Post-print of Research on the Classification and Evaluation of the Health Status of Artificial Haloxylon ammodendron Forests on the Northeastern Edge of the Ulan Buh Desert

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Abstract

Artificial Haloxylon ammodendron forest is the most widely distributed windbreak and sand-fixation forest with the largest area in the northeastern margin of the Ulan Buh Desert. Accurately assessing its health status is crucial for ensuring ecological protection functions and implementing precision restoration. A health evaluation system was constructed based on the "zoning-classification-grading" framework, and the health status of artificial Haloxylon ammodendron forests in the northeastern margin of the Ulan Buh Desert was quantitatively evaluated through ecological surveys and the combined weighting TOPSIS model. The results indicate that: (1) Constructing a health evaluation system with stand structure, community structure, environmental conditions, and health risks as the criterion layers can accurately assess the health degree of artificial Haloxylon ammodendron forests in the Ulan Buh Desert. Soil moisture content, new shoot length, mortality rate, dieback rate, and pest and disease factors contribute significantly to the health evaluation. (2) The artificial Haloxylon ammodendron forests in the northeastern margin of the Ulan Buh Desert are overall in a state of moderate degradation, showing a trend toward severe degradation. (3) The degradation phenomenon is caused by the combined effects of various factors, including abnormal water conditions, low soil organic matter content, frequent pests and diseases, and insufficient maintenance and management. The research results provide a scientific basis for the ecological protection and restoration of artificial Haloxylon ammodendron forests in this region, aiming to provide reference ideas for the health assessment and hierarchical restoration of degraded forests in the "Three-North" Shelterbelt Forest Program.

Full Text

Preamble

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Evaluation and Classification of the Health Status of Artificial *Haloxylon ammodendron* Forests on the Northeastern Edge of the Ulan Buh Desert

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摘要

Artificial Haloxylon ammodendron forests are the most widely distributed and largest windbreak and sand-fixation forests on the northeastern edge of the Ulan Buh Desert. Accurately assessing their health status is essential for maintaining the ecological stability of the region.

Understanding the health status of artificial *Haloxylon ammodendron* forests is crucial for maintaining ecological protection functions and implementing precision restoration. This study establishes a health evaluation framework based on a "Zoning-Classification-Grading" approach. By integrating ecological field surveys with a combined weighting TOPSIS model, we evaluated the health status of artificial *Haloxylon ammodendron* forests in the northeastern margin of the Ulan Buh Desert.

quantitative evaluation. The results indicate that:

(1) The construction of a health evaluation system based on the criteria layers of stand structure, community structure, environmental conditions, and health risks can accurately assess the health status of artificial *Haloxylon ammodendron* forests in the Ulan Buh Desert. Soil moisture content, new shoot length, mortality rate, dieback rate, and pest and disease factors contribute significantly to the health evaluation.

(2) The artificial *Haloxylon ammodendron* forests in the northeastern fringe of the Ulan Buh Desert are generally in a state of moderate degradation, with a trend toward severe degradation.

(3) The degradation phenomenon is caused by the combined effects of multiple factors, including abnormal water conditions, low soil organic matter content, frequent occurrences of pests and diseases, and insufficient maintenance and management. The research results provide a scientific basis for the ecological protection and restoration of artificial *Haloxylon ammodendron* forests in this region, aiming to offer reference ideas for the health assessment and hierarchical restoration of degraded engineering forests.

Keywords: *Haloxylon ammodendron*; Health evaluation; Combined weighting method; TOPSIS model; Northeastern Ulan Buh Desert
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Introduction

Haloxylon ammodendron is a critical structural species in arid and semi-arid desert ecosystems, playing a vital role in windbreak, sand fixation, and the maintenance of regional ecological stability. In the northeastern region of the Ulan Buh Desert, *H. ammodendron* communities serve as a primary ecological barrier. However, due to prolonged exposure to extreme environmental stressors—including water scarcity, soil salinization, and climate fluctuations—many of these stands have exhibited varying degrees of degradation. Assessing the health status of these communities is therefore essential for developing effective restoration strategies and ensuring the long-term sustainability of desert ecosystems.

Traditional health assessment methods often rely on single-indicator systems or subjective weighting techniques, which may fail to capture the complex, multidimensional nature of desert vegetation health. To address these limitations, this study employs a comprehensive evaluation framework integrating a combined weighting method with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model. By synthesizing objective data with expert knowledge, this approach provides a more robust and nuanced understanding of the health dynamics of *H. ammodendron* in the northeastern Ulan Buh Desert.

Materials and Methods

Study Area

The study was conducted in the northeastern portion of the Ulan Buh Desert. This region is characterized by a typical continental arid climate, with low annual precipitation and high potential evaporation. The soil types are predominantly aeolian sandy soil and gray-brown desert soil. *Haloxylon ammodendron* is the dominant woody species, often found in association with other xerophytic plants such as *Nitraria tangutorum* and *Reaumuria soongorica*.

Data Collection and Indicator Selection

Field surveys were conducted to collect data on various ecological and physiological parameters. A total of [Figure 1: see original paper] illustrates the distribution of sampling plots across the study area. The health evaluation index system was constructed based on three primary dimensions: individual growth characteristics, community structure, and environmental adaptability.

Key indicators include: - **Growth Indicators:** Plant height, crown width, basal diameter, and annual shoot growth.

Introduction

Facing the severe challenges of land desertification, the "Three-North"Shelterbelt Forest Program plays a vital role in windbreaking and sand fixation. Among the species utilized, *Haloxylon ammodendron* (梭梭) is a cornerstone of these ecological efforts.

[Figure 1: see original paper]

Haloxylon ammodendron is a quintessential desert plant, characterized by its remarkable drought tolerance, salt-alkali resistance, and ability to withstand sand burial. These physiological adaptations make it an ideal candidate for stabilizing shifting sands and restoring degraded arid ecosystems. In the context of the Three-North Shelterbelt, these forests act as a critical biological barrier, significantly reducing wind speeds at the surface and trapping saltating sand particles, thereby preventing the further encroachment of deserts into arable land and human settlements.

The ecological stability of these regions depends heavily on the health and spatial distribution of *Haloxylon ammodendron* populations. Understanding the growth patterns and survival strategies of this species under extreme environmental stress is essential for the long-term management and sustainability of the shelterbelt system. Recent research has increasingly focused on the intersection of climate change and the resilience of these woody shrubs, emphasizing the need for precise monitoring and adaptive conservation strategies to ensure the continued efficacy of windbreaking and sand-fixation functions in Northern China.

spatial distribution characteristics, it can also facilitate the formulation of corresponding renewal and tending programs for different degradation zones.

Haloxylon ammodendron is a primary tree species used for windbreak and sand fixation in desertified regions. It possesses significant ecological value due to its exceptional drought tolerance and ability to stabilize shifting sands. In arid environments, the survival and growth of *H. ammodendron* are closely linked to soil moisture availability and nutrient distribution. Researching the physiological characteristics and adaptive mechanisms of this species is crucial for understanding desert ecosystem dynamics and improving reforestation efforts in degraded lands.

Introduction

Forest health assessment is a research field that has received extensive international attention. It serves as a critical foundation for forest resource management and ecological conservation. As global climate change intensifies and human activities increasingly impact natural ecosystems, maintaining and enhancing forest health has become a core objective of sustainable forestry development.

Traditional forest health assessment methods primarily rely on field surveys and manual monitoring. While these approaches provide high-precision data at the local scale, they are often limited by high costs, long timeframes, and difficulties in covering large, remote areas. Furthermore, the complexity of forest ecosystems—comprising diverse species, structural variations, and intricate ecological processes—makes it challenging for traditional statistical models to capture the non-linear relationships and multi-dimensional interactions inherent in forest health dynamics.

In recent years, the integration of remote sensing technology and machine learning has revolutionized the field. Remote sensing provides continuous, multi-temporal, and multi-spectral data, enabling the monitoring of forest conditions across vast spatial scales. Simultaneously, deep learning and other advanced machine learning algorithms have demonstrated superior performance in processing high-dimensional data and identifying complex patterns. These technologies allow researchers to integrate various indicators, such as leaf area index (LAI), biomass, biodiversity indices, and disturbance history, into comprehensive assessment frameworks.

Despite these advancements, several challenges remain in forest health evaluation. These include the standardization of health indicators across different forest types, the integration of multi-source data (e.g., combining satellite imagery with ground-based IoT sensors), and the interpretability of complex "black-box" models in a management context. Addressing these issues is essential for developing robust, predictive models that can support real-time decision-making and long-term ecological planning.

It possesses ecological characteristics such as salt-alkali tolerance and wind erosion resistance, enabling it to function effectively in stabilizing sand dunes.

In this field, a comprehensive evaluation is conducted by employing a methodology based on regional partitioning, categorical classification, and hierarchical grading.

It is an excellent tree species primarily used for windbreak and sand fixation in the Ulan Buh Desert. However,

…thereby providing a comprehensive reflection of forest health status [?]. The health of windbreak and sand-fixation forests…

Based on the data from the Third National Land Survey and subsequent field investigations, this study provides a comprehensive analysis of land use patterns and spatial distribution. By integrating high-resolution remote sensing imagery with ground-truth verification, we ensure the accuracy and reliability of the land classification results. The methodology adheres to the technical standards established by the national survey, utilizing geographic information systems (GIS) to process and analyze the multi-temporal spatial data.

[Figure 1: see original paper]

The field investigation phase served as a critical validation step, allowing for the correction of spectral misclassifications and the refinement of land category boundaries. Special attention was given to transitional zones between agricultural land and urban development, where land use changes are most frequent. Through this rigorous data integration process, we established a robust baseline for evaluating regional land resources and their ecological implications.

Evaluation is an important extension of forest health assessment research, particularly concerning *Haloxylon ammodendron*.

[Figure 1: see original paper]

1. Introduction

The health of forest ecosystems is a critical indicator of ecological stability and sustainability. As an extension of forest health assessment, the evaluation of specific desert species like *Haloxylon ammodendron* provides essential insights into arid land restoration. *Haloxylon ammodendron*, a dominant shrub species in Central Asian deserts, plays a vital role in windbreak and sand fixation. Understanding its health status through systematic evaluation is fundamental to maintaining the ecological integrity of desert environments.

2. Methodology

The evaluation framework integrates multi-source data to quantify the physiological and structural characteristics of the forest. By employing advanced machine learning techniques and deep learning architectures, we can process complex ecological variables to derive a comprehensive health index.

2.1 Data Collection and Preprocessing

Field surveys were conducted to collect primary data on tree height, crown width, and biomass. These metrics were supplemented by remote sensing data to provide a multi-scale perspective on forest vitality. The integration of ground-truth measurements with satellite imagery allows for a more robust assessment of the spatial distribution of health states.

2.2 Evaluation Indicators

The selection of indicators is based on their sensitivity to environmental stressors. Key parameters include: - **Growth Metrics:** Annual increment in height and diameter at ground level. - **Physiological Indicators:** Chlorophyll content and leaf water potential. - **Structural Integrity:** Canopy density and the ratio of dead to live branches.

3. Results and Discussion

The application of the evaluation model reveals significant spatial heterogeneity in the health status of *Haloxylon ammodendron* populations. Areas with higher groundwater accessibility exhibit superior health indices compared to those in hyper-arid zones.

3.1 Model Performance

The machine learning model demonstrated high accuracy in predicting forest health categories. By utilizing $\mathcal{F}$-score and R^2 values as performance metrics, we observed that the integration of deep learning significantly improved the classification of degraded stands. The relationship between environmental variables and health status can be expressed as:

$$H = \sum_{i=1}^{n} w_i x_i + \epsilon$$

where H represents the health index, w_i denotes the weight of the i-th indicator x_i,

Abstract

Recent observations indicate that artificial *Haloxylon ammodendron* forests on the northeastern edge of the Ulan Buh Desert are experiencing premature or accelerated senescence. This phenomenon poses a significant challenge to ecological restoration efforts in the region. Understanding the underlying mechanisms of this degradation is crucial for developing sustainable management strategies for desert ecosystems.

Introduction

The Ulan Buh Desert, located in the Inner Mongolia Autonomous Region, serves as a critical ecological barrier against sandstorms in Northern China. Since the 1970s, extensive afforestation projects using *Haloxylon ammodendron* have been implemented to stabilize shifting dunes and protect local infrastructure. However, in recent years, researchers have discovered that these artificial forests are exhibiting signs of decline earlier than expected.

Analysis of Forest Decline

The premature senescence of *Haloxylon ammodendron* is characterized by reduced biomass production, thinning canopies, and increased mortality rates. Several factors contribute to this accelerated degradation:

1. Hydrological Constraints

As a phreatophyte, *Haloxylon ammodendron* relies heavily on groundwater. Long-term monitoring suggests that the expansion of artificial plantations has led to a significant drawdown of the local water table. When the root systems can no longer reach the receding groundwater, the plants suffer from chronic water stress, leading to physiological failure.

2. Soil Nutrient Depletion

The sandy soils of the Ulan Buh Desert are inherently nutrient-poor. High-density planting of *Haloxylon ammodendron* exerts intense pressure on the limited soil nutrient pool. Over time, the depletion of essential elements such as nitrogen and phosphorus limits the regenerative capacity of the forest, accelerating the aging process.

3. Stand Density and Competition

Initial planting densities were often too high for the carrying capacity of the arid environment. Intense intraspecific competition for limited resources—primarily water and nutrients—weakens individual plants, making the entire stand more susceptible to pests, diseases, and extreme climatic events.

[Figure 1: see original paper]

Ecological Implications

The degradation of these artificial forests has profound implications for regional environmental stability. As the *Haloxylon ammodendron* canopy thins, the wind-breaking and sand-fixing functions of the forest diminish, potentially leading to the reactivation of stabilized dunes. Furthermore, the loss of these primary producers impacts the biodiversity of the associated desert flora and fauna.

Conclusion and Recommendations

The discovery of accelerated senescence in the artificial *

Introduction

The research on the health assessment of windbreak and sand-fixation forests, represented by *Pinus sylvestris* var. *mongolica*, is of significant importance. These forest ecosystems play a critical role in maintaining ecological stability in arid and semi-arid regions. Evaluating their health status is essential for understanding their protective functions and ensuring the long-term sustainability of regional ecological barriers.

Entering the stage of physiological decline, extensive deterioration and even widespread mortality have occurred.

Research Methodology and Framework

The research typically follows a structured process consisting of "baseline data collection, indicator screening, and system construction." This systematic approach ensures that the resulting evaluation framework is both scientifically rigorous and practically applicable.

1.1 Baseline Data Collection

The initial phase involves the comprehensive gathering of raw data from diverse sources. This includes empirical measurements, historical records, and qualitative observations relevant to the study area. By establishing a robust data foundation, the research can account for various environmental and operational variables that influence the final outcomes.

1.2 Indicator Screening and Selection

Following data collection, a rigorous screening process is employed to identify the most significant indicators. This step utilizes statistical methods and expert consultation to eliminate redundant variables and retain those with high sensitivity and representativeness. The goal is to ensure that the selected indicators accurately reflect the core characteristics of the phenomenon under investigation while maintaining computational efficiency.

1.3 System Construction

The final stage involves integrating the screened indicators into a cohesive evaluation system. This system defines the hierarchical relationships between different metrics and establishes the weighting schemes necessary for comprehensive analysis. By synthesizing these elements, the research provides a standardized tool for assessment, enabling consistent comparison and decision-making across different scenarios.

This phenomenon ultimately leads to a decline in the health of forest stands, which in turn results in the degradation of critical ecological functions, such as windbreak and sand fixation.

Technical Path for Construction

The technical path for construction involves scientifically screening evaluation indicators and establishing a robust framework. This process begins with a comprehensive literature review and expert consultation to identify key metrics that accurately reflect the system' s performance and characteristics. By employing rigorous statistical methods and qualitative analysis, we ensure that the selected indicators are both representative and non-redundant.

Following the selection of indicators, the next phase focuses on the systematic integration of these metrics into a cohesive model. This involves defining the relationships between different variables and determining their respective weights through objective weighting methods. The goal is to create a multidimensional evaluation system that provides a holistic view of the subject matter, ensuring that the final construction is both scientifically sound and practically applicable for subsequent analysis and decision-making.

health issues. However, regarding such phenomena, current research in this region···

The establishment of a comprehensive evaluation index system is a critical component of this research [**?**]. Currently, in response to

focused on restoration and management measures [**?**], the environmental adaptability of *Haloxylon ammodendron*, and the characteristics of its populations.

Forest ecosystem health assessment methods are primarily divided into indirect judgment methods, single-indicator assessment methods, and multi-indicator comprehensive assessment methods. Indirect judgment methods typically rely on qualitative descriptions or expert experience to evaluate the health status of a forest. Single-indicator assessment methods focus on specific ecological parameters, such as forest productivity, biodiversity, or pest and disease incidence, to reflect health conditions. In contrast, multi-indicator comprehensive assessment methods integrate various ecological, social, and economic factors, utilizing mathematical models and statistical techniques to provide a more holistic and objective evaluation of the forest ecosystem' s state.

1. Introduction

Forest ecosystem health is a critical component of global ecological security and sustainable development. As human activities and climate change intensify, forest ecosystems face unprecedented pressures, including habitat fragmentation, loss of biodiversity, and diminished ecosystem services. Consequently, developing robust assessment frameworks is essential for effective forest management and conservation.

2. Assessment Methodologies

2.1 Indirect Judgment Methods

Indirect judgment methods are often the most traditional approach, where health is inferred through observable symptoms or historical data. While these methods are accessible and require less intensive data collection, they are frequently criticized for their subjectivity and lack of quantitative precision.

2.2 Single-Indicator Assessment

Single-indicator methods simplify the complexity of forest ecosystems by selecting a representative metric. For instance, net primary productivity (NPP) is often used as a proxy for ecosystem vigor. However, relying on a single metric may overlook critical stressors or internal structural changes that do not immediately manifest in that specific indicator.

2.3 Multi-Indicator Comprehensive Assessment

The multi-indicator approach is currently the most widely adopted framework in academic research. This method involves the selection of indicators across multiple dimensions, such as: - **Vigor:** Measuring the energy input and nutrient cycling of the system. - **Organization:** Assessing the complexity and diversity of the ecosystem structure. - **Resilience:** Evaluating the system' s ability to recover from disturbances.

By combining these indicators through weight-assignment techniques—such as the Analytic Hierarchy Process (AHP) or entropy weight methods—researchers can derive a comprehensive health index.

3. Mathematical Framework

The comprehensive health index (H) is often calculated using a weighted sum of normalized indicators. Let x_i represent the normalized value of the i-th indicator and w_i represent its corresponding weight. The general model can be

Dynamic Evolutionary Characteristics and Socioeconomic Impacts

While scholars have already focused on the dynamic evolutionary characteristics and socioeconomic impacts of these phenomena, research in this area remains ongoing. Existing studies have laid a foundational understanding of how these systems shift over time, yet the intricate relationship between their structural transformations and the resulting societal consequences requires further investigation. Understanding these dynamics is crucial for developing robust models that can predict future trends and inform policy decisions.

Direct judgment methods and weight evaluation models represent three major categories of assessment. Indirect judgment⋯

It has been observed that the *Haloxylon ammodendron* forests in this region are experiencing significant degradation; however, at present, there is still a lack of ...

Methods for determination include the indicator species method, grey relational analysis, and cluster analysis.

Establishing a Systematic Health Evaluation Framework

To effectively assess the ecological status of *Haloxylon ammodendron* forests, it is essential to establish a systematic health evaluation framework. This process involves conducting comprehensive health assessments that integrate multi-dimensional indicators to reflect the stability, productivity, and resilience of these desert ecosystems.

Evaluation of *Haloxylon ammodendron* Forest Health

The health assessment of *Haloxylon ammodendron* forests focuses on quantifying their structural integrity and functional vitality. By selecting key ecological parameters—such as vegetation coverage, biomass, age structure, and natural regeneration rates—researchers can determine the current physiological state of the forest. Furthermore, the evaluation incorporates environmental stressors, including soil moisture availability, salinity levels, and the impact of groundwater depth, to understand the external pressures affecting forest sustainability.

The systematic approach utilizes hierarchical analysis and machine learning models to weight these indicators, providing a standardized "health score." This score serves as a critical diagnostic tool for identifying degraded areas, enabling land managers to implement targeted restoration strategies and optimize water resource allocation in arid regions. Through continuous monitoring and periodic health evaluations, the long-term ecological trajectory of *Haloxylon ammodendron* populations can be scientifically managed and preserved.

While these methods are capable of identifying trends in ecosystem degradation, they often fall short in terms of robustness and early-warning precision. Traditional indicators frequently rely on linear assumptions that fail to capture the complex, non-linear dynamics inherent in ecological transitions. Consequently, there is a critical need for more sophisticated analytical frameworks that can integrate multi-source data to provide more reliable precursors to systemic shifts.

Evaluation research not only enables the precise identification of degradation gradients within a region but also provides a scientific basis for ecological restoration and sustainable management. By integrating multi-source data and advanced analytical frameworks, researchers can quantify the spatial heterogeneity of environmental changes and assess the effectiveness of various conservation interventions. This systematic approach is essential for understanding the complex interactions between anthropogenic pressures and natural ecosystem processes.

There are significant limitations regarding the classification of health levels [9]. Direct judgment methods include…

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Common methodologies for assessment include the index evaluation method, fuzzy comprehensive evaluation, and artificial neural networks.

Health Grading Evaluation and Accurate Quantification of the Ulan Buh Desert

The health status of the Ulan Buh Desert ecosystem is a critical indicator for regional ecological security and sustainable development. To address the complexities of desert environments, this study utilizes advanced machine learning and deep learning models to conduct a comprehensive health grading evaluation. By integrating multi-source geospatial data, we aim to accurately quantify the ecological health levels of the Ulan Buh Desert, providing a scientific basis for targeted restoration and management strategies.

Methodology and Model Framework

The evaluation framework is built upon a multi-dimensional indicator system that accounts for soil stability, vegetation cover, and hydrological conditions. We employ a hybrid modeling approach, combining traditional statistical methods with state-of-the-art deep learning architectures to capture non-linear relationships within the desert ecosystem.

[Figure 1: see original paper]

The quantification process involves the following key steps: 1. **Data Integration**: Harmonizing remote sensing imagery, meteorological records, and field survey data. 2. **Feature Engineering**: Extracting relevant ecological indices, such as the Normalized Difference Vegetation Index (NDVI) and the Albedo-MSAVI feature space, to represent surface conditions. 3. **Model Training**: Utilizing a supervised learning approach where historical health assessments serve as labels for the training set. 4. **Grading and Mapping**: Classifying the desert into distinct health grades (e.g., Excellent, Good, Fair, Poor, and Critical) based on the model' s quantitative output.

Quantitative Analysis of Ecological Health

The model' s performance is validated using standard metrics to ensure the accuracy of the health grading. By applying the function $\mathscr{F}$ to the input feature vector x_{ab}, we derive the health score S:

$$S = \sum_{i=1}^{n} w_i \cdot f_i(x_{ab})$$

where w_i represents the weight assigned to each ecological indicator and f_i denotes the normalized value of the i-th feature. This quantitative approach allows for a granular analysis of spatial variations across the Ulan Buh region.

As shown in , the distribution of health grades reveals significant spatial heterogeneity. Areas with higher moisture availability and successful sand-fixation projects exhibit "Good" to "Excellent" health status, while the core shifting dune areas remain in the "Critical" category. The integration of machine learning allows for the identification

Although health levels can be directly determined, such methods require a substantial amount of labeled data for training. In practical industrial applications, obtaining precise health status labels for equipment is often difficult and costly, which limits the widespread implementation of supervised learning approaches. Furthermore, direct classification methods frequently struggle to capture the subtle, continuous degradation trends of machinery over time, making it challenging to provide early warnings before a failure occurs. Consequently, researchers are increasingly focusing on unsupervised or semi-supervised approaches that can model equipment degradation trajectories without relying on extensive manual labeling.

Health Classification and Degradation Factor Identification of *Haloxylon ammodendron* Forests

The health status classification of *Haloxylon ammodendron* (saxaul) forests and the identification of their degradation factors are critical for ecological restoration and management. By analyzing the physiological characteristics and environmental stressors affecting these desert ecosystems, researchers can categorize the vitality of these forests into distinct levels, ranging from healthy to severely degraded.

Health Status Classification

The classification of *Haloxylon ammodendron* health typically relies on a combination of structural parameters and physiological indicators. Key metrics include canopy density, biomass accumulation, and the ratio of live to dead branches.

1. **Healthy Status:** Characterized by high canopy cover, robust terminal shoot growth, and minimal branch dieback. These stands exhibit strong resilience to environmental fluctuations and maintain stable seed production.

2. **Moderately Degraded Status:** Marked by a noticeable reduction in leaf area index (LAI) and the appearance of withered branch tips. While the primary structure remains intact, the growth rate slows, and the forest' s ability to recover from drought diminishes.
3. **Severely Degraded Status:** Defined by extensive crown dieback, low plant density, and a significant loss of reproductive capacity. In these areas, the ecological function of sand fixation is severely compromised, often leading to soil erosion and the encroachment of invasive species.

Identification of Degradation Factors

Identifying the drivers of degradation is essential for developing targeted conservation strategies. These factors are generally categorized into abiotic stressors and anthropogenic disturbances.

- **Hydrological Stress:** Groundwater depletion is the primary driver of *Haloxylon ammodendron* decline. As the water table drops below the reach of the root system, plants experience chronic water stress, leading to xylem cavitation and eventual mortality.
- **Soil Salinization:** Increased soil salinity affects the osmotic potential, making it difficult for the roots to absorb moisture even when water is present. This chemical stress manifests as reduced photosynthetic efficiency and stunted growth.
- **Climate Change:** Rising temperatures and increased frequency of extreme drought events exacerbate the atmospheric vapor pressure deficit (VPD), placing further strain on the plant' s water-use efficiency.
- **Anthropogenic Impact:** Overgrazing and unsustainable land use practices disrupt the natural regeneration cycles of the forest. Livestock pressure often leads to the destruction of seedlings and the compaction of soil, preventing effective seed germination.

By integrating remote sensing data

The dataset was processed accordingly [**?**]. The weight evaluation model was developed by constructing a health assessment framework.

It is of great significance for the formulation of targeted, hierarchical restoration programs for windbreak and sand-fixation forests.

Evaluation System and Weight Calculation

To achieve a comprehensive assessment, we first establish a robust evaluation system and perform weight calculations, which subsequently facilitate the implementation of the evaluation model.

Weight Determination Methodology

The determination of weights is a critical step in ensuring the objectivity and accuracy of the model. We employ a hybrid approach that combines subjective expertise with objective data characteristics. By integrating methods such as the Analytic Hierarchy Process (AHP) and entropy weight methods, we can effectively balance the theoretical importance of specific indicators with their actual statistical significance within the dataset.

Implementation of the Evaluation Model

Once the weights are established, the evaluation model is implemented to process the input data. The model integrates various metrics according to their assigned weights to produce a final score or classification. This process involves:

1. **Data Normalization**: Ensuring that all indicators are on a comparable scale to prevent variables with larger absolute values from dominating the results.
2. **Weighted Aggregation**: Applying the calculated weights to the normalized indicators using the following general form:

$$S_i = \sum_{j=1}^{n} w_j \cdot x_{ij}$$

   where S_i represents the final score for the i-th observation, w_j is the weight of the j-th indicator, and x_{ij} is the normalized value.
3. **Result Analysis**: Interpreting the output of the evaluation model to provide actionable insights or decision support.

By following this systematic approach, the evaluation system ensures that the final outputs are both mathematically rigorous and contextually relevant to the specific research domain.

Health grade classification is currently the most widely used method in environmental assessment. Within evaluation models, the Ecosystem Health Index (EHI) is the most frequently utilized metric.

1 数据与方法

index (HI) evaluation models, their primary shortcoming lies in their limited ability to distinguish between multiple evaluation criteria or states.

1.1 研究区概况

When dealing with objects, precision may be insufficient; however, within the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) evaluation model, it is possible to incorporate···

effectively distinguish between multiple evaluation objects. In existing research, forest health evaluation has not yet established a unified set of standards or methodologies. Consequently, scholars have constructed various independent indicator systems tailored to different types of windbreak and sand-fixation forests [?].

However, significant differences exist across various studies regarding the quantity and nature of the selected indicators [?]. Furthermore, some research suffers from indicator redundancy; for instance, while factors such as litter conditions are included in the evaluation systems, they often carry low weight values and offer limited practical contribution to the overall results.

Some indicator systems focus on health risks and human intervention.

[Figure 1: see original paper]

3.2 Construction of the Evaluation Indicator System

Based on the principles of scientific rigor, systematicity, and data availability, this study constructs a comprehensive evaluation indicator system. This system integrates multiple dimensions to assess the complex interactions between environmental factors and human health.

The selection of these indicators is informed by existing literature and empirical research in the fields of environmental science and public health. Specifically, the framework accounts for both natural environmental stressors and the mitigating effects of policy-driven human interventions. By incorporating these diverse metrics, the model aims to provide a holistic view of regional health vulnerabilities and the efficacy of current management strategies.

···insufficient consideration of key factors such as interference. Therefore, constructing a model that is both representative and robust is essential for addressing these complexities.

Study Area

The study area is located on the northeastern edge of the Ulan Buh Desert, falling under the administrative jurisdiction of Dengkou County, Inner Mongolia. This region is characterized by a temperate continental arid climate, with an annual average···

The average annual temperature is 7.8 °C, with a recorded maximum temperature of 39.0 °C and a minimum of -29.6 °C. The average annual precipitation is approximately 145 mm, which is primarily concentrated between June and September.

···accounting for 70% to 80% of the total annual precipitation. The average annual evaporation is approximately 2380.6 mm, with a sunshine duration of about 3200 h. The average annual wind speed is 3.70 $\mathrm{m \cdot s^{-1}}$, while the instantaneous wind speed···

The maximum wind speed can reach up to 24.0 $m \cdot s^{-1}$. The terrain is characterized by higher elevations in the southwest and lower elevations in the northeast, with altitudes ranging from 1028 to 1054 m. The primary soil type consists of aeolian sandy soil [**?**]. The tree species utilized for windbreak and sand fixation forests mainly include *Haloxylon ammodendron* and *Hedysarum scoparium*.

Establishing a representative yet simple health evaluation index system for windbreak and sand-fixation forests has become a critical task in ecological restoration and management. Such a system is essential for accurately assessing the functional stability and protective efficacy of these vital ecosystems.

The vegetation is primarily composed of *Artemisia scoparia*, while the natural vegetation predominantly includes *Artemisia ordosica*.

This represents a critical problem that urgently requires a solution.

···including *Artemisia ordosica*, *Nitraria tangutorum*, and other species.

In light of this, the present study focuses on the artificial *Haloxylon ammodendron* plantations located on the northeastern edge of the Ulan Buh Desert. By integrating field observations with advanced analytical techniques, we aim to characterize the ecological adaptations and physiological responses of these plantations to the hyper-arid environment.

[Figure 1: see original paper]

The Ulan Buh Desert represents a critical transition zone where desertification control measures are of paramount importance. *Haloxylon ammodendron*, as a dominant xerophytic shrub species, plays a vital role in sand fixation and windbreak systems. However, the long-term stability of these artificial forests is increasingly threatened by fluctuating groundwater levels and intensifying drought stress. Understanding the water-use efficiency and biomass allocation strategies of these stands is essential for developing sustainable management practices in the region.

This research utilizes a combination of stable isotope analysis and high-resolution remote sensing data to quantify the spatial distribution of soil moisture and its influence on plant growth. By establishing a robust correlation between environmental variables and physiological traits, we provide a scientific basis for evaluating the ecological health of artificial vegetation in the northeastern Ulan Buh Desert. The findings are expected to contribute to the theoretical framework of desert ecology and offer practical insights for ecological restoration projects in similar arid regions globally.

1.2 研究方法

Taking the *Pinus sylvestris* var. *mongolica* (Mongolian Scots pine) as the research object, this study integrates domestic and international research achievements in forest health assessment to develop a comprehensive evaluation framework.

1. Introduction

Forest health assessment is a critical component of sustainable forest management. As a primary species used for windbreaks and sand fixation in northern China, *Pinus sylvestris* var. *mongolica* plays an indispensable role in ecological stability. However, in recent decades, these forests have faced challenges such as physiological decline, poor natural regeneration, and increased susceptibility to pests and diseases. To address these issues, it is essential to establish a scientifically robust evaluation system that can accurately reflect the ecological status and vitality of these forest stands.

2. Methodology and Framework

By synthesizing established methodologies from both domestic and international literature, this research constructs a multi-dimensional indicator system. The evaluation framework transitions from traditional qualitative descriptions to quantitative analysis, utilizing advanced statistical methods and machine learning algorithms to ensure the objectivity of the results.

2.1 Indicator Selection

The selection of indicators follows the principles of representativeness, operability, and systematicity. The primary indicators include:

- **Tree Vitality:** Measured by growth parameters such as diameter at breast height (DBH), tree height, and crown density.
- **Ecosystem Structure:** Analyzing species composition, age structure, and spatial distribution patterns.
- **Soil Quality:** Evaluating physical and chemical properties, including nutrient content and moisture retention.
- **Resilience:** Assessing the forest' s capacity to recover from disturbances such as drought, frost, and insect infestations.

2.2 Assessment Models

The study employs a combination of the Analytic Hierarchy Process (AHP) and fuzzy comprehensive evaluation methods. By assigning weights to different indicators, we calculate a Forest Health Index (FHI) to categorize the health status of the *Pinus sylvestris* var. *mongolica* stands into distinct levels: healthy, sub-healthy, weak, and unhealthy.

3. Research Objectives

The primary goal of this research is to provide a theoretical basis and practical guidance for the restoration and management of *Pinus sylvestris* var. *mongolica* forests. By identifying the key factors limiting forest health, management strategies can be optimized to enhance the ecological functions of these vital forest ecosystems. This approach not only contributes to the local ecological security but also

1.2.1 野外样地调查以乌兰布和沙漠东北缘人工

Based on the results and local conditions, field plot surveys and data collection were conducted.

Taking the *Haloxylon ammodendron* forest as the research object, the study area was categorized based on distribution locations and stand ages as follows:

In this study, we constructed a comprehensive health evaluation index system for artificial *Haloxylon ammodendron* forests, utilizing a "Zoning-Classification-Grading" framework. To ensure robust assessment, we employed a combined weighting TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach.

The nine regions are shown in Figure 1 [Figure 1: see original paper]. Based on the planting methods and distribution patterns of *Haloxylon ammodendron* in each region…

Based on the characteristics of the vegetation state and the ecological environment, representative *Haloxylon ammodendron* forests were selected as the study subjects.

1 Distribution of artificial Haloxylon ammodendron forest plots on the northeast edge of Ulan Buh Desert

Min et al.: Research on the Health Grading Evaluation of Artificial *Haloxylon ammodendron* Forests on the Northeastern Edge of the Ulan Buh Desert

To investigate the sample plots, a comprehensive ecological survey and simultaneous sampling of the artificial *Haloxylon ammodendron* forests were conducted between August and September 2024.

By integrating plot-based and quadrat-based methodologies, the basic information of each sample plot was recorded (Table 1). Table 1: Basic information of artificial *Haloxylon ammodendron* forests.

Nailun Lake NE District

Nailun Lake NE-1

Nailun Lake NE District

Nailun Lake NE-3

Nailun Lake NE District; Nailun Lake N District

Nailun Lake N District; Nailun Lake N District; Nailun Lake S District; Nailun Lake S District

Experimental Farm 1 Xidatan Area A; Experimental Farm 1 Xidatan Area A; Experimental Farm 1 Xidatan Area A; Experimental Farm 1 Xidatan Area B; Experimental Farm 1 Xidatan Area B; Experimental Farm 1 Xidatan Area B; Liuguaishatou District

Nailun Lake NE-2; Nailun Lake N-1; Nailun Lake N-2; Nailun Lake N-3; Nailun Lake S-1; Nailun Lake S-2

Experimental Farm 1 Xidatan A-1; Experimental Farm 1 Xidatan A-2; Experimental Farm 1 Xidatan A-3; Experimental Farm 1 Xidatan B-1; Experimental Farm 1 Xidatan B-2; Experimental Farm 1 Xidatan B-3; Liuguaishatou-1

Liuguaishatou District

Liuguaishatou-2

Liuguaishatou District

Liuguaishatou-3

Innovation Base District

Experimental Farm 4 Nandatan District

Experimental Farm 4 Nandatan-A

Experimental Farm 4 Nandatan District

Experimental Farm 4 Nandatan-B

Stand age (a); Site conditions

2 Layout schematic of sample plot

Due to variations in the distribution patterns and site types of *Haloxylon ammodendron* across different regions, the sample plots were established to cover various site conditions, specifically including upper slopes and slopes.

The comprehensive impacts of pests and diseases were assessed. Within the 1 m × 1 m herbaceous quadrats nested inside each standard sample plot, we recorded the

herbaceous species information and calculated the richness index, evenness index, diversity

index, and dominance index. Soil samples were collected from a depth of 0–50 cm (with three replicates per

standard sample plot). All samples were transported back to the laboratory to determine their soil moisture content, soil electrical conductivity, and soil pH.

1.2.2 评价指标体系构建与权重测定在评价指

…middle slope, lower slope, and flat sandy land. Taking the east-west direction as the X-axis and the north-south direction as the…

In the construction of the indicator system, a methodology combining quantitative and qualitative analysis is adopted.

Along the the Y-axis, three points were established at the top, middle, and bottom of the slope, respectively, with a spacing of 50 m between each.

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It was developed by Thomas L. Saaty in the 1970s and has since been extensively refined. AHP provides a comprehensive and rational framework for structuring a decision problem, representing and quantifying its elements, relating those elements to overall goals, and evaluating alternative solutions.

By decomposing a complex problem into a multi-level hierarchical structure, AHP allows decision-makers to focus on specific aspects of the problem. This hierarchy typically consists of an overall goal, a group of options or alternatives, and a set of criteria that relate the alternatives to the goal. The method utilizes pairwise comparisons to derive scale preferences among the various factors, enabling the integration of both objective data and subjective expert judgments into a single decision-making framework.

20 m Haloxylon ammodendron standard plots. Simultaneously, within each standard plot, along···

Based on the actual conditions of the site, the evaluation indicators were screened to establish a hierarchical structure.

20 m standard sampling plots of *Haloxylon ammodendron*. In the flat sandy areas, 20 m × 20 m plots were established.

Introduction

In recent years, the evaluation of shelterbelt health has become a critical focus in ecological research and environmental management. This review synthesizes domestic and international literature from the past 15 years to examine the evolving methodologies and theoretical frameworks used to assess the vitality and sustainability of these essential ecosystems. Shelterbelts play a vital role in mitigating wind erosion, protecting biodiversity, and enhancing carbon sequestration; however, their efficacy is increasingly threatened by climate change, pests, and aging.

Current Trends in Shelterbelt Health Assessment

The assessment of shelterbelt health has transitioned from simple structural observations to complex, multi-dimensional evaluations. Modern research emphasizes the integration of remote sensing data with ground-based surveys to provide a more comprehensive view of forest vitality. Key indicators often include biomass production, leaf area index (LAI), and physiological stress markers. Furthermore, the application of machine learning and deep learning algorithms has significantly improved the accuracy of health classification and the prediction of future degradation patterns.

[Figure 1: see original paper]

Methodological Frameworks

Current evaluation frameworks typically categorize indicators into three primary dimensions: vigor, organization, and resilience. Vigor refers to the metabolic activity and growth rate of the trees; organization describes the complexity and diversity of the forest structure; and resilience measures the capacity of the shelterbelt to recover from external disturbances such as droughts or infestations. By quantifying these parameters, researchers can assign a health index score to specific forest stands, facilitating targeted management interventions.

Challenges and Future Directions

Despite significant advancements, several challenges remain in the field of shelterbelt health evaluation. There is a notable lack of standardized indicators that can be applied across different climatic zones and species compositions. Additionally, the long-term monitoring of shelterbelt dynamics requires more robust temporal datasets. Future research should focus on developing dynamic evaluation models that account for the synergistic effects of multiple stressors and the socio-economic benefits provided by healthy shelterbelt systems.

Along the diagonal from the northeast corner to the southwest corner, three 1 m × 1 m plots were established at equal intervals.

Measurements were conducted in the laboratory. The schematic diagram of the sample plot layout is shown in Figure 2 [Figure 2: see original paper].

Natural Disasters and Human-Animal Factors Affecting the Growth of *Haloxylon ammodendron*

The growth and survival of *Haloxylon ammodendron* are significantly influenced by various natural disasters, including fire and acid rain, as well as pressures from human activities and livestock grazing. These factors collectively shape the ecological stability and distribution of this critical desert species.

Fire and Acid Rain Impacts

Fire represents a catastrophic disturbance for *Haloxylon ammodendron* communities. Due to the arid environment and the accumulation of dry biomass, fires can spread rapidly, leading to the direct mortality of mature shrubs and the destruction of the seed bank. Even in cases where individuals survive, the physiological stress induced by high temperatures can impair long-term growth and reproductive capacity. Similarly, although less frequent in remote desert regions, the increasing reach of industrial pollutants has made acid rain a growing concern. Acidic deposition can alter soil pH, mobilize toxic aluminum ions, and leach essential nutrients such as calcium and magnesium, thereby inhibiting the root development and water-use efficiency of *Haloxylon ammodendron*.

Human and Livestock Interference

Beyond abiotic disasters, the impact of human activities and livestock grazing is profound. Overgrazing by sheep and camels remains a primary driver of degradation in *Haloxylon* forests. Livestock not only consume the succulent young assimilation shoots, which are vital for photosynthesis, but also cause soil compaction through trampling. This compaction reduces soil porosity and water infiltration rates, making it increasingly difficult for seedlings to establish. Furthermore, human interventions—such as the unsustainable collection of firewood and the harvesting of *Cistanche deserticola* (a parasitic plant that grows on the roots of *Haloxylon*)—often lead to mechanical damage to the root systems and a decline in the overall vigor of the host plants.

Ecological Consequences

The cumulative effect of these stressors leads to a reduction in vegetation cover and a weakening of the desert ecosystem's carbon sequestration potential. When *Haloxylon ammodendron* stands are degraded by fire, pollution, or overgrazing, the protective barrier against wind erosion is compromised, accelerating land desertification. Understanding the interplay between these natural disasters and anthropogenic pressures is essential for developing effective conservation strategies and restoration protocols for these vital arid-zone forests.

Within the standard sample plots, a systematic individual plant survey was conducted for all *Haloxylon ammodendron* shrubs.

Due to the interference of human and animal activities, the indicators for natural disasters and human-livestock interference were excluded.

scale, and recorded the ecological indicators of the shrubs as well as their health risk indicators.

and exclude soil physical and chemical properties that have demonstrated minimal influence in existing research.

Ecological indicators include height, crown width, basal diameter, stand age, and new shoots.

quality indicators and litter indicators [**?**]. Ultimately, the stand vigor of the plants was selected.

Number of branches, length of new shoots, diameter of new shoots, coverage, total number of plants, branches

(plant height, crown width, basal diameter, stand age, branch length, and new shoot length)

length; health risk indicators primarily refer to factors that interfere with the growth status of *Haloxylon ammodendron*, increasing⋯

number of branches, length of new shoots, diameter of new shoots), community structure (coverage, total⋯

Risk Factors Increasing the Probability of Adverse Health Outcomes, Including Mortality

In the field of clinical medicine and public health, identifying specific risk factors that increase the probability of adverse health outcomes is essential for risk stratification and the development of preventive interventions. These detrimental factors span a wide spectrum, ranging from physiological biomarkers and genetic predispositions to socioeconomic determinants and lifestyle behaviors. When these factors converge, they significantly elevate the risk of chronic disease progression, acute clinical events, and, ultimately, all-cause mortality.

Physiological and Pathological Determinants

The primary drivers of adverse health outcomes are often rooted in underlying physiological dysregulation. Chronic inflammatory states, metabolic syndrome, and cardiovascular impairments serve as critical precursors to systemic failure. For instance, elevated levels of specific biomarkers—such as C-reactive protein (CRP) or glycated hemoglobin (HbA_{1c})—are strongly correlated with an increased risk of cardiovascular events and metabolic complications. Furthermore, the presence of comorbid conditions creates a synergistic effect, where the interaction between multiple pathologies accelerates functional decline and increases the likelihood of a fatal outcome.

Behavioral and Environmental Risk Factors

Beyond biological markers, behavioral patterns play a decisive role in determining long-term health trajectories. Modifiable risk factors, including tobacco use, excessive alcohol consumption, sedentary behavior, and poor nutritional intake, are primary contributors to the global burden of non-communicable diseases. These behaviors often lead to intermediary clinical conditions such as hypertension and obesity, which are robust predictors of premature death. Additionally, environmental exposures—such as prolonged inhalation of particulate matter ($PM_{2.5}$) or exposure to heavy metals—act as external stressors that exacerbate existing vulnerabilities and trigger acute health crises.

Socioeconomic and Demographic Influences

The probability of adverse health outcomes is also heavily influenced by the "social determinants of health." Factors such as low socioeconomic status, limited access to quality healthcare, and inadequate health literacy create barriers to early diagnosis and effective management of diseases. Demographic variables, particularly advanced age, remain the most significant non-modifiable risk factors for mortality. As physiological resilience diminishes with age, the impact of both acute injuries and chronic stressors becomes more pronounced, leading to a higher frequency of adverse clinical endpoints.

Predictive Modeling and Risk Assessment

To quantify the impact of these detrimental factors, modern medicine increasingly relies on advanced statistical methods and machine learning algorithms. By integrating multi-dimensional data—including genomic sequences, electronic health records (EHR), and patient-reported outcomes—researchers can develop predictive models that estimate the probability of specific

Number of individuals, richness index, evenness index, diversity index, and dominance.

···mortality rate, shoot dieback rate, powdery mildew, root rot, as well as a series of insect infestations and rodent damage.

degree index), environmental conditions (soil moisture content, soil electrical conductivity, soil

herbaceous quadrats, within which soil samples were collected and transported back to the laboratory.

Because the artificial *Haloxylon ammodendron* forests in this region have been well-protected, no occurrences of···

pH value, soil organic matter), and health risks (mortality rate, branch dieback rate, disease incidence).

The performance is evaluated and scored based on specific criteria. For the detailed scoring standards, please refer to the index levels provided in .

evaluation metrics ([Figure 3: see original paper]).

The questionnaires were collected and screened, with only those passing the consistency test being retained for subsequent organization and statistical analysis.

A total of 21 indicators across four dimensions—growth status, forest structure, site conditions, and biological disasters (pests and diseases)—were selected as the health evaluation criteria for the artificial *Haloxylon ammodendron* forest. To determine the weights of these indicators, this study employed a combined weighting approach integrating the Analytic Hierarchy Process (AHP) and the Entropy Weight Method.

Combined Weighting Method

The combined weighting method is employed to mitigate the inherent subjectivity associated with the Analytic Hierarchy Process (AHP). By integrating objective weighting techniques with the subjective judgments of AHP, this approach achieves a more balanced and scientifically rigorous determination of attribute weights.

Mitigation of Subjectivity in AHP

While AHP is a powerful tool for structuring complex decision-making problems, its primary limitation lies in its heavy reliance on expert opinion and pairwise comparisons. This subjectivity can lead to inconsistencies or biased results if the decision-maker' s preferences are not adequately validated. To address this, the combined weighting method introduces objective data-driven components —such as entropy weight methods or CRITIC methods—to calibrate the final weight distribution.

The mathematical framework for this integration typically involves a linear or non-linear combination of the subjective weight vector (ω_s) and the objective weight vector (ω_o). The combined weight ω_j for a given criterion j can be expressed as:

$$\omega_j = \alpha \cdot \omega_{sj} + \beta \cdot \omega_{oj}$$

where α and β represent the relative importance assigned to the subjective and objective components, respectively, satisfying the constraint $\alpha + \beta = 1$. By optimizing these coefficients, researchers can ensure that the resulting weights reflect both the empirical characteristics of the data and the specialized knowledge of domain experts. This hybrid approach enhances the robustness of the evaluation model and provides a more credible basis for multi-criteria decision analysis.

The final scores are determined by calculating the mean values. Utilizing the yaahp software, we generated the weights for each hierarchical layer.

4.2 Calculation of Comprehensive Evaluation Scores

Based on the evaluation index system and the weights determined for each indicator, the comprehensive evaluation score for the development level of the digital economy in the Yangtze River Delta is calculated using the following formula:

$$S = \sum_{i=1}^{n} w_i \times x_i$$

In this equation, S represents the comprehensive evaluation score, w_i denotes the weight assigned to the i-th indicator, and x_i represents the standardized value of that indicator. Following this methodology, we calculated the comprehensive development scores for the digital economy across various provinces and cities within the Yangtze River Delta from 2015 to 2022. The specific results are presented in Table 2.

4.3 Analysis of Evaluation Results

The calculation results indicate that the overall development level of the digital economy in the Yangtze River Delta region has maintained a steady upward trend. However, significant spatial disparities persist between different provinces and cities. Shanghai and Hangzhou continue to lead the region in terms of digital infrastructure and industrial digitalization, while other areas are gradually narrowing the gap through policy support and increased investment in innovation.

[Figure 1: see original paper]

As illustrated in [Figure 1: see original paper], the growth rate of the digital economy in the region has accelerated significantly since 2018, coinciding with the national strategy for the integrated development of the Yangtze River Delta. This suggests that regional integration policies have played a crucial role in fostering digital transformation and cross-border resource sharing.

the judgment matrix for the secondary evaluation indicators. To ensure the rationality of the judgment matrix,

3.3 Combination Weighting Method

In this study, we employ a combination weighting method to determine the importance of each evaluation indicator. This approach integrates subjective expertise with objective data characteristics, thereby enhancing the scientific rigor and reliability of the assessment results.

3.3.1 Subjective Weighting via AHP

The Analytic Hierarchy Process (AHP) is utilized to determine subjective weights based on expert judgment. By constructing a judgment matrix and performing consistency tests, we quantify the relative importance of indicators within the hierarchical structure. For a given set of indicators, the subjective weight vector is denoted as $w_s = (w_{s1}, w_{s2}, \dots, w_{sn})$.

3.3.2 Objective Weighting via Entropy Method

To account for the information inherent in the data itself, the Entropy Weight Method is applied. This method calculates weights based on the degree of dispersion in the indicator values; a higher degree of dispersion implies a greater amount of information and, consequently, a higher weight. The objective weight vector is denoted as $w_o = (w_{o1}, w_{o2}, \dots, w_{on})$.

3.3.3 Calculation of Combined Weights

To balance the strengths of both subjective and objective approaches, the final combined weight W_j for each indicator is calculated using the principle of minimum relative entropy or a weighted linear combination. The formula for the combined weight is expressed as:

$$W_j = \frac{w_{sj} \cdot w_{oj}}{\sum_{i=1}^{n} w_{si} \cdot w_{oi}}$$

where W_j represents the final weight of the j-th indicator. This integrated method ensures that the evaluation reflects both the theoretical significance of the indicators and the empirical variations present in the dataset.

As shown in , the combination weighting results provide a more balanced distribution compared to using a single weighting method. This approach mitigates the potential bias of subjective preferences while preventing the mathematical artifacts that can sometimes arise from purely data-driven methods. The resulting weights serve as the foundation for the subsequent comprehensive evaluation and machine learning model training.

Calculate the consistency test parameters within the software. If $0 <$ Consistency Ratio < 0.1, the consistency of the judgment matrix is considered acceptable.

4.3 Determination of Index Weights

Based on the calculated results, the weight of each index is determined. The weight of the criterion layer relative to the target layer is denoted as W, and the weight of the indicator layer relative to the criterion layer is denoted as w_i. The final weight of each indicator relative to the target layer is calculated as $W_i = W \times w_i$. The specific weights for each indicator are shown in Table 2.

4.4 Evaluation Results and Analysis

By applying the established evaluation index system and the calculated weights to the sample data, the comprehensive score for the software' s performance can be derived. The results indicate that the proposed method effectively quantifies the qualitative indicators, providing a more objective basis for software quality assessment. Furthermore, the consistency test ensures that the subjective judgments made during the Analytic Hierarchy Process (AHP) are logically sound and reliable. This approach facilitates a systematic comparison between different software versions or competing products in the same category.

When using the Analytic Hierarchy Process (AHP) to determine weights, the first step involves consulting experts in relevant fields. Based on their professional knowledge and practical experience, these experts perform pairwise comparisons of the importance of various indicators at the same level. These qualitative judgments are then quantified using a scale from 1 to 9.

By organizing these comparison results, a judgment matrix A is constructed:

$$A = (a_{ij})_{n\times n} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}$$

where $a_{ij} > 0$, $a_{ij} = 1/a_{ji}$, and $a_{ii} = 1$.

After constructing the judgment matrix, the weight of each indicator is calculated using the eigenvalue method. Specifically, we solve the characteristic equation $Aw = \lambda_{\max} w$ to find the maximum eigenvalue $\lambda_{\max}$ and its corresponding normalized eigenvector w. The components of w represent the weights of the respective indicators.

To ensure the scientific validity and reliability of the weights, a consistency check must be performed on the judgment matrix. The Consistency Index (CI) is calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

where n is the order of the matrix. The Consistency Ratio (CR) is then determined by:

$$CR = \frac{CI}{RI}$$

The value of the Random Index (RI) can be obtained from standard reference tables based on the order of the matrix. If $CR < 0.1$, the judgment matrix is considered to have acceptable consistency, and the calculated weights are valid. Otherwise, the matrix must be adjusted and re-evaluated.

The proposed method is both reasonable and effective. The comprehensive weight of each indicator within the indicator layer is determined by the weights assigned at the criterion layer.

The subjectivity of traditional weighting methods and the absolute objectivity of the entropy weight method are central considerations in multi-criteria decision-making. While subjective weighting techniques rely on expert judgment and qualitative assessments, they are often criticized for their inherent bias and lack of reproducibility. In contrast, the entropy weight method provides a purely mathematical approach to determining weights based on the dispersion of data. By calculating the information entropy of each indicator, this method assigns higher weights to variables with greater variation, as they provide more information for distinguishing between alternatives. This ensures an objective evaluation process that is entirely driven by the internal logic of the dataset, effectively eliminating the influence of human preference and cognitive limitations.

This methodology is employed during the weight calculation phase of the research. Experts and forest management personnel evaluate the relative importance of each evaluation index.

2.2 Scoring and Scale Division

After the experts complete the scoring process, the majority of the collected questionnaires are processed to establish the final evaluation criteria. The scoring system is typically structured to ensure consistency and objectivity across different expert assessments. To quantify the qualitative judgments provided by the experts, a clear scale division is implemented, allowing for the transformation of subjective opinions into numerical data suitable for further statistical analysis. This process involves defining specific intervals and linguistic variables that correspond to the intensity of importance or performance levels for each evaluated criterion. By aggregating these scores, the research team can derive a consensus-based metric that reflects the collective expertise of the panel, ensuring that the subsequent machine learning models are trained on high-quality, validated data.

If the consistency ratio (CR) satisfies the condition $CR < 0.1$, the final weights for each indicator are determined by multiplying the local weight of the indicator by the weight of its corresponding criterion relative to the goal layer.

Note: The values in parentheses represent the frequency of the term's occurrence within the literature.

3 Health evaluation index system for artificial Haloxylon ammodendron forests on the northeast edge of Ulan Buh Desert

When establishing evaluation criteria, it is essential to integrate the specific environmental conditions of arid sandy regions. Following the methodology proposed by Li Xue [**?**], the assessment framework should account for the unique ecological constraints and hydrological dynamics inherent to these landscapes.

The evaluation process must prioritize indicators that reflect the fragility of the ecosystem, such as soil moisture retention, vegetation coverage, and wind erosion resistance. By synthesizing these localized factors with established machine learning metrics, the model can provide a more accurate representation of environmental stability and degradation risks in arid zones. This approach ensures that the resulting analysis is both scientifically rigorous and practically applicable to the management of desertified lands.

2 Classification of indicators and scales

Based on the relevant research by Ning et al. [**?**], a corresponding scale for evaluating the relative importance of criteria was developed.

The relative importance of the indicators is determined as follows:

Each evaluation indicator is classified into three levels, with assigned numerical values of 1.00,

One indicator is slightly more important than another; one indicator is more important than another; one indicator is significantly more important than another; or one indicator is absolutely more important than another. Intermediate values between 1, 3, 5, 7, and 9 are used to represent intermediate levels of importance.

One indicator is relatively less important than another.

0.62, and 0.38. The specific criteria for these grade classifications are detailed in , which outlines the evaluation indicator levels.

In view of the objectives of the health assessment,

a higher degree of pests and diseases corresponds to a lower level of health. Consequently, the mortality rate and

2、4、6、8

Plant height and the number of new branches were designated as positive indicators.

branching rate and pest/disease incidence are designated as negative indicators. In contrast, the remaining 18 indicators are treated as positive indicators.

The reciprocals of the aforementioned numbers.

Methodology

3.2 Weight Determination and Indicator Calculation

Based on the quantified dataset, the entropy value for each indicator is calculated. To ensure a robust weighting scheme, this study employs a combined weighting method based on additive synthesis normalization. This approach integrates the weights derived from the Analytic Hierarchy Process (AHP)—which reflects expert subjective judgment—with the weights obtained from the Entropy Weight Method (EWM), which captures the objective information contained within the data.

The integration of these two methods mitigates the potential bias of purely subjective weighting and the over-reliance on data fluctuations inherent in purely objective weighting. By synthesizing these perspectives, we achieve a more balanced and scientifically rigorous evaluation framework for the indicators. The final composite weights are then applied to the normalized data to compute the comprehensive performance scores for each observation in the dataset.

When applying the entropy weight method to determine weights, the initial step involves the standardized processing of data collected from field surveys. This normalization is essential to eliminate the influence of different units and scales among the indicators, ensuring that the calculated weights objectively reflect the information carrying capacity of each variable.

1. Data Standardization

To address the dimensional differences between various evaluation indicators, we employ the range normalization method. For positive indicators (where higher values are more desirable), the transformation is defined as:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

Conversely, for negative indicators (where lower values are more desirable), the transformation is:

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$$

In these equations, x_{ij} represents the original value of the j-th indicator for the i-th sample, while x'_{ij} denotes the standardized value.

2. Calculation of Information Entropy

After standardization, the proportion of the i-th sample value under the j-th indicator, denoted as p_{ij}, is calculated. Subsequently, the information entropy e_j for each indicator is determined using the following formula:

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln(p_{ij})$$

where $k = 1/\ln(n)$ is a constant that ensures $0 \leq e_j \leq 1$. A higher entropy value e_j indicates that the indicator provides less information, suggesting that the differences between samples for that specific attribute are small.

3. Determination of Weights

The final step involves calculating the redundancy (or information utility) $d_j = 1 - e_j$. The weight w_j for each indicator is then derived by normalizing these redundancy values:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

By utilizing the entropy weight method, we minimize the influence of subjective bias, allowing the weights to be determined solely by the intrinsic dispersion of the field survey data. This approach enhances the scientific rigor and objectivity of the subsequent comprehensive evaluation.

The indicator weights obtained through the Analytic Hierarchy Process (AHP) and the Entropy Weight Method are combined in equal proportions.

The data is processed and integrated to construct datasets for each indicator layer. Due to the inherent differences in the dimensions and scales of the raw data, direct comparisons or calculations could lead to biased results. Therefore, it is necessary to perform data normalization to ensure that all variables are mapped to a comparable range, typically $[0, 1]$, thereby improving the stability and convergence of the subsequent machine learning models.

Summation is performed, followed by a normalization process to obtain the comprehensive score for each indicator.

The measurement methods for different indicators vary significantly, and the raw data for certain indicators may exhibit substantial differences in scale or units. To ensure comparability across variables and to improve the convergence speed and stability of the machine learning models, it is necessary to perform data normalization or standardization. This process transforms the raw data into a dimensionless form, typically within a specific range such as $[0, 1]$ or following a standard normal distribution with a mean of zero and a unit variance. By addressing these discrepancies in measurement, we can effectively eliminate the influence of disparate units and magnitudes, thereby enhancing the overall accuracy and reliability of the subsequent analytical results.

weights. The two methods are combined using the following formula:

A portion of the data for the indicators was obtained directly from field surveys, while data for other indicators required laboratory analysis. If the raw values of these evaluation indicators were used directly for calculation, the resulting evaluation outcomes would be inconsistent with reality, leading to a failure of the assessment. Therefore, this study adopts the golden section method to process the data.

The original data underwent quantization processing. During the development of health assessment protocols for artificial *Haloxylon ammodendron* forests, specific indicators were established to evaluate ecological stability and growth vigor. These metrics facilitate a systematic analysis of the forest' s condition, allowing for the transformation of qualitative field observations into structured datasets suitable for subsequent modeling and analysis.

Q = aQ1 +(1 - a)Q 2

In the equation: Q represents the integrated weight; Q_1 denotes the weight determined by the Analytic Hierarchy Process (AHP);

Q_2 represents the weight determined by the entropy weight method; a is a constant, which is set to 0.5 in this study.

1.2.3 评价模型选取 TOPSIS 模型在本研究中用于

In the health evaluation phase, the weights derived from the combined weighting method are integrated with the evaluation indices.

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3 Classification of evaluation index levels

Plant height/cm

Evaluation Criteria: Poor (<0.38)

Moderate (0.38~0.62)

Good (0.62~1.00)

100~180

Basal diameter/cm

Uneven-aged or near-mature/mature forests

Crown area/cm^2

Branch length/cm; Number of new shoots

Diameter of new shoots/cm

Total number of plants; Understory richness index

Understory diversity index

Soil electrical conductivity/$\mu S \cdot cm^{-1}$

Soil organic matter/$g \cdot kg^{-1}$

0.3~0.5

30~55

Mortality Rate / %

Pests and Diseases / %

20~40

0.80

0.5~1.0

0.4~0.7

0.3~0.5

0.6~1.5

550~600

8.3~8.6

25%~55%

30%~60%

Dieback rate/%

0.45~0.80

10~15

<0.45

Soil moisture content (%) / Soil pH

Understory dominance index

Understory evenness index

20~32

50~120

New shoot length/cm

190~310

35%~65%

The standardized dataset is combined and subsequently input into the TOPSIS model.

D+i = $\sum$ y max j - y ij

In the model, the distances between each evaluation unit and the positive ideal solution, as well as the negative ideal solution, are calculated.

Furthermore, the health status of each region was analyzed across different site types and stand age classes. Currently, this model is widely applied in fields such as benefit evaluation and…

D-i = $\sum$ y min j - y ij

Calculation of Relative Proximity:

Through hierarchical analysis, the relative health proximity of different regions can be obtained, thereby clearly identifying

the health status of each region. Building upon this foundation and incorporating actual conditions, this metric is used to measure the health level of artificial *Haloxylon ammodendron* forests in various areas. Its value ranges

from 0 to 1, representing the Euclidean distance. The relative proximity is thus derived; a higher value indicates a better health condition. Through this analysis,

D+i + D-i

In the formula: $(y_{\max 1}, y_{\max 2}, \cdots, y_{\max n})$ represents the maximum values for each indicator; $(y_{\min 1},$

$y_{\min 2}, \cdots, y_{\min n})$ represents the minimum values for each indicator; $y_{\max j}$ is the maximum value of the j-th indicator;

$y_{\min j}$ is the minimum value of the j-th indicator; and y_{ij} denotes the value of the j-th indicator for the i-th

In the fields of soil and water conservation and desertification control, this method is utilized to evaluate the performance of soil and water conservation

evaluation unit; C_i represents the health level of the *Haloxylon ammodendron* forest in region i.

This approach has been widely cited by scholars in research areas such as water resource carrying capacity.

projects and the health status of ecosystems [**?**]. After inputting the combined weights, the calculation formula for the TOPSIS model is as follows:

2 结果与分析

Determine the positive ideal solution Y^+ and the negative ideal solution Y^- for each indicator:

$$Y^+ = (y_{\max 1}, y_{\max 2}, \cdots, y_{\max n})$$
$$Y^- = (y_{\min 1}, y_{\min 2}, \cdots, y_{\min n})$$

Calculate the Euclidean distances D_i^+ and D_i^- between each evaluation unit and the positive ideal solution Y^+ and negative ideal solution Y^-, respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^+)^2}$$
$$D_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^-)^2}$$

The relative closeness coefficient is defined as C_i $(0 \leq C_i \leq 1)$. A higher C_i value indicates a higher level of health.

2.1 人工梭梭林健康评价指标权重分析

Through the comprehensive application of the Analytic Hierarchy Process (AHP), the Entropy Weight Method, and the Combined Weighting Method, this study determined the weights for each indicator in the health assessment of artificial *Haloxylon ammodendron* forests on the northeastern edge of the Ulan Buh Desert.

The weight values and consistency test parameters for each evaluation indicator of the artificial *Haloxylon ammodendron* forest health assessment are presented in . The results calculated by the three methods demonstrate that their respective trends are fundamentally consistent.

4 Health evaluation indicators and analytic hierarchy process weights for artificial Haloxylon ammodendron forests

Artificial Haloxylon ammodendron stand 0.1534 Haloxylon ammodendron health and vitality

Plant height / cm

Crown area / cm^2

Branch length / cm; Number of new shoots / individual; Length of new shoots / cm; Diameter of new shoots / cm; Total number of plants / individual; Under

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.