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An Integrated Framework for Ecological Security Assessment, Early Warning, and Future Prediction in the North Eastern Himalayan Region of India

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Abstract

The North Eastern Himalayan Region (NEHR) of India is one of the world's most ecologically diverse yet environmentally fragile regions, where rapid socio-economic development and climate change are intensifying ecological pressures. Developing reliable ecological security early-warning systems is therefore essential to supporting sustainable environmental management. This study developed an Ecological Security Early Warning Index (ESEWI) based on the Pressure–State–Response (PSR) framework to assess historical ecological security and forecast future trends across the NEHR at the district level. Based on 21 PSR indicators, ecological security was evaluated using a combined weighting and multilevel weighted comprehensive index method, projected using the Grey Model (GM), and the dominant driving factors were identified using the Geodetector model. The results reveal fluctuations in ecological security during 2000–2020, with mean Ecological Security Index (ESI) values ranging from 0.541 to 0.577. Model projections indicate a gradual decline in ecological security, with the ESEWI decreasing from 0.547 in 2025 to 0.522 in 2040, an overall reduction of 4.57%. The fraction of districts under a huge warning is projected to increase from 9.09% to 18.18%, whereas the fraction of districts under a serious warning is expected to rise from 29.09% to 40.00%, indicating a deterioration in regional ecological conditions. Geodetector analysis identified population density as the dominant driver of ecological security, with interactions between population density and forest cover showing greater explanatory power than either factor alone. This study demonstrates that the proposed framework provides a robust basis for ecological assessment, early warning, and sustainable environmental management in the ecologically fragile Himalayan region of India.

Keywords Ecological security, Ecological security early warning, PSR, Gray prediction model, North Eastern Himalayan Region

1 Introduction

Environmental problems have intensified globally and regionally as a consequence of rapid population growth, urbanisation, and socio-economic development. The collective pressures from land degradation, soil erosion, biodiversity loss, habitat fragmentation, and declining ecosystem services undermine the resilience and functioning of natural systems upon which human well-being depends (1–4). Against this backdrop, ecological security has emerged as a fundamental concept for understanding and maintaining the balance between human activities and ecosystem sustainability. The concept of ecological security was first introduced by R. Brown in 1981 (5). It refers to the capacity of ecosystems to maintain their structure, functions, and resilience while providing a stable and sustainable ecological environment that supports human development (6–8). In recent years, ecological security assessment has attracted increasing research attention across a wide range of geographical regions and spatial scales. Previous studies have evaluated ecological security in river basins (9)urban agglomerations (10), ecological function zones (11), nature reserves (12), mountainous regions (13), and agricultural areas (14) by integrating remote sensing products, land-use and land-cover information, socio-economic statistics, climatic variables, and ecosystem service indicators within GIS- and model-based analytical frameworks (15,16). These studies have substantially improved our understanding of ecological security patterns, spatio-temporal dynamics, and the factors influencing ecosystem sustainability.

Despite the value of ecological security assessments in providing insights into ecosystem conditions, most existing studies rely on retrospective evaluation frameworks that primarily examine current conditions and historical changes (17,18). While such approaches improve understanding of ecological processes, they offer limited support for proactive environmental governance because they do not anticipate future ecological changes (4). This is a significant limitation, given that many drivers of ecological change, including climate change, land-use transformation, urban expansion, and socio-economic development, which continuously reshape ecosystem dynamics and intensify ecological risks, are highly dynamic (12,19). Consequently, there is an increasing need to complement conventional ecological security assessments with early warning systems that can forecast future ecological conditions and support timely management interventions.

Ecological security early warning has therefore emerged as an important extension of ecological security assessment by integrating natural, social, and economic indicators to identify potential ecological risks before they become critical (18). Ecological security early warning differs from conventional ecological security assessment in that it is a predictive approach that identifies the likelihood of future ecological deterioration before critical thresholds are reached. This property enables early warning systems to detect emerging ecological risks in a timely manner and provides decision-makers with opportunities for preventive intervention and adaptive environmental management (12,18). A wide range of ecosystem settings have been evaluated through the ecological early warning approach, including nature reserves, agricultural landscapes, arid regions, plateaus, mountainous areas, and rapidly urbanising regions. These studies have provided valuable scientific evidence for ecological conservation, environmental planning, and sustainable resource management.

To support ecological security early warning, researchers have developed numerous predictive techniques, including gray prediction models, Nonlinear autoregressive neural networks, Markov models, classification tree analysis, system dynamics, cellular automata, and logistic regression (14,18,24–28). Among these, the gray prediction model is particularly suitable for forecasting ecological trends under limited and uncertain data (14). Several conceptual frameworks have been proposed for constructing ecological security early warning indicator systems, including the Pressure–State–Response (PSR), Driving Force–Pressure–State–Impact–Response (DPSIR), Driving Force–Pressure–State–Response (DPSR), State–Danger–Immunity (SDI), and Driving Force–Pressure–State–Impact–Response–Management (DPSIRM) frameworks (16,24,29–31). The PSR framework has been applied more extensively than the other frameworks because it provides a systematic representation of the interactions among anthropogenic pressures, ecosystem conditions, and management responses (32).

Despite these methodological advances, their application in India remains limited, particularly in the North Eastern Himalayan Region (NEHR) of India (33–35). Existing studies have largely focused on isolated environmental issues or retrospective ecological assessments, with little emphasis on integrated ecological security early warning. Furthermore, no previous study has integrated the PSR framework with the grey prediction model to develop an ecological security early warning system for the NEHR. Consequently, a methodological and regional research gap remains in the development of predictive ecological security assessment frameworks to support proactive environmental governance in this ecologically sensitive region.

India is one of the world's megadiverse countries and encompasses four of the 36 global biodiversity hotspots, namely the Himalayas, the Western Ghats, the Indo-Burma region, and Sundaland (39). The North Eastern Himalayan Region (NEHR), located within both the Indo-Burma Biodiversity Hotspot and the Eastern Himalaya, is among the country's most ecologically significant landscapes (40,41). Although the region occupies only 7.7% of India's geographical area, it supports more than one-third of the nation's biodiversity and exhibits exceptionally high levels of endemism (42). The region provides critical ecosystem services and plays a vital role in maintaining regional ecological stability. Additionally, it is also characterised by extensive forest cover, rugged mountainous terrain, and complex socio-ecological systems. However, increasing pressures from deforestation, biodiversity loss, land-use change, infrastructure expansion, population growth, and climate change are accelerating ecological degradation and increasing ecosystem vulnerability (42,43). The increasing multidimensional threat to the region's environment underscores the urgent need for an early-warning system for ecological security that supports sustainable environmental management.

Against this background, the present study develops an integrated ecological security early warning framework for the NEHR. The specific objectives of the study are as follows: (i) to construct a PSR-based ecological security early warning indicator system, (ii) to evaluate the current ecological security status of the region, (iii) to forecast future ecological security trends using the gray model GM(1,1), and (iv) to identify the dominant drivers of ecological security warning conditions using the Geo-Detector approach. By integrating ecological assessment, prediction, and driver analysis, this study provides a scientific basis for proactive environmental governance. It deepens understanding of interactions between human activities and ecosystem dynamics in one of the world's most ecologically fragile mountain regions.

2 Materials and methods

2.1 Study area

The North Eastern Himalayan Region (NEHR) comprises the seven northeastern states of India: Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura, together with the hill districts of Assam (Fig. 1). The region covers a geographical area of 176,646 km², representing approximately 8% of India's total land area. It is located between 22°00′ N and 29°05′ N latitude and 88°00′ E and 97°30′ E longitude, and shares international boundaries with Nepal, Bhutan, China, Myanmar, and Bangladesh. Owing to its strategic location, the region holds considerable geopolitical importance. According to the 2011 Census of India, the NEHR has a population of approximately 45 million. The NEHR is predominantly mountainous, with nearly 70% of its landscape consisting of hills interspersed with valleys and river plains, while more than 80% of its population resides in rural areas (44). Elevation ranges from the low-lying floodplains of the Brahmaputra River to the high Himalayan summits, reaching approximately 7,940 m above sea level. This pronounced elevational gradient creates substantial climatic variability across the region. Consequently, the NEHR is characterized by abundant rainfall, extensive forest cover, exceptional biological diversity, ecologically fragile mountain ecosystems, and high seismic vulnerability. The region is also recognized for its remarkable ecological and cultural significance. It is home to more than 225 tribal communities, reflecting exceptional ethnic diversity and a rich repository of indigenous knowledge systems. Furthermore, the NEHR is among the most heavily forested regions in India, with forests covering more than 64% of its geographical area. This extensive forest

cover supports rich biodiversity and enables the region to retain substantial forest resources despite increasing developmental pressures (45).

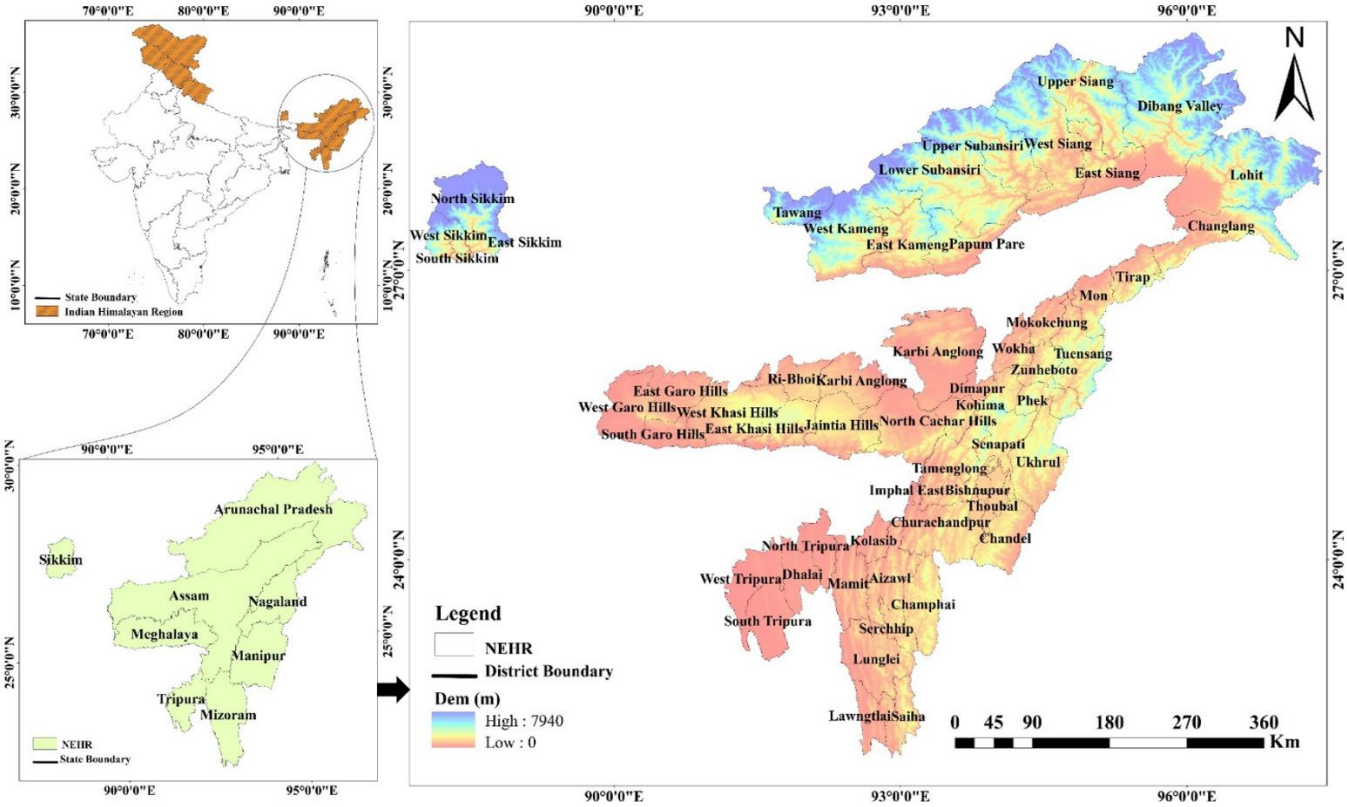


Fig. 1 Location map of the North Eastern Himalayan Region

2.2 Data sources

Meteorological, socio-economic, environmental, and land-use/land-cover (LULC) datasets were compiled to analyse the spatiotemporal dynamics of ecological security in the NEHR. The meteorological variables included annual mean temperature and precipitation. The gridded annual mean temperature dataset, with a spatial resolution of 9 km, was obtained from the ERA5-Land reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF; https://cds.climate.copernicus.eu). Annual mean precipitation data, with a spatial resolution of 5 km, were derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; https://www.chc.ucsb.edu/data/chirps3). Socio-economic datasets comprised night-time light intensity, population density, road network information, and health infrastructure. Harmonized night-time light data (1992–2021) at a spatial resolution of 1 km were obtained from the Harmonized Global Night-Time Lights dataset (https://doi.org/10.6084/m9.figshare.9828827.v5). Gridded population density data at 1 km resolution were sourced from WorldPop (https://www.worldpop.org/), while road density was calculated from vector road network data obtained from OpenStreetMap (https://www.geofabrik.de/data/download.html). The number of health institutions per 10,000 population was compiled from the Rural Health Statistics database (https://www.data.gov.in/). The LULC data were obtained from the Global Land Analysis and Discovery (GLAD) dataset. Human Activity Intensity (HAI) and Ecosystem Service Value (ESV) were derived from the 30m resolution LULC data (https://glad.umd.edu/dataset/GLCLUC2020). In addition, landscape metrics, including Shannon's Diversity Index (SHDI), Largest Patch Index (LPI),

and Patch Density (PD), were computed from the same dataset. Environmental pollution indicators, including $PM_{2.5}$, SO_2, and CO_2 emissions, were obtained from the Emissions Database for Global Atmospheric Research (EDGAR) at a spatial resolution of 10 km. Vegetation and ecosystem productivity indicators were derived from MODIS products. The Normalized Difference Vegetation Index (NDVI) was obtained from the MOD13Q1 dataset at 250 m resolution, whereas Net Primary Productivity (NPP) data were acquired from the MOD17A3HGF dataset at 500 m resolution. Both datasets were downloaded from https://ladsweb.modaps.eosdis.nasa.gov. Forest dynamics were assessed using multiple datasets. Deforestation rates were calculated using the 30 m resolution Global Forest Change v1.13 dataset (https://glad.earthengine.app/view/global-forest-change. Forest gain data at 30 m resolution were derived using Google Earth Engine from the dataset developed by Du et al. (46)(https://code.earthengine.google.com/?asset=projects/eetufangbobo/assets/ForestGain/forestGainFinal). Forest cover statistics were obtained from the Forest Survey of India (https://fsi.nic.in/). Topographical variables, including digital elevation models (DEMs) and slope, were derived from the 30 m Shuttle Radar Topography Mission (SRTM) dataset (https://earthexplorer.usgs.gov/).

Table 1 Index system of ecological security assessment in NEHR

Target level	Criterion level	Index level	Unit	Indicator Attributes	AHP	EWM	Combined Weight
ESI	Pressure	Harmonized night-time light	NA	Negative	0.0744	0.1071	0.0302
		Road density	Length of road per Km^2	Negative	0.1329	0.2243	0.0595
		Human activity intensity	%	Negative	0.2206	0.1352	0.0593
		Population density	Persons/ km^2	Negative	0.1128	0.0968	0.0349
		$PM_{2.5}$ emission	10000 tons	Negative	0.0532	0.0928	0.0243
		Deforestation rate	%	Negative	0.3626	0.2192	0.0969
		CO_2 emission	10000 tons	Negative	0.0321	0.0586	0.0151
		SO_2 emission	10000 tons	Negative	0.0213	0.0655	0.0144
	State	Annual average temperature	°C	Negative	0.0843	0.2417	0.0543
		Annual average rainfall	mm	Positive	0.1456	0.0569	0.0337
		Slope	°	Negative	0.0458	0.1246	0.0284
		Elevation	m	Negative	0.0591	0.0305	0.0149
		NPP	NA	Positive	0.1773	0.0475	0.0374
		NDVI	NA	Positive	0.1976	0.0457	0.0405
		Patch density	NA	Negative	0.0376	0.0502	0.0146
		Shannon diversity index	NA	Positive	0.1415	0.3530	0.0824
		Largest patch index	NA	Positive	0.1112	0.0495	0.0267
	Response	Forest coverage rate	%	Positive	0.5647	0.0356	0.1000
		Forest gain area	Km^2	Positive	0.2517	0.7239	0.1626
		Number of health institution per 10000 people	Number/10,000 people	Positive	0.0606	0.0657	0.0210
		Ecosystem service value (ESV)	$	Positive	0.1228	0.1746	0.0495

2.3 Methods

2.3.1 Constructing an index system of ecological security early warning

Developing a scientifically robust and well-structured indicator system is fundamental for accurately evaluating ecological security early warning (47). Ecological security is governed by the interactions between natural environmental conditions and socio-economic development (48). Accordingly, the Pressure–State–Response (PSR) framework, originally developed by the Organization for Economic Co-operation and Development (OECD) and the United Nations Environment Program (UNEP), was adopted to construct the ecological security early-warning index system (Table 1) (49). The PSR is based on the concept of cause-and-effect relationship and consists of three interrelated components: pressure, state, and response. The pressure component represents the environmental stress generated by anthropogenic activities, such as population growth, land-use change, and natural resource exploitation. The state component describes the condition and functioning of the ecosystem, reflecting both the quality and quantity of ecosystem attributes, including per capita arable land, vegetation cover, and wetland area. The response component represents the actions undertaken by society through policies, management strategies, and decision-making processes to mitigate environmental pressures and improve ecosystem conditions (32,50).

The assessment framework of this study is organised into three hierarchical levels: the target layer, the project layer, and the indicator layer. The target layer represents the Ecological Security Early Warning Index (ESEWI) of the NEHR. The project layer consists of the three PSR components: pressure, state, and response, while each component is represented by a set of corresponding indicators within the indicator layer. Following the principles of the PSR framework and considering regional characteristics, data availability, expert knowledge, and previous studies (8,29,51), a total of 21 indicators were selected. These indicators encompass the social, economic, and environmental dimensions of the study area, forming a comprehensive ecological security early-warning index system for the NEHR (Table 1).

2.3.2 Index weight determination

Data normalization is a crucial procedure in ecological security assessment, as it enhances the consistency and comparability of various indicators (52). The min–max normalization method was used in this study to eliminate dimensional discrepancies across variables. The indicators were categorized into positive and negative types based on their influence on ecological security. Higher values of positive indicators correspond to better ecological security, whereas higher values of negative indicators indicate greater ecological stress. For example, higher population density is treated as a negative indicator since it intensifies resource demand per unit area and waste generation, thereby increasing environmental pressure. On the other hand, the Normalized Difference Vegetation Index (NDVI) is considered a positive indicator, as higher NDVI values indicate denser and healthier vegetation cover, thereby improving the ecosystem's capacity to sustain ecological security. (Eq. 1 and 2).

For positive indicators, where higher values indicate better ecological security conditions:

$$A_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

For negative indicators, where higher values correspond to lower ecological security:

$$A_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}} \quad (2)$$

Here, A_{ij}denotes the standardized value of the j-th indicator for the i-th sample, while X_{ij}represents the original value of that indicator. $X_{\min}$and $X_{\max}$ refer to the minimum and maximum values of the j-th indicator across all samples, respectively.

In this study, indicator weights are determined using the combined weighting method. In multi-criteria decision-making (MCDM) studies, subjective weighting techniques based on expert judgment can reflect the theoretical importance of indicators, but they are often susceptible to human bias. On the other hand, objective weighting methods based on statistical data can lessen human subjectivity; they might not fully capture the indicators' real-world significance (53). Therefore, to overcome the limitations of individual weighting methods and to enhance the reliability of the assessment, a combined weighting technique was used in this study.

The final composite weights for indicators belonging to the same criterion layer were calculated by combining the weight vectors obtained from the Entropy Weighting Method (EWM) and the Analytic Hierarchy Process (AHP) using a coefficient $\alpha \in [0,1]$ Eq. (3).

$$W_{\Lambda,j} = \alpha\, w_{\Lambda,j}^{\text{AHP}} + (1-\alpha)\, w_{\Lambda,j}^{\text{Entropy}} \quad (3)$$

where $W_{\Lambda,j}$denotes the combined weight of the indicator $j$under dimension Λ(with $\Lambda \in \{P, S, R\}$, representing Pressure, State, and Response dimensions). $w_{\Lambda,j}^{\text{AHP}}$represents the subjective weight derived from AHP, while $w_{\Lambda,j}^{\text{Entropy}}$denotes the objective weight obtained through EWM.

In this study, the coefficient α was set to 0.5 to ensure equal impact from both weighting techniques.

2.4.3 Ecological security index (ESI)

Using the multilevel weighted comprehensive evaluation method, the Ecological Security Index (ESI) was calculated to assess the overall security status of the NEHR. This method combines standardized indicator values with their corresponding weights to obtain an integrated measure of ecological security (Eq. 4).

$$ESI = \sum_{j=1}^{n} X_j \cdot W_j \quad (4)$$

where *ESI* represents the ecological security index, with higher values indicating better ecological security conditions. $X_j$denotes the standardized value of the j-th indicator, $W_j$is the corresponding weight of that indicator, and $n$refers to the total number of indicators included in the evaluation system.

2.4.4 Model robustness verification using Monte Carlo simulation

In the model robustness verification, a Monte Carlo simulation was performed to evaluate the sensitivity of the ESI (53). The original weights were perturbed within a ±10% range by generating 300 randomized weight sets according to: $w_j' = w_j(1+\delta)$ where $w_j$is the original weight of the indicator j, $\delta \sim U(-0.1, 0.1)$is a random perturbation factor following a uniform distribution, and w_j'represents the perturbed weight. The perturbed weights were subsequently normalized and used to recalculate the ESI for each district. The coefficient of variation (CV) of the simulated ESI values was computed as (Eq. 5):

$$CV_i = \frac{\sigma(ESI_i)}{\mu(ESI_i)} \times 100\% \quad (5)$$

where $\sigma(ESI_i)$and $\mu(ESI_i)$denote the standard deviation and mean of the simulated ESI values for the district i, respectively. A lower CV value indicates lower sensitivity of the assessment results to weight perturbations and therefore higher model robustness.

2.4.5 Ecological security early-warning prediction

The Gray model (GM) was first developed by Deng (54) and is a quantitative technique for analyzing relationships among variables based on their developmental trends. The model is particularly useful for handling uncertain systems by supporting analysis, forecasting, and decision-making. Due to its reliability and adaptability, the model has been extensively applied in early warning research across various disciplines (51,55).

The GM framework comprises several models, including GM (1,1) and GM (1, N), among which GM (1,1) is the most frequently used for forecasting. The basic idea behind the GM (1,1) model is to convert irregular original data into a more structured sequence via the Accumulated Generating Operation (AGO), which typically yields an exponential trend. A first-order differential equation is then created from the converted data series to describe the system's dynamics, combining known and unknown data for forecasting and prediction (51).

The GM(1,1) is widely preferred for its simple structure and strong forecasting capability. Furthermore, the gray model performs particularly well on datasets with small sample sizes and low regularity (18). In this study, the ecological security-early warning Index (ESEWI) from 2025 to 2040 was forecast using the GM (1,1) model to predict future ecological security conditions in NEHR.

The procedure for constructing the GM (1,1) model can be summarized as follows from Eqs. 6 to 13:

(1) Construction of the original and accumulated sequences: Let the original time series be defined as:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\} \quad 6$$

To reduce randomness and enhance regularity, a first-order accumulated generating operation (AGO) is applied to obtain a new sequence:

$$x^{(1)}(m) = \sum_{i=1}^{m} x^{(0)}(i), m = 1,2,3, \dots, n \quad 7$$

where $n$represents the total number of observations, and $m$denotes the time index.

(2) Construction of matrices and model formulation: A neighbouring mean sequence is generated from the accumulated sequence to form a matrix B, while the original data are used to construct a vector Y:

$$B = \begin{bmatrix} -0.5(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -0.5(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \cdots & \cdots \\ -0.5(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \quad 8$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(n) \end{bmatrix} \quad 9$$

Based on these, the whitening differential equation of the GM (1,1) model is expressed as:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \quad 10$$

where $a$is the development coefficient and u is the gray input.

(3) Parameter estimation: The parameters $a$and $u$are estimated using the least squares method:

$$\begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y \quad 11$$

(4) Time response function: By substituting the estimated parameters into the model, the time response function of the accumulated sequence is obtained:

$$x^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{u}{a}\right) e^{-at} + \frac{u}{a} \quad 12$$

(5) Inverse accumulation (IAGO): Finally, the predicted values of the original sequence are obtained through inverse accumulation:

$$x^{(0)}(t+1) = x^{(1)}(t+1) - x^{(1)}(t) \quad 13$$

where $x^{(0)}(t+1)$represents the predicted value at time $t+1$.

2.4.6 Classification standard of early-warning grade

The Ecological Security Early Warning Index (ESEWI) was used to assess the NEHR's ecological security warning status. However, a universally accepted classification scheme for ecological security early-warning grades has not yet been established. Therefore, considering the regional characteristics of the NEHR and previous studies (8,18,51), the Natural Breaks classification method was adopted to classify the ESEWI values into five early-warning grades: no warning, light warning, medium warning, serious warning, and huge warning (Table 2).

Table 2 Classification standard of ESEW grades in the NEHR

ESEWI Range	Security situation	Warning situation
≤ 0.429	Very Low	Huge Warning (HW)
0.429 – 0.526	Low	Serious Warning (SE)
0.526 – 0.562	Moderate	Medium Warning (MW)
0.562 – 0.613	High	Light Warning (LW)
> 0.613	Very High	No Warning (NW)

2.4.7 Driving factors of ES of NEHR (Geo-detector method)

The Geo-detector model (GDM) is a collection of statistical techniques developed by Wang and Xu (56) to identify spatial variability and quantitatively examine the driving forces underlying spatial differentiation (19). The GDM framework consists of several detectors, including the factor detector, interaction detector, risk detector, and ecological detector, each

designed to perform distinct analytical functions to explain spatial heterogeneity and identify influencing mechanisms (51).

To systematically identify the primary driving factors influencing early-warning of ecological security in the NEHR, this study used two components of the Geographical Detector Model (GDM): the factor detector and the interaction detector.

Factor detectors are used to measure the influence of an independent variable x on a dependent variable y and to explain the mechanism underlying the spatial differentiation by the q value. The q value indicates the explanatory power of a particular factor; the value ranges from 0 to 1. The greater the q value is, the larger the explanatory power of the factor (57).

The q value can be calculated as described by Wang et al. (2016), Eq. 14.

$$q = 1 - \frac{SSW}{SST} = 1 - \frac{\sum_{t=1}^{m} N_t \sigma_t^2}{N\sigma^2} \quad 14$$

where SSW and SST represent the within-group sum of squares for the subregions and the total sum of squares for the entire study area, respectively. Here, $t = 1,2,\dots,m$ denotes the different subregions corresponding to the ESI values or influencing factors; N_t and N indicate the number of units in the subregion t and the entire study area, respectively, while σ_t^2 and σ^2 represent the variance of the ESI values within the subregion t and across the whole study area, respectively.

An interaction detector was performed by comparing the q values of individual factors with those of paired factors to determine whether two variables have independent or interactive effects on ecological security and to pinpoint the nature of the interaction between them (19). Initially, the q values of the two individual factors (X1 and X2) were calculated separately for the ecological security assessment. Subsequently, the q value for the interaction between the two factor layers was computed. The interactions between the factors were categorized into groups based on comparisons of these q values, as shown in Table 3.

Table 3 Types of interactions between two variables

Interaction types	Description
Weaken, nonlinear	$q(X_1 \cap X_2) < min[q(X_1), q(X_2)]$
Weaken, uni-factor	$min[q(X_1), q(X_2)] < q(X_1 \cap X_2) < max[q(X_1), q(X_2)]$
Enhance, bi-factor	$q(X_1 \cap X_2) > max[q(X_1), q(X_2)]$
Independent	$q(X_1 \cap X_2) = q(X_1) + q(X_2)$
Enhance, nonlinear	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$

3 Results and discussion

3.1 Model robustness verification results

The Monte Carlo simulation demonstrated that the ecological security assessment model is highly robust to uncertainties in indicator weights. By perturbing the original indicator weights within a ±10% range across 300 randomized simulations, multiple ESI values were generated for each district. The variability of these simulated values was evaluated using the coefficient of variation (CV). Across the 55 districts, the CV ranged from 0.643% to 2.056%, with a mean value of 0.984%. These consistently low CV values indicate that random perturbations in indicator weights produced only minor changes in the calculated ESI, demonstrating that the

assessment results are insensitive to weight uncertainty. Overall, the findings confirm the robustness, reliability, and stability of the ecological security assessment model.

3.2 Ecological security evaluation results

According to Eq. (4), the district-level Ecological Security Index (ESI) for the NEHR was calculated (Table 4). The average ESI values for 2000, 2005, 2010, 2015, and 2020 were 0.541, 0.577, 0.542, 0.546, and 0.551, respectively. The regional ESI increased markedly from 2000 to 2005, declined in 2010, and recovered slightly between 2015 and 2020, indicating an overall fluctuating trend. In 2000, Imphal West recorded the lowest ESI value, whereas Lower Subansiri had the highest. A similar pattern was observed in 2020, with Imphal West and Lower Subansiri continuing to record the lowest and highest ESI values, respectively. Throughout the study period, several districts consistently exhibited relatively high ESI values, including Lower Subansiri, Lohit, North Sikkim, and East Kameng, all located in the densely forested, mountainous regions of Arunachal Pradesh and Sikkim. In contrast, Dimapur, Imphal West, Thoubal, Imphal East, and Bishnupur consistently recorded relatively low ESI values. These districts are mainly situated in lowland plains characterized by intense anthropogenic activities (Table 4). Between 2000 and 2020, the most notable improvements in ESI were observed in Churachandpur (+0.119), Chandel (+0.109), West Tripura (+0.089), Mokokchung (+0.082), and North Cachar Hills (+0.065). Conversely, Jaintia Hills, North Sikkim, West Siang, Dhalai, Tamenglong, and Senapati experienced declining ESI values of −0.070, −0.068, −0.051, −0.046, −0.031, and −0.029, respectively.

Based on the Natural Breaks classification method, the ESI values were classified into five grades: very high, high, moderate, low, and very low, using the thresholds presented in Table 2. The spatial distribution of these grades reveals considerable heterogeneity across the NEHR during the study period (Fig. 2). Overall, the high ecological security grade predominated, accounting for approximately 21.82%–38.18% of districts. These districts were concentrated mainly in the mountainous areas of Arunachal Pradesh, particularly Changlang, East Kameng, East Siang, Papum Pare, and Upper Siang, as well as several districts in Meghalaya, Mizoram, and the hill districts of Manipur. The moderate ecological security grade accounted for 14.55%–30.91% of districts and became the dominant class by 2020 (30.91%). These districts were widely distributed across the central and southern parts of the region, particularly in Manipur, Mizoram, and Meghalaya. The low ecological security grade exhibited the greatest temporal fluctuation, rising from 7.27% in 2005 to 30.91% in 2010, then declining to 21.82% in 2020. Districts within this category were primarily located in Nagaland, Sikkim, Meghalaya, and Mizoram.

The very high ecological security grade accounted for 10.91%–32.73% of districts. Its highest proportion was recorded in 2005 (32.73%), after which it gradually declined to 12.73% in 2020. Districts in this category were mainly concentrated in Arunachal Pradesh, particularly Lower Subansiri, Lohit, Dibang Valley, Upper Subansiri, West Kameng, and West Siang, as well as a few hill districts of Manipur. These areas are characterized by mountainous forested landscapes, relatively low levels of anthropogenic disturbance, and well-preserved ecosystems which contribute to higher ecological security.

By contrast, the very low ecological security grade consistently accounted for only 7.27%–9.09% of districts throughout the study period. These districts were concentrated primarily in the central valley of Manipur, particularly Thoubal, Bishnupur, Imphal West, and Imphal East, together with Dimapur in Nagaland. The proportion of districts within this category remained

relatively stable over time, indicating the persistence of chronic ecological stress. This pattern is likely associated with high population density, intensive urban expansion, agricultural pressure, and wetland loss. In contrast, ecological security remained consistently stronger in the northern mountainous districts of Arunachal Pradesh, where extensive forest cover and relatively limited anthropogenic disturbance have helped maintain favourable ecological conditions.

Overall, the temporal pattern indicates substantial shifts among ecological security categories rather than a continuous improvement across the region. Although some districts experienced noticeable improvements, reflected by the expansion of the high ecological security grade in 2005, this trend was not sustained. Instead, the proportion of districts in the moderate grade increased again by 2020, making it the most widespread ecological security class in the region. These findings suggest that the NEHR continues to face considerable ecological challenges. The continued dominance of the moderate grade indicates that many districts remain highly vulnerable to both ecological improvement and deterioration. At the same time, the persistent presence of very low ecological security zones, together with the fluctuating extent of low ecological security areas, reflects ongoing ecological vulnerability across the region. Moreover, the decreasing number of districts attaining very high ecological security further underscores that the study area continues to face ecological challenges.

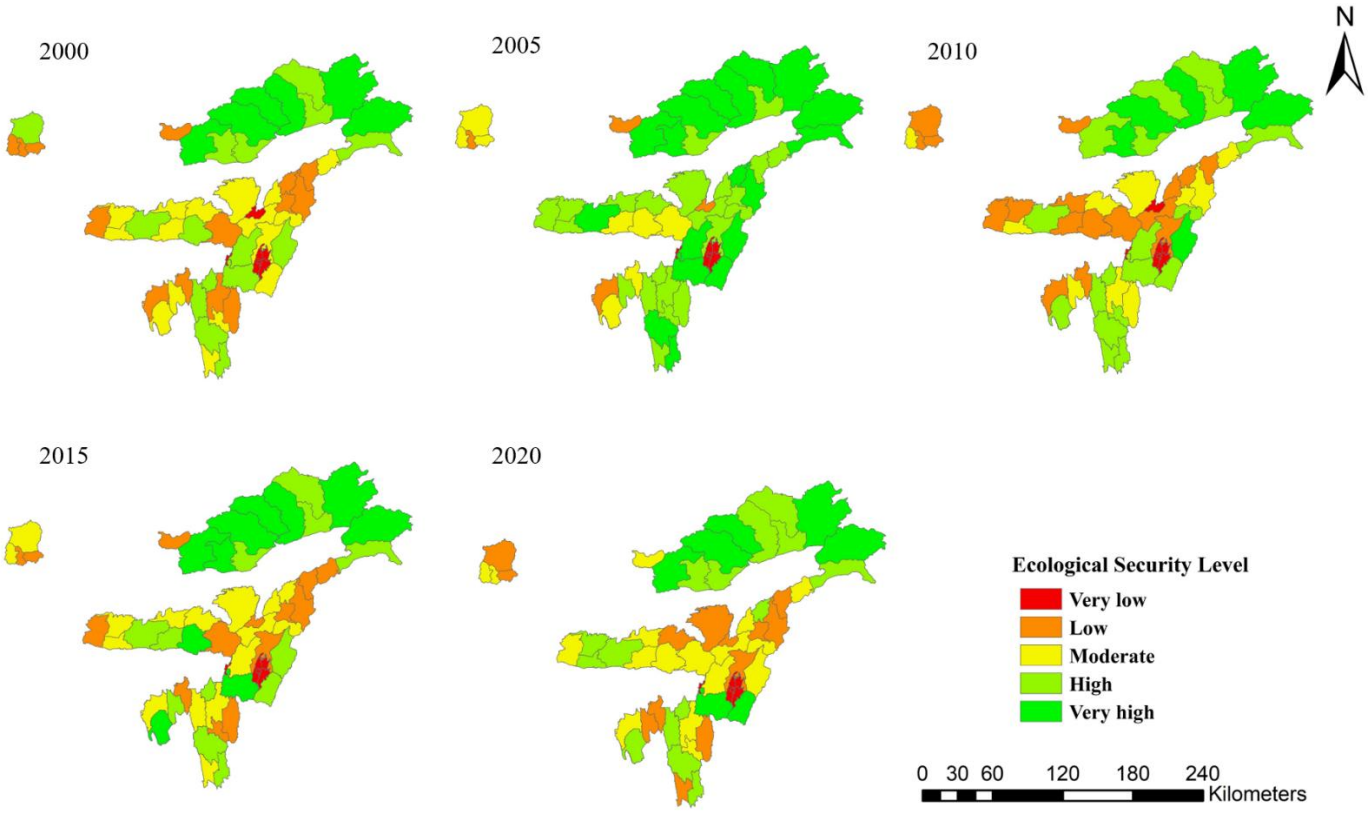


Fig. 2 Spatial distribution map of Ecological security grade in NEHR from 2000 to 2020

Table 4 District-level ESI value in the NEHR

District	2000	2005	2010	2015	2020	District	2000	2005	2010	2015	2020
Changlang	0.571	0.630	0.578	0.608	0.596	South Garo Hills	0.559	0.598	0.559	0.546	0.593
East Kameng	0.591	0.627	0.641	0.621	0.608	West Garo Hills	0.522	0.563	0.510	0.523	0.554
East Siang	0.578	0.61	0.604	0.604	0.580	West Khasi Hills	0.572	0.616	0.603	0.608	0.613
Lower Subansiri	0.692	0.65	0.68	0.652	0.737	Aizawl	0.519	0.587	0.539	0.530	0.526
Lohit	0.681	0.645	0.629	0.750	0.721	Champhai	0.524	0.599	0.539	0.518	0.509
Dibang Valley	0.636	0.639	0.637	0.631	0.654	Kolasib	0.582	0.612	0.574	0.575	0.570
Papum Pare	0.567	0.605	0.573	0.594	0.584	Lawngtlai	0.547	0.602	0.587	0.543	0.523
Tawang	0.514	0.522	0.519	0.512	0.544	Lunglei	0.571	0.629	0.609	0.571	0.564
Tirap	0.538	0.568	0.559	0.503	0.542	Mamit	0.576	0.613	0.581	0.557	0.569
Upper Siang	0.594	0.631	0.611	0.607	0.612	Saiha	0.568	0.619	0.575	0.570	0.563
Upper Subansiri	0.624	0.634	0.612	0.658	0.643	Serchhip	0.555	0.579	0.564	0.523	0.527
West Kameng	0.653	0.627	0.613	0.621	0.633	Dimapur	0.429	0.457	0.398	0.438	0.457
West Siang	0.620	0.667	0.624	0.625	0.569	Kohima	0.538	0.590	0.504	0.537	0.553
Karbi Anglong	0.537	0.588	0.528	0.534	0.514	Mokokchung	0.482	0.649	0.508	0.557	0.564
North Cachar Hills	0.491	0.549	0.469	0.470	0.556	Mon	0.508	0.567	0.478	0.473	0.490
Bishnupur	0.407	0.390	0.421	0.401	0.410	Phek	0.544	0.586	0.581	0.538	0.528
Chandel	0.557	0.662	0.586	0.584	0.666	Tuensang	0.508	0.645	0.551	0.463	0.487
Churachandpur	0.589	0.703	0.612	0.642	0.708	Wokha	0.537	0.593	0.514	0.539	0.551
Imphal East	0.369	0.386	0.386	0.380	0.384	Zunheboto	0.526	0.586	0.541	0.488	0.504
Senapati	0.533	0.582	0.520	0.510	0.504	East	0.499	0.530	0.503	0.513	0.522
Tamenglong	0.591	0.672	0.587	0.560	0.560	North Sikkim	0.594	0.542	0.51	0.561	0.525
Thoubal	0.355	0.349	0.384	0.376	0.378	South Sikkim	0.506	0.526	0.515	0.464	0.528
Ukhrul	0.566	0.654	0.663	0.569	0.559	West Sikkim	0.511	0.539	0.539	0.552	0.542
Imphal West	0.286	0.298	0.312	0.304	0.301	Dhalai	0.562	0.581	0.553	0.562	0.516
East Garo Hills	0.553	0.578	0.518	0.548	0.574	North Tripura	0.523	0.552	0.491	0.526	0.524
East Khasi Hills	0.535	0.530	0.492	0.563	0.531	South Tripura	0.545	0.553	0.573	0.637	0.601
Jaintia Hills	0.613	0.552	0.495	0.634	0.543	West Tripura	0.470	0.481	0.441	0.528	0.559
Ri-Bhoi	0.553	0.570	0.506	0.557	0.536						

3.3 Early-warning results

3.3.1 Accuracy verification

The performance of the early warning model must be evaluated in order to ensure the accuracy of its forecasts. With reference to the existing literature (58,59), the model's accuracy was assessed using the relative accuracy method. Simultaneously, the samples were split into calibration and validation sets. Data from 2000 to 2015 were used for training, and data from 2020 were used for validation. Table 5 presents the statistical findings of the accuracy evaluation. We can deduce that the average relative error is 7.39% and that the relative errors are primarily between 0 to 5%. The early-warning model has high reliability and can be applied to ecological security early-warning (18,59,60).

Table 5 Error statistics of the early-warning model.

Percentage of relative error intervals					Average relative error
0-5%	5%-10%	10%-15%	15%-20%	>20%	
43.63%	25.45%	18.18%	9.09%	3.63%	7.39%

Table 6 Statistical results of the ESEWI and ratio of grades in the NEHR

Year	ESEWI		The proportion of warning grades (No. of Districts)					
	Minimum	Maximum	Mean	HW	SW	MW	LW	NW
2025	0.3042	0.7784	0.547	9.09% (5)	29.09% (16)	29.09% (16)	14.55% (8)	18.18% (10)
2030	0.3044	0.819	0.532	10.91% (6)	41.82% (23)	16.36% (9)	14.55% (8)	16.36% (9)
2035	0.3045	0.8618	0.527	16.36% (9)	40.00% (22)	12.73% (7)	14.55% (8)	16.36% (9)
2040	0.2921	0.9068	0.522	18.18% (10)	40.00% (22)	10.91% (6)	12.73% (7)	18.18% (10)

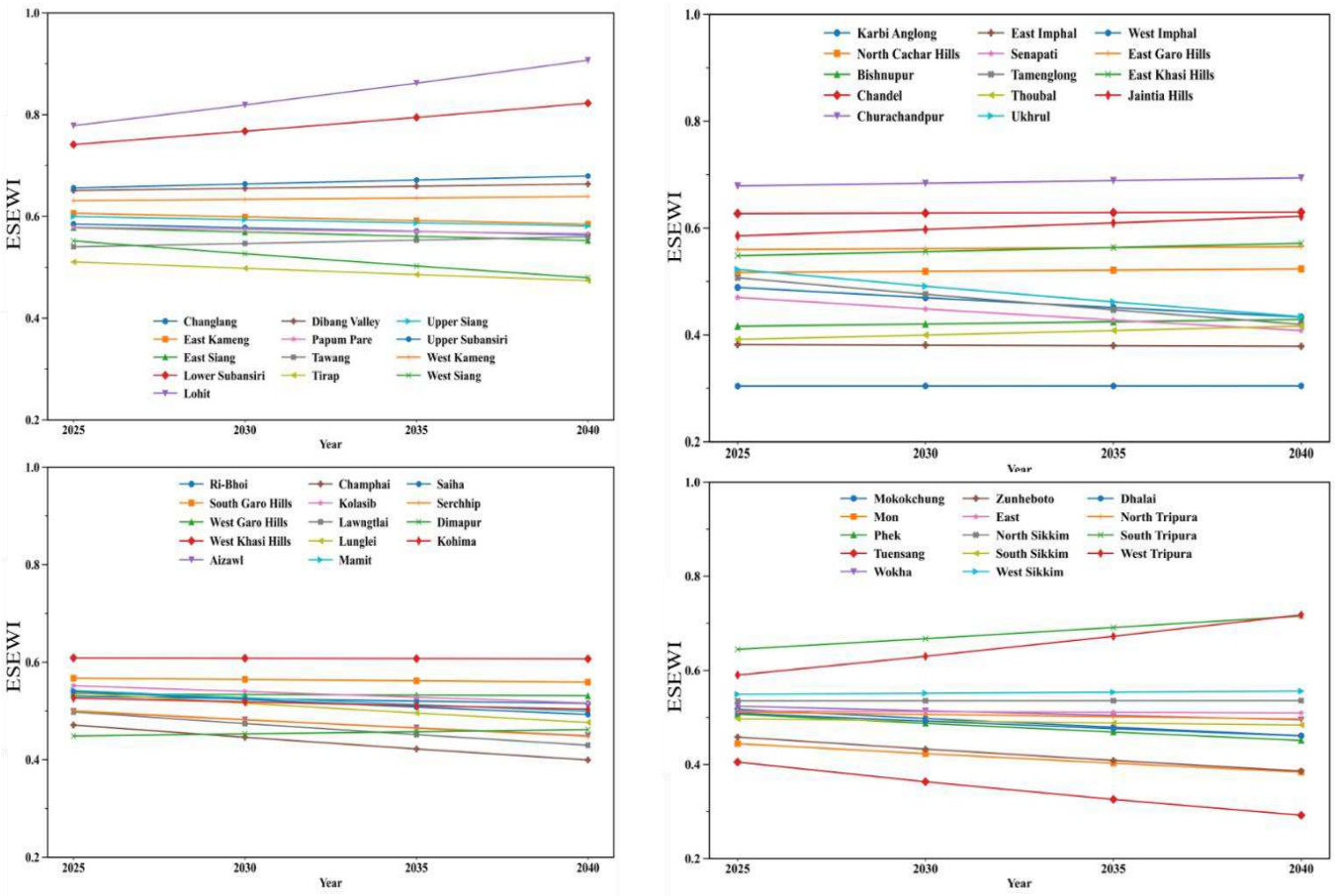


Fig. 3 ESEWI in NEHR from 2025 to 2040

3.3.2 Ecological security early warning analysis

As shown in Fig. 3 and Table 6, the average Ecological Security Early Warning Index (ESEWI) values for 2025, 2030, 2035, and 2040 are projected to be 0.547, 0.532, 0.527, and 0.522, respectively, representing an overall decline of 4.57% during the prediction period. This trend indicates a gradual deterioration in ecological security across the NEHR from 2025 to 2040. Throughout the forecast period, Imphal West is projected to record the lowest ESEWI value, whereas Lower Subansiri consistently maintains the highest.

To further examine the spatial pattern of ecological security, the predicted ESEWI values were classified into five warning grades using the same Natural Breaks classification method applied to the historical ESI (Section 3.2; Table 2). The resulting spatial distribution (Fig. 4) reveals clear spatial differentiation in ecological security warning grades across the study area. The huge warning grade is projected to increase steadily over the forecast period, rising from 5 districts (9.09%) in 2025 to 6 districts (10.91%) in 2030, 9 districts (16.36%) in 2035, and 10 districts (18.18%) in 2040. Similarly, the serious warning grade is expected to increase from 16 districts (29.09%) in 2025 to 23 districts (41.82%) in 2030 before declining slightly to 22 districts (40.00%) in both 2035 and 2040. In contrast, the number of districts in the medium warning grade is projected to decrease substantially from 16 (29.09%) in 2025 to only 6 (10.91%) by 2040. The light warning grade shows a slight decline from 8 districts (14.55%) during 2025–2035 to 7 districts (12.73%) in 2040. Meanwhile, the no warning grade remains relatively stable, decreasing from 10 districts (18.18%) in 2025 to 9 districts (16.36%) during 2030–2035, before returning to 10 districts (18.18%) by 2040.

District-level transitions further illustrate the projected deterioration in ecological security. In Manipur, Senapati is projected to deteriorate from the serious warning grade in 2025 to the huge warning grade by 2035, while Tamenglong follows a similar trend, reaching the huge warning grade by 2040. Ukhrul is also expected to shift from the medium warning grade to the serious warning grade during the prediction period. Notably, Thoubal, Bishnupur, Imphal West, and Imphal East in the central valley of Manipur, together with Tuensang in Nagaland, remain within the huge warning grade throughout the forecast period. This persistent pattern is consistent with the historical ESI results (Fig. 2), which identified these districts as having consistently low ecological security. Between 2030 and 2040, Zunheboto and Mon in Nagaland, and Champhai in Mizoram are also projected to deteriorate from the serious warning grade to the huge warning grade.

Further deterioration is projected in several other districts. In Arunachal Pradesh, West Siang is expected to shift from the medium warning grade to the serious warning grade, while East Siang declines from the light warning grade to the medium warning grade. East Kameng is projected to change from the no warning grade to the light warning grade. In Assam, North Cachar Hills is expected to deteriorate from the medium warning grade to the serious warning grade. Similarly, Champhai in Mizoram is projected to deteriorate from the serious warning grade to the huge warning grade. Lunglei and Saiha in Mizoram, together with Kohima, Mokokchung, and Wokha in Nagaland, are expected to decline from the medium warning grade to the serious warning grade. Mamit and Kolasib are also projected to experience worsening ecological conditions, with Kolasib entering the serious warning grade by 2040.

Only a limited number of districts are projected to show improvement during the prediction period. West Tripura is expected to improve from the light warning grade in 2025 to the no warning grade from 2030 onwards. Likewise, Jaintia Hills in Meghalaya is projected to improve from the light warning grade in 2035 to the no warning grade by 2040. In addition, Lower Subansiri, Lohit, Dibang Valley, Upper Subansiri, and West Kameng in Arunachal Pradesh, together with Chandel in Manipur, consistently remain within the no warning grade throughout the prediction period.

Overall, the projected results indicate that the ecological security situation in the NEHR is likely to deteriorate by 2040. The increasing dominance of the serious and huge warning grades, coupled with the continued decline in the medium warning category, suggests that a growing

number of districts may experience worsening ecological conditions. These findings highlight the need for future development strategies that balance socio-economic growth with environmental conservation. Greater emphasis should be placed on integrating sustainable development practices with ecosystem protection to ensure the long-term ecological stability and resilience of the region.

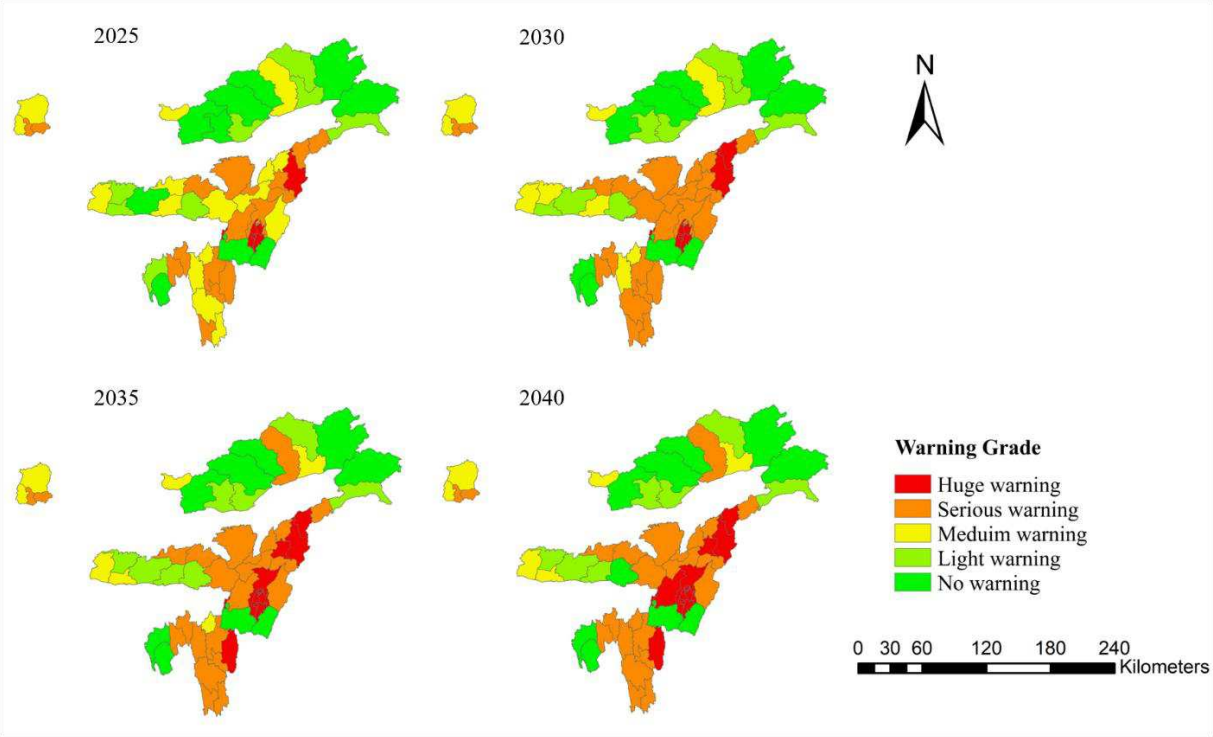


Fig. 4 Spatial Distribution of ESEW grades in the NEHR.

3.4 Driving factors of the NEHR

3.4.1 Factor Detector

The geographical detector model was utilized to determine the contribution of various indicators to the ecological security of NEHR. Based on the factor detector, this paper quantitatively assesses the effects of the factors driving the overall pattern of ecological security in NEHR using q-values.

The primary factors influencing ecological security early warning were examined using factor detector analysis. The results show that early warning systems for ecological security are influenced by social, economic, and environmental factors, with varying degrees of influence (Fig. 5). The chosen indicators have q-statistic values ranging from 0.011 to 0.578 (Table 7). The variables with the highest explanatory power were (X4) Population Density (q = 0.578), (X3) Human Activity Intensity (q = 0.472), (X2) Road Density (q = 0.443), (X18) Forest Coverage Rate (q = 0.423), and (X21) Ecosystem Service Value (ESV) (q = 0.406). The NEHR ecological security early warning was shown to be primarily influenced by these indicators. Furthermore, (X11) Slope (q = 0.391), (X15) Patch Density (q = 0.344), (X14) NDVI (q = 0.338), (X16) Shannon Diversity Index (q = 0.332), (X17) Largest Patch Index (q = 0.320), and (X10)

Annual Rainfall (q = 0.304) demonstrated comparatively high explanatory capacity, with q-values exceeding 0.300, indicating that these variables also played a significant secondary role in determining ecological security conditions. On the other hand, Health Institutions per 10,000 Population (X20), Net Primary Productivity (X13), Harmonised Night-Time Light (X1), PM2.5 Emissions (X5), Elevation (X12), Deforestation Rate (X6), Forest Gain Area (X19), Annual Temperature (X9), SO_2 Emissions (X7), and CO_2 Emissions (X8) showed comparatively weaker explanatory power, indicating their relatively limited contribution to ecological security early warning.

The mean q-values of social, economic, and environmental factors were 0.401, 0.285, and 0.213, respectively. The findings imply that, compared with economic and environmental factors, social factors had the greatest impact on ecological security early warning in the NEHR, demonstrating their dominant role in shaping the region's ecological security conditions.

Table 7 Results of the factor detector

Indicator ID	Indicator name	q-value	Significance level	Rank
X4	Population density	0.577	***	1
X3	Human activity intensity	0.472	***	2
X2	Road density	0.442	***	3
X18	Forest coverage rate	0.422	***	4
X21	ESV	0.406	***	5
X11	Slope	0.391	***	6
X15	Patch Density	0.343	***	7
X14	NDVI	0.337	***	8
X16	Shannon Diversity Index	0.331	***	9
X17	Largest Patch Index	0.319	***	10
X10	Average Annual rainfall	0.303	***	11
X20	Health institutions per 10,000 population	0.154	*	12
X13	NPP	0.134	*	13
X1	Harmonized night-time light	0.126	*	14
X5	$PM_{2.5}$ emission	0.109	*	15
X12	Elevation (m)	0.091	-	16
X6	Deforestation rate	0.066	-	17
X19	Forest gain area (sq. km)	0.064	-	18
X9	Average Annual temperature	0.035	-	19
X8	CO_2 emission	0.032	-	20
X7	SO_2 emission	0.011	-	21

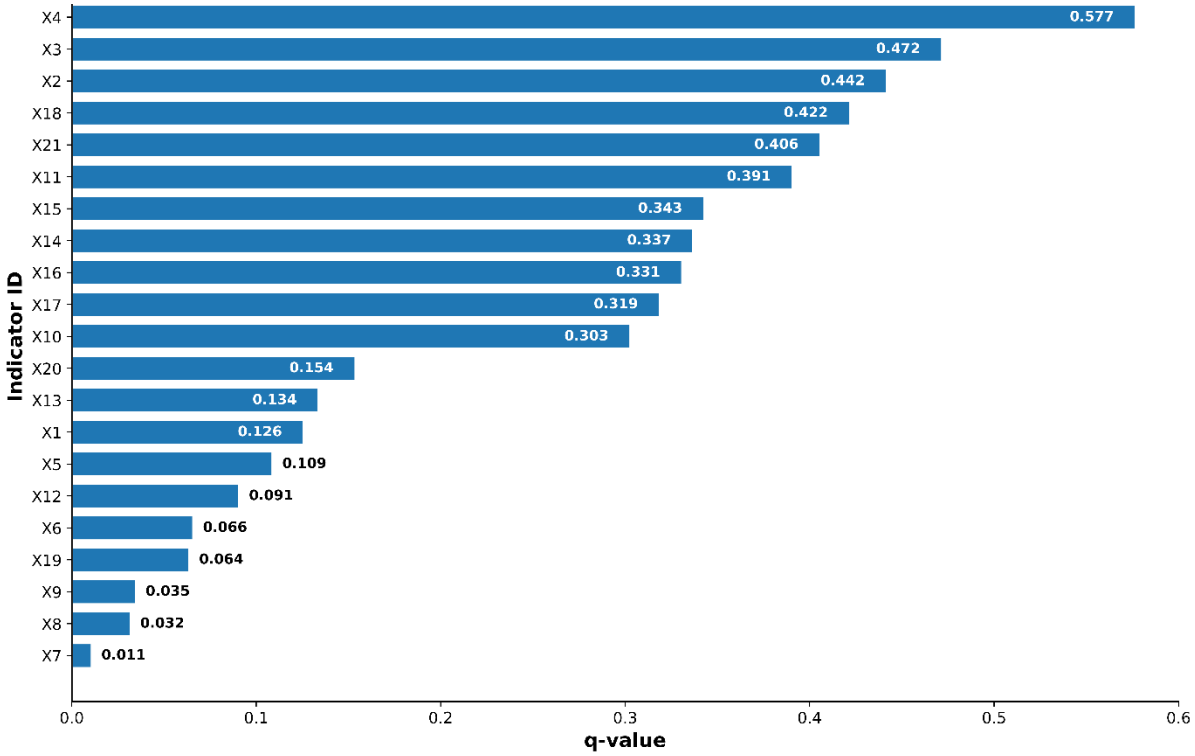


Fig. 5 Explanatory power (q-values) of individual factors affecting the distribution of ES

3.4.2 Interaction detector

To investigate the interaction between influencing factors and ecological security, an interaction detection was performed (Fig. 6). The findings showed that the variables interacted rather than being independent. These interactions typically increased the explanatory power of the dependent variable, mainly through nonlinear and two-factor enhancement effects. Nonlinear enhancement takes place when the total explanatory power of two interacting factors surpasses the sum of their separate effects. While the two-factor enhancement effect is comparatively weaker than the nonlinear enhancement effect, it has greater explanatory power than each factor acting independently (9).

Among the 210 interaction pairs, nonlinear enhancement was the dominant interaction type, accounting for 118 pairs, followed by two-factor enhancement, which accounted for 79 pairs. Furthermore, only a small number of interactions displayed single-factor attenuation, and just one interaction demonstrated nonlinear attenuation. This suggests that the isolated influence of individual characteristics does not control the regional pattern of ecological security in the NEHR. Instead, it is mostly determined by two interacting factors, which typically result in a stronger explanatory effect on patterns of ecological security.

The highest interaction q-value was observed between X18 and X4 (q = 0.860), indicating a very strong combined influence on spatial differentiation. Similarly, strong interaction effects were identified for X21 ∩ X17 (q = 0.806), X11 ∩ X2 (q = 0.786), X21 ∩ X16 (q = 0.769), X21 ∩ X3 (q = 0.755), X12 ∩ X2 (q = 0.753)and X12 ∩ X2 (q = 0.751). These high q-values suggest that the interaction among environmental, climatic, and socio-economic factors substantially enhanced their explanatory power. Indicators such as X21, X18, X4, X2, and X11 frequently appeared in strong interaction pairs, highlighting their critical role in controlling the spatial variability of ecological security in the study area.

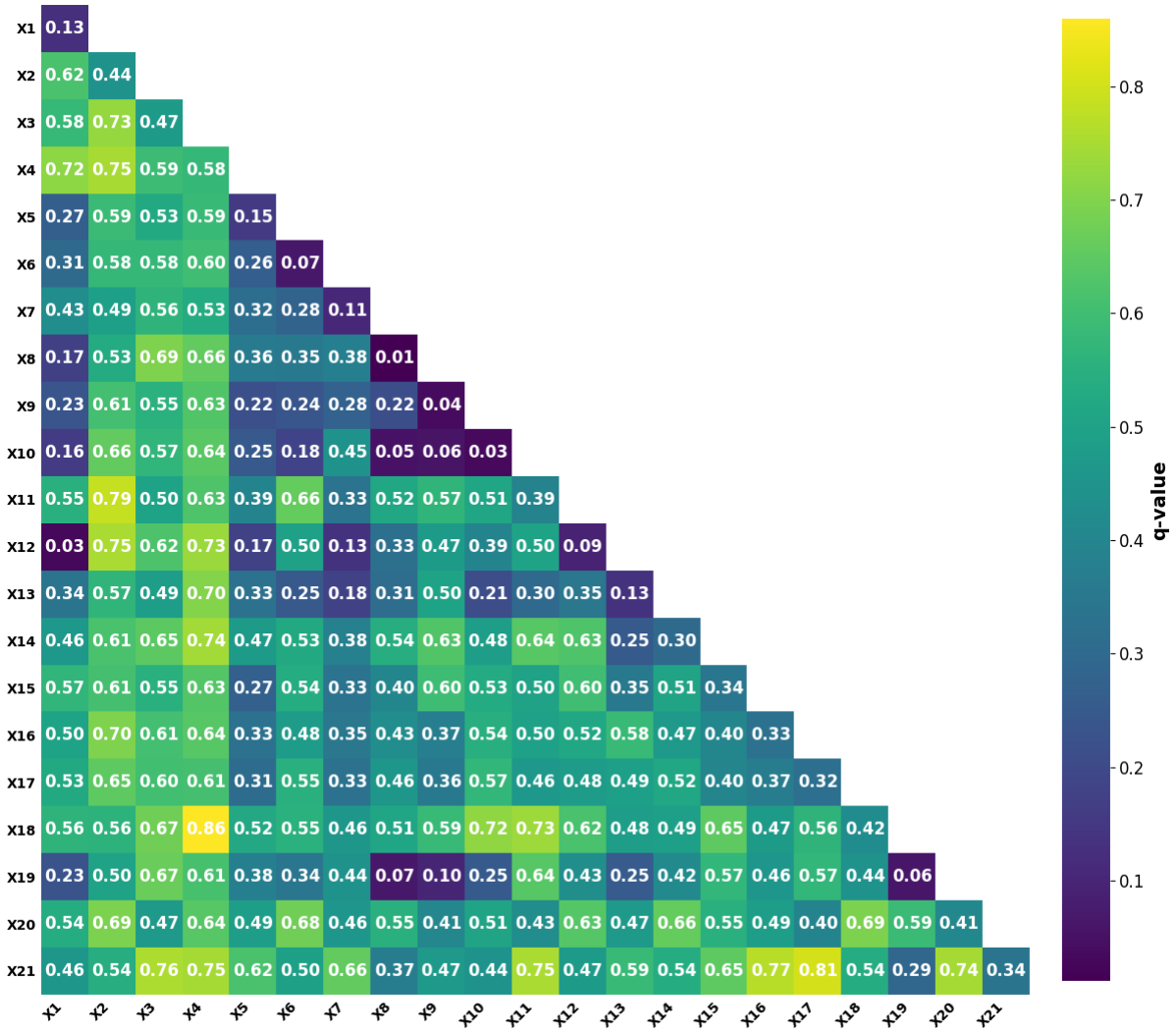


Fig. 6 Interaction effects between paired factors

3.5 Reliability and limitations of the early-warning model

Ecological security early warning is still in its infancy, yet it is an essential part of ecological security research. The inherent lack of fine-scale datasets, both gridded and at the district level, mostly socio-economic statistics, affects the analysis of the ecological security early-warning assessment (61,62). So, this study integrates a range of data sources and indicators, including natural geographic variables, socio-economic variables, and landscape ecological pattern indices derived from remote-sensing gridded datasets, in order to fully capture the ecological security conditions of the NEHR and provide a more reliable and comprehensive assessment of the region's ecological security status. The average relative error of the Gray early warning model is 7.39%, indicating satisfactory prediction accuracy. The results show that the suggested early-warning model is reliable and effective for forecasting ecological security conditions, compared with earlier research (18,60,63). Despite the results showing that the gray early-warning model achieved reasonably high prediction accuracy and effectively reflects the real conditions of the study area, several limitations remain. First, there is still limited research on ecological security early warning, and the lack of a single quantitative criterion for determining warning grades makes it more difficult to compare results across

studies. Second, although the gray early-warning model works well for short- and medium-term forecasting, its reliability and usefulness for long-term projection are still somewhat limited (64,65).

Scenario analysis has been widely used in change-prediction studies and is useful for investigating potential future development patterns. However, this study has adopted the trend extrapolation strategy using the gray model. The primary cause is the difficulty in reliably obtaining numerous crucial scenario characteristics needed for ecological security assessment, including those required for land-use simulation. The gray early-warning model developed in this study, in contrast, exhibits excellent reliability and practical viability, making it more appropriate for forecasting future shifts in ecological security circumstances (18).

Lastly, the availability of some indicator data remains limited, and ecological security is inherently dynamic and complex. Because of this, the current evaluation index system still needs improvement. For example, the early-warning evaluation did not include crucial elements such as economic indicators (e.g., GDP) and policy-related variables. To create a more thorough and reliable early-warning system for ecological security, future research should focus on strengthening the assessment framework by incorporating multi-source, high-resolution, and long-term time-series data.

While ecological security has become a significant research focus globally, particularly in China through initiatives such as the United Nations Millennium Development Goals and the 2030 Sustainable Development Goals (66), contributions from other countries appear less substantial, particularly in the Indian subcontinent. This geographic disparity underscores the need for global engagement in this research and fosters cross-border collaborations that would facilitate the sharing of diverse perspectives, methodologies, and datasets, thereby enhancing the applicability of ESA research worldwide (18).

4.2 Analysis of the spatial heterogeneity and impact factors of the ESEW

The results show that ecological security in the NEHR is projected to deteriorate in the future, and its spatial distribution will remain unbalanced. In terms of the evaluation results, the poor ecological security situation was mainly located in the central and southern parts of the NEHR from 2000 to 2020. The poor ecological security in these areas indicates that environmental pressures and habitat fragmentation caused by population aggregation and high-intensity development are also important factors affecting ecological security (43).

From 2000 to 2020, the central valley districts of Manipur, situated in the central region of the NEHR, consistently exhibited a serious warning status, while the other districts experienced fluctuations in their ecological security warning grade. The Central Valley of Manipur is under a severe ecological security warning due to several factors, including excessive population concentration, rapid urban expansion, declining forest cover, wetland degradation, and the ongoing conversion of agricultural land to built-up areas (67–70).

In the study area, an overall declining trend in ESEWI forecasts from 2025 to 2040 was observed, with a small magnitude. Several factors are contributing to the decline of ecological security, such as the adverse impact of uncontrolled forest fire (71), shifting cultivation, agriculture expansion and land use changes which have been reported to cause unprecedented forest degradation, deforestation, and biodiversity loss in the region (72–74).

A study by Mandal et al. (75), which assessed ecosystem health in a mountainous city of the Eastern Himalayan region using a multi-criteria decision-making approach from 2000 to 2021, reported a significant decline in ecosystem health over the past two decades. The study identified vegetation loss and urban expansion driven by rapid population growth as the primary factors contributing to ecosystem degradation. Similar trends have been observed across many mountainous cities in India, where rapid urbanization, socio-economic development, and population growth have exerted increasing pressure on natural ecosystems, extending their impacts beyond urban boundaries. As the NEHR is part of the Eastern Himalayan region, the findings of this previous study provide supporting evidence for the present study. The persistent occurrence of serious and huge warning grades in the central and southern districts, particularly in the highly urbanized Central Valley of Manipur, suggests anthropogenic activities are major drivers of ecological insecurity. These findings indicate that areas under intense anthropogenic pressure are more likely to exhibit a lower ecological security grade and a higher warning status.

However, we also observe higher ESEWI values in most of the northern districts of NEHR in the state of Arunachal Pradesh, the southern districts of Manipur, in the central part of NEHR, and two districts of Tripura, in the southern part of NEHR, indicating comparatively better ecological conditions in these parts of the NEHR. Despite these relatively favourable conditions, without active and effective measures, such as strengthening ecosystem management and biodiversity conservation, promoting ecological awareness, and continuously advancing ecological civilization, ecological security is likely to deteriorate gradually in the future. Therefore, timely and sustained conservation efforts are essential to prevent further ecological degradation (8,74).

4.3 Policy implications

Ecological sustainability and the accomplishment of the Sustainable Development Goals (SDGs) depend on the efficient management and maintenance of mountain ecosystems. Local people in the Himalayan region mostly depend on mountain ecosystems for resources and economic prosperity. Degradation of these ecosystems can thereby worsen poverty, jeopardize livelihood security, and impede the achievement of SDG 1 (No Poverty) (76). Mountain ecosystems provide a range of ecosystem services, including climate regulation, water conservation, and air quality maintenance (77,78). Ecosystem health degradation may impair these functions, making it more difficult to solve climate-related problems and accomplish SDG 13 (Climate Action) (75). Furthermore, the loss of biodiversity, land degradation, and ecological habitat quality are highly cross-cutting issues that threaten SDG 15 (Life on Land) in the Himalayan region, which emphasizes the sustainable use of terrestrial ecosystems (79). Consequently, maintaining the ecological security of the NEHR is necessary through effective conservation and management practices for sustaining the Himalayan ecosystem

In the past 20 years, realizing the Himalayan ecosystem is important for the ecological security of the country, the government of India has taken up multiple long-term and integrated programs at the national level for the conservation of the highly fragile Indian Himalayan ecosystem, such as the National Mission for Sustaining the Himalayan Ecosystem (NMSHE) anchored by the Department of Science and Technology (DST) under National Action Plan on Climate Change (NAPCC)and the National Mission on Himalayan Studies (NMHS) implemented by Ministry of Environment, Forest and Climate Change (80,81). These

programs aim to preserve biodiversity, protect traditional ecological knowledge, improve local livelihoods, and advance sustainable planning and management strategies for Himalayan ecosystems (75).

Both nationally and locally, these initiatives have significantly contributed to protecting the ecological environment. However, the ESEW findings show that the NEHR must formulate context-specific management plans that account for local environmental conditions and development requirements, rather than merely implementing national ecological protection regulations.

Districts identified as serious and huge warning zones should be prioritized for ecological restoration, environmental monitoring, and conservation investment. The observed concentration of ecological insecurity in highly urbanized, densely populated districts underscores the need for integrated land-use planning, regulation of urban expansion, and protection of ecologically sensitive landscapes.

Therefore, the construction and application of an ecological security early warning framework index system can provide actionable strategies to address these pressing environmental challenges and to establish a roadmap for sustainable and inclusive development in the region.

5 Conclusion

This study evaluates and predicts the ecological security status of the ecologically fragile and biodiverse area of the NEHR using a multilevel, comprehensive evaluation index based on PSR framework and a GM (1,1) model. Finally, the Geo-detector model is used in order to determine the main driving factors of the ESEW situation. According to the evaluation results, the ESI of the study area exhibited a fluctuating trend between 2000 and 2020. The ESI of the NEHR increased markedly from 0.541 in 2000 to 0.577 in 2005, declined to 0.542 in 2010, and subsequently recovered gradually to 0.546 in 2015 and 0.551 in 2020. The Ecological security forecasting results for 2025-2040 show that during this period, the ESEWI shows a declining trend, with average values ranging from 0.547 to 0.522, resulting in an overall decline of 4.57%. The spatial distribution of ecological security warning grades shows clear spatial differentiation in warning grades across the study area from 2025 to 2040. The serious warning grade dominates across all districts and increased significantly from 29.09% in 2025 to 40% in 2040. Overall, there is a decline in Moderate warning districts from 29.09% to 0.91% from 2025 to 2040, and an increase in huge warning districts from 9.09% to 18.18%, with a slight decline in light warning districts from 14.55% to 1.73%. By 2040, the no-warning grade decreased slightly from 18.18% in 2025 to 16.36% in 2030 and 2035, then increased again to 18.18% in 2040. The ESEW is affected by various environmental and socio-economic development factors. The population density, Human activity intensity index, Road density, Forest coverage rate, and Ecosystem service value were the main drivers of the ESEW of the NEHR. Furthermore, the interaction between factors affects ESEW more than a single factor, with the interaction between population density and Forest coverage rate being the most influential combination. The results of the study highlight that the ESEWI based on the PSR framework and the gray prediction model provided reliable insights into eco-environmental management in the study area and may serve as a reference for evaluating ES in other parts of the Indian Himalayan region.

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