Analysis of the spatial pattern and causes of ecological environmental quality in Myanmar based on the RSEI model and the Geodetector-GCCM method

Shuangfu Shi[1,2], Shuangyun Peng[1,2]*, Zhiqiang Lin[1,2]*,
Bangmei Huang[3], Dongling Ma[1,2], Ziyi Zhu[1,2], Yilin Zhu[1,2],
Rui Zhang[1] and Ting Li[1]

[1]Faculty of Geography, Yunnan Normal University, Kunming, China, [2]GIS Technology Research Center of
Resource and Environment in Western China of Ministry of Education, Yunnan Normal University,
Kunming, China, [3]Kunming No. 10 High School, Kunming, China

Facing the challenges brought about by global climate change and biodiversity
loss, accurately assessing ecological environmental quality (EEQ), and its driving
factors are crucial for formulating effective strategies for ecological protection
and restoration. However, there remains limited understanding of the
interactions and causal relationships between multiple factors, with existing
studies mainly focusing on the impact of individual factors on EEQ and their
correlations. This study took Myanmar as the research area, employing a Remote
Sensing Ecological Index (RSEI) model and spatial autocorrelation analysis to
quantitatively evaluate the spatial distribution characteristics of Myanmar's EEQ in
2020 and reveal its spatial dependence. Furthermore, by innovatively integrating
the Geodetector and Geographical Convergent Cross Mapping (GCCM)
methods, this study systematically analyzed the impacts and causal
relationships of various factors on the spatiotemporal differentiation of EEQ.
The results indicate that: (1) Myanmar's overall EEQ was relatively good, but there
is significant spatial heterogeneity; (2) Local spatial autocorrelation analysis
revealed a clear spatial clustering pattern of EEQ in Myanmar; (3) Geodetector
analysis identified DEM, slope, Net Primary Productivity (NPP), land use, and
human footprint as the dominant factors influencing EEQ, with significant
interactions among these factors; (4) GCCM analysis further verified the
significant causal effects of DEM, slope, NPP, and human footprint on EEQ,
while the causal effects of temperature, precipitation, and land use are relatively
weaker. This study established a technical framework for analyzing the spatial
differentiation and causes of EEQ, unveiling the mechanisms of ecological
evolution driven by natural and human factors. It enriched the understanding
of human-environment interactions within coupled systems and delved into the
complex mechanisms and causal effects among multiple factors within the
ecological system. These insights enhanced our understanding of the intricate
relationships between EEQ and its influencing factors, providing valuable
references for ecological protection and sustainable development in Myanmar.

KEYWORDS

GCCM, causation, RSEI, spatial heterogeneity, Myanmar

1 Introduction

The world's ecological environment faces unprecedented challenges. Climate change (Wilkes et al., 2024), population growth (Xiao et al., 2022), overexploitation of resources (Yang et al., 2022) and the intensification of human activities have increased the vulnerability of ecosystems. The degradation of natural ecosystems not only affects biodiversity but also threatens human sustainable development and ecological security (Zhu et al., 2023; Huang C. et al., 2024). Globally, many regions experience continuous deterioration in water resources, soil, and air quality, making the assessment and protection of EEQ urgent priorities (Reed et al., 2015; Vasseur et al., 2017). Against this backdrop, the scientific community has increasingly recognized the importance of timely assessing the current state of EEQ, revealing its spatiotemporal variation patterns, and exploring the driving mechanisms of ecological changes. However, despite a substantial amount of existing research, there are still many shortcomings in EEQ assessment, particularly in the analysis of causal relationships between EEQ and its influencing factors, which urgently require more in-depth exploration (Geng et al., 2022; Duo et al., 2023). This work is essential in order to develop strategies to protect and restore the environment and to achieve a harmonious relationship between humans and nature.

EEQ assessment is a key topic in both ecological and geographical research. Traditional approaches to EEQ assessment often rely on single indicators or simplistic index systems, such as environmental quality indices and ecological footprints, which fail to fully capture the structure and function of ecosystems (Zhang L. et al., 2022; Sun et al., 2023). These traditional methods struggle to fully reveal complex ecological relationships and to comprehensively assess ecosystems and their dynamic evolution (Wang et al., 2024). Since the 1990s, new tools for large-scale EEQ assessment have been made available through the rapid development of remote sensing technology. To effectively characterise the spatio-temporal patterns of EEQ, Xu et al. introduced the Remote Sensing Ecological Index (RSEI), which is based on remote sensing data and integrates four indicators (Xu et al., 2019). Since then, many scholars have applied the RSEI model in regional EEQ assessments, producing promising results. For example, Liu et al. applied the RSEI model to analyse the spatio-temporal evolution of EEQ in grassland areas in Xinjiang, China, and found that grassland ecological environments showed improving trends with significant spatial differentiation and clustering characteristics (Liu et al., 2023). Similarly, Wan et al. used the RSEI model to evaluate the EEQ of the Yangtze River Economic Belt, revealing regional disparities in EEQ and their driving factors (Wang et al., 2024). Zhang J. et al. (2024) using the RSEI model, analyzed the spatiotemporal patterns of EEQ in the Yellow River Basin, finding a fluctuating improvement in EEQ, with significant regional differences closely related to human activities. These studies indicate that remote sensing data provides higher spatial resolution and temporal continuity for EEQ assessment at both regional and global scales, facilitating dynamic monitoring of ecological changes (Pettorelli et al., 2014; Wu et al., 2021). It also enables more accurate identification of ecological changes and stressors in different regions, offering support for the formulation of regional ecological protection policies.

The formation of the spatiotemporal patterns of EEQ is the result of long-term interactions between natural factors and human activities (Li et al., 2022; Bai et al., 2023). Existing studies show that topography, climate, vegetation, and land use are important factors affecting EEQ (He and Shi, 2022; Lu et al., 2022; Xiao et al., 2022). Zhang X. et al. (2024) found that topographic complexity and vegetation cover are key determinants of EEQ in the Heilongjiang region of China (Li et al., 2021). Demonstrated that temperature and precipitation exert stable effects on production, living spaces, and ecological spaces, and these effects vary spatially. Yu et al. (2023) analysed the impact of land use on EEQ, identifying urban expansion and agricultural development as the main drivers of ecosystem degradation, using a geographically weighted regression model. This series of studies highlights the interactive effects between natural factors and human activities, emphasizing the importance of local differences in influencing EEQ (Shi et al., 2024). Previous research has typically focused on single factors or localized impacts, while in cross-regional and multi-scale comparisons, how to comprehensively consider whether causal relationships exist between different factors and EEQ remains a challenge in current research (Liang L. et al., 2024). However, most studies to date have focused on the individual impacts of natural factors or human activities, or their interactions, while the analysis of the complex interactions and causal mechanisms between these factors remains relatively insufficient (Li et al., 2022; Xiao et al., 2023; Lin et al., 2024). In reality, ecosystems are complex, coupled human-environment systems, characterised by complex interactions and feedbacks between natural factors and human activities (Franzke et al., 2022; Reed et al., 2022; Tan et al., 2023). This understanding has prompted researchers to shift towards more dynamic and systematic analytical frameworks, promoting the application of interdisciplinary methods to gain a more comprehensive understanding of complex ecological relationships and mechanisms of ecological change (Liang L. et al., 2024). Therefore, the analysis of EEQ driving factors must consider both the independent effects of natural and socio-economic factors, as well as their interactions and causal mechanisms.

Although scholars worldwide have made substantial progress in assessing EEQ and its driving mechanisms, several shortcomings still exist. First, most studies focus on the correlation between EEQ and influencing factors, but there is limited exploration of causal relationships (Liang C. et al., 2024). While correlation analysis can reveal the strength and direction of relationships between variables, it cannot determine causal dependencies or pathways of influence (Huang Z. et al., 2024; Li et al., 2024; Tang et al., 2024). Relying solely on correlation analysis makes it difficult to address the root causes of EEQ changes and may lead to biased decision-making in ecological management. Second, many studies rely on traditional statistical models, such as multiple linear regression, which are often based on the assumption of linear relationships between variables. These models often fail to capture the nonlinear relationships and complex interactions between EEQ and its influencing factors (Wang et al., 2015; Ankori-Karlinsky et al., 2024; Ma et al., 2024). In reality, the ecological environment system is a complex nonlinear system characterized by multi-scale interactions and feedback mechanisms among its elements. Traditional linear

models cannot accurately reveal the evolutionary patterns and driving mechanisms. Therefore, combining the Geodetector and GCCM models to overcome the limitations of traditional statistical models has become an important trend in current research (Yang S. et al., 2024). These models can more accurately reveal the nonlinear relationships and causal mechanisms between factors, providing more effective tools for future ecological and environmental management.

In order to address these limitations, this study selects Myanmar as the area of study. Based on the quantitative assessment of Myanmar's EEQ spatiotemporal patterns in 2020, this study applies the Geodetector and GCCM models to systematically analyze the influencing factors of EEQ and their interactions. This study reveals the nonlinear relationships and causal mechanisms between various factors and EEQ. The Geodetector method effectively identifies the interactions between influencing factors, while the GCCM model reveals the nonlinear causal dependencies between variables. A broader and deeper understanding of the spatial differentiation mechanisms of EEQ is gained by combining these two methods.

2 Materials and methods

2.1 Study area and data sources

2.1.1 Study area

Myanmar was located on the central southern peninsula, stretching from 92°20′ to 101°11′ east longitude and 9°58′ to 28°31′ north latitude (Figure 1). The country had a complex geography with rich ecosystems and extensive biodiversity. Myanmar had a diverse climate, dominated by a tropical monsoon climate with marked seasonal variations in rainfall and temperature. It was important for ecological and environmental protection, agricultural development and climate change research because of its unique geographical location and rich natural resources. However, Myanmar's environment had been severely degraded by increasing deforestation, air pollution, land degradation and water pollution as a result of accelerated urbanisation and rapid economic development. Therefore, there was an urgent need for a systematic assessment of the quality of Myanmar's ecological environment and research into the causal relationships behind these environmental problems.

2.1.2 Data and preprocessing

The data used in this study can be divided into two parts, one of which is used to evaluate the EEQ of Myanmar. The relevant data are based on MODIS datasets provided by the United States Geological Survey (USGS), with a spatial resolution of 500 m. These datasets include three types of data from 2020: MOD13A1 (vegetation index products, reflecting vegetation cover), MOD11A2 (land surface temperature products, monitoring temperature variations), and MOD09A1 (surface reflectance products, representing surface spectral characteristics). These datasets were acquired and processed using the Google Earth Engine (GEE) platform, which enables efficient handling of long-term series and large-scale datasets, facilitating the rapid generation of EEQ assessments for Myanmar. The other part of the data focuses on analyzing the

driving factors of EEQ changes in Myanmar, encompassing both natural and social factors. These factors include nightlight (X1), temperature (X2), human footprint (X3), population density (X4), precipitation (X5), slope (X6), NPP (X7), land use (X8), GDP (X9), and DEM (X10). Temperature and precipitation data were mainly obtained from the University of East Aaglia (https://crudata.uea.ac.uk); slope, slope direction and elevation data were obtained from Geospatial Data Cloud (https://www.gscloud.cn); NPP data were obtained from the GEE platform MODIS/006/MOD17A3HGF dataset; human footprint data were obtained from the 2020 global human footprint data provided by the Urban Environmental Monitoring and Modelling (UEMM) team of the School of Land Science and Technology, China Agricultural University; nighttime lighting data were obtained from the National Geosystems Science Data Centre (http://nnu.geodata.cn); GDP data were obtained from the Jiandong Chen and other scholars pub. All TIF format data used in the study were resampled with a uniform spatial resolution of 5 km and projected to the GCS_WGS_1984 coordinate system.

2.2 Methodology

2.2.1 Technological route

In this paper, we constructed an integrated technical framework for spatial and temporal differentiation of EEQ and causal analysis (Figure 2). First, the spatial distribution characteristics of EEQ in Myanmar were quantitatively assessed using the RSEI model by acquiring MODIS image data of the study area in 2020 based on the GEE platform. The local spatial autocorrelation technique has been used to reveal the spatial dependence and clustering pattern of EEQ and to identify the spatial differentiation pattern of EEQ. Then, the intensity of influence and contribution of each factor and their interactions on the spatial and temporal variability of EEQ were quantitatively analysed using the geodetector model for 10 key influencing factors such as climate, topography, vegetation, land use and human activities. Finally, the GCCM model was used to reveal the causal dependence and direction of action between the influencing factors and the EEQ, and to explore the intrinsic driving mechanism of the ecological environment evolution.

2.2.2 RSEI model

The Remote Sensing Ecological Index (RSEI) was a comprehensive method for evaluating the EEQ, which differed from the traditional ecological index. It coupled four natural indicators, namely, NDVI, WET, LST and NDBSI, through principal component analysis to objectively reflect the EEQ, with the value ranging from 0 to 1, and the larger the value represented the better the EEQ; moreover, the method removed the influence of subjective anthropogenic factors, and it was a kind of objective monitoring and evaluation of the regional EEQ (Xu et al., 2019; Zhou et al., 2024). Among them, two indicators, greenness and dryness, could reflect the land cover changes caused by human activities, and humidity and heat could reveal the response of EEQ to climate change, therefore, by combining these four ecological and natural factors that are closely related to human survival, the strengths and weaknesses of regional EEQ were intuitively reflected (Du et al., 2024). Initially, it was been used as an
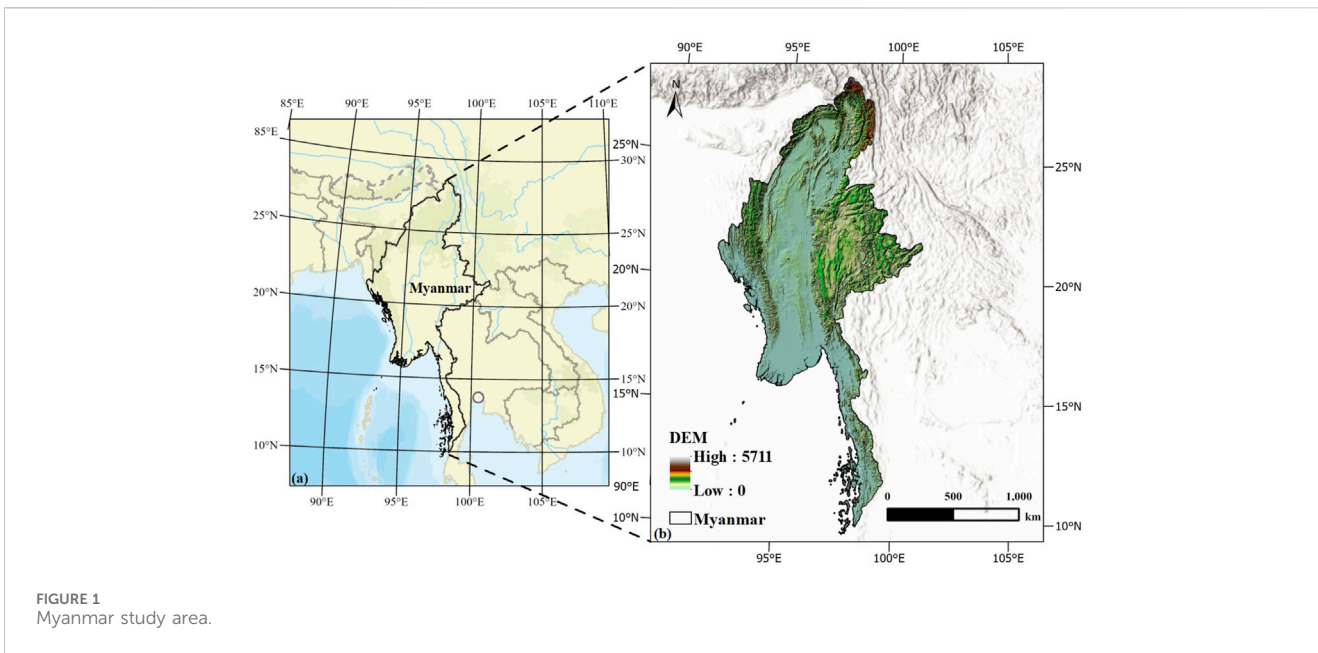
FIGURE 1
Myanmar study area.

FIGURE 2
Research framework.
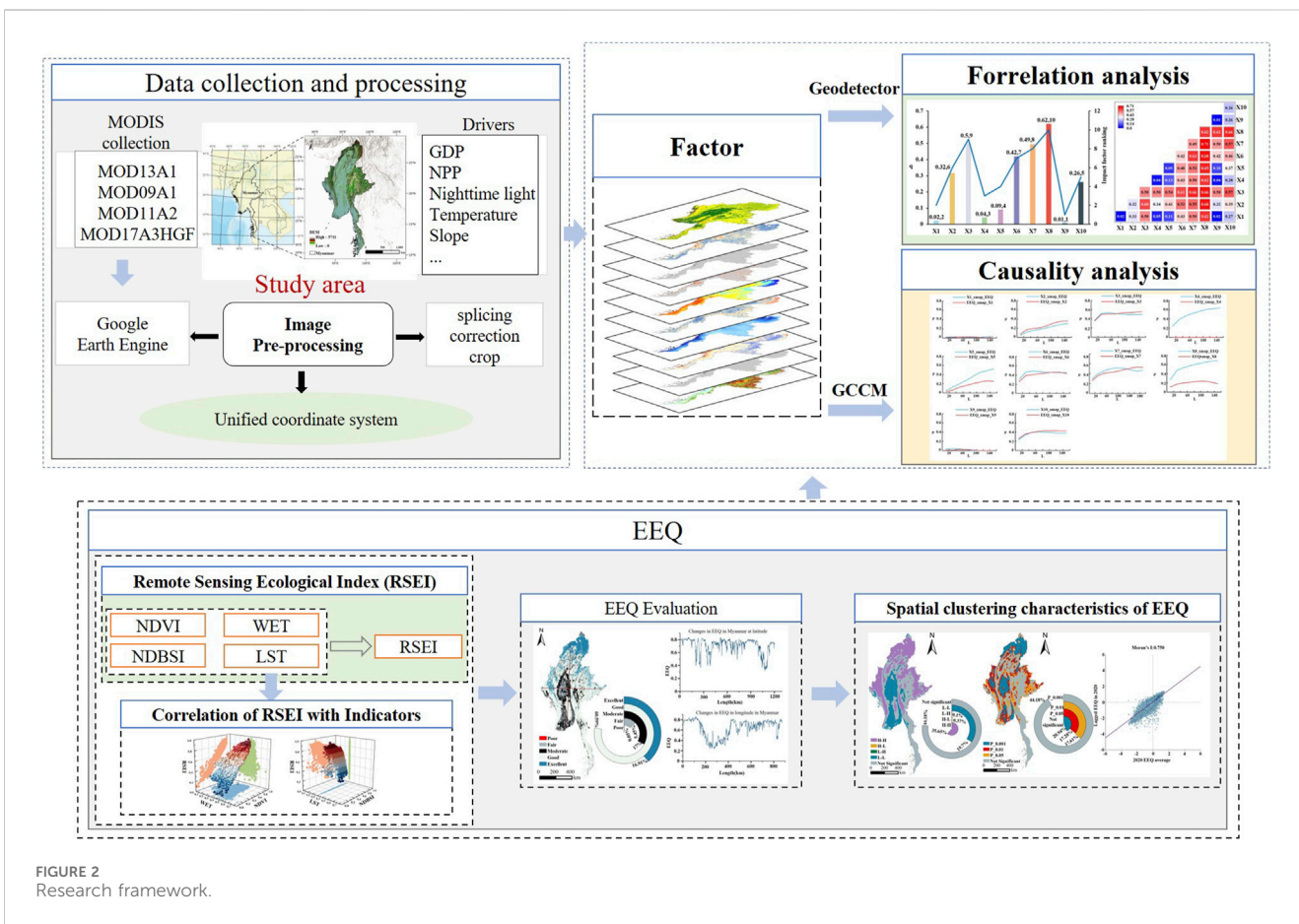
assessment index for the evaluation of the status of the urban ecological environment and, in the course of its development, it was been widely used in the assessment of the ecological environment.

2.2.2.1 Greenness

The Normalised Vegetation Index (NDVI) reflects the vegetation cover in the region and can be used to provide a comprehensive understanding of the spatial distribution of

vegetation and vegetation density across the study area from remote sensing data. The formula is calculated as in Equation 1 below:

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

In the formula: ρ_{NIR} and ρ_{RED} are the near-infrared band and red band reflectivity.

2.2.2.2 Wetness

Moisture can reflect the ecological environment in the soil moisture, through the soil moisture composition characterisation of surface water body conditions, to reflect the degree of EEQ, so it is an important indicator for monitoring the environment, which is inverted by remote sensing tassel cap transformation. The formula is as in Equation 2:

$$WET = c_1\rho_{blue} + c_2\rho_{green} + c_3\rho_{RED} + c_4\rho_{NIR} + c_5\rho_{swir1} + c_6\rho_{swir2} \quad (2)$$

2.2.2.3 Dryness

Dryness characterized the dryness of the land and consisted of the normalized building bare soil index and the normalized building index. Calculate the formula as in Equations 3–5:

$$SI = \frac{[(\rho_{swir1} + \rho_{red}) - (\rho_{blue} + \rho_{nir})]}{[(\rho_{swir1} + \rho_{red}) + (\rho_{blue} + \rho_{nir})]} \quad (3)$$

$$IBI = \frac{\frac{2\rho_{swir1}}{\rho_{swir1}+\rho_{nir}} - \left(\frac{\rho_{nir}}{\rho_{nir}+\rho_{red}} + \frac{\rho_{green}}{\rho_{green}+\rho_{swir1}}\right)}{\frac{2\rho_{swir1}}{\rho_{swir1}+\rho_{nir}} + \left(\frac{\rho_{nir}}{\rho_{nir}+\rho_{red}} + \frac{\rho_{green}}{\rho_{green}+\rho_{swir1}}\right)} \quad (4)$$

$$NDBSI = \frac{IBI + SI}{2} \quad (5)$$

2.2.2.4 Heat

Heat is represented by surface temperature, which plays an important role in vegetation growth and is also an extremely important part of measuring environmental change, and surface temperature inversion provides insight into the spatial distribution of surface temperature and changes in surface temperature across the region. The formula is calculated as in Equation 6 below:

$$LST = 0.02 * DN - 273.15 \quad (6)$$

2.2.3 Local spatial autocorrelation

Local spatial autocorrelation analysis explored the spatial similarities and distribution characteristics of geographic phenomena (Ding et al., 2024). Commonly used metrics were Moran's I and Local Moran's I. Local Moran's I could reveal the degree of autocorrelation between each geographic unit and its neighbouring units, helped to identify agglomeration or discrete patterns, and accurately identified the spatial location and extent of agglomerations, thus revealing spatial heterogeneity. The method consisted mainly of the following steps: firstly, identifying the study area and its geographical units; secondly, calculating the local autocorrelation value of each unit; and finally, identifying areas with significant autocorrelation through the significance test (Ai et al., 2024). This analysis provided a scientific basis for spatial planning and policy-making by providing an in-depth

understanding of the structure and distribution of spatial data. The formula is calculated as in Equation 7 below:

$$I_i = \frac{X_i - X_0}{S^2} \sum_{j=1, j \neq 1}^{n} w_{ij}(x_j - x_0) \quad (7)$$

In the formula: S is the standard deviation of each individual observation, w_{ij} is the row-standardised spatial weight matrix; the range of I values lies in [-1, 1], and for a given level of significance, the observations in the region are spatially clustered when I is significantly positive, spatially dispersed when I is significantly negative, and independently randomly distributed among the observations when the value of I is zero.

2.2.4 Geographical convergent cross mapping model (GCCM)

The geographically convergent cross-mapping model was a method for the identification of causal relationships and the estimation of causal effects on the basis of spatial cross-sectional data by integrating the theory of dynamical systems and the generalised embedding theory (Gao et al., 2023). Based on dynamical systems theory, if the independent variable X and the dependent variable Y were observed from the same dynamical system and controlled by the same manifold M, then the relationship of one-to-one mapping between Mx and My could be obtained.

$$\hat{Y}_s \bigg|_{M_x} = \sum_{i=1}^{L+1} (w_{si}Y_{si}|M_x) \quad (8)$$

$$w_{si} \bigg|_{M_x} = \frac{weight[\Psi(x, s_i), \Psi(x, s)]}{\sum_{i=1}^{L+1} weight[\Psi(x, s_i), \Psi(x, s)]} \quad (9)$$

$$weight[\Psi(x, s_i), \Psi(x, s)] = exp\left\{-\frac{dis[\Psi(x, s_i), \Psi(x, s)]}{dis[\Psi(x, s_1), \Psi(x, s)]}\right\} \quad (10)$$

In Equations 8–10, s is the spatial unit in which the value of Y is predicted; $\hat{Y}_s$ is the prediction result; L is the dimension of the embedding; s_i is the spatial unit used in the prediction; Y_{si} is the observation at s_i and is simultaneously the first component of the state in My, denoted $\Psi(y, s_i)$; and w_{si} is the corresponding weights defined in Equation 8. $\Psi(y, s_i)$ is determined by its one-to-one mapping point $\Psi(x, s_i)$, and in addition, $\Psi(x, s_i)$ is the L+1 nearest neighbour of the focal state $\Psi(x, s)$ in the state space M_x. Weight ( ) is the weight function between two states in the shadow manifold; exp ( ) is the exponential function; dis ( ) is the distance between two states in the shadow manifold function.

The cross-mapping prediction effect is measured by the Pearson's correlation coefficient ρ between the true observations and the corresponding predicted values with the following formula:

$$\rho = \frac{Cov(Y, \hat{Y})}{\sqrt{VarYVar\hat{Y}}} \quad (11)$$

In Equation 11, Cov(Y, Ŷ); Var(Y) is the variance of Y; Var(Ŷ) is the variance of Ŷ.

2.2.5 Geodetector

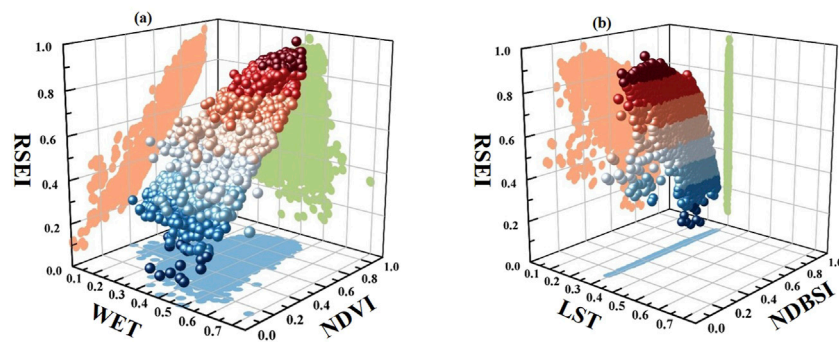Geodetector was an exploratory method based on spatial heterogeneity to analyze the impact of driving factors on

FIGURE 3
Correlation of components with RSEI. **(A)** is the correlation between WET and NDVI RSEI, **(B)** is the correlation between LST and NDBSI RSEI.

indicators (Wang and Xu, 2017). This method was based on the similarity in the spatial distribution of independent and dependent variables. The advantage of this method was that it could analyze both categorical and qualitative data and identify interactions between two factors. It was widely used in the study of spatial differentiation of geographic elements. The formula is calculated as in Equation 12 below:

$$q = 1 - \frac{\sum\limits_{h=1}^{L} N_h * \sigma_h^2}{N * \sigma^2} \qquad (12)$$

In the formula, q is the size of the influence of the driver factor on the indicator, the value is between 0 and 1, the larger the value, the stronger the influence; N is the sample of the study area; is the variance of the indicator; h is the grading, L is the number of grading strata, h = 1, 2, 3, . . . , L.

3 Result

3.1 RSEI correlation with component indicators

To verify the effectiveness of the RSEI in assessing EEQ, this study analyzed the correlation between the RSEI and its component indices. The principal component analysis (PCA) results indicated that the four principal components for Myanmar in 2020 were 79.08%, 15.93%, 4.95%, and 0.03%, respectively. The first principal component (PC1) had a variance contribution rate of 79.08%, showing that it effectively integrated the information from the four indicators: NDVI, WET, NDBSI, and LST, thus providing a comprehensive reflection of the EEQ. Correlation analysis (Figure 3) further revealed the quantitative relationships between the RSEI and each of the indices. NDVI and WET were found to be significantly positively correlated with the RSEI, while NDBSI and LST were significantly negatively correlated with it. This indicated that indices with positive effects on EEQ (such as vegetation coverage) increased as the RSEI value rose, whereas indices with negative effects (such as built-up land) decreased as the RSEI value rose. The strong correlations between the RSEI and its component indices confirmed the reliability and effectiveness of the RSEI in providing a comprehensive assessment of EEQ.

3.2 Assessment of EEQ in Myanmar

To more accurately assess and quantify the spatial distribution characteristics of Myanmar's EEQ in 2020, the RSEI model was used for evaluation. The EEQ values were divided into five categories with an interval of 0.2: Excellent (0.8–1), Good (0.6–0.8), Moderate (0.4–0.6), Fair (0.2–0.4), and Poor (0–0.2) (Figure 4). The results indicated that Myanmar's EEQ exhibited significant spatial heterogeneity. Overall, the EEQ was higher in the eastern and western mountainous regions and the northern areas, while it was lower in the central plains and southern coastal regions. The "Excellent" and "Good" categories accounted for 16.91% and 60.05% of the total land area, respectively, while the "Moderate," "Fair," and "Poor" categories accounted for 17.00%, 5.45%, and 0.05%, respectively. This suggests that Myanmar's overall ecological environment was relatively good, with areas of high-quality EEQ significantly larger than those of low-quality EEQ.

To further explore the spatial variation of EEQ, latitude and longitude profile analyses were conducted. The latitude profile analysis (from north to south) showed a complex fluctuating trend in EEQ. The northern regions generally had higher EEQ values, but two areas with relatively low EEQ are observed at 150–450 km and 1,000–1,100 km from the northern border. These areas might be associated with higher population density and dense industrial and agricultural activities. In contrast, the regions between 600–900 km from the northern border showed relatively stable EEQ values, likely due to less human interference and favorable natural conditions. The longitude profile analysis (from west to east) revealed that the EEQ values in the range of 100–400 km from the western border were relatively low, while those between 0–100 km and 400–900 km maintained higher EEQ levels. The lower EEQ in the central region might be attributed to high population density, frequent human activities, and rapid urban expansion. Conversely, the eastern and western regions, dominated by mountains and plateaus, exhibited higher EEQ, which could be attributed to extensive forest cover, favorable natural conditions, and stable ecosystems.

3.3 Characterisation of EEQ spatial clustering in Myanmar

The spatial clustering characteristics of Myanmar's EEQ showed significant positive spatial correlation (Moran's I = 0.75, P < 0.001),
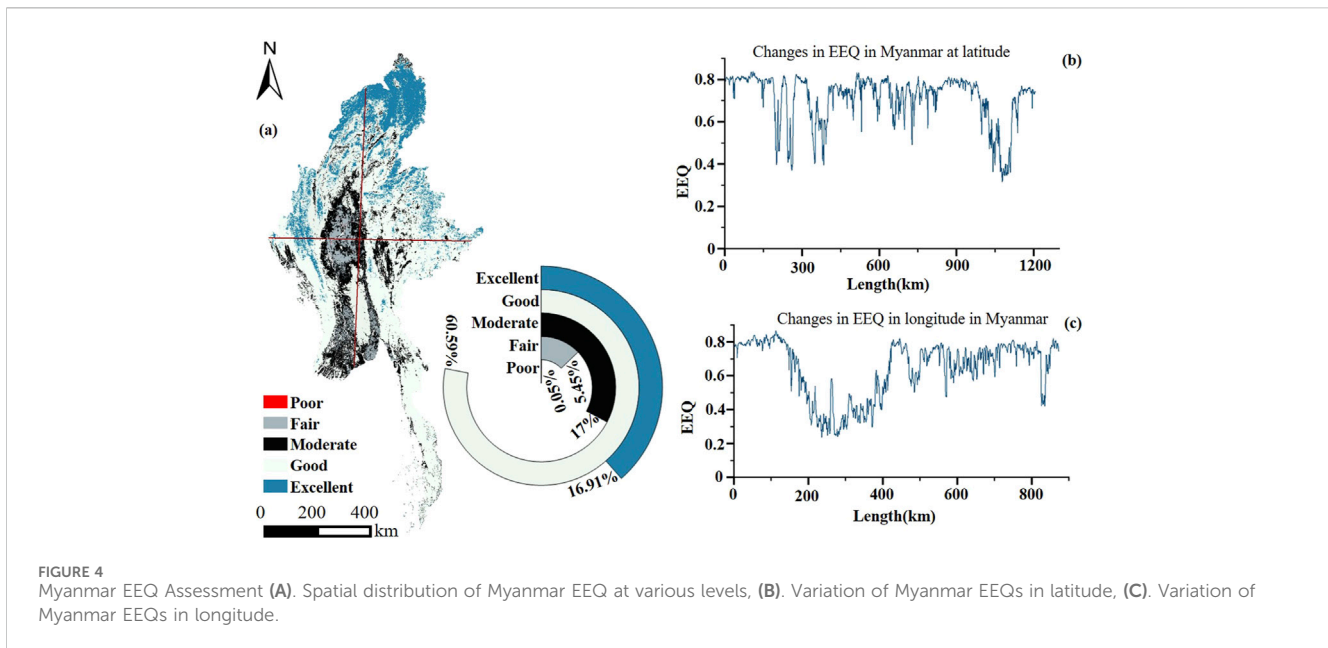
FIGURE 4
Myanmar EEQ Assessment **(A)**. Spatial distribution of Myanmar EEQ at various levels, **(B)**. Variation of Myanmar EEQs in latitude, **(C)**. Variation of Myanmar EEQs in longitude.
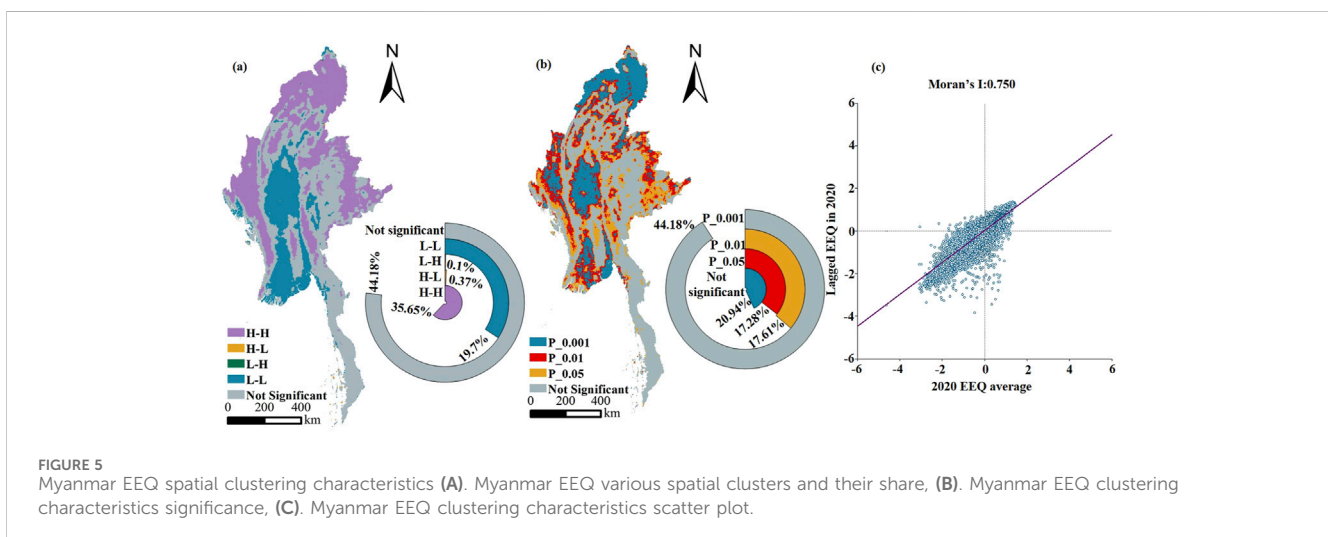

FIGURE 5
Myanmar EEQ spatial clustering characteristics **(A)**. Myanmar EEQ various spatial clusters and their share, **(B)**. Myanmar EEQ clustering characteristics significance, **(C)**. Myanmar EEQ clustering characteristics scatter plot.

indicating a strong clustering trend (Figure 5). Specifically, high-high clusters were mainly distributed in the eastern, western, and northern mountainous regions, accounting for 35.65% of the total land area, while low-low clusters are primarily concentrated in the central plains and southern coastal areas, covering 19.70% of the total land area. Additionally, at the 0.001 significance level, 44.18% of the area exhibited spatial autocorrelation; at the 0.01 significance level, 17.61% of the area showed spatial autocorrelation; and at the 0.05 significance level, 17.28% of the area demonstrated spatial autocorrelation. This indicates that the spatial clustering pattern of Myanmar's EEQ was statistically significant. High clustering areas were mainly located in the complex terrain regions of the eastern, western, and northern parts of Myanmar, where forest cover was high. These regions were subject to minimal human disturbance, which helped maintain ecological stability. In contrast, low clustering areas were concentrated in the central plains and southern coastal regions, where human activities were more

frequent, and the areas were heavily influenced by agricultural expansion and urbanization. These regions have sparse vegetation and fragile ecosystems, leading to lower EEQ values.

3.4 Correlation analysis between EEQ and factors in Myanmar

The study used the Geodetector model to analyse the correlation and interaction between these factors in order to quantitatively assess the impact of various factors on Myanmar's EEQ (Figure 6). The results showed that the explanatory power of the different factors differed significantly from each other. X8 (q = 0.62), X3 (q = 0.50), X7 (q = 0.49), and X6 (q = 0.42) were identified as the dominant factors influencing Myanmar's EEQ, with q-values all greater than 0.40. X2 (q = 0.32) and X10 (q = 0.26) also demonstrated some explanatory power, whereas X5 (q = 0.09),
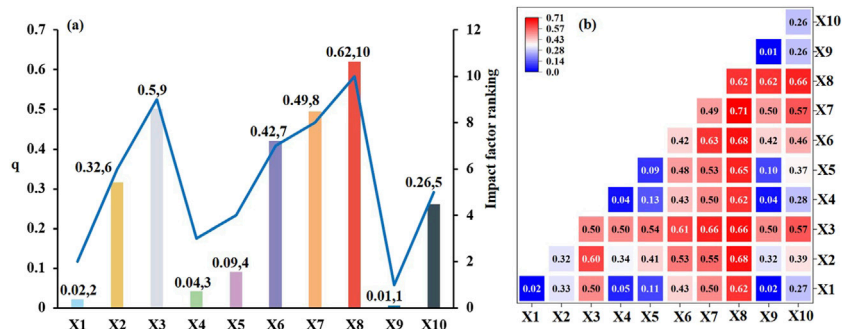
FIGURE 6
Influences affecting EEQ in Myanmar **(A)**. Contribution, ranking of influences, **(B)**. Interactions.

X4 (q = 0.04), X1 (q = 0.02), and X9 (q = 0.01) had relatively weaker influences. This suggests that land use, human footprint, NPP, and slope are the key drivers of the spatial and temporal variations in Myanmar's EEQ.

Additionally, the Geodetector analysis revealed significant interactions between the influencing factors. X2∩X3 (q = 0.60), X6∩X3 (q = 0.61), X7∩X3 (q = 0.66), X8∩X7 (q = 0.71), X8∩X3 (q = 0.71), and X10∩X3 (q = 0.61) exhibited notable bivariate enhancement effects, indicating synergistic effects between these factors that jointly influence EEQ. On the other hand, X2∩X5 (q = 0.41) and X5∩X10 (q = 0.37) showed significant nonlinear enhancement effects, uncovering potential interactive influences of climate and topography on the ecological environment. These findings from the Geodetector model highlight the complex driving mechanisms behind the changes in Myanmar's EEQ, revealing significant correlations and interactions between natural and socio-economic factors.

3.5 Causal analysis of Myanmar EEQ with factors

To further investigate the causal relationships between EEQ and its influencing factors, the study employed the GCCM model for causal inference and estimation of causal strength (Figure 7). The results showed significant causal relationships between EEQ and factors such as X10 (ρ = 0.43, P < 0.001), X7 (ρ = 0.54, P < 0.001), X6 (ρ = 0.46, P < 0.001), and X3 (ρ = 0.56, P < 0.001), with causal strength (ρ) values exceeding 0.40. These findings suggested that these factors were the key drivers of changes in Myanmar's EEQ. Additionally, X2 (ρ = 0.30, P < 0.001), X5 (ρ = 0.26, P < 0.001), and X8 (ρ = 0.23, P < 0.001) also showed some causal relationships with EEQ, with ρ values ranging between 0.20 and 0.30. However, X9 (ρ = 0.02, P < 0.001), X1 (ρ = 0.20, P < 0.001), and X4 (ρ = 0.00, P > 0.05) exhibited weak or insignificant causal relationships with EEQ.

Overall, factors such as DEM, slope, NPP, and human footprint were identified as the primary drivers influencing Myanmar's EEQ, with significant causal relationships. Temperature, precipitation, and land use also had some causal effects on EEQ, but their impact strength was relatively weaker. Meanwhile, socio-economic factors (X9 and X4) showed either weak causal links or no direct causal relationships with EEQ. The causal relationships revealed by the GCCM model corroborated the findings from the

Geodetector analysis, highlighting the crucial roles of both natural environmental factors and human activities in shaping the spatiotemporal patterns of Myanmar's EEQ.

4 Discussion

4.1 Spatial pattern of EEQ in Myanmar based on RSEI

This study, based on the RSEI model, quantitatively assesses Myanmar's EEQ in 2020, revealing its spatial differentiation characteristics and clustering patterns. The results show that Myanmar's overall EEQ is relatively good but exhibits significant spatial heterogeneity. The EEQ is higher in the eastern, western, and northern mountainous areas, while it is lower in the central plains and southern coastal regions. This spatial differentiation pattern is closely related to the region's natural geographic conditions and the intensity of human activities. The EEQ differences across regions reflect the spatial imbalance of natural resource endowments and socioeconomic development levels. Specifically, the complex terrain and good vegetation cover in mountainous areas provide a superior ecological background, whereas the intense agricultural development and urbanization processes in the plains and coastal areas lead to environmental degradation. This differential distribution is closely related to the terrain, vegetation coverage, population distribution, and socioeconomic development levels of different regions. Wang et al. (2022) research in northern Anhui finds that areas with higher terrain complexity and vegetation cover tend to have better EEQ. Zhang Y. et al. (2022) demonstrated in metropolitan areas demonstrates that regions with higher population density, higher levels of urbanization, and stronger economic development typically exhibited lower EEQ due to the intensity of human activities. Similarly, Hui et al. found in their study of Hunan that natural conditions were extremely important factors influencing EEQ, while human activities were the primary drivers of its degradation (Hui and Cheng, 2024). These findings align with the results of this study, demonstrating that both natural geographic features and human activities jointly shape the spatial pattern of regional EEQ. Additionally, Liao used an improved RSEI with information granulation to assess the spatiotemporal changes of EEQ in the ASEAN countries from 2000 to 2021 (Liao, 2022). The results showed that the overall EEQ was relatively good, with 40.36% of the
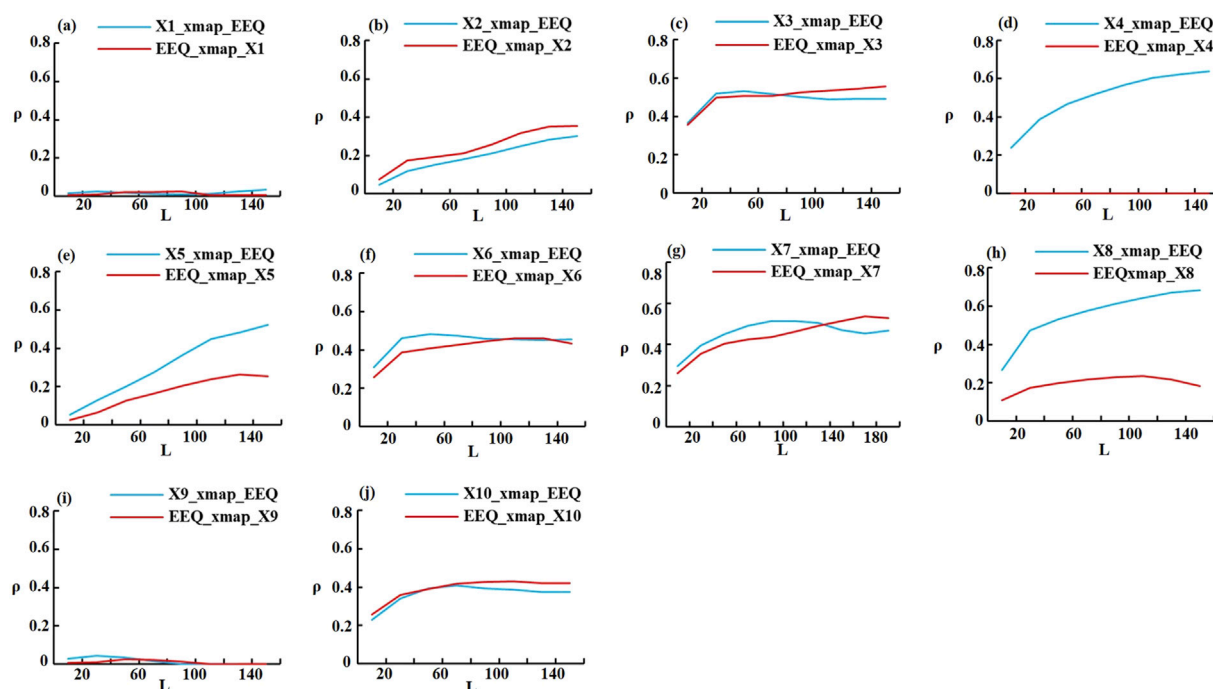
FIGURE 7
Causal relationship between influencing factors and EEQ. (**A–J** represent the causal relationship between influences X1~X10 and EEQ).

areas being in a good condition, and the areas with extremely poor or extremely good EEQ were relatively small. Similarly, Jin et al. monitored the EEQ of coastal East Asia and Southeast Asia using the Continuous Remote Sensing Ecological Index (CRSEI) (Jin et al., 2023). They found that the overall EEQ remained stable, with the EEQ in Myanmar's coastal regions staying relatively stable, while the EEQ of some Southeast Asian countries, especially the continental coasts of Vietnam and Cambodia, had significantly declined. The findings of these studies are both similar and different to those of this research. The similarity lies in the overall good EEQ, with some coastal areas having relatively poor EEQ, and the areas with extremely poor or poor EEQ occupying a smaller proportion. The difference, however, is that the proportion of areas with extremely good EEQ in Myanmar is relatively high.

Spatial autocorrelation analysis further reveals the spatial dependence characteristics of Myanmar's EEQ. Local spatial autocorrelation analysis not only identifies the spatial clustering trend of EEQ but also identifies the high-high and low-low clustering areas, corresponding to regions with relatively good and poor EEQ, respectively. The high-high clustering pattern is found to be concentrated in the eastern, western, and northern mountainous areas, while the low-low clustering pattern is concentrated in the central plains and southern coastal areas. This spatial clustering pattern reflects, on the one hand, the controlling effect of stable natural environments on EEQ and, on the other hand, shows that similar natural conditions and human activity intensity lead to convergence in the EEQ of adjacent regions. Xiong et al. (2021) pointed out that the spatial autocorrelation of EEQ reflected the spatial spillover effects of ecosystem services, with high-quality ecological environments typically concentrated in regions with superior natural environments and less human interference, while low-quality environments were commonly found in areas of frequent human activity. Zhang et al. (2023) also found in their study of

northeastern China that regions with high and low EEQ exhibited significant spatial clustering, closely related to regional development imbalances. Therefore, the spatial pattern of EEQ is not only determined by local natural conditions and human activities but is also significantly influenced by surrounding areas. This highlights the importance of considering spatial relationships and differences when formulating ecological protection and restoration policies and suggests that tailored ecological management measures should be implemented based on local conditions.

Overall, the RSEI model effectively assesses and characterizes regional EEQ, and through local spatial autocorrelation analysis, provides empirical support for a deeper understanding of the interaction between human activities and the natural environment in Myanmar's spatiotemporal patterns.

4.2 Driving mechanisms of the spatial pattern of EEQ in Myanmar

The results from the Geodetector and GCCM models indicate that land use, human footprint, NPP, and slope are the dominant factors influencing the spatial pattern of EEQ in Myanmar. Factors such as temperature, precipitation, and land use patterns also have some influence, while socioeconomic factors like population density, nighttime light, and GDP show a relatively weak relationship with EEQ. These findings are similar to the study conducted by Xu et al. in China, which highlighted the significant impact of terrain complexity and vegetation cover on EEQ, followed by the intensity of human activities and land use patterns (Xin et al., 2014). Similarly, Zhao et al. found in their research on northeast China that natural factors (terrain, climate, and vegetation) primarily determined the spatial differentiation

of EEQ, while human factors (land use and urbanization levels) had a relatively smaller impact (Zhao et al., 2025). These studies suggest that the spatiotemporal patterns of EEQ exhibit certain universality across regions, though the relative importance of influencing factors may vary based on regional natural endowments and human activity characteristics.

It is noteworthy that the Geodetector analysis revealed significant interactions among the driving factors of EEQ, indicating that these factors do not operate independently but are interrelated and mutually constrained. This aligns with the complexity and nonlinearity of ecosystems. Some studies have shown that natural elements such as terrain, climate, vegetation, and soil exhibit intricate interactions and feedback mechanisms that collectively affect ecosystem structure and function. Simultaneously, human activities, through changes in land use, resource exploitation, and environmental pollution, directly or indirectly influence natural ecological processes, thus affecting EEQ. This finding is similar to Waseem et al.'s study, which found that urban expansion degraded natural vegetation, affecting local microclimates and hydrological processes, ultimately reducing EEQ (Waseem et al., 2021). At the same time, the study by Li et al. is similar, as they found that urban expansion led to the degradation of natural vegetation, which affected local microclimates and hydrological processes, ultimately reducing EEQ (Li et al., 2013). Additionally, Yu et al. emphasized in their study in Beijing, China, that urban expansion is one of the main causes of many ecological and environmental issues in urban and surrounding areas, pointing out the complex interactions between socioeconomic factors and natural factors (Yu et al., 2023).

The causal relationships revealed by the GCCM model further validate the results of the Geodetector analysis, confirming that terrain (elevation, slope), NPP, and human activities are key factors driving the spatial pattern of EEQ in Myanmar, while temperature, precipitation, and land use show strong causal relationships with EEQ. This finding is supported by Guo et al. based on the GCCM model, which identified vegetation cover, climate, and GDP as key factors driving regional ecological changes. The causal relationships between population density, NPP, and ecosystem health are found to be weaker (Guo et al., 2024). Similar to this finding, Yang et al. also reached a similar conclusion in their study on ecosystem services, stating that vegetation cover, climate, and GDP are key drivers of regional ecological changes, while the causal relationships between population density, net primary productivity, and ecosystem health are relatively weak (Yang Y. et al., 2024).

Additionally, the study finds that correlation analysis and causal analysis reveal different aspects of the human-environment relationship. Correlation analysis focuses on describing the strength and direction of the relationship between variables but cannot determine causality. Causal analysis, on the other hand, identifies the causal dependencies and direction of influence between variables, though it is somewhat limited in depicting the interactions and feedback effects within complex systems. Therefore, combining correlation and causal analyses, while considering the complexity and nonlinearity of human-environment systems, is crucial for understanding the mechanisms behind the formation of EEQ. In future studies, there is a need to expand the applicability of causal inference models like GCCM, enhancing their ability to represent complex interactions and feedback effects. Furthermore, the integration of data-driven analysis with mechanistic models should be strengthened to simulate the dynamic evolution of

human-environment systems at multiple spatiotemporal scales, more comprehensively revealing the mechanisms and driving processes behind the spatiotemporal patterns of EEQ.

4.3 Recommendations for ecological environmental protection and sustainable development in Myanmar

The spatial differentiation patterns and driving mechanisms of Myanmar's EEQ provide important scientific evidence for regional ecological management. Targeted ecological protection and restoration strategies should be developed for areas with different EEQ levels. In regions with "Excellent" and "Good" EEQ, such as the eastern, western, and northern mountainous areas, ecological protection should be prioritized, with strict restrictions on human activities to maintain a strong natural ecological baseline. In contrast, for areas with "Poor" and "Very Poor" EEQ, such as the central plains and southern coastal regions, ecological restoration should be carried out through measures such as adjusting land use structure, increasing vegetation cover, controlling pollution, and improving the stability and resilience of ecosystems. For areas with "Moderate" EEQ, regional coordination should be strengthened, with a focus on protecting native vegetation, increasing plant cover, and prioritizing ecological restoration to maintain ecosystem integrity. Additionally, the interactions between various influencing factors and regional differences should be fully considered. For example, in areas with complex terrain and rich vegetation, the protection of native vegetation and the maintenance of ecosystem integrity should be prioritized. In densely populated and highly developed areas, land use management should be strengthened, with strict adherence to ecological red-line policies, aiming to improve land use efficiency. Furthermore, ecological protection and socio-economic development are not mutually exclusive, but rather complementary and mutually reinforcing. A healthy ecological environment is the foundation for sustainable socio-economic development, while the green transformation of the economy helps improve environmental and economic quality. Therefore, while promoting ecological civilization construction, Myanmar should also accelerate economic structural adjustment, vigorously develop green industries, adopt clean production technologies, and implement energy-saving and emission-reduction technologies. By exploring mechanisms for realizing the value of ecological products, a win-win outcome for both environmental protection and socio-economic development can be achieved.

4.4 Limitations and future prospects of the study

This study establishes a comprehensive technical framework for spatial differentiation and attribution analysis of EEQ. Based on revealing the spatial pattern of EEQ, it further explores the interactive effects and causal mechanisms of natural and socio-economic factors on EEQ, providing a new perspective for the study of human-environment interactions. This comprehensive framework is not only applicable to exploring EEQ in Myanmar or a specific region, but can also be extended to other countries and regions to study the spatial patterns of EEQ in these areas,

uncovering the interactions and causal relationships between factors influencing EEQ, and gaining a deeper understanding of their driving mechanisms. Furthermore, although this study innovatively combines the Geodetector model and the GCCM model to quantitatively express the interactions and causal relationships between the factors influencing EEQ, thereby overcoming the limitations of traditional statistical models and effectively identifying non-linear relationships and complex interactions among variables, some limitations still exist.

Firstly, this study only evaluates the EEQ of Myanmar for the year 2020 and analyzes its driving mechanisms, without conducting a comprehensive analysis over a longer time scale. The study lacks an investigation into temporal changes. Secondly, the interactions and feedback mechanisms within ecosystems are highly complex. In this study, only 10 key factors, such as topography, climate, vegetation, land use, and human activities, were selected. However, this does not mean that other factors do not affect EEQ. Additionally, although this study innovatively combines the Geodetector model with the GCCM model, the Geodetector model can only analyze the interactions between two factors and cannot assess the interactions among multiple factors. Therefore, future research could extend across multiple temporal and spatial scales, incorporate multi-source data, and use interdisciplinary methods. Further inclusion of more natural and socio-economic factors would help explore long-term changes in EEQ and their driving mechanisms, thus enhancing the applicability of this framework. Furthermore, future studies could consider using more advanced statistical methods, machine learning models, or improving existing models to enhance the accuracy of EEQ assessments and further explore the interactions and causal relationships between influencing factors and EEQ. Improving the accuracy and reliability of EEQ evaluation and prediction would provide more comprehensive and reliable decision-making support for regional sustainable development.

5 Conclusion

This study focuses on Myanmar as the research area and constructs a comprehensive technical framework for EEQ assessment, using the RSEI model, spatial autocorrelation, geographic detector, and GCCM model, as well as the quantitative expression of multi-factor interactions and causal relationships. This framework is applied to analyze the spatial differentiation of EEQ and its driving factors. The main conclusions of the study can be summarized as follows.

1) The distribution of EEQ exhibits significant spatial heterogeneity and regional differences. Areas with intensive human activity have poorer EEQ, while regions with complex terrain and higher vegetation cover have better EEQ.
2) EEQ exhibits spatial dependence and significant geographic regionality. High-quality areas are concentrated in regions with complex terrain and good vegetation, while low-quality areas are located in regions with frequent human activity.
3) DEM, slope, NPP, land use, and human footprint are the key drivers of spatial differentiation in EEQ. Significant interactions exist between these factors, revealing the

complex mechanisms driving ecological and environmental changes, emphasizing the importance of comprehensively analyzing the interrelationships of various driving factors.
4) DEM, slope, NPP, and human footprint have significant causal effects on EEQ, indicating that both natural and socio-economic factors have a significant impact on EEQ.

In conclusion, this study proposes a comprehensive technical framework for analyzing the spatial differentiation of EEQ and its causal mechanisms, expanding traditional ecological environment assessment methods. The framework allows for the quantitative expression of multi-factor interactions and causal relationships, thereby broadening the research paradigm of human-environment interactions.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Funding

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Ai, M., Chen, X., and Yu, Q. (2024). Spatial correlation analysis between human disturbance intensity (HDI) and ecosystem services value (ESV) in the Chengdu-Chongqing urban agglomeration. *Ecol. Indic.* 158, 111555. doi:10.1016/j.ecolind.2024.111555

Ankori-Karlinsky, R., Hall, J., Murphy, L., Muscarella, R., Martinuzzi, S., Fahey, R., et al. (2024). Chronic winds reduce tropical forest structural complexity regardless of climate, topography, or forest age. *Ecosystems* 27, 479–491. doi:10.1007/s10021-024-00900-5

Bai, T., Cheng, J., Zheng, Z., Zhang, Q., Li, Z., and Xu, D. (2023). Drivers of eco-environmental quality in China from 2000 to 2017. *J. Clean. Prod.* 396, 136408. doi:10.1016/j.jclepro.2023.136408

Ding, Y., Wang, H., Liu, Y., Chai, B., and Bin, C. (2024). The spatial overlay effect of urban waterlogging risk and land use value. *Sci. Total Environ.* 947, 174290. doi:10.1016/j.scitotenv.2024.174290

Du, Z., Ji, X., Liu, J., Zhao, W., He, Z., Jiang, J., et al. (2024). Ecological health assessment of Tibetan alpine grasslands in Gannan using remote sensed ecological indicators. *Geo-spatial Inf. Sci.*, 1–19. doi:10.1080/10095020.2024.2311862

Duo, L., Wang, J., Zhang, F., Xia, Y., Xiao, S., and He, B.-J. (2023). Assessing the spatiotemporal evolution and drivers of ecological environment quality using an enhanced remote sensing ecological index in lanzhou city, China. *Remote Sens.* 15 (19), 4704. doi:10.3390/rs15194704

Franzke, C. L., Ciullo, A., Gilmore, E. A., Matias, D. M., Nagabhatla, N., Orlov, A., et al. (2022). Perspectives on tipping points in integrated models of the natural and human Earth system: cascading effects and telecoupling. *Environ. Res. Lett.* 17 (1), 015004. doi:10.1088/1748-9326/ac42fd

Gao, B., Yang, J., Chen, Z., Sugihara, G., Li, M., Stein, A., et al. (2023). Causal inference from cross-sectional earth system data with geographical convergent cross mapping. *Nat. Commun.* 14, 5875. doi:10.1038/s41467-023-41619-6

Geng, J., Yu, K., Xie, Z., Zhao, G., Ai, J., Yang, L., et al. (2022). Analysis of spatiotemporal variation and drivers of ecological quality in Fuzhou based on RSEI. *Remote Sens.* 14 (19), 4900. doi:10.3390/rs14194900

Guo, J., Wei, X., Zhang, F., Cai, J., and Ding, Y. (2024). Remote sensing assessment of ecosystem health and its key driving factors: a case study of the urban agglomeration in the Middle reaches of the Yangtze River. *Environ. Sci.*, 1–15. doi:10.13227/j.hjkx.202406285

He, J., and Shi, X. (2022). Detection of social-ecological drivers and impact thresholds of ecological degradation and ecological restoration in the last three decades. *J. Environ. Manag.* 318, 115513. doi:10.1016/j.jenvman.2022.115513

Huang, C., Cheng, J., Liu, S., Wan, Y., Zhou, J., Liu, Z., et al. (2024a). Impacts of landscape dynamics on terrestrial ecosystem health in the Three Gorges Reservoir Area, China. *J. Clean. Prod.* 467, 142928. doi:10.1016/j.jclepro.2024.142928

Huang, Z., Li, S., Peng, J., Ma, X., Ding, H., Cheng, F., et al. (2024b). Assessing ecosystem service dynamics and drivers for sustainable management in the Agro-pastoral ecotone of northern China: a spatiotemporal analysis. *Ecol. Indic.* 165, 112213. doi:10.1016/j.ecolind.2024.112213

Hui, J., and Cheng, Y. (2024). Evolution and spatiotemporal response of ecological environment quality to human activities and climate: case study of hunan province, China. *Remote Sens.* 16 (13), 2380. doi:10.3390/rs16132380

Jin, W., Li, H., Wang, J., Zhao, L., Li, X., Fan, W., et al. (2023). Continuous remote sensing ecological index (CRSEI): a novel approach for multitemporal monitoring of eco-environmental changes on large scale. *Ecol. Indic.* 154, 110739. doi:10.1016/j.ecolind.2023.110739

Li, J., Sun, W., Li, M., and Meng, L. (2021). Coupling coordination degree of production, living and ecological spaces and its influencing factors in the Yellow River Basin. *J. Clean. Prod.* 298, 126803. doi:10.1016/j.jclepro.2021.126803

Li, S., Qu, S., Zhang, G., Zhou, Y., Sun, X., Li, J., et al. (2024). Spatiotemporal pattern and drivers of ecological quality in inner Mongolia. *Land* 13 (5), 568. doi:10.3390/land13050568

Li, W., Wang, L., Yang, X., Liang, T., Zhang, Q., Liao, X., et al. (2022). Interactive influences of meteorological and socioeconomic factors on ecosystem service values in a river basin with different geomorphic features. *Sci. Total Environ.* 829, 154595. doi:10.1016/j.scitotenv.2022.154595

Li, X., Zhou, W., and Ouyang, Z. (2013). Forty years of urban expansion in Beijing: what is the relative importance of physical, socioeconomic, and neighborhood factors? *Appl. Geogr.* 38, 1–10. doi:10.1016/j.apgeog.2012.11.004

Liang, C., Zhang, M., Wang, Z., Xiang, X., Gong, H., Wang, K., et al. (2024). The strengthened impact of water availability at interannual and decadal time scales on vegetation GPP. *Glob. Change Biol.* 30 (1), e17138. doi:10.1111/gcb.17138

Liang, L., Song, Y., Shao, Z., Zheng, C., Liu, X., and Li, Y. (2024). Exploring the causal relationships and pathways between ecological environmental quality and influencing Factors: a comprehensive analysis. *Ecol. Indic.* 165, 112192. doi:10.1016/j.ecolind.2024.112192

Liao, W. (2022). Temporal and spatial variations of eco-environment in Association of Southeast Asian Nations from 2000 to 2021 based on information granulation. *J. Clean. Prod.* 373, 133890. doi:10.1016/j.jclepro.2022.133890

Lin, Y., Zhang, X., Zhu, H., and Li, R. (2024). Spatiotemporal evolution and mechanisms of habitat quality in nature Reserve land: a case study of 18 nature reserves in hubei province. *Land* 13 (3), 363. doi:10.3390/land13030363

Liu, Y., Peng, J., Li, G., Han, W., Liu, L., Guan, J., et al. (2023). Eco-environmental assessment of kurustai grassland based on Google earth engine. *Chin. J. Ecol.* 42 (11), 2776–2785. doi:10.13292/j.1000-4890.202311.010

Lu, D., Wang, Y., Yang, Q., Wang, Z., Lin, A., Tang, Y., et al. (2022). Effects of population spatial redistribution on vegetation greenness: a case study of Chongqing, China. *Ecol. Indic.* 138, 108803. doi:10.1016/j.ecolind.2022.108803

Ma, J., Shen, Z., Jiang, Y., Liu, P., Sun, J., Li, M., et al. (2024). Potential ecological risk assessment for trace metal (loid) s in soil surrounding coal gangue heaps based on source-oriented. *Sci. Total Environ.* 954, 176465. doi:10.1016/j.scitotenv.2024.176465

Pettorelli, N., Laurance, W. F., O'brien, T. G., Wegmann, M., Nagendra, H., and Turner, W. (2014). Satellite remote sensing for applied ecologists: opportunities and challenges. *J. Appl. Ecol.* 51 (4), 839–848. doi:10.1111/1365-2664.12261

Reed, M. S., Stringer, L., Dougill, A., Perkins, J., Atlhopheng, J., Mulale, K., et al. (2015). Reorienting land degradation towards sustainable land management: linking sustainable livelihoods with ecosystem services in rangeland systems. *J. Environ. Manag.* 151, 472–485. doi:10.1016/j.jenvman.2014.11.010

Reed, P., Hadjimichael, A., Moss, R., Brelsford, C., Burleyson, C., Cohen, S., et al. (2022). Multisector dynamics: advancing the science of complex adaptive human-earth systems. *Earths Future* 10, e2021EF002621. doi:10.1029/2021ef002621

Shi, S., Peng, S., Lin, Z., Zhu, Z., Ma, D., Yin, Y., et al. (2024). Analysis of ecological environment quality heterogeneity across different landform types in Myanmar and its driving forces. *Ecol. Indic.* 168, 112755. doi:10.1016/j.ecolind.2024.112755

Sun, J., Hu, Y., Li, Y., Weng, L., Bai, H., Meng, F., et al. (2023). A temporospatial assessment of environmental quality in urbanizing Ethiopia. *J. Environ. Manag.* 332, 117431. doi:10.1016/j.jenvman.2023.117431

Tan, J., Duan, Q., Xiao, C., He, C., and Yan, X. (2023). A brief review of the coupled human-Earth system modeling: current state and challenges. *Anthropocene Rev.* 10 (3), 664–684. doi:10.1177/20530196221149121

Tang, Q., Hua, L., Tang, J., Jiang, L., Wang, Q., Cao, Y., et al. (2024). Advancing ecological quality assessment in China: introducing the ARSEI and identifying key regional drivers. *Ecol. Indic.* 163, 112109. doi:10.1016/j.ecolind.2024.112109

Vasseur, L., Horning, D., Thornbush, M., Cohen-Shacham, E., Andrade, A., Barrow, E., et al. (2017). Complex problems and unchallenged solutions: bringing ecosystem governance to the forefront of the UN sustainable development goals. *Ambio* 46, 731–742. doi:10.1007/s13280-017-0918-6

Wang, J., Wang, T., Skidmore, A. K., Shi, T., and Wu, G. (2015). Evaluating different methods for grass nutrient estimation from canopy hyperspectral reflectance. *Remote Sens.* 7 (5), 5901–5917. doi:10.3390/rs70505901

Wang, J., and Xu, C. (2017). Geodetector: principle and prospective. *Acta Geogr. Sin.* 72 (1). doi:10.11821/dlxb201701010

Wang, R., Wang, L., Dai, W., Cao, Q., and Niiu, Z. (2024). Spatial–temporal evolution and driving force analysis of eco-quality in Yangtze River Basin. *Resour. Environ. Yangtze Basin*, 1–17.

Wang, X., Yao, X., Jiang, C., and Duan, W. (2022). Dynamic monitoring and analysis of factors influencing ecological environment quality in northern Anhui, China, based on the Google Earth Engine. *Sci. Rep.* 12 (1), 20307. doi:10.1038/s41598-022-24413-0

Waseem, L. A., Khokhar, M. a. H., Naqvi, S. a. A., Hussain, D., Javed, Z. H., and Awan, H. B. H. (2021). Influence of urban sprawl on microclimate of abbottabad, Pakistan. *Land* 10 (2), 95. doi:10.3390/land10020095

Wilkes, L. N., Barner, A. K., Keyes, A. A., Morton, D., Byrnes, J. E., and Dee, L. E. (2024). Quantifying co-extinctions and ecosystem service vulnerability in coastal

ecosystems experiencing climate warming. *Glob. Change Biol.* 30 (7), e17422. doi:10.1111/gcb.17422

Wu, P., Yin, Z., Zeng, C., Duan, S.-B., Göttsche, F.-M., Ma, X., et al. (2021). Spatially continuous and high-resolution land surface temperature product generation: a review of reconstruction and spatiotemporal fusion techniques. *IEEE Geoscience Remote Sens. Mag.* 9 (3), 112–137. doi:10.1109/mgrs.2021.3050782

Xiao, J., Song, F., Su, F., Song, S., and Wei, C. (2023). Exploring the interaction mechanism of natural conditions and human activities on wetland ecosystem services value. *J. Clean. Prod.* 426, 139161. doi:10.1016/j.jclepro.2023.139161

Xiao, Z., Liu, R., Gao, Y., Yang, Q., and Chen, J. (2022). Spatiotemporal variation characteristics of ecosystem health and its driving mechanism in the mountains of southwest China. *J. Clean. Prod.* 345, 131138. doi:10.1016/j.jclepro.2022.131138

Xin, Z., Xiao, Y., Wang, D., Li, Y., Ren, Y., and Li, Q. (2014). Spatial patterns of riparian vegetations and its optimization in Lijiang River: an intensive tourism karsts river in the southern subtropical China. *Ecol. Sci.* 33, 631–641. doi:10.14108/j.cnki.1008-8873.2014.04.002

Xiong, Y., Xu, W., Lu, N., Huang, S., Wu, C., Wang, L., et al. (2021). Assessment of spatial–temporal changes of ecological environment quality based on RSEI and GEE: a case study in Erhai Lake Basin, Yunnan province, China. *Ecol. Indic.* 125, 107518. doi:10.1016/j.ecolind.2021.107518

Xu, H., Wang, Y., Guan, H., Shi, T., and Hu, X. (2019). Detecting ecological changes with a remote sensing based ecological index (RSEI) produced time series and change vector analysis. *Remote Sens.* 11 (20), 2345. doi:10.3390/rs11202345

Yang, S., Peng, S., Li, X., Wei, X., Pan, Y., and Jiao, Y. (2024a). Spatial heterogeneity and interacting intensity of drivers for trade-offs and synergies between carbon sequestration and biodiversity. *Glob. Ecol. Conservation* 56, e03256. doi:10.1016/j.gecco.2024.e03256

Yang, Y., Yuan, X., An, J., Su, Q., and Chen, B. (2024b). Drivers of ecosystem services and their trade-offs and synergies in different land use policy zones of Shaanxi Province, China. *J. Clean. Prod.* 452, 142077. doi:10.1016/j.jclepro.2024.142077

Yang, Z., Zhan, J., Wang, C., and Twumasi-Ankrah, M. J. (2022). Coupling coordination analysis and spatiotemporal heterogeneity between sustainable development and ecosystem services in Shanxi Province, China. *Sci. Total Environ.* 836, 155625. doi:10.1016/j.scitotenv.2022.155625

Yu, P., Zhang, S., Yung, E. H., Chan, E. H., Luan, B., and Chen, Y. (2023). On the urban compactness to ecosystem services in a rapidly urbanising metropolitan area: highlighting scale effects and spatial non–stationary. *Environ. Impact Assess. Rev.* 98, 106975. doi:10.1016/j.eiar.2022.106975

Zhang, J., Gu, Y., Shen, J., Zhang, M., Cong, M., Sun, Y., et al. (2024a). Analysis of spatiotemporal changes and driving factors of ecological environment quality in the Yellow River Basin. *Environ. Sci.*, 1–23. doi:10.13227/j.hjkx.202401141

Zhang, L., Wang, X. C., Dzakpasu, M., Cao, T., Zhang, H., Liu, Y., et al. (2022a). Integrated environmental influences quantification of pilot-scale constructed wetlands based on modified ecological footprint assessment. *Sci. Total Environ.* 843, 157039. doi:10.1016/j.scitotenv.2022.157039

Zhang, X., Jia, W., and He, J. (2023). Spatial and temporal variation of ecological quality in northeastern China and analysis of influencing factors. *J. Clean. Prod.* 423, 138650. doi:10.1016/j.jclepro.2023.138650

Zhang, X., Jia, W., Lu, S., and He, J. (2024b). Ecological assessment and driver analysis of high vegetation cover areas based on new remote sensing index. *Ecol. Inf.* 82, 102786. doi:10.1016/j.ecoinf.2024.102786

Zhang, Y., She, J., Long, X., and Zhang, M. (2022b). Spatio-temporal evolution and driving factors of eco-environmental quality based on RSEI in Chang-Zhu-Tan metropolitan circle, central China. *Ecol. Indic.* 144, 109436. doi:10.1016/j.ecolind.2022.109436

Zhao, X., Li, Y., Tan, S., Liu, L., and Liu, F. (2025). Analyse of spatial and temporal evolution patterns and driving forces of ecological environment quality in Chengdu-Chongqing Economic Circle. *Acta Ecol. Sin.* (01), 1–15. doi:10.20103/j.stxb.202403210585

Zhou, M., Li, Z., Gao, M., Zhu, W., Zhang, S., Ma, J., et al. (2024). Revealing the eco-environmental quality of the Yellow River Basin: trends and drivers. *Remote Sens.* 16 (11), 2018. doi:10.3390/rs16112018

Zhu, X., Jiao, L., Wu, X., Du, D., Wu, J., and Zhang, P. (2023). Ecosystem health assessment and comparison of natural and constructed wetlands in the arid zone of northwest China. *Ecol. Indic.* 154, 110576. doi:10.1016/j.ecolind.2023.110576