Study on Inversion and Spatiotemporal Variation of Soil Organic Matter in Northeast China Based on MODIS Data

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Abstract. This study focused on the Northeast China as the research area, utilizing MODIS data and the XGBoost model to invert soil organic matter content from 2000 to 2024. The inversion results were analyzed for spatiotemporal variation characteristics, in conjunction with the soil nutrient grading standards from the second national soil census in China. The results indicate that the proportion of soil with a rich organic matter grade was the highest, accounting for 52% to 60% of the total, followed by the relatively rich grade, which accounted for 24% to 36%. The proportion of soil with an adequate grade significantly decreased, dropping from 12% to 9%, showing an overall trend of soil organic matter transitioning to higher grades. The central and northwestern regions were the main areas of improvement, while some areas in the northern and southwestern parts experienced soil degradation. The soil organic matter content was highest and most stable under forested surfaces, remained stable under agricultural surfaces, and fluctuated more under grassland surfaces, possibly due to the influences of climate change and land use patterns. The findings reveal the spatiotemporal dynamics of soil organic matter in Northeast China, providing a scientific basis for the development of soil protection and management policies.

Keywords: Soil Organic Matter; Northeast Region; Machine Learning

1 Introduction

Soil Organic Matter (SOM) is a crucial component of soil, playing a key role in physical, chemical, and ecological processes. It serves as an important indicator for measuring soil fertility and functionality[1-2]. As a core factor in soil quality assessment and a foundation for ecosystem stability, SOM is also a focal point for agricultural monitoring

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and soil management[3]. In terms of agricultural production, research by Kane et al.[4] indicates that SOM content is a vital indicator for predicting soil adaptability under future climate change scenarios, especially under more frequent drought conditions. Moreover, the increase of SOM contributes to enhancing the storage of Soil Organic Carbon (SOC) and strengthening the environmental resilience of ecosystems. Additionally, the increase in hydrophobic components within SOM can improve the stability of SOC, thereby reducing greenhouse gas emissions from soil[5]. Understanding the spatial and temporal distribution characteristics and dynamic changes of SOM not only helps improve soil fertility but also provides a basis for formulating scientific soil protection and management policies. Traditional methods for analyzing and assessing the spatial and temporal variation characteristics of SOM are both costly and time-consuming[6]. In recent years, the application of geostatistical methods in the inversion of SOM content has been increasing, but these methods usually require sampling points to be uniform, dense, and representative, and still have limitations in expressing local details[7-8]. The rapid development of remote sensing technology offers a new research approach for SOM inversion. Due to its advantages of wide coverage and real-time dynamic imaging, it has been widely used in the study of SOM spatial distribution characteristics. This study focuses on the Northeast region (including the three provinces of Northeast China and the eastern four leagues of Inner Mongolia) as the research area, conducting a temporal and spatial inversion analysis of SOM from 2000 to 2024. The aim is to reveal the spatial distribution characteristics and temporal variation patterns of SOM in this region. By comparing SOM data from different periods, analyzing trends, and providing a scientific basis for soil protection and management, this study offers valuable insights into the temporal and spatial variation characteristics of SOM in the Northeast region.

2 Study Area and Data

2.1 Overview of the Study Area

The study area is located in the Northeast region of China, encompassing Heilongjiang Province, Jilin Province, Liaoning Province, and the eastern four leagues of Inner Mongolia. It lies between 37°24'N and 53°33'N latitude, and 97°12'E and 135°05'E longitude. The southeastern part of the region includes the Changbai Mountains, Zhangguangcai Ridge, and Hada Ridge. The central area comprises the Songnen Plain, Sanjiang Plain, and Liaohe Plain, characterized by flat terrain. The western part is dominated by the Greater Khingan Range, while the northern part features the Lesser Khingan Range. The southern region borders the Bohai Sea. Influenced by a combination of latitude, topography, and the location between land and sea, the area exhibits a typical temperate continental monsoon climate. Winters are cold and dry, while summers are hot and rainy. The average annual temperature ranges from -1.3°C to 10.5°C, with precipitation decreasing from southeast to northwest, ranging between 250 m and 1000 m[9].

2.2 Remote Sensing Data

The study utilized the MODIS MCD43A3 V6 dataset from 2000 to 2024 during the bare soil period (Table 1). The MCD43A3 V6 albedo dataset is a 16-day composite product with a resolution of 500 meters per pixel. It includes seven bands of MODIS surface reflectance data, as well as the black-sky and white-sky albedos for the visible, near-infrared, and shortwave spectral bands. Additionally, each albedo band is accompanied by corresponding quality assessment data. The images are generated based on 16-day data, represented by the central date. To comprehensively characterize the ecological environment, various remote sensing vegetation indices and topographic factors were employed. The vegetation indices included the Normalized Difference Vegetation Index (NDVI))[10], the Green Normalized Difference Vegetation Index (GNDVI)[11], and the Ratio Vegetation Index (RVI)[12], which are used to measure vegetation coverage, nitrogen content, and health status, respectively. The topographic factors encompassed basic parameters such as elevation, slope, and aspect, as well as complex features like profile curvature, plan curvature, terrain relief, terrain roughness, and surface cutting depth[13-15]. These data provide essential support for exploring the spatiotemporal variations of soil, vegetation, and their ecological processes using remote sensing technology.

Table 1. MCD43A3 V6 impact band parameter information

Band Name	Spectral properties	Center wavelength (nm)	Wavelength range (nm)	Spatial resolution (m)
Band1	Red Band	645	620-670	500
Band2	Near-Infrared Shortwave-1 (NIR-SW1)	858.5	841-876	500
Band3	Blue Band	469	459-479	500
Band4	Green Band	555	545-565	500
Band5	Near-Infrared Shortwave-2 (NIR-SW2)	1240	1230-1250	500
Band6	Shortwave Infrared-1 Band (SWIR-1)	1640	1628-1652	500
Band7	Shortwave Infrared-2 Band (SWIR-2)	2130	2105-2155	500

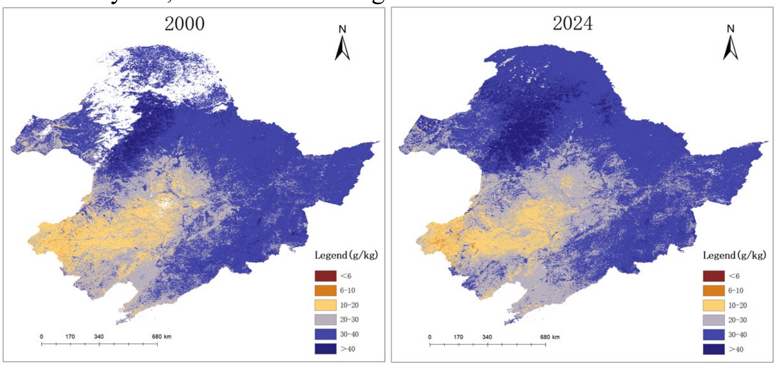
2.3 Soil Organic Matter Data

The national standard grading for soil organic matter monitoring is established based on the outcomes of the second national soil census in China, and is categorized according to soil nutrient grading standards[16]. The second national soil census is the largest soil resource survey in the history of China, systematically collecting and analyzing soil types and their nutrient characteristics across different regions, laying the foundation for the development of scientifically rational soil organic matter grading standards. In this study, 128 topsoil samples (0-20 cm) were collected and their organic matter content was measured, providing fundamental data for the subsequent model construction. Specifically, the samples were distributed across 25 points in eastern Inner Mongolia, 12 points in Liaoning, 16 points in Heilongjiang, and 75 points in Jilin.

3 Results and Analysis

3.1 Accuracy Analysis of Soil Organic Matter Inversion Using XGBoost Model

The soil sample data was divided randomly into a training set (80%) and a test set (20%). An XGBoost algorithm model was developed using the training set, and its performance in predicting soil organic matter content was assessed with the test set. The model incorporated various factors, including MODIS bands 1-7, Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Ratio Vegetation Index (RVI), as well as topographical features such as elevation, slope, aspect, profile curvature, plan curvature, terrain relief, terrain roughness, and surface cutting depth. The model's accuracy was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE), with values of $R^2 = 0.675$ and RMSE = 5.3715 g/kg. These results indicate a relatively low prediction error (as evidenced by the small RMSE) and a high inversion accuracy (as indicated by the high R^2), showcasing the XGBoost algorithm's effectiveness in predicting soil organic matter content. The XGBoost model was then applied to estimate soil organic matter content for different years, as illustrated in Fig. 1.



a. 2000year b. 2024year

Fig. 1. Remote sensing inversion map(a.2000year, b.2024year)

3.2 Analysis of Temporal Variation Characteristics of Soil Organic Matter Based on MODIS Data

From 2000 to 2024, significant changes in the proportions of different soil organic matter (SOM) levels were observed. The proportion of extremely rich SOM showed an overall upward trend, increasing from 4.74% in 2000 to 7.15% in 2024, with the lowest value recorded in 2010 (1.50%). The proportion of rich SOM remained relatively stable, ranging between 52% and 60%, reaching its highest value in 2003 (59.91%) and its lowest in 2010 (52.25%). The proportion of moderately rich SOM fluctuated significantly, ranging from 24% to 36%, with the highest value in 2004 (35.13%) and the lowest in 2009 (24.71%). The proportion of adequate SOM showed a downward trend, ranging from 6% to 14%, peaking in 2010 (14.43%) and dropping to its lowest in 2012 (6.16%). The proportions of poor and extremely poor SOM showed smaller fluctuations, with the former ranging from 0.04% to 0.35%, reaching the highest value in 2015 (0.35%) and the lowest in 2011 (0.04%); the latter remained below 0.06%, with the highest value recorded in 2023 (0.06%). Overall, rich and moderately rich SOM accounted for the majority of the proportions, with the extremely rich soil proportion gradually increasing, while the adequate soil proportion showed a decreasing trend; the proportions of poor and extremely poor soils were low, with small amplitude changes (Fig. 2). From 2000 to 2024, the average annual SOM content under different land cover types showed significant differences and trends (Fig. 3). Forest soils had the highest SOM content, with an average of 36.34 g/kg, showing small fluctuations and indicating a stable organic matter accumulation capacity in their ecosystems. Farmland soils had a relatively stable SOM content, with an average of 28.92 g/kg and a small range of variation, suggesting a generally balanced content change. Grassland soils exhibited larger fluctuations in SOM content, ranging from 24.45 g/kg to 26.51 g/kg, which may be significantly influenced by climate change and land use intensity. In the long term, although forest soils maintained high SOM levels, there was a slight downward trend. Farmland soils showed stable changes, while grassland soils exhibited more pronounced fluctuating characteristics.

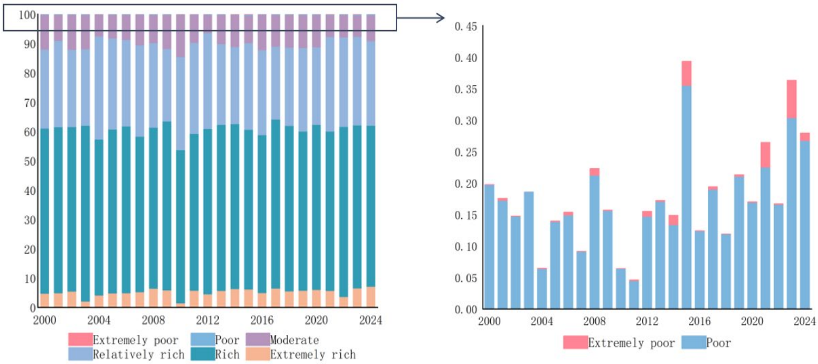


Fig. 2. Interannual Variation of Soil Organic Matter Inversion Grade Proportions from 2000 to 2024 (%)

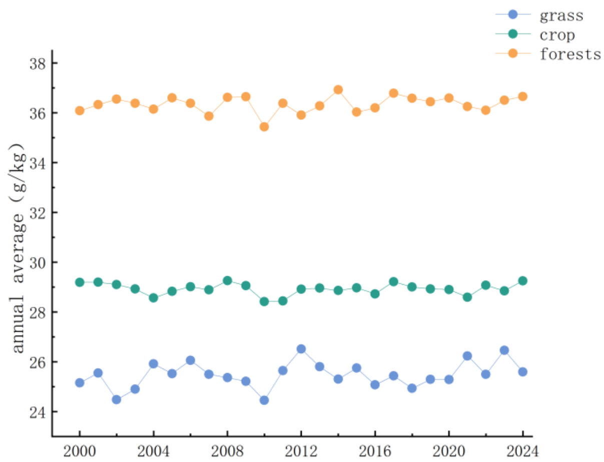


Fig. 3. Interannual Variation of Average Annual Content of Soil Organic Matter Inversion for Different Underlying Surfaces from 2000 to 2024

3.3 Analysis of Spatial Variation Characteristics of Soil Organic Matter Based on MODIS Data

Based on the overlay of soil organic matter (SOM) inversion data from 2000 and 2024, the grade transfer matrix of SOM during the period from 2000 to 2024 was obtained, and the changes in each grade were calculated (Table 2). The moderately rich grade of SOM was the main area of improvement, with a net increase in area of 63,450.25 km² and a transfer rate of 48.32%. At the same time, the rich grade of SOM experienced a net decrease in area of 45,055.25 km², with the reduction transferring to the extremely rich grade. The moderate grade of SOM showed a net decrease in area of 27,458.75 km², indicating a large-scale transformation of SOM from the moderate grade to higher grades. The changes in the less rich and poor grades were small, suggesting limited improvement potential for low-grade soils. The spatial distribution map (Fig. 4) shows that the central and northwestern parts of the study area were the main areas of improvement, with soil transforming into rich and extremely rich grades. This is closely related to ecological measures such as agricultural fertilization, irrigation improvement, and vegetation restoration, reflecting the positive effects of ecological management. The unchanged areas accounted for the majority of the spatial distribution, indicating that the SOM in these regions was in a state of balance with minimal external influence. The northern and southwestern parts of the study area were the main areas of degradation, with soil degrading to moderate and moderately rich grades, possibly due to the combined effects of over-cultivation, human activities, and climate change. Overall, the areas of improved soil quality were concentrated, while the degraded areas were more scattered. This suggests that ecological restoration measures have achieved significant results in certain areas, while other areas face the risk of degradation.

Table 2. Grade Transition Matrix for Soil Organic Matter Inversion in Northeast China from 2000 to 2024 km²

2000	2024					
	Extremely poor	Poor	Moderate	Relatively rich	Rich	Extremely rich
Extremely poor	0	0.5	7	0.75	0.5	0
Poor	27.75	449.5	1767.5	281.5	18	2
Moderate	144	3222.25	86153.525	58848.75	3507.25	89
Relatively rich	4.75	159.75	34461.5	229237.25	79387.25	2812.25
Rich	0.25	4.75	2052.25	120402	565930	35309
Extremely rich	0.25	0	64.25	742.75	29800	30353.75

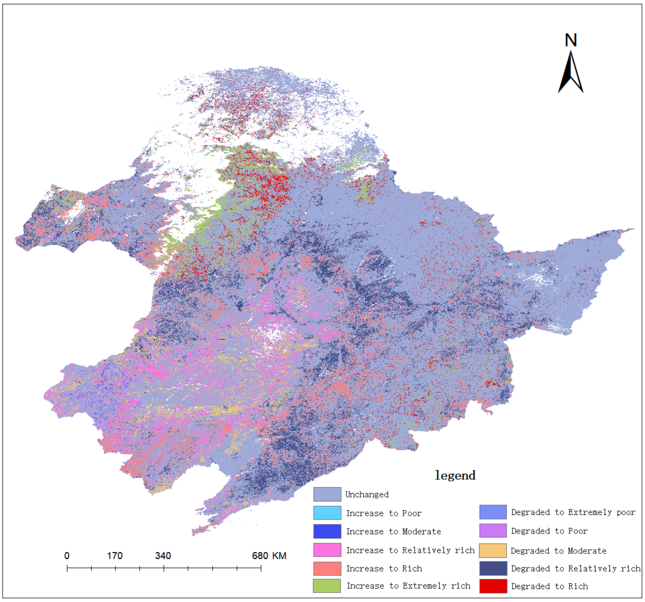


Fig. 4. Changes in spatial pattern of soil organic matter from 2000 to 2024

4 Conclusions

The main conclusions of this study, based on the spatiotemporal mapping analysis of soil organic matter data in Northeast China from 2000 to 2024 using MODIS data, are as follows:

(1) From 2000 to 2024, the proportion of high-grade SOM in the Northeast region increased, with a significant rise in the proportion of rich and extremely rich grade soils, while the proportion of moderate-grade soils continued to decrease.

(2) The central and plain areas were the main areas of improvement, with a significant increase in the area of rich and extremely rich grade soils. Soil degradation

occurred in some areas in the northern and southwestern parts, which require focused protection and management.

(3) The SOM content under forest land cover was the highest, with an average of 36.34 g/kg and minimal fluctuation, indicating the stability of forest ecosystems. The SOM content under farmland land cover was relatively stable, with an average of 28.92 g/kg and minimal influence from external factors. The SOM under grassland land cover showed significant fluctuations, ranging from 24.45 to 26.51 g/kg, and further targeted protection and management measures are needed.

This study provides an important basis for the monitoring and management of spatiotemporal changes in SOM in the Northeast region. However, it is necessary to further explore the driving factors and mechanisms of SOM changes. In the future, combining factors such as climate change and land use change will enhance the precision and timeliness of the analysis, providing more scientific decision support for the sustainable management of regional soil resources and ecological protection.

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