Spatiotemporal Changes and Driving Forces of the Ecological Environment in Altay City Based on the MRSEI Model: Postprint

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Abstract

To timely, objectively, and quantitatively assess the ecological environment of Altay City, Xinjiang, this study constructed a Modified Remote Sensing Ecological Index (MRSEI) based on multi-source remote sensing data, combined with standard deviation ellipse and centroid migration models to analyze its spatiotemporal variation characteristics, and utilized the Geodetector model to conduct factor detection on five indicators: greenness, dryness, humidity, temperature, and air quality. The results demonstrate: (1) During 2015–2021, greenness and humidity indicators exerted a significant positive correlation effect on the regional ecological environment in Altay City, while temperature, dryness, and air quality exhibited a significant negative correlation effect; (2) The mean MRSEI value in Altay City showed an upward trend from 2015 to 2021. Spatially, Grade I and Grade II ecological index areas displayed stronger spatial migration capacity, whereas Grade III–V areas, i.e., high ecological index regions, remained relatively stable in spatial structure. The centroids of Grade I–IV ecological indices shifted northward overall, while the centroid of Grade V ecological index moved southward overall, indicating a pronounced growth in the distribution of high ecological index areas in southern Altay City. (3) The dominant factors driving changes in ecological environment quality varied across years, and the spatial evolution of ecological environment quality in Altay City represented the combined effect of multiple factors. (4) The ecological monitoring results derived from MRSEI and RSEI (Remote Sensing Ecological Index) exhibited generally consistent trends for Altay City. The differences in their spatial distribution and magnitude were associated with the spatial distribution of Aerosol Optical Depth (AOD), indicating that even in Altay City with favorable air quality, AOD still influences its ecological quality in terms of spatial distribution. From 2015 to 2021, the ecological environment of Altay City

demonstrated a trend of improvement towards the south under the influence of multiple factors.

Full Text

Spatio-temporal Variation and Driving Forces Analysis of Ecological Environment in Altay City Based on MRSEI Model

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Abstract

To evaluate the ecological environment of Altay City, Xinjiang in a timely, objective, and quantitative manner, this study constructed a Modified Remote Sensing Ecological Index (MRSEI) based on multi-source remote sensing data. The spatio-temporal variation characteristics were analyzed using standard deviation ellipse and gravity center migration models, and a geographical detector model was employed to examine five key indicators: greenness, dryness, humidity, temperature, and air quality. The results indicate that: (1) From 2015 to 2021, the greenness and humidity indexes showed significant positive correlations with regional ecological conditions, while temperature, dryness, and air quality exhibited significant negative correlations. (2) The MRSEI values in Altay City demonstrated an overall upward trend during the study period. Spatially, areas with ecological index grades I and II exhibited strong spatial migration capability, while grades III-V remained relatively stable in their spatial structure. The centers of gravity for grades I-IV moved northward, whereas the center for grade V moved southward, indicating a notable increase in high ecological index distribution in southern Altay City. (3) The dominant factors driving eco-environmental quality changes varied by year, confirming that the spatial evolution of ecological quality in Altay City results from multiple interacting factors. (4) Although differences exist between MRSEI and RSEI in spatial distribution and magnitude, their overall monitoring trends for Altay City are consistent. These differences correlate with the spatial distribution of Aerosol Optical Depth (AOD), demonstrating that even in Altay City where air quality is relatively good, AOD still influences the spatial distribution of ecological quality. Overall, from 2015 to 2021, the ecological environment of Altay City was influenced by multiple factors and showed a tendency toward improvement in the southern region.

Keywords: modified remote sensing ecological index; ecological environment quality; geographical detector; center of gravity migration model; Altay City

Introduction

The ecological environment constitutes the foundation of human survival and development and serves as a crucial basis for achieving sustainable regional socioeconomic growth. Consequently, scientifically and accurately understanding regional ecological conditions is essential. As concentrated centers of population, economy, and culture, cities represent important subjects for ecological environment research. However, rapid urbanization has accelerated human impacts on the land surface, posing severe challenges to urban ecosystems. Traditional ecological assessment methods, while simple, struggle to comprehensively reveal systematic environmental changes due to the diversity and complexity of influencing factors. Remote sensing technology, with its advantages of rapid, real-time, large-scale monitoring and open data access, has been widely applied in ecological research.

Current remote sensing-based ecological monitoring and evaluation models fall into two main categories: single-index models and comprehensive-index models. While single-index models are straightforward, they cannot fully capture the complexity of ecological systems. Xu Hanqiu addressed this limitation by constructing the Remote Sensing Ecological Index (RSEI) for urban ecosystems through principal component analysis that integrates four indicators: greenness (NDVI), humidity (WET), dryness (NDBSI), and temperature (LST). This index, based entirely on remote sensing data and considering multiple factors, enables systematic analysis of regional ecological spatio-temporal changes and has been widely applied in urban ecological quality assessment.

However, each study area possesses unique ecological characteristics requiring tailored analytical approaches. Scholars have continuously improved the RSEI model: some added land degradation indicators to create ARSEI for arid regions, while others incorporated vegetation net primary productivity (NPP) for mining area assessments. Liu et al. introduced air quality indicators to develop the Modified Remote Sensing Ecological Index (MRSEI), proving more suitable for urban ecological quality evaluation. In ecological research, the geographical detector model has gained prominence for its robust capability to detect spatial heterogeneity and reveal underlying driving forces.

Altay City, located in an arid region with fragile ecological conditions, has received limited systematic ecological research. Comprehensive, quantitative assessment of its eco-environmental spatio-temporal variation and driving factors remains scarce. This study employs time-series remote sensing imagery to investigate MRSEI dynamics and applies geographical detector models for single-factor and multi-factor interaction detection across the five indicators, analyzing their influence on the regional ecological index.

1.1 Study Area Overview

Altay City (86°53 –88°27 E, 47°14 –48°39 N) is situated at the southern foothills of the Altai Mountains and the northern edge of the Junggar Basin [Figure 1: see original paper]. The city exhibits a distinct stepped vertical distribution from north to south, comprising three natural geomorphic units: northern mountainous areas, southern hilly regions, and intermountain alluvial plains. Spanning 146 km from north to south and 84 km from east to west, Altay City covers an area of 1.15×10^4 km^2. The region belongs to the mid-temperature sub-arid and arid climate zones, with significant climatic differences between north and south. Monitoring data indicate that the city's air quality meets national Grade II standards, with primary pollutants being inhalable particulate matter (PM_{10}) and fine particulate matter ($PM_{2 \cdot 5}$).

1.2 Data Sources and Processing

This study utilized administrative boundary data, Landsat 8 imagery, and MODIS MCD19 A2 product data. Data processing included radiometric calibration, atmospheric correction using FLAASH, image mosaic and clipping, index calculation, normalization, and principal component analysis, all performed using ENVI 5.6 software.

Table 1 Data sources

Data Type	Spatial Resolution	Data Source
Administrative boundaries	1:1,000,000	National Earth System Science Data Center
Landsat 8 OLI L1	30 m	Geospatial Data Cloud
MCD19 A2	1 km	NASA
DEM	30 m	Geospatial Data Cloud

2.1 Construction of MRSEI and RSEI Models

The Remote Sensing Ecological Index (RSEI) model employs principal component analysis to couple four indicators: greenness (NDVI), dryness (NDBSI), humidity (WET), and temperature (LST), expressed as:

$$RSEI = PC1[NDVI, WET, LST, NDBSI]$$

The Modified Remote Sensing Ecological Index (MRSEI) builds upon this foundation by introducing air quality indicators—Aerosol Optical Depth (AOD)—making it more suitable for urban ecological quality assessment. The MRSEI function is expressed as:

$$MRSEI = PC1[NDVI, WET, LST, NDBSI, AOD]$$

Greenness Indicator (NDVI): Normalized Difference Vegetation Index reflects vegetation coverage:

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

Temperature Indicator (LST): Land Surface Temperature is calculated as:

$$LST = \frac{T}{1 + (\lambda \times T/\rho)\ln\varepsilon}$$

where T is the temperature at the sensor, λ is the central wavelength of Landsat 8's thermal band ($\lambda = 10.895\mu m$), $\rho = 1.438 \times 10^{-2}$, ε is land surface emissivity, and L_λ is the spectral radiance.

Humidity Indicator (WET): The Tasseled Cap transformation humidity component:

$$WET = 0.1511\times\rho_1 + 0.3407\times\rho_2 + 0.1972\times\rho_3 - 0.7117\times\rho_4 + 0.3283\times\rho_5 - 0.4559\times\rho_6$$

Dryness Indicator (NDBSI): Normalized Difference Built-up and Soil Index combines IBI and SI:

$$IBI = \frac{2 \times \rho_{SWIR1}}{\rho_{SWIR1} + \rho_N}$$

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

Air Quality Indicator (AOD): MODIS MCD19 A2 data, based on the MAIAC algorithm, effectively reflects particulate matter air quality and shows high correlation with $PM_{2\cdot5}$ concentration. Given that $PM_{2\cdot5}$ is the primary pollutant in Altay City, AOD was selected to represent air quality.

To eliminate dimensional differences, all indicators were normalized to [0,1]:

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

Principal component analysis determined indicator weights. The first principal component (PC1) with the highest eigenvalue contribution rate was selected as it effectively integrated all indicator information. To ensure MRSEI values positively correlate with ecological quality, $1 - PC1$ was used as the initial MRSEI_0:

$$MRSEI_0 = 1 - PC1[NDVI, WET, LST, NDBSI, AOD]$$

For convenient comparison, MRSEI_0 was further normalized:

$$MRSEI = \frac{MRSEI_0 - MRSEI_{0_{min}}}{MRSEI_{0_{max}} - MRSEI_{0_{min}}}$$

Higher values indicate better ecological conditions.

2.2 MRSEI Classification

For regional differentiation and temporal change analysis, MRSEI values were classified into five levels at 0.2 intervals based on the "Technical Specification for Ecological Environment Evaluation" .

Table 2 MRSEI classification

MRSEI Range	Ecological Status
$0.8 < \mathrm{MRSEI} \leq 1.0$	Excellent
$0.6 < \mathrm{MRSEI} \leq 0.8$	Good
$0.4 < \mathrm{MRSEI} \leq 0.6$	Moderate
$0.2 < \mathrm{MRSEI} \leq 0.4$	Poor
$0 \leq \mathrm{MRSEI} \leq 0.2$	Very Poor

2.3 Standard Deviation Ellipse and Gravity Center Migration Model

The gravity center migration method, traditionally applied in economic and demographic studies, was introduced to ecological quality assessment to reveal spatial dynamic changes in Altay City's ecological quality, including migration direction, distance, and dispersion degree for each grade. Using ArcGIS 10.7, gravity centers and migration paths were calculated:

$$\bar{X} = \frac{\sum_{i=1}^{n} C_{ti} X_i}{\sum_{i=1}^{n} C_{ti}}, \quad \bar{Y} = \frac{\sum_{i=1}^{n} C_{ti} Y_i}{\sum_{i=1}^{n} C_{ti}}$$

where $\bar{X}$ and $\bar{Y}$ represent the longitude and latitude of the gravity center; C_{ti} is the area of ecological index grade i in year t; X_i, Y_i are the centroid coordinates; and n is the number of patches.

2.4 Geographical Detector

Geographical detector models detect spatial heterogeneity and reveal underlying driving forces. Two detectors were employed:

Factor Detection: Measures spatial heterogeneity and the degree to which a factor explains spatial differentiation using the q statistic:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where h is the factor stratification, N_h and N are stratum and total sample sizes, and σ_h^2 and σ^2 are variances.

Interaction Detection: Analyzes whether two factors' combined effect on Y is enhanced or weakened .

Table 3 Two-factor interaction results

Interaction Type	Description
$q(X1 \cap X2) < \min(q(X1), q(X2))$	Nonlinear weakening
$\min(q(X1), q(X2)) < q(X1 \cap X2) < \max(q(X1), q(X2))$	Single-factor nonlinear weakening
$q(X1 \cap X2) > \max(q(X1), q(X2))$	Bifactor enhancement
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear enhancement

3.1 Comparative Analysis of RSEI and MRSEI in Altay City

Based on MRSEI calculation results from 2015–2021, the ecological quality grades were classified . Altay City's ecological quality is predominantly poor, moderate, and good, with relatively small areas of excellent quality. Very poor regions accounted for over 26.88% of the study area, mainly distributed in built-up areas, rural settlements, and industrial zones. Poor regions comprised over 29.81%, primarily in bare land areas of the northern study region. Moderate quality areas exceeded 34.31%, mainly in northern woodlands, southern grasslands, and wetlands. Good quality areas accounted for over 8.52%, distributed in northern and southern woodlands. Excellent quality areas, primarily in cultivated land, woodlands, and wetlands, comprised 0.74% of the study area.

Table 4 Percentage of ecological quality levels

Grade	MRSEI (%)	RSEI (%)
Very Poor	26.88	29.81
Poor	29.81	34.31
Moderate	34.31	38.52
Good	8.52	2.93
Excellent	0.74	2.54

Although MRSEI and RSEI show differences in spatial distribution and magnitude, their overall monitoring trends for Altay City are consistent. The deteriorated or improved areas align closely with AOD severity distribution [Figure 2: see original paper], indicating that urban ecological quality is affected by air quality indicators. In the built-up area where AOD is more severe, the proportion of very poor and poor ecological grades increased compared to RSEI, while moderate, good, and excellent grades decreased. This reflects the overall improvement in Altay City's ecological environment quality from 2015–2021, attributable to afforestation programs, forest industry development, and returning farmland to forest initiatives launched in Xinjiang since 2000. The differences between MRSEI and RSEI are related to AOD spatial distribution, demonstrating that even in Altay City with good air quality, AOD still influences ecological quality spatial patterns.

3.2.1 Spatio-temporal Variation Analysis of MRSEI

Altay City's ecological environment was generally good from 2015–2021 [Figure 3: see original paper]. Poor environmental quality concentrated in southern hilly and intermountain alluvial plain areas, where diverse land use types, suitable climate conditions, dense population, and developed economy led to frequent human activities and comparatively poor ecological quality. Areas near Tangba Lake, the Kelan River, and the Wulumuqi Gaiti River, along with northern mountainous regions, showed better ecological quality due to high vegetation coverage, abundant water resources, and nature reserve advantages.

The average MRSEI values for 2015, 2018, and 2021 were 0.42, 0.45, and 0.47, respectively, showing an upward trend and indicating overall ecological improvement. Analysis of spatial changes across different grades revealed that grade V had the largest gravity center offset distance at 9.720 km, followed by grade I (3.747 km) and grade II (3.044 km), demonstrating substantial spatial shifts. Conversely, grade IV showed the smallest offset at 0.808 km, indicating relatively stable spatial distribution .

Table 5 Center of gravity offset distance and azimuth statistics

Grade	2015–2018	2018–2021	2015–2021
I	2.598 km, 283.4°	1.393 km, 167.5°	3.747 km, 232.0°
II	0.874 km, 218.9°	2.429 km, 203.0°	3.044 km, 198.0°
III	0.661 km, 348.5°	1.759 km, 294.6°	2.342 km, 56.9°
IV	0.243 km, 96.0°	0.661 km, 24.9°	0.808 km, 187.4°
V	9.892 km, 27.1°	5.434 km, 39.0°	9.720 km, 27.1°

The migration directions showed that grade V's center moved consistently northward, while grade I's center moved southward overall, indicating gradual improvement in southern Altay City's ecological quality. Grade II showed complex migration patterns within Qiemuerqieke Township. Grade III shifted southwest in 2015–2018 then northeastward across Balibagai and Qiemuerqieke townships. Grade IV showed a "V-shaped" pattern: first southwest, then continuously northeast. Grade V demonstrated a consistent southward trend, though with some northward movement in 2018–2021, remaining south of the 2015 center position [Figure 5: see original paper].

3.2.2 Standard Deviation Ellipse Analysis

Standard deviation ellipse parameters revealed spatial distribution patterns . For grade V, the long axis shortened from 58.1 km to 47.2 km while the short axis decreased from 57.7 km to 42.3 km, with flattening rate increasing, indicating reduced directional orientation but increased dispersion. Grade I showed opposite trends: long axis increased while short axis decreased, with flattening rate growing, suggesting enhanced directional concentration and reduced dispersion. Grades II-IV generally showed decreasing directional orientation.

Table 6 Standard deviational ellipse parameters for different levels (2015–2021)

Grade	Year	Long Axis (km)	Short Axis (km)	Flattening Rate
I	2015	52.3	33.8	0.35
I	2021	58.1	42.3	0.27
V	2015	58.1	57.7	0.01
V	2021	47.2	42.3	0.10

3.3.1 Single-Factor Detection Analysis

Single-factor detection showed all five factors were significant [Figure 6: see original paper]. The q value measures influence magnitude: larger q indicates greater impact. Overall, humidity, temperature, and air quality showed relatively strong effects, while dryness and greenness were weaker but still significant.

Table 7 PC1 loadings from principal component analysis

Indicator	PC1 Loading
NDVI	+0.515
WET	+0.471
LST	-0.386
NDBSI	-0.502
AOD	-0.363

Dominant factors varied temporally: humidity, temperature, and air quality dominated in 2015; humidity and air quality in 2018; dryness and greenness in 2021, though their influence decreased compared to 2015. Temperature's impact diminished substantially by 2021 ($q = 0.386$). The PC1 loadings show temperature, dryness, and air quality negatively impact ecology, while greenness and humidity have positive effects, consistent with single-factor detection results.

3.3.2 Interaction Analysis

Interaction detection generated ten results, all showing bifactor enhancement or nonlinear enhancement [Figure 7: see original paper]. No independent or weakening relationships existed, indicating that any two-factor interaction's effect exceeds single-factor impacts. The strongest interactions were $AOD \cap LST$ and $LST \cap WET$ ($q = 0.971$). In 2015, six bifactor enhancements and four nonlinear enhancements occurred. In 2018, the pattern was similar but with $AOD \cap NDVI$ showing strongest interaction. In 2021, nonlinear enhancements dominated, with $AOD \cap LST$ remaining strongest but all interaction q values increasing significantly compared to previous years.

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4 Conclusions

This study employed the MRSEI model to investigate spatio-temporal dynamics of ecological quality in Altay City from 2015–2021 and analyzed influencing factors using geographical detector models. The main conclusions are:

1. Greenness and humidity positively correlated with MRSEI, while temperature, dryness, and air quality negatively correlated. Dryness and greenness showed substantial influence, benefiting from forestry ecological projects.

2. Altay City's overall ecological quality improved. Spatially, grades I-II showed strong migration capability while grades III-V remained stable. The grade V center moved southward, indicating improving southern ecological quality, while grades I-IV centers moved northward.
3. All five factors showed significant temporal variation in their influence intensity. Dominant factors shifted from humidity, temperature, and air quality in 2015 to greenness and dryness in 2021. All two-factor interactions exhibited enhancement effects, confirming that ecological quality evolution results from multiple co-acting factors.
4. Despite spatial and magnitude differences between MRSEI and RSEI, their monitoring trends are consistent. These differences relate to AOD spatial distribution, proving that even in areas with good air quality like Altay City, AOD affects ecological quality patterns.

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