Dynamic Monitoring and Prediction of Eco-Environmental Quality in Yining City Based on RSEI and ANN-CA-Markov Model: Postprint

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Abstract

Yining City is located in the Ili River Valley in the northwestern border region of Xinjiang, China, featuring fertile land, abundant water resources, and rich biological resources that provide superior natural conditions for agricultural, forestry, and pastoral development. However, excessively rapid urbanization has caused ecological damage and a continuous decline in ecological environment quality. Therefore, utilizing the Remote-sensing Ecological Index (RSEI) and ANN-CA-Markov model to scientifically and rationally employ Landsat TM5/OLI-TIRS8 remote sensing data for dynamic evaluation and prediction of Yining City' s ecological environment from 2006 to 2021 is of significant importance. The results demonstrate: (1) Greenness and humidity positively influence Yining City's ecological level, while dryness and heat negatively influence it. The primary factors affecting Yining City' s ecological environment quality, in order of importance, are greenness, heat, dryness, and humidity, which is consistent with the ecological conditions exhibited in the Ili River Valley region. (2) The average RSEI value for Yining City is 0.451, indicating an overall medium level. Although changes in ecological environment quality show a trend of gradually decreasing polarization, the area of medium and poor RSEI zones is increasing year by year, indicating an overall trend of stable but deteriorating ecological conditions. (3) It is anticipated that the ecology of Yining City' s northern slope area will improve to a certain extent by 2026 and 2031. According to the "Overall Plan for Yining City, Xinjiang (2018-2035)," the urban area will maintain a medium level of ecological environment quality in the future, the city will continue to expand outward, and the area of arable land will continue to decrease.

Full Text

Dynamic Monitoring and Prediction of Eco-environmental Quality in Yining City Based on RSEI and ANN-CA-Markov Model

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Abstract

Yining City, located in the Ili River Valley at the northwestern border of Xinjiang, China, possesses fertile land, abundant water resources, and rich biological resources, providing favorable natural conditions for developing agriculture, forestry, and animal husbandry. However, rapid urbanization has caused ecological damage and declining eco-environmental quality. Therefore, it is crucial to scientifically and rationally utilize Landsat TM5/OLI-TIRS8 remote sensing data to conduct dynamic evaluation and prediction of Yining City' s ecological environment from 2006 to 2021 based on the Remote Sensing Ecological Index (RSEI) and ANN-CA-Markov model. The results show that: (1) Greenness and humidity positively impact Yining City' s ecological level, while dryness and heat have negative impacts. The main factors affecting eco-environmental quality are, in descending order, greenness, heat, dryness, and humidity, which aligns with the ecological conditions observed in the Ili River Valley region. (2) The average RSEI value for Yining City is 0.451, indicating a moderate overall level. The ecological environment quality change exhibits a trend of gradually narrowing extremes, but areas with medium and poor RSEI indices are increasing annually, showing a stable-to-worsening development trend. (3) Predictions indicate that by 2026 and 2031, the ecological environment in Yining City' s northern slope region will improve to some extent. Combined with the *Overall Urban Planning of Yining City, Xinjiang (2018-2035)*, the urban area' s eco-environmental quality will remain at a moderate level, while the city will continue expanding outward, leading to continuous reduction in arable land area.

Keywords: Remote Sensing Ecological Index; Landsat; eco-environmental quality prediction; ANN-CA-Markov model; Yining City

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Eco-environmental quality results from the interaction between human activities and the ecological environment. The natural environment is closely related to human survival and socio-economic development. With social progress and technological advancement, human material civilization has reached unprecedented heights, but this has been accompanied by increasingly severe ecological and environmental problems. Human over-exploitation of natural resources and blind pursuit of economic benefits have intensified the contradiction between economic development and resource allocation, posing serious threats to human survival and development. This has led to growing global concern for ecological and environmental issues. The concept of "sustainable development" was proposed at the 1992 United Nations Conference on Environment and Development in Brazil, making it clear that economic development must be accompanied by ecological protection, representing a formidable task facing the world.

China' s ecological and environmental problems are particularly severe. While China' s economy has developed rapidly, this process has over-consumed natural resources, triggering a series of ecological issues. Land degradation, soil erosion, and air pollution are among the major environmental challenges China faces. People are paying increasing attention to ecological and environmental issues, as their quality directly affects regional sustainable development. Therefore, using scientific methods for quantitative eco-environmental evaluation is particularly important. Currently, various feasible research methods exist, and satellite remote sensing, with its advantages of large-scale monitoring, periodicity, and real-time capability, has been widely applied in regional eco-environmental evaluation.

However, most current studies rely on single indicators to describe specific aspects of the ecological environment, such as monitoring urban heat islands through thermal infrared band inversion from remote sensing imagery or constructing various drought indices to assess regional drought conditions. Due to ecosystem complexity, single indicators often cannot comprehensively and effectively describe the ecological environment. Some scholars have used the Analytic Hierarchy Process (AHP) and Pressure-State-Response (PSR) models to construct multiple indicators for eco-environmental evaluation, but these approaches face challenges such as difficult weight determination and strong subjectivity. Since Xu Hanqiu first proposed using the Remote Sensing Ecological Index (RSEI) to characterize eco-environmental quality, this index employs Principal Component Analysis (PCA) to integrate four ecological indicators. Its advantages include simple acquisition and no need for manual weight determination, which has been validated by numerous scholars.

Zhang et al. analyzed ecological environment changes in Huaibei City from 1995 to 2015 based on the RSEI, finding that urban construction' s encroachment on various land types was the direct cause of declining eco-environmental quality. Wang et al. studied Urumqi, revealing that the average RSEI gradually decreased over the past 20 years, with overall ecological environment deterioration but significant differences among districts. Wang Jinjie et al. studied Turpan and Hami cities, establishing and mapping multi-temporal RSEI models for the Tuha region, showing a slightly declining trend in eco-environmental quality. Nong Lanping et al. dynamically monitored Kunming' s eco-environmental quality using the RSEI model, finding a fluctuating "rise-decline" pattern from 2000 to 2018. To date, research has primarily focused on dynamic evaluation of RSEI. Zhang et al. predicted regional ecological environments by coupling the CA-Markov model, but traditional Markov models have strong subjectivity and limited accuracy for complex ecological changes. Artificial Neural Networks (ANN) can simulate complex non-linear problems, so this study constructs an ANN-CA-Markov model using four ecological indicators as driving factors for more scientific and reasonable predictions.

This study selects Yining City in Ili Prefecture, Xinjiang as the research area. As a city in the Ili River Valley, Yining has been honored as an "Excellent Tourism City in China," "National Garden City," and a national pilot city for new urbanization, with extremely rich land, mineral, animal husbandry, and forestry resources. Therefore, scientifically and reasonably conducting dynamic monitoring and prediction research on Yining City' s eco-environmental quality changes can not only explore the spatiotemporal distribution characteristics of ecological changes and analyze influencing factors but also provide suitable suggestions for optimizing ecological space control and future sustainable development decision-making to ensure national territorial ecological security. This research is of great significance for dynamic monitoring and prediction of Yining City' s eco-environmental quality, providing references and scientific basis for sustainable development strategies and ecological protection planning to improve Yining' s eco-environmental quality.

1. Study Area Overview

Yining City is located at the northwestern border of China in the central Ili River Valley basin, geographically positioned between 80°04 ~81°29 E and 43°50 ~44°09 N. It connects to Yining County in the east, borders Huocheng County in the west, and faces Qapqal Xibe Autonomous County across the Ili River to the south [Figure 1: see original paper]. Yining City has fertile land, abundant water and heat resources, and rich biological resources, providing favorable natural conditions for developing agriculture, forestry, and animal husbandry. The total area is 674.42 km^2, with a permanent population of 582,700 at the end of 2021. Yining City has a temperate continental climate with an annual average temperature and average precipitation of 275.5 mm, rich ecological resources, and diverse plant species.

2. Materials and Methods

2.1 Data Sources and Preprocessing

The data used in this study were obtained from the United States Geological Survey (USGS), with data parameters shown in . The remote sensing images have a spatial resolution of 30 m and use the WGS_{{{1984}}*{{UTM}}*}{{{Zone}}_{{44N}}} projection coordinate system. The image coverage is 185$×$185 km for Landsat5 TM and 180 km for Landsat OLI/TIRS8. The vector data for the study area’ s administrative boundaries were obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/).

Before extracting and constructing the RSEI, the original images were preprocessed using ENVI 5.3, including geometric correction, radiometric calibration, atmospheric correction, and image clipping. The preprocessed results underwent false-color composition (synthesized from Near IR, Red, and Green bands) [Figure 2: see original paper].

2.2 Remote Sensing Ecological Index

This study employs Principal Component Analysis (PCA) to first integrate greenness (NDVI), humidity (WET), dryness (NDSI), and heat (LST), calculated separately through models. To reduce errors, the 5%~95% confidence interval was filtered, and normalization was performed. The normalized data were combined through band synthesis, concentrating the information of the four indicators onto the first principal component. The weight values are determined based on each indicator’ s contribution rate to the principal component and its inherent properties, avoiding manual weight assignment errors and improving objectivity and credibility. The indicator models are as follows.

2.2.1 Greenness (Vegetation Index) The Normalized Difference Vegetation Index (NDVI), proposed by Rouse et al., has become the most widely used vegetation index in remote sensing for monitoring surface green vegetation coverage. This study uses this indicator to represent greenness in the RSEI. The formula is:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}}$$

where ρ_{NIR} is the near-infrared band and ρ_{red} is the red band. Wavelength parameters are shown in .

2.2.2 Humidity (Wetness Index) The wetness index can be calculated through Tasseled Cap Transformation (also called K-T transformation) to extract parameters from Landsat data. This study uses this indicator to characterize humidity. However, due to differences in sensor parameters between Landsat TM5 and Landsat OLI8, the wetness component model parameters differ:

For Landsat TM5:

$$WET_{TM} = \rho_{blue}\times 0.0315 + \rho_{green}\times 0.2021 + \rho_{red}\times 0.3102 + \rho_{NIR}\times 0.1594 - \rho_{SWIR1}\times 0.6806 - \rho_{SWIR2}\times 0.6109$$

For Landsat OLI8:

$$WET_{OLI} = \rho_{blue}\times 0.1511 + \rho_{green}\times 0.1973 + \rho_{red}\times 0.3283 + \rho_{NIR}\times 0.3407 - \rho_{SWIR1}\times 0.7117 - \rho_{SWIR2}\times 0.4559$$

where ρ_{blue} is the blue band, ρ_{green} is the green band, ρ_{SWIR1} and ρ_{SWIR2} are shortwave infrared bands. Wavelength parameters are shown in .

2.2.3 Dryness (Building-Soil Index) The Normalized Difference Soil Index (NDSI) effectively monitors environmental dryness by calculating the average of the Building Index (IBI) and Soil Index (SI). This study uses this indicator to represent dryness in the RSEI:

$$IBI = \frac{\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}} - \frac{\rho_{NIR}}{\rho_{NIR} + \rho_{red}} + \frac{\rho_{green}}{\rho_{green} + \rho_{SWIR1}}$$

$$SI = \frac{\rho_{SWIR1} + \rho_{red}}{\rho_{SWIR1} + \rho_{red} + \rho_{NIR}} - \frac{\rho_{NIR}}{\rho_{NIR} + \rho_{SWIR1} + \rho_{green}}$$

$$NDSI = \frac{IBI + SI}{2}$$

2.2.4 Heat (Land Surface Temperature) Land Surface Temperature (LST) was retrieved using the atmospheric correction method. Fractional Vegetation Cover (FVC) was used to calculate surface emissivity. The original remote sensing image’ s Digital Number (DN) values were radiometrically corrected to obtain top-of-atmosphere radiance, which was then atmospherically corrected to remove water vapor effects and converted to blackbody radiance. Through Planck function conversion, blackbody radiance was transformed into blackbody brightness temperature, i.e., surface temperature:

$$FVC = \begin{cases} 0 & NDVI < 0.05 \\ 1 & NDVI > 0.7 \\ \frac{NDVI_{0.05\ \ 0.7} - 0.05}{NDVI_{0.05\ \ 0.7} \times (1 - 0.05)} & 0.05 \leq NDVI \leq 0.7 \end{cases}$$

$$\varepsilon_{(water)} = 0.995$$

$$\varepsilon_{(building)} = 0.9589 + 0.086 \times FVC - 0.0671 \times FVC^2$$

$$\varepsilon_{(natural)} = 0.9625 + 0.0614 \times FVC - 0.0461 \times FVC^2$$

$$\varepsilon_{ref} = NDVI \leq 0 \times \varepsilon_{(water)} + NDVI_{0\ \ 0.7} \times \varepsilon_{(natural)} + NDVI \geq 0.7 \times \varepsilon_{(building)}$$

$$LST = \frac{K_2}{\ln\left(\frac{K_1}{B(T_s)} + 1\right)}$$

where $B(T_s) = \frac{L_{TIRS1} - L_{up} - \tau \times (1-\varepsilon_{ref}) \times L_{down}}{\tau \times \varepsilon_{ref}}$, L_{TIRS1} is the thermal infrared band radiance, L_{up} is atmospheric upward radiance, L_{down} is atmospheric downward radiance, and τ is atmospheric transmittance in the thermal infrared band (data for L_{up}, L_{down}, and τ obtained from the atmospheric profile calculator at atmcorr.gsfc.nasa.gov/). K_1 and K_2 are satellite emission preset constants: for Landsat TM5, $K_1 = 607.76$ and $K_2 = 1260.56$; for Landsat OLI TIRS8, $K_1 = 774.89$ and $K_2 = 1321.08$. Parameters are shown in .

2.2.5 RSEI Model Establishment The four factors obtained above were coupled through Principal Component Analysis (PCA), using the first principal component (PC1). The greatest advantage is that the comprehensive index weights are automatically and objectively determined based on each indicator' s contribution, avoiding result deviations from subjective weight settings and improving objectivity and credibility.

Since the four factors have non-uniform dimensions, direct PCA would create unbalanced weights. Therefore, before PCA, the four factors should be normalized to convert each indicator value to a dimensionless range of 0-1. The normalization formula is:

$$XI_i = \frac{I_i - I_{min}}{I_{max} - I_{min}}$$

where XI_i is the normalized value, I_i is the pre-normalization value, and I_{max} and I_{min} are the maximum and minimum pre-normalization values, respectively.

After normalizing the four factors, band synthesis was performed using ENVI 5.3' s band combination module and PCA. In some cases, higher PC1 values indicate better ecological conditions, while in others, higher values indicate worse conditions. Therefore, the sign was adjusted to ensure higher values represent better ecology:

$$RSEI = 1 - PC1[NDVI, WET, NDSI, TEM]$$

2.3 Prediction Model

The Cellular Automata (CA) model can simulate complex system spatiotemporal evolution processes, but traditional CA models have strong subjectivity and limitations. Artificial Neural Networks have sufficient capability to simulate complex non-linear problems, with strong parallel, distributed storage, processing, self-organizing, adaptive, and self-learning abilities. The essence is to continuously train samples to obtain network parameter values with minimum error, then input similar data to output results with minimum error.

The Markov model is a method for predicting event occurrence probabilities and has been widely applied in regional land use change prediction. However, due to the strong spatial distribution randomness of land use, traditional Markov models have limitations and difficulty achieving prediction effects. This study constructs an ANN-CA-Markov model by combining ANN with the CA-Markov model. This model is generally suitable for simulating and predicting land use changes, and since eco-environmental quality is also raster data with high spatial autocorrelation, this study attempts to use it for prediction.

Using the GeoSOS-FLUS V2.4 software developed by Professor Liu Xiaoping' s team at Sun Yat-sen University, predictions for 2026 and 2031 were made. The Kappa coefficient was used to determine accuracy, where $Kappa > 0.75$ indicates high credibility and good simulation results; the figure of merit (FOM) index is a sensitivity value, generally less than 0.3, indicating high simulation accuracy.

3. Results and Analysis

3.1 Principal Component Analysis of Four Indicators

Principal component analysis results for the four indicators from 2006-2021 are shown in , where PC1-PC4 represent the first to fourth principal components. PC1 concentrates most features of the four indicators and can represent the overall ecological condition of the study area. Greenness and humidity have positive eigenvalues, indicating positive impacts on Yining City's ecological level, while dryness and heat have negative eigenvalues, indicating negative impacts. Analyzing the absolute eigenvalues shows the indicator ranking as greenness > heat > dryness > humidity, indicating that the main factors affecting Yining City' s eco-environmental quality are greenness, heat, dryness, and humidity, respectively, consistent with ecological conditions in the Ili River Valley region.

3.2 Spatiotemporal Variation Analysis of Eco-environmental Quality in Yining City

Statistical values of the four indicators and RSEI from 2006-2021 were compiled and plotted in Excel [Figure 3: see original paper]. According to the *Technical Specification for Eco-environmental Status Evaluation (HJ 192-2015)* issued by China' s Ministry of Ecology and Environment, eco-environmental status was classified using RSEI as the grading standard: good (0.6-0.8), better (0.4-0.6), moderate (0.2-0.4), poor (0.0-0.2), and bad (<0.0).

Temporal analysis shows the average RSEI value is 0.451, indicating an overall moderate level. The RSEI shows an upward trend, suggesting overall ecological environment improvement in Yining City, with a 13.34% increase during 2006-2021, rising more significantly by 11.28% during 2010-2016, mainly due to ecological restoration of desert steppes on Yining City' s northern slopes. In 2016-2021, accelerated urbanization in Yining' s development zone and land use transformation caused RSEI to decline.

Among the four indicators, greenness, dryness, and heat show relatively stable change trends. Due to Yining's location in the Ili River Valley and continuously increasing precipitation since 2006, humidity shows a more significant increase, and the ecological environment has improved and returned to a moderate level.

Using ArcGIS 10.5 to reclassify annual RSEI data according to the above grading standards, ecological environment quality maps for Yining City from 2006-2021 were obtained [Figure 4: see original paper]. Area extraction and calculation were performed for each grade using ArcGIS and Excel .

Analysis reveals that Yining City's eco-environmental quality is at poor or moderate levels, mainly because the northern mountainous area relies on the Tianshan Mountains, with nearly 1.3×10^{3} km^2 of northern slope area belonging to semi-desertified grassland, an ecologically fragile zone. The overall development remains stable, with improvement trends during 2006-2010 but rebound later. The southern Ili River urban area's eco-environmental quality is basically at moderate and better levels, primarily due to abundant water and heat resources near the Ili River, providing an excellent ecological foundation. The central urban area shows a clear outward expansion trend. Compared with 2006, the area with good ecological quality decreased by 9.27 km^2 (1.37% of total area), remaining relatively stable; the better area decreased by 31.47 km^2 (4.67%); the moderate area remained relatively stable, increasing by 4.06 km^2 (0.60%); the poor area increased by 49.59 km^2 (7.35%), requiring urgent restoration measures; the bad area decreased by 12.92 km^2 (1.92%), with a significant decline during 2006-2010 but subsequent increase, mainly due to continuous urban expansion and land use type transformation after 2010.

In summary, Yining City's eco-environmental quality change shows gradually narrowing extremes, but medium and poor areas are increasing annually, presenting a stable-to-worsening trend requiring intensified ecological restoration efforts.

3.3 Analysis of Spatiotemporal Variation Differences in Yining City's Eco-environmental Quality

Based on the above grading, to obtain spatiotemporal distribution information on eco-environmental quality changes between different years, differential processing was applied to RSEI from different years. Changes were categorized as improved (+), unchanged (=), and degraded (-), with improvement and degradation further divided into three levels by magnitude, and mapped [Figure 5: see original paper].

Statistical results show area changes: improved area 312.99 km^2 (46.41%), unchanged area 159.14 km^2 (23.60%), and degraded area 202.30 km^2 (30.00%). Overall, Yining City's ecological environment is relatively stable, but the overall quality remains concerning. Without timely ecological restoration, the future ecological environment will further deteriorate.

Specifically, temporal analysis shows area changes for 2006-2010: improved

315.53 km^2 (46.78%), unchanged 178.40 km^2 (26.45%), degraded 180.49 km^2 (26.76%), with the northern slope area showing annual improvement. For 2010-2016: improved 268.45 km^2 (39.80%), unchanged 228.30 km^2 (33.85%), degraded 177.66 km^2 (26.34%). For 2016-2021: improved 247.89 km^2 (36.76%), unchanged 182.73 km^2 (27.09%), degraded 243.80 km^2 (36.15%). The ecological environment quality is developing toward degradation.

3.4 RSEI Prediction

Using the ANN-CA-Markov model in GeoSOS-FLUS V2.4, with 2006-2021 RSEI classification data as the basis and the four indicators as driving factors, conversion rules were determined to obtain 2021 simulation predictions, which were compared with actual 2021 RSEI classification maps. The comparison shows high accuracy with a Kappa coefficient of 0.8265 and OA index of 0.8947, proving the simulation data is reliable.

Using 2021 as the baseline, the model predicted 2026 and 2031 RSEI [Figure 6: see original paper]. Analysis shows that by 2026 and 2031, Yining City' s eco-environmental quality will continue the 2006-2021 trend, with the northern slope area improving to some extent. However, due to the poor ecological area in western Yining being close to the Yili Tukai Desert, ecological improvement faces difficulties. Combined with the *Overall Urban Planning of Yining City, Xinjiang (2018-2035)*, the urban area' s eco-environmental quality will remain moderate, but the city will continue expanding outward. Since 2010, Yining' s arable land area decreased from 286.13 km^2 to 229.20 km^2, and this reduction will continue. It is recommended to strengthen regional ecological protection alongside economic and social development.

4. Conclusion

This study constructs the RSEI to dynamically monitor and evaluate Yining City' s ecological quality from 2006-2021, analyzes the impact mechanisms of four influencing factors, identifies ecological space deficiencies in urban development, and uses the ANN-CA-Markov model combining neural networks to predict Yining' s ecological quality over the next 10 years. The prediction accuracy (Kappa coefficient) reaches 0.8265, far exceeding traditional prediction models, though it cannot yet achieve dynamic prediction anytime and anywhere. Future research could employ Convolutional Neural Networks for deep learning of images, training on large volumes of historical image data to achieve AI algorithm accuracy above 0.9 and enable long-term accurate prediction.

Principal component analysis shows greenness and humidity positively impact Yining City' s ecological level, while dryness and heat have negative impacts. The main factors affecting eco-environmental quality are greenness, heat, dryness, and humidity, consistent with the Ili River Valley' s ecological conditions. The average RSEI is 0.451, at a moderate level overall. The northern mountainous area belongs to semi-desertified grassland, an ecologically fragile zone with medium-low quality; the southern area near the Ili River has abundant water and heat resources, maintaining medium-high quality; the western development zone and eastern urban area showed declining quality before 2010 but recovered to moderate levels after greening and park construction. Yining City's eco-environmental quality shows gradually narrowing extremes, but medium and poor areas are increasing annually, presenting a stable-to-worsening trend requiring intensified ecological restoration.

Predictions indicate the northern slope area will improve by 2026 and 2031, but western poor ecological areas near the Yili Tukai Desert face improvement difficulties. Combined with the *Overall Urban Planning of Yining City, Xinjiang (2018-2035)*, urban eco-environmental quality will remain moderate, but urban expansion will continue, further reducing arable land. It is recommended to strengthen ecological protection alongside economic and social development.

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