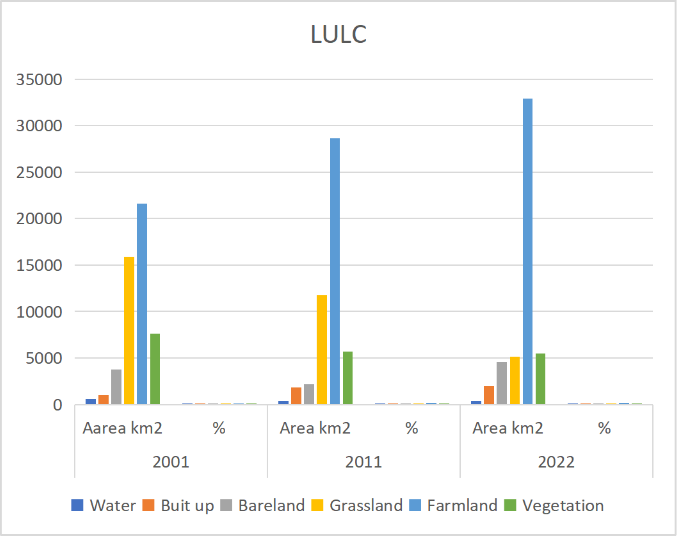

Figure 3. Temporal trends in land use/land cover area (2001-2022).

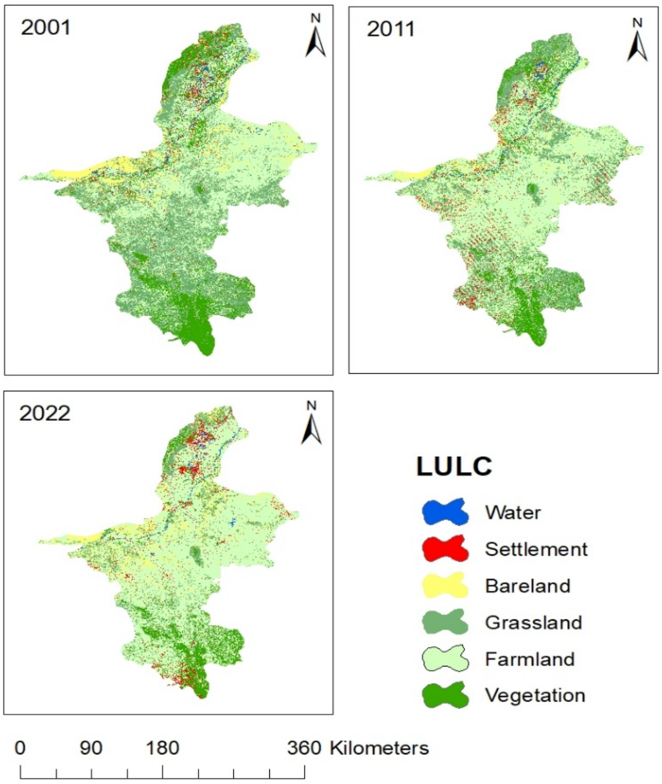

Figure 4. Spatial distribution of land use classes in the study area.

4.2 Quality Indices Distribution

4.2.1 Quality Indices in 2001

Figure 5 and Table 9 below provide the initial snapshot (2001) of the four MEDALUS quality indices in the region of interest. The first thing that stands out is that, at baseline, the region generally appeared to be in a moderate to poor state environmentally, particularly in the northern and northeastern parts of the region where aridity increases and soil type is sandy. SQI indicates that 70.8% of the region had moderate soil quality, while 29.06% were of weak quality. The latter indicates poor soil depth, coarse soil texture, and a high susceptibility to erosion. Only a minuscule 0.14% of the region had high-quality soil, which was largely in the southern Loess Plateau, were loamy soils with good soil structure increased soil fertility and quality. Moving on to the VQI, it is clear that 42.42% of the region had weak vegetation quality. This indicated that vegetation was sparse, had low NDVI values, and was highly drought-stressed. In other words, the baseline assessment revealed a large degree of vegetation degradation.

The MQI shows that only 39.82% of the study area reached a high level of managerial performance, and the rest of the sectors were characterized by moderate to weak management influence. A lack of land-use control, widespread overgrazing, and insufficient investment in sustainable conservation activities at the time of investigation indicate such spatial distribution.

The CQI, which reflects conservation quality, was mainly moderate, accounting for 73.53%. This observation goes in line with the semi-arid climatic regime of the area whereby the average precipitation levels per annum range between 200-400 mm.

4.2.2 Quality Indices in 2011

Figure 6 and Table 10 display, respectively, the geographical distribution of the MEDALUS quality

Table 9. Quality indices class distribution in 2001 (km^2).

Index	Class Range	Intensity	Area (km^2)	%
SQI	1.10-1.19	High	71.09	0.14
SQI	1.19-1.50	Moderate	35,683.60	70.80
SQI	1.50-1.70	Weak	14,649.20	29.06
VQI	1.00-1.10	High	13,411.22	26.61
VQI	1.10-1.40	Moderate	15,613.33	30.98
VQI	1.40-1.79	Weak	21,379.34	42.42
MQI	1.10-1.19	High	20,070.27	39.82
MQI	1.19-1.39	Moderate	15,613.33	30.98
MQI	1.39-1.79	Weak	14,720.29	29.20
CQI	1.10-1.19	High	13,340.13	26.47
CQI	1.19-1.50	Moderate	37,063.76	73.53
CQI	1.50-1.79	Weak	0.00	0.00

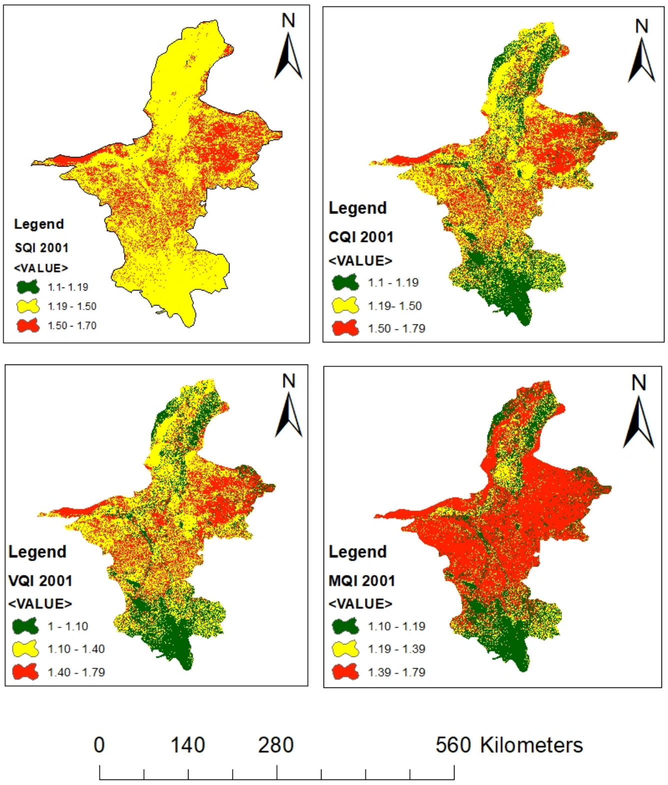

Figure 5. Spatial distribution of quality indices (SQI, VQI, MQI, CQI) for the year 2001.

indices in 2011 in such a way that one can see a significant positive change in various environmental indicators compared to the situation in 2001. This is credited to the introduction of national and regional environmental intervention programs, such as soil conservation and reforestation programs, which were implemented during the last decade. The SQI had a strong upward movement, the moderate soil increased to 79.24%, and the poor soils reduced to 20.45%. This positive trend suggests that the erosion prone areas are partially stabilized and the soil qualities are also increased, which is likely due to better land-use management and less surface erosion.

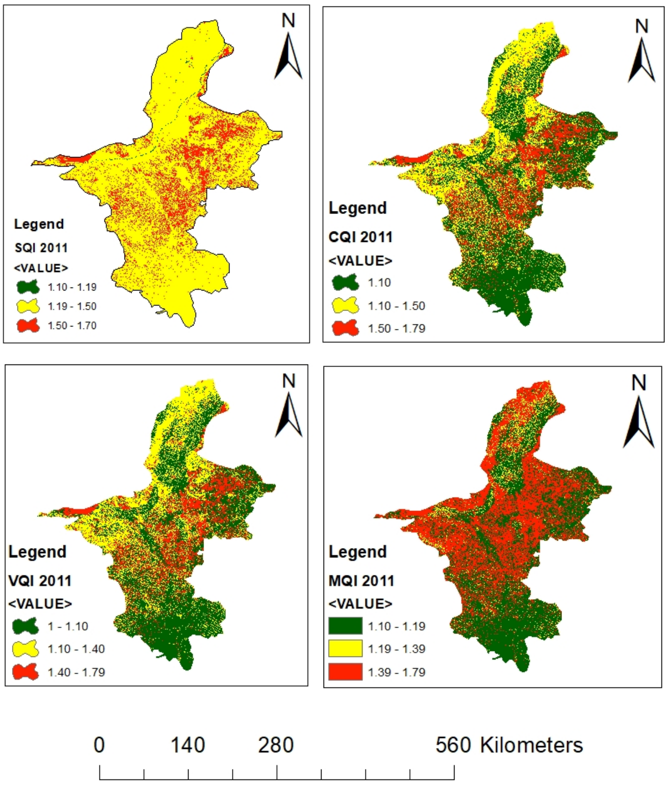

Figure 6. Spatial distribution of quality indices (SQI, VQI, MQI, CQI) for the year 2011.

The percentage of areas with high vegetation quality rose to 48.58% in the VQI which is a significant positive change in vegetation density and quality. The

Table 10. Quality indices class distribution in 2011 (km^2).

Index	Class Range	Intensity	Area (km^2)	%
SQI	1.10-1.19	High	160.59	0.32
SQI	1.19-1.50	Moderate	39,938.15	79.24
SQI	1.50-1.70	Weak	10,305.15	20.45
VQI	1.00-1.10	High	24,485.42	48.58
VQI	1.10-1.40	Moderate	12,114.80	24.04
VQI	1.40-1.79	Weak	13,803.67	27.39
MQI	1.10-1.19	High	27,823.35	55.20
MQI	1.19-1.39	Moderate	12,114.80	24.04
MQI	1.39-1.79	Weak	10,465.74	20.76
CQI	1.10-1.19	High	24,324.84	48.26
CQI	1.10-1.50	Moderate	26,079.06	51.74
CQI	1.50-1.79	Weak	0.00	0.00

preferred cause of this recovery is the effort of the Grain-for-Green reforestation program and the natural reclaiming in areas of earlier degradation.

4.2.3 *Quality Indices in 2022*

Figure 7 and Table 11 show the spatial distribution of the MEDALUS quality indices in 2022, indicating a mixed but positive environmental trend compared to 2001 and 2011. Although great progress has been made in management, and moderate progress has been achieved in soil and vegetation, the weaknesses that have long characterized the northern and northeastern ecological zones have continued. The SQI remained generally moderate (80.66%), indicating stability in most areas of the region. However, the areas of poor soil quality (18.95%) continued to be found in the arid north, where sand dunes, salinity, and low organic matter have continued to affect soil fertility and quality. This shows that although management efforts have been made, soil quality has not been restored as quickly as other environmental factors.

The VQI showed that high vegetation areas (46.81%) had decreased slightly from 2011. This is a result of the frequent droughts, increased agricultural land, and land pressure, which have started to affect the previously restored areas. The continued areas of low vegetation (36.6%) indicate the vulnerability of vegetation cover, particularly in semi-arid and desert transition areas.

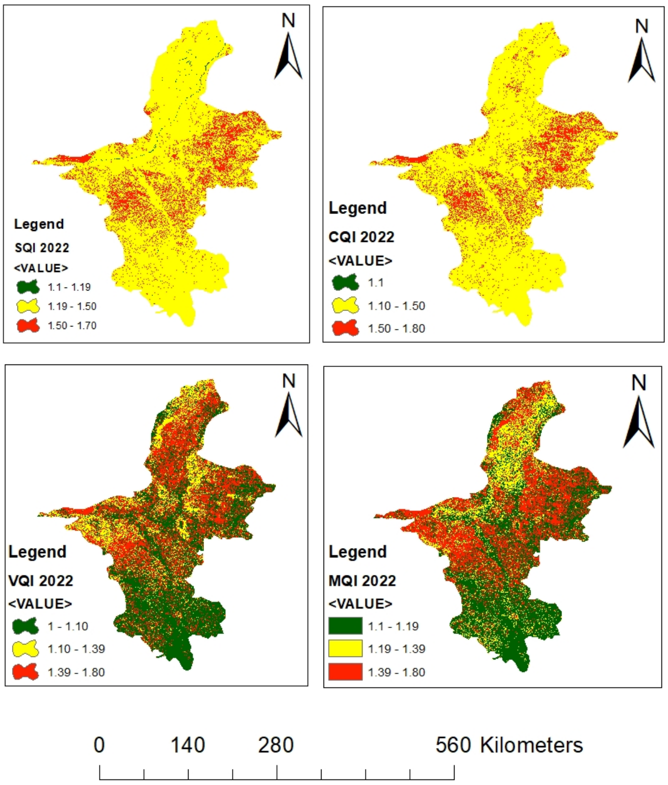

Figure 7. Spatial distribution of quality indices (SQI, VQI, MQI, CQI) for the year 2022.

In contrast, the MQI reached its highest level of improvement, with 64.08% of the area classified under high management quality. This demonstrates growing institutional capacity in land-use governance, greater adoption of sustainable farming techniques, and improved enforcement of environmental policies and restoration programs. The CQI displayed a near-even distribution between high (46.42%) and moderate (53.58%) quality zones, indicating that while adaptive land-use strategies have enhanced local resilience, broader climatic aridity and rainfall variability continue to constrain ecological recovery.

Table 11. Quality indices class distribution in 2022 (km^2).

Index	Class Range	Intensity	Area (km^2)	%
SQI	1.10-1.19	High	193.79	0.38
SQI	1.19-1.50	Moderate	40,657.61	80.66
SQI	1.50-1.70	Weak	9,552.49	18.95
VQI	1.00-1.10	High	23,593.51	46.81
VQI	1.10-1.39	Moderate	8,360.38	16.59
VQI	1.39-1.80	Weak	18,449.99	36.60
MQI	1.10-1.19	High	32,297.23	64.08
MQI	1.19-1.39	Moderate	8,360.38	16.59
MQI	1.39-1.80	Weak	9,746.28	19.34
CQI	1.00-1.19	High	23,399.72	46.42
CQI	1.10-1.50	Moderate	27,004.18	53.58
CQI	1.50-1.80	Weak	0.00	0.00

Table 12. DSI Distribution in Ningxia (2001-2022).

DSI Class	Area 2001 (km^2)	% 2001	Area 2011 (km^2)	% 2011	Area 2022 (km^2)	% 2022
Stable	13,340.13	26.47	24,324.84	48.26	23,399.72	46.42
Low Desertification	22,414.56	44.47	15,773.90	31.30	17,451.69	34.62
Medium Desertification*	0.00	0.00	0.00	0.00	0.00	0.00
High Desertification	14,649.20	29.06	10,305.15	20.45	9,552.49	18.95

4.3 Desertification Sensitivity Index (DSI) Dynamics

Figure 8 and Table 12 show the dynamics of the intensities of desertification of the years 2001, 2011, and 2022 computed using the MEDALUS integrated indices. The data show that the spatial range of territories with high desertification has been decreasing progressively and that stable zones are expanding, which indicates that the environment is recovering and ecosystems are becoming more resilient in the last 20 years.

The condition in 2001 was that of land degradation where high level of desertification covered 14,649.20 km^2, which was 29.06% of the study area. The low desertification regions occupied 22,414.56 km^2 (44.47%), and the stable areas occupied 13,340.13 km^2 (26.4%). These data indicate the negative environmental situation that existed in the beginning of the 21st century, which could be explained by the frequent drought periods, deforestation, and overgrazing as well as the absence of appropriate land-management systems.

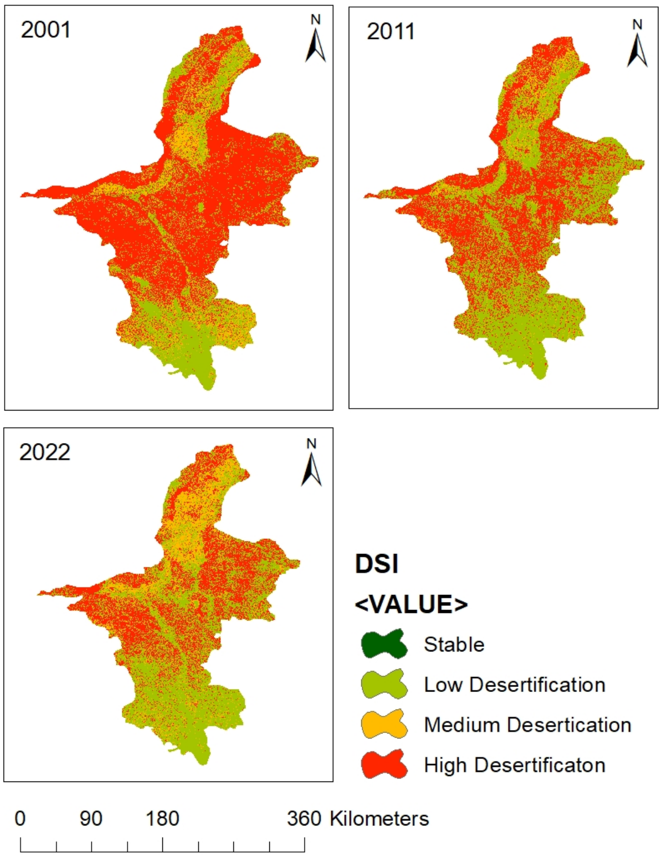

Figure 8. Temporal variation in desertification intensity (DSI classes) across Ningxia for 2001, 2011, and 2022.

As of 2011, the situation with the environment had been improved considerably. The proportion of stable areas had increased to almost 24,324.84 km^2 (48.26%) whilst the proportions of high desertification areas had reduced to 10,305.15 km^2 (20.45%). The low desertification areas also shrunk to 15,773.90 km^2 (31.30%). Such transitions testify to the effectiveness of large-scale ecological restoration programs, such as reforestation, soil erosion and community-led soil conservation programmes, which led to reducing the extent of land degradation.

It is necessary to add that the medium desertification (DSI 1.0-1.25) was the most constant at 0 in the years, which can be explained by a high level of ecological gradient in Ningxia in this area, the transition between degraded and stable sites is quite abrupt. The general trend was positive in 2022, although the trend was already at the plateau rather than improving. The contraction in the stable areas was modest to 23,399.72 km^2 which comprised 46.42% of the total area surveyed whereas low desertification was slightly more at 17451.69 km^2 which comprised 34.62% of the area surveyed. The high desertification areas further reduced to 9,552.49 km^2 (18.95%), which showed that extreme desertification was still in the process of eradication though not completely. Such stabilization is attributed to presumably a balance between long-run restoration processes and new forces, such as population increase, agricultural activities and occasional droughts.

Geographically, the stable areas were expanded down the south and inwards, and high desertification was concentrated on the northern arid belt, where sandy soils and low precipitation allow maintaining a fragile environmental situation. The given trend can be interpreted as a long-term reduction of the severity of desertification, which speaks in the favor of the efficiency of policy measures, and land-management changes conducted in 2001-2022. However, the presence of the degraded regions in the north is an indication of the continued need for long-term land-restoration degraded.

5 Discussion

5.1 Drivers of Desertification Change

The difference in sensitivity of desertification in Ningxia is explained by the combination of anthropogenic and climatic factors. It is necessary to have a detailed idea of the relative role of these variables to come up with effective intervention strategies.

Human Factors: Agricultural growth became the major anthropogenic process as the area of farmland increased by 52.5% during the research period. This expansion was supported by the irrigation infrastructure construction along the Yellow River, which was done by government agencies to ensure food security [40–42]. However, the process of transforming the grasslands and native plants into farmlands has caused a decrease in the resistance of the ecosystem to desertification and hence the soil has increased vulnerability during fallow periods. Urbanization was also small-scale.

The significant increase in the MQI was 39.82% to 64.08% of high-quality zones indicates the effectiveness of the implemented policies. The major interventions include the Grain-for-green program, which replenished the vegetation cover on 2,300 km^2 of marginal farmlands between 2000 and 2015 [32] the prohibition of continuous grazing and the implementation of rotational grazing systems, which relieved the burden on the degraded grasslands; and water-saving irrigation projects, which increased the agricultural output and reduced soil salinization [38, 39, 44].

Climatic Drivers: Climate variability is a constant factor in limiting ecological recovery. The moderate Climate Quality Index over the entire period of study (73.53% moderate in 2001 to 53.58% in 2022) indicates the natural aridity constraints of the region [34, 35]. The analysis of CHIRPS precipitation data shows that the inter-annual rainfall variability has increased by about 15% over the period 2001-2022, with an increasing trend of extreme dry years in 2007, 2015, and 2021. These drought years are associated with the temporary setbacks in vegetation recovery, as indicated by the VQI trends. The ecological lag between vegetation and soil recovery is a major result. Vegetation quality has shown faster improvement (weak coverage decreasing from 42.42% to 36.6%) than soil quality (weak soils decreasing only from 29.06% to 18.95%), as predicted by ecological theory, which proposes that soil recovery may take longer time scales (decades to centuries) than vegetation recovery (years to decades).

5.2 Regional and Global Context

The desertification processes in Ningxia are consistent with other dryland areas around the world, as described in the literature, but also have their own specific features in the context of China's strong ecological restoration policies. Compared with Mediterranean areas, where Bajocco et al. [9] found that land degradation continued despite conservation policies, Ningxia shows stronger signs of recovery, which can be attributed to the extent and effectiveness of China's ecological restoration policies. The reduction in High Desertification from 29.06% to 18.95% is greater than the 5-10% change reported in southern European MEDALUS areas over a similar period. Nevertheless, Ningxia, like the Mediterranean area, has climate limitations that impede complete recovery, with Moderate CQI being dominant in both areas.

Unlike Sub-Saharan African drylands, where Muluneh (2021) found that the acceleration of degradation continued due to poverty and poor governance, Ningxia shows that effective policy intervention can reverse the trend of degradation. This difference underlines the importance of institutional capacity and investment in desertification processes. The strong binary pattern of the distribution of stable and degraded areas (lack of Medium Desertification class) differentiates Ningxia from areas with more gradual degradation patterns, which reflect the specific ecological division between the Tengger Desert and the Yellow River irrigated corridor.

5.3 Limitations and Uncertainties

These results have several limitations that need to be taken into consideration during their interpretation. First, Landsat based classifications have a 30-meter spatial resolution which might not be able to detect fine scale degradation patterns especially in heterogeneous landforms. More detailed imagery (e.g., Sentinel-2 at 10 m) may be beneficial in detecting the hotspots of degradation in local areas in future research. Second, MEDALUS framework, as it is a popular framework, entails subjectivity in the selection of thresholds and the weighting of indices. Even though the thresholds adopted in this study are because of established literature and regional validation, other parameterizations might give different sensitivity classifications. Monte Carlo simulations on threshold variations would help to strengthen confidence of the results.

Third, the analysis presupposes the fact that indexes that are obtained with the help of satellites are appropriate in reflecting the situation on the ground. Although the classification based on the RF reported a high level of accuracy (87-90%), the validation of the classification was based mainly on visual criteria of high-resolution images instead of systematic field surveys. Ground-truthing campaigns, especially in the desert margins to the north where the accuracy of classification is likely largest would enhance the faith of the LULC and quality index maps. Lastly, the study period, which is 21 years, might not be a complete reflection of the long-term climatic cycles. The observed seemingly stabilized situation of 2011-2022 might be the sign of true balance or this may be one of the periods in multi-decadal changes. Further examination to cover the pre-2001 data of the previous Landsat missions would offer a more extended perspective.

6 Conclusion

The conclusion of this research is that Ningxia has experienced a great deal of land change from 2001 to 2022, including agricultural expansion, urbanization, and land degradation. The expansion of agricultural land and urban areas came at the cost of grassland and vegetation, which increased the pressure on these vulnerable lands. Soil quality was still poor in most areas, vegetation quality had partially recovered but was still unstable, management quality had improved greatly, and climate quality was moderately stressed. The DSI has confirmed that desertification is still a threat, with almost one-fifth of the land area (18.95%, or 9,552.49 km^2) being highly vulnerable in 2022. Although great improvements were achieved between 2001 and 2011, with stable land areas nearly doubling from 26.47% to 48.26%, these improvements showed signs of stabilization in 2022, and high-risk areas still dominated the northern and central desert-margin belts.

This paper has determined a high ecological lag wherein vegetation quality has been restored faster than soil quality thus reinforcing the need to ensure long term dedication to soil restoration programs. The significant improvement in the Management Quality Index, i.e. the increase in the index of 39.82% to 64.08% in the high-quality zones is evidence of the beneficial effect of national ecological policies, i.e. Grain-for-Green, grazing management, and modernization of irrigation systems. However, the fact that the climatic limitations persisted and were recorded by moderate values of Climate Quality Index over the period of the study shows that climate adaptation interventions have to be combined with land-management ones.

Desertification in Ningxia is a complex process, which is pushed by the ecological and socio-economic forces including population growth, unsustainable farming practices, overgrazing and global warming. Despite the positive results of afforestation and enhanced land-use practices, the region is susceptible to effects of the same in long term hence a complex and sustained response is needed. In line with the previous studies carried out on the arid areas in China, the Mediterranean basin [9], and sub-Saharan Africa, this study validates that desertification will continue to be a significant impediment to sustainable development in arid areas without adopting constant ecological restoration, policy implementation, and adapting strategies. Subsequently, future studies must concentrate on: (1) high-resolution spatial mapping to pinpoint the localized areas of degradation, (2) integration of the socio-economic survey data to enhance evaluation of human impact, (3) climate scenario modeling in order to forecast future changes of desertification under different warming regimes, and (4) cost-benefit analysis of ecological restoration measures in order to guarantee optimal resource allocation.

Data Availability Statement

Data will be made available on request.

Acknowledgment

The authors would like to acknowledge the United States Geological Survey (USGS) and NASA for providing free access to Landsat satellite data. We also gratefully acknowledge the Google Earth Engine platform for enabling cloud-based geospatial analysis. The authors sincerely thank the anonymous reviewers for their valuable comments and constructive feedback, which significantly improved the quality of this manuscript.

Funding

This work was supported by the Natural Science Foundation of Shandong Province under Grant ZR2023QD073, Grant ZR2024QD156, and Grant ZR2020GF067, and by the Central Guiding Local Science and Technology Development Fund of Shandong under Grant YDZX2023019.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Safriel, U. N. (2007). The assessment of global trends in land degradation. In *Climate and land degradation* (pp. 1-38). Berlin, Heidelberg: Springer Berlin Heidelberg. [CrossRef]

[2] Ambalam, K. (2014). United nations convention to combat desertification: Issues and challenges. *E-Int. Rel, 30*.

[3] Karmaoui, A., El Jaafari, S., Chaachouay, H., & Hajji, L. (2022). The socio-ecological system of the pre-Sahara zone of Morocco: a conceptual framework to analyse the impact of drought and desertification. *GeoJournal, 87*(6), 4961-4974. [CrossRef]

[4] Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B. L., Mortimore, M., Batterbury, S. P., ... & Walker, B. (2007). Global desertification: building a science for dryland development. *science, 316*(5826), 847-851. [CrossRef]

[5] Kairis, O., Karavitis, C., Salvati, L., Kounalaki, A., & Kosmas, K. (2015). Exploring the impact of overgrazing on soil erosion and land degradation in a dry Mediterranean agro-forest landscape (Crete, Greece). *Arid land research and management, 29*(3), 360-374. [CrossRef]

[6] Kosmas, C., Ferrara, A. M. S., Briasouli, H., & Imeson, A. (1999). Methodology for mapping environmentally sensitive areas (ESAs) to desertification. In *'The Medalus project Mediterranean desertification and land use. Manual on key indicators of desertification and mapping environmentally sensitive areas to desertification* (pp. 31-47). European Commission.

[7] De Paola, F., Ducci, D., & Giugni, M. (2013). Desertification and erosion sensitivity. A case study in southern Italy: the Tusciano River catchment. *Environmental earth sciences, 70*(5), 2179-2190. [CrossRef]

[8] Morianou, G., Kourgialas, N. N., Pisinaras, V., Psarras, G., & Arambatzis, G. (2021). Assessing desertification sensitivity map under climate change and agricultural practices scenarios: the island of Crete case study. *Water Supply, 21*(6), 2916-2934. [CrossRef]

[9] Bajocco, S., De Angelis, A., Perini, L., Ferrara, A., & Salvati, L. (2012). The impact of land use/land cover changes on land degradation dynamics: a Mediterranean case study. *Environmental management, 49*(5), 980-989. [CrossRef]

[10] Ladisa, G., Todorovic, M., & Liuzzi, G. T. (2012). A GIS-based approach for desertification risk assessment in Apulia region, SE Italy. *Physics and Chemistry of the Earth, Parts a/B/C, 49*, 103-113. [CrossRef]

[11] Rivera-Marin, D., Dash, J., & Ogutu, B. (2022). The use of remote sensing for desertification studies: A review. *Journal of Arid Environments, 206*, 104829. [CrossRef]

[12] Abuzaid, A. S., & Abdelatif, A. D. (2022). Assessment of desertification using modified MEDALUS model in the north Nile Delta, Egypt. *Geoderma, 405*, 115400.

[CrossRef]

[13] Khaldi, Z., Weng, J., Antezana Lopez, F. P., Zhou, G., Ghedjatti, I., & Ali, A. (2025). PyGEE-ST-MEDALUS: AI Spatiotemporal Framework Integrating MODIS and Sentinel-1/-2 Data for Desertification Risk Assessment in Northeastern Algeria. *Remote Sensing, 17*(19), 3350. [CrossRef]

[14] Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing, 114*, 24-31. [CrossRef]

[15] Shah, A. A., & Iqbal, M. F. (2024, December). Flood Susceptibility Mapping in District Jhang Using Remote Sensing and Advanced Machine Learning Techniques. In *2024 International Conference on Frontiers of Information Technology (FIT)* (pp. 1-6). IEEE. [CrossRef]

[16] Ait Lamqadem, A., Pradhan, B., Saber, H., & Rahimi, A. (2018). Desertification sensitivity analysis using MEDALUS model and GIS: a case study of the Oases of Middle Draa Valley, Morocco. *Sensors, 18*(7), 2230. [CrossRef]

[17] Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. [CrossRef]

[18] Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS journal of photogrammetry and remote sensing, 67*, 93-104. [CrossRef]

[19] Al-Tameemi, N., Xuexia, Z., Shahzad, F., Mehmood, K., & Zhou, J. (2025). Enhancing desertification risk mapping with entropy-based weighting and machine learning: Insights from Iraq. *Journal of Environmental Management, 396*, 127976. [CrossRef]

[20] Wang, D., Hao, H., Liu, H., Sun, L., & Li, Y. (2024). Spatial–temporal changes of landscape and habitat quality in typical ecologically fragile areas of western China over the past 40 years: A case study of the Ningxia Hui Autonomous Region. *Ecology and Evolution, 14*(1), e10847. [CrossRef]

[21] Liu, Z., Sun, Q., Dai, P., Lei, J., Zeng, B., Wang, L., ... & Wang, J. (2023). An Analysis of the Spatiotemporal Variation in Wind Erosion–Climate Erosion Force in the Ningxia Region and Its Driving Factors. *Atmosphere, 14*(6), 963. [CrossRef]

[22] Li, W., Zhao, S., Chen, Y., Wang, Q., & Ai, W. (2021). State of China's climate in 2020. *Atmospheric and Oceanic Science Letters, 14*(4), 100048. [CrossRef]

[23] Forster, P. M., Smith, C. J., Walsh, T., Lamb, W. F., Lamboll, R., Hauser, M., ... & Zhai, P. (2023). Indicators of Global Climate Change 2022: annual update of large-scale indicators of the state of the climate system and human influence. *Earth system science data, 15*(6), 2295-2327. [CrossRef]

[24] Zhao, M., & Running, S. W. (2010). Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *science, 329*(5994), 940-943. [CrossRef]

[25] Li, R., Han, R., Yu, Q., Qi, S., & Guo, L. (2020). Spatial heterogeneous of ecological vulnerability in arid and semi-arid area: A case of the Ningxia Hui autonomous region, China. *Sustainability, 12*(11), 4401. [CrossRef]

[26] Huang, L., Xiao, T., Zhao, Z., Sun, C., Liu, J., Shao, Q., ... & Wang, J. (2013). Effects of grassland restoration programs on ecosystems in arid and semiarid China. *Journal of Environmental Management, 117*, 268-275. [CrossRef]

[27] Guo, X., & Shao, Q. (2019). Spatial pattern of soil erosion drivers and the contribution rate of human activities on the Loess Plateau from 2000 to 2015: A boundary line from northeast to southwest. *Remote Sensing, 11*(20), 2429. [CrossRef]

[28] Siyu, X., Zhixun, X., & Pingwu, W. (1996). Soil salinity in the irrigated area of the Yellow River in Ningxia, China. *Arid Land Research and Management, 10*(1), 95-101. [CrossRef]

[29] Mao, Z., Dong, B., & Pereira, L. S. (2004). Assessment and water saving issues for Ningxia paddies, upper Yellow River Basin. *Paddy and Water Environment, 2*(2), 99-110. [CrossRef]

[30] Yao, Y., Zheng, C., Tian, Y., Li, X., & Liu, J. (2018). Eco-hydrological effects associated with environmental flow management: A case study from the arid desert region of China. *Ecohydrology, 11*(1), e1914. [CrossRef]

[31] Legg, S. (2021). IPCC, 2021: Climate change 2021-the physical science basis. *Interaction, 49*(4), 44-45. [CrossRef]

[32] Qi, L., Jiaqiang, L., Xiaosong, L., Youlin, Y. A. N. G., & Feng, W. A. N. G. (2020). China's combating desertification: national solutions and global paradigm. *Bulletin of Chinese Academy of Sciences (Chinese Version), 35*(6), 655-664. [CrossRef]

[33] Ogbue, C., Igboeli, E., Ajaero, C., Ochege, F. U., Yahaya, I. I., Yeneayehu, F., ... & Wang, Y. (2024). Remote sensing analysis of desert sensitive areas using MEDALUS model and GIS in the Niger River Basin. *Ecological Indicators, 158*, 111404. [CrossRef]

[34] Awais, M., Zaheen, Z., Fatima, Z., Shahwar, M., Jan, N., & Ali, S. (2024). Spatiotemporal drought assessment in Ningxia autonomous region: A machine learning and remote sensing approach. Asian Bull. *Big Data Manage, 4*(2), 1-16. [CrossRef]

[35] Lu, Q., Ma, H., Zhou, Y., Liu, J., & Shen, Y. (2023). Restoration of soil quality of degraded grassland can be accelerated by reseeding in an arid area of Northwest China. *Frontiers in Plant Science, 14*, 1101295. [CrossRef]

[36] Salmurzauly, R., Zulpykharov, K., Tokbergenova, A., Kaliyeva, D., & Bilalov, B. (2025). Ecological Vulnerability of Lands of Western Kazakhstan:

Analysis Based on MEDALUS Model and Remote Sensing. *Sustainability, 17*(22), 9990. [CrossRef]

[37] Ferrara, A., Kosmas, C., Salvati, L., Padula, A., Mancino, G., & Nolè, A. (2020). Updating the MEDALUS-ESA framework for worldwide land degradation and desertification assessment. *Land Degradation & Development*, *31*(12), 1593-1607. [CrossRef]

[38] Jia, H., Tian, B., Song, X., Sun, W., & Mu, X. (2025). Hydrological shifts from vegetation restoration in semi-arid regions: insights from the typical watersheds of the Yellow River. *Ecological Indicators*, *178*, 113924. [CrossRef]

[39] Liu, Q., Zhang, Q., Yan, Y., Zhang, X., Niu, J., & Svenning, J. C. (2020). Ecological restoration is the dominant driver of the recent reversal of desertification in the Mu Us Desert (China). *Journal of Cleaner Production*, *268*, 122241. [CrossRef]

[40] Chen, Y., Ma, L., Wang, X., Liu, T., & Qiao, Z. (2025). Spatiotemporal patterns of desertification sensitivity and influencing factors across the Western Inner Mongolia Plateau, China. *Ecological Informatics*, *89*, 103190. [CrossRef]

[41] ZhanNing, J., Liu, J., Kuang, W., Xu, X., Zhang, S., Yan, C., ... & Ning, J. (2018). Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. *Journal of Geographical Sciences*, *28*(5), 547-562. [CrossRef]

[42] Li, J., Yang, X., Jin, Y., Yang, Z., Huang, W., Zhao, L., ... & Xu, B. (2013). Monitoring and analysis of grassland desertification dynamics using Landsat images in Ningxia, China. *Remote Sensing of Environment*, *138*, 19-26. [CrossRef]

[43] Liu, H., Wang, H., Teng, Y., Zhan, J., Wang, C., Liu, W., ... & He, Y. (2024). Controlling desertification brings positive socioeconomic benefits beyond regional environmental improvement: Evidence from China's Gonghe Basin. *Journal of Environmental Management*, *354*, 120395. [CrossRef]

[44] Zhao, X., Tan, Q., Wu, T., Cai, Y., & Sun, K. (2025). Detecting cropland abandonment and intentional afforestation using MODIS and landsat across agroclimatic zones. *Ecological Informatics*, 103512. [CrossRef]

Munaza Nawaz is a Master's student at the College of Computer Science and Technology, Qingdao University, China. Her research focuses on remote sensing, GIS, machine learning, and environmental change analysis. (Email: munazanawaz95@gmail.com)

Wilson Kalisa is post-doc in Remote Sensing Information and Digital Earth Center, College of Computer Science and Technology, Qingdao University, Qingdao 266071, China. (Email: 2020020669@qdu.edu.cn)

Zakria Zaheen is student at Qingdao University, majoring in Software Engineering. (Email: Zakriazaheen10@gmail.com)

Jiahua Zhang received the Ph.D. degree in cartography and remote sensing from the Institute of Remote Sensing Applications, CAS, and China in 1998. Currently he is a Professor with Qingdao University, Qingdao, China. (Email: zhangjh@radi.ac.cn)

Moughal Tauqir is a post-doc in Qingdao University, majoring in Software Engineering. (Email: 2021020707@qdu.edu.cn)

Adnan Abbas Shah has completed his Master's degree in Remote Sensing and GIS from COMSATS University Islamabad, Pakistan. He has strong expertise in advanced machine learning techniques, including image segmentation and spatial downscaling. (Email: syedadnanshahn@gmail.com)

Kalim Ullah is a lecturer in Electrical Engineering Department University of Science and Technology Bannu. (Email: engr_kalim125@yahoo.com)