Quantifying the Relative Contributions of Climate Change and Human Activities to Vegetation Recovery in Shandong Province of China

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Abstract

As global climate change intensifies, with frequent extreme weather events, the stability of vegetation is severely threatened. This study (2002–2023) uses NDVI, temperature, and precipitation data, along with methods like pixel binary, trend analysis, and multiple regression residual analysis, to simulate vegetation coverage changes in Shandong Province and its 16 cities. By comparing potential and actual NDVI, it assesses the benefits provided by climate change and human activities to vegetation recovery. Results show that from 2002 to 2023, Shandong's cities had moderate to high vegetation coverage. Linyi City has the highest, while Tai'an City has the lowest. CC and HA jointly boosted rapid growth of the vegetation NDVI during the growing period (growth rate of $5.36 \times 10^{-3} \cdot a^{-1}$), with 72.1% of the area experiencing significant growth. Within the cities, the fastest NDVI increase was observed in Rizhao (growth rate of $7.22 \times 10^{-3} \cdot a^{-1}$). HA had a substantial positive effect on vegetation recovery in Shandong, while climate change primarily had a moderate positive effect. The relative contribution

rates were 73.4% and 21.2%, respectively. In cities such as Liaocheng, Jining, and Zibo, human activities accounted for more than 90% of the contribution, while climate change notably promoted vegetation recovery in Rizhao. NDVI showed a significant decline in areas where climate change exerted slight suppression and human activities had a moderate suppressive effect, particularly in the border areas of Qingdao, Rizhao, Zaozhuang, and some city centres.
Keywords: Climate change; Vegetation coverage; Normalised Difference Vegetation Index (NDVI); Human activities; Contribution analysis

1.Introduction

Since the 1990s, CC and the enforcement of major habitat restoration projects have significantly promoted vegetation recovery in the eastern part of China and the Yellow River Basin (Li et al., 2019; Wang et al.,2024). Shandong Province, found in the middle reaches of the Yellow River, is situated in a transition zone with a predominantly mountainous terrain, turning it into a typical ecologically fragile area (Wen et al., 2024). Conducting articles on the dynamic changes in vegetation and the driving mechanisms in Shandong Province is of crucial importance for evaluating the effectiveness of ecosystem rehabilitation in fragile areas and further advancing ecological governance in the North China Plain and the Yellow River Basin (Feng et al., 2022).

Against the background of climate warming, extreme climatic events have had a profound impact on the structure and ecological framework of ecosystems. Vegetation, one of the essential components of terrestrial ecosystems, is also the most sensitive to climate transition (Wernberg et al., 2013). The proportion of land warming in China is significantly higher than the global average (Sun et al., 2016), leading to frequent natural disasters such as extreme droughts, high temperatures, and heavy rainfall. These events have caused land degradation, vegetation decline, and soil erosion, severely affecting human life and production (Wen et al.,2024). The response of ecosystems to CC is a crucial measure of resilience, with less resilient ecosystems being more sensitive to external disturbances or environmental changes (Forzieri et al., 2022). In some regions, vegetation recovery is slow under extreme climatic conditions. Moreover, in areas with higher sensitivity, vegetation systems respond more intensely to external disturbances, increasing the risk of vegetation degradation (Huang et al., 2016). Consequently, quantifying the sensitivity of vegetation in China to CC and HA under global warming provides a deeper understanding of regional ecological changes and has significant practical implications for protecting the ecological environment and easing the adverse impacts of CC (Chen et al., 2020).

The Normalised Difference Vegetation Index (NDVI) is an effective indicator of extensive vegetation coverage and growth status (Zhang et al., 2016), influenced by factors such as climate (Dubovyk et al., 2016), topography (Nie et al., 2021), and human activities (HA) (Gu et al., 2022). Among these factors, air temperature and rainfall are considered key climate variables that influence the spatial distribution of NDVI (Gao et al., 2019), while ecological protection projects have been found to exhibit a highly significant correlation with NDVI and are considered the key human activity driving regional vegetation recovery (Cai et al., 2015). However, the effectiveness of ecological protection projects remains controversial, largely due to the consequence of regional natural geographical conditions (Liu et al., 2020; Zeng et al., 2024). The distinction between potential vegetation NDVI and actual vegetation NDVI reflects the impact of HA on vegetation change. Residual analysis has been proven effective in isolating the influence of climate components on vegetation coverage and assessing the contribution of human activities (Huang et al., 2021).

Recent studies based on long-term NDVI datasets have assessed vegetation coverage in Shandong Province and its relationship with CC and HA. These articles have shown that both CC and HA have jointly promoted vegetation recovery in Shandong (Naeem et al., 2020). Throughout the province, both temperature and precipitation exhibited increasing trends (Zeng et al., 2016), accompanied by a sequence of ecological protection projects, such as the conversion of farmland to forests in the northern sandy and hilly areas, and afforestation along the Yellow River and in the Tai Mountain range. These efforts have led to noticeable improvements in vegetation greening, with some areas showing slight vegetation degradation but an overall improving trend. Except for certain years when vegetation coverage declined significantly, the growth rate of vegetation coverage in Shandong ranked among the top in the country (Chao et al., 2018; Zeng et al., 2025). However, regional disparities were significant, with vegetation coverage showing a gradual transition from high in the southeast to low in the northwest, and the vegetation coverage being highest in mountainous areas, followed by plains, with the lowest coverage in plateau and hilly areas (Wang et al.,2024). The southeastern region exhibited relatively high vegetation coverage, while the northwestern region showed lower coverage, and the central basin had relatively sparse vegetation. During the growing season, vegetation recovery in the province was rapid and strongly influenced by human activities, which contributed more than 60% to the recovery (Shen et al.,2024). The overall pattern was characterised by higher vegetation coverage rising in the west and falling in the east, while frequent human activities in the central urban areas inhibited vegetation improvement (Wang et al.,2024).

Up to now, numerous articles have employed partial correlation analysis and autoregressive models to investigate the sensitivity of vegetation to climate change (CC), achieving significant results (Lu et al., 2024). Previous article has explored the response of vegetation to climatic factors across different climatic zones using sensitivity indices (Luo et al., 2023), and has analysed the spatial variability in vegetation sensitivity across regions. However, most existing studies on vegetation sensitivity have only considered the impact of climatic factors in the current month, neglecting the cumulative and lagged effects of these factors on vegetation. With the rapid advancement of remote sensing technology and the increasing deployment of ecological remote sensing, multi-source remote sensing data products have been utilised in conjunction with autoregressive models to examine the responsiveness of vegetation to CC (Yang et al., 2024). Existing research has identified that the sensitivity of vegetation is primarily influenced by precipitation, solar radiation, and temperature, although few studies have quantitatively analysed vegetation sensitivity. Given that vegetation sensitivity varies across regions due to differing climatic conditions, and that most current research focuses on a global scale while neglecting China's unique climatic characteristics, few studies have categorically explored vegetation sensitivity according to climatic zones (Liu et al., 2013). Therefore, this study, from a quantitative perspective, comprehensively considers the impact of cumulative and lagged effects and focuses on the spatial distribution patterns of vegetation sensitivity across different climatic zones in Shandong Province, China, to furnish a scientific basis for addressing extreme climatic events.

Previous studies have conducted in-depth analyses of vegetation coverage changes and their dominant factors in Shandong Province and certain key cities over different periods (Ma et al.,2024). However, research on the proportional contributions of CC and HA to vegetation dynamics and ecological restoration has been limited, with few studies exploring the differences between the cities of Shandong (Ren et al., 2024). Therefore, this study employed methods such as the pixel binary method, trend analysis, and multiple regression residual analysis to examine the spatio-temporal changes in vegetation coverage from 2002 to 2023 during the growing period (April–October) across Shandong Province and its 16 cities. By comparing potential vegetation NDVI with actual vegetation NDVI, the study aimed to determine the relative contributions of CC and HA to vegetation recovery in Shandong (Wen et al.,2024). The results of this study are intended to provide a theoretical foundation for the composition of land use and ecosystem protection strategies in Shandong, facilitate the dynamic adjustment of sustainable governance measures based on the actual ecological restoration situation in each city, and support the development of ecological zoning for protection and restoration.

This study contributes to the understanding of vegetation recovery in Shandong Province through four key advancements: (1) Quantitative assessment: It evaluates the combined effects of CC and HA on vegetation recovery applying multiple regression residual analysis and pixel dichotomy methods, unlike previous studies focusing solely on climate change. (2) Lag effects analysis: The study incorporates the cumulative lag effects of CC on vegetation, providing a more accurate assessment of its role by addressing long-term and indirect impacts often overlooked in traditional research. (3) Regional variations: Analysis across 16 cities reveals significant regional differences in the impacts of CC and HA. For instance, HA contributed over 90% to vegetation recovery in Liaocheng, Jining, and Zibo, while climate change was more prominent in Rizhao. (4) Relative contributions: Both CC and HA jointly promoted vegetation recovery, with human activity being more influential in southern regions. The study identifies areas needing enhanced ecological restoration efforts and highlights potential underrepresentation of climate change effects.

By considering the lag effects of CC, this study fills a gap in previous research and presents new perspectives and methods for advancing vegetation restoration.

This study is organized as follows, Chapter 2 explores the area of study and research methodology, Chapter 3 describes the findings and analysis of this paper, Chapter 4 discusses the results of this paper, and Chapter 5 the conclusions of this paper.

2. Research area and methodology

2.1 Overview of the study area

Shandong Province (34°30′–38°15′N, 114°50′–122°50′E) is positioned in the eastern-central part of China, situated between the middle reaches of the Yellow River and the North China Plain. It covers a total size of about 157,900 km² and is divided into 16 administrative cities. The region's topography is characterised by typical mountainous terrain, with mountainous and hilly areas owing to over 80% of the total land area. The elevation decreases from southeast to northwest. The area experiences a temperate monsoon climate with continental features, with significant diurnal temperature variation (Dong et al., 2023). The annual average temperature varies from -4°C-23°C. Precipitation varies between 437.6 mm and 849.4 mm per year, with rainfall concentrated between June and August, attributing to about 80% of the annual total (Lu and Zeng, 2023; Li et al.,2024). As a crucial ecological defensive barrier in China, Shandong has long been committed to the formation of ecological civilization (Zeng et al., 2023; Wu et al.,2024). The province has pioneered a new model for ecological restoration and protection, characterised by basin-wide planning, integrated mountain system management, and regional implementation (Cui et al.,2022). The area of afforested land has ranked first in China for three consecutive years, contributing to the continuous expansion of the green landscape (Zeng et al.,2024). Figure 1 shows the schematic map of the Shandong Province.

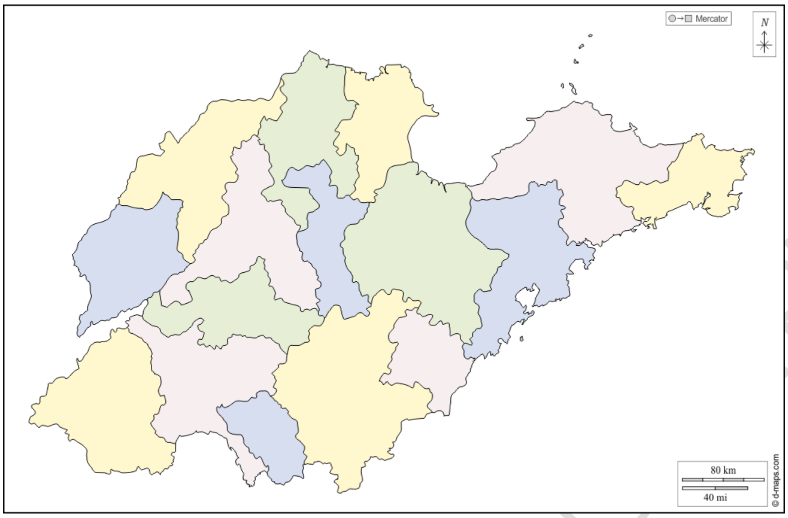

Figure 1. Schematic map of the Shandong Province

2.2 Data collection and processing

The 1 km resolution monthly vegetation NDVI dataset, average temperature dataset, and precipitation dataset required for this study were derived from the National Earth System Science Data Centre (https://www.geodata.cn). The administrative boundaries of Shandong Province and elevation data were acquired from the Resources and Environmental Science Data Centre (https://www.resdc.cn). The data were pre-processed through format conversion, coordinate transformation, and clipping to produce the vegetation NDVI, average temperature, and cumulative precipitation data for the growing period in Shandong Province from 2002 to 2023.

2.3 Calculation methods

2.3.1 Vegetation coverage

Due to the absence of field observational data, the article assumed that the images of the research area consisted of two parts: areas with vegetation cover and areas without vegetation cover. Vegetation coverage (FVC) was estimated applying the pixel binary function (Zhang et al., 2023).

$$FVC = \frac{NDVI - NDVI_{\text{soil}}}{NDVI_{\text{veg}} - NDVI_{\text{soil}}} \tag{1}$$

In the equation, $\mathrm{NDVI_{soil}}$ represents the NDVI amount of bare soil pixels, which is taken as the 5th percentile of NDVI. $\mathrm{Neg_{veg}}$ represents the NDVI value of pure vegetation-covered pixels, which is taken as the 95th percentile (Wilker et al., 2014; Wu et al., 2025). Grounded in the calculation findings, vegetation coverage was categorised as follows: low vegetation coverage (<30%), low-moderate vegetation coverage (30%-45%), moderate vegetation coverage (45%-60%), moderate-high vegetation coverage (60%-75%), and high vegetation coverage (≥75%) (Zhang and Wang, 2023).

2.3.2 Trend analysis

NDVI was applied as the dependent variable, and the year was treated as the independent variable. A univariate linear regression function was established to analyse and quantify the degree and direction of the trend in NDVI over time.

$$\text{slope} = \frac{n\times\sum_{i=1}^{n}(i\times NDVI_i)-\sum_{i=1}^{n} i\sum_{i=1}^{n} NDVI_i}{n\times\sum_{i=1}^{n} i^2-\sum_{i=1}^{n} i} \tag{2}$$

In the equation, slope represents the average trend rate of NDVI, n denotes the number of years, which was set to 21 in this article. i represents the time variable, ranging from 1 to n (integer values), and $NDVI_i$ represents the mean NDVI value for the growing time in year *i*.

2.3.3 Multiple regression residual analysis

Following the way of Hou et al. (2015) and Xia et al. (2024), multiple regression analysis was accustomed to examine the connection between vegetation NDVI, average temperature, and cumulative precipitation. Residual analysis was then conducted to evaluate the model's fit and the degree to which it satisfied the assumptions.

$$NDVI_{CC} = a \times T + b \times P + c \tag{3}$$

$$NDVI_{HA} = NDVI_{OB} - NDVI_{CC} \tag{4}$$

In the equation, a, b, and c show the framework parameters. T denotes the average temperature, P represents cumulative precipitation, $NDVI_{CC}$ refers to the NDVI value under the impact of climate transition. $NDVI_{HA}$ refers to the NDVI value under the impact of human activities, and $NDVI_{OB}$ represents the NDVI value from remote sensing imagery.

2.3.4 Determination of NDVI change drivers and contribution calculation

Based on the criteria proposed by Liu et al (2021) and Zou et al (2024), the influence of CC and HA on regional vegetation recovery was classified according to the trend rate of NDVI under their influence. The NDVI trend rates under climate change or human activity influences were categorised as follows: < -2.0, $[-2.0, -1.0)$, $[-1.0, -0.2)$, $[-0.2, 0.2)$, $[0.2, 1.0)$, $[1.0, 2.0)$, and ≥ 2.0. These ranges represented the influence of CC and HA on regional vegetation recovery as: significant, moderate and slight inhibition, negligible effect, slight promotion, moderate promotion, and significant promotion, respectively. Furthermore, the main drivers of NDVI change were identified, and the relative contributions of CC and HA to regional NDVI change were calculated. Negative signs in the results indicated that the factor had a negative impact on NDVI change, implying vegetation degradation or a reduced level of recovery.

3. Findings and analysis

3.1 Temporal and spatial variation of vegetation NDVI and coverage in Shandong province

From 2002-2023, the overall NDVI in Shandong Province indicated a significant fluctuating upward trend, with values ranging from 0.36-0.60. The average trend rate was $5.36 \times 10^{-3} \cdot a^{-1}$, with the maximum and minimum values occurring in 2023 and 2002, respectively (Figure 2). The area with an rise in NDVI during the growing period of the study period accounted for 96.8%, with 72.1% of the area showing a significant increase in NDVI (slope $\geq 4 \times 10^{-3} \cdot a^{-1}$). The area with a decrease in NDVI attributed to only 3.2% of the total area, located at the borders of Qingdao, Rizhao, and Zaozhuang cities, as well as parts of urban centres (Figure 3). The NDVI in all 16 prefecture-level cities exhibited an increasing trend, with average NDVI values ranging from 0.36 to 0.60. Among them, Linyi had the highest average NDVI, while Tai'an had the lowest. Rizhao exhibited the fastest NDVI growth, while Linyi showed the slowest (Table 1).

Between 2002 and 2022, the average vegetation coverage was 84.21%. The spatial distribution of vegetation coverage gradually increased from the northwest to the southeast, exhibiting distinct strip-like characteristics. Vegetation coverage was predominantly in the moderate (26.8%), moderate-high (32.7%), and high (37.4%) coverage categories, while low vegetation coverage (0.3%) and low-moderate vegetation coverage (2.8%) were relatively minor. Overall, the vegetation coverage was high (Figure 4). Dongying, Rizhao, and Tai'an were areas with moderate vegetation coverage, while Jinan, Weifang, Binzhou, and Heze were areas with moderate-high vegetation coverage. Liaocheng, Zibo, Dezhou, Zaozhuang, Qingdao, Yantai, and Weihai were regions with high vegetation coverage. Among these, Jining had the lowest vegetation coverage at 54.76%, while Zibo had the highest at 77.30% (Table 1).

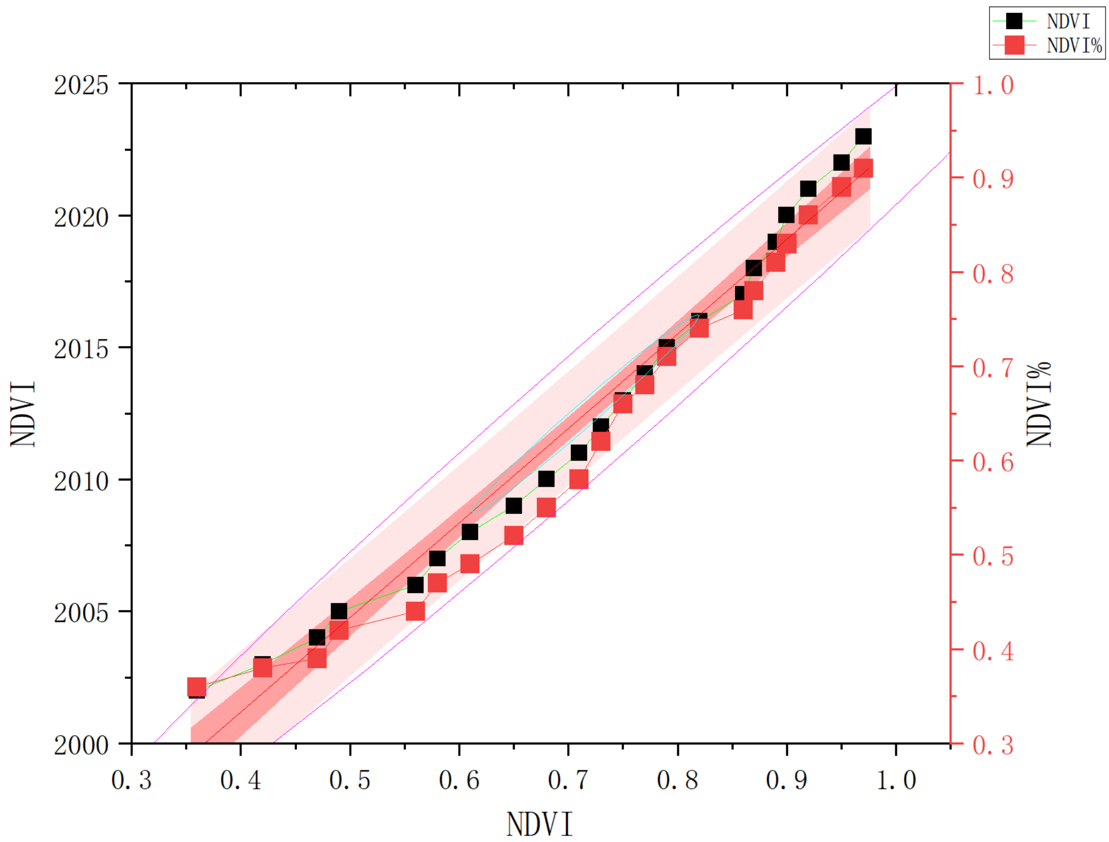

Figure 2. Interannual variation of vegetation NDVI in Shanxi Province from 2002 to 2023.

NDVI: Normalized difference vegetation index.

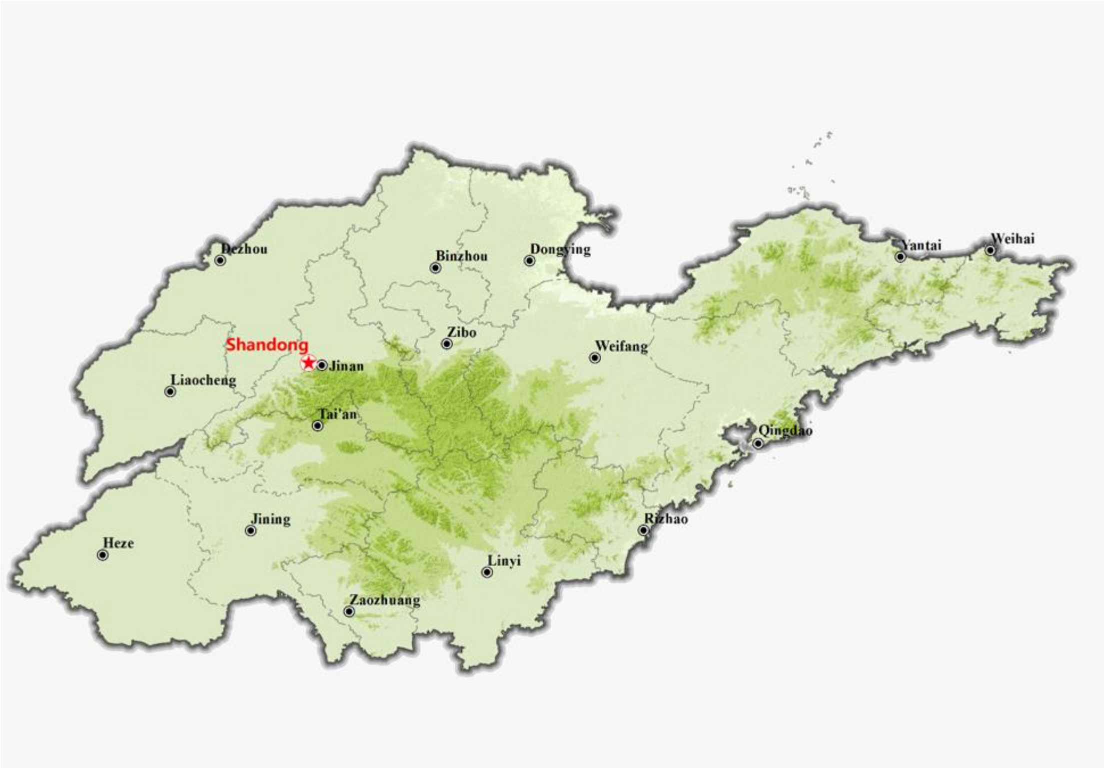

Figure 3. Annual average fractional vegetation cover (FVC)

Table 1. Annual average NDVI and vegetation cover of 16 prefecture-level cities in Shandong Province

Region	Annual average NDVI	Slope (NDVIOB)/（$\times10^{-3}\cdot a^{-1}$）	Fractional vegetation cover/%
Jining	0.41	5.14	54.76
Jinan	0.48	5.84	69.29
Dongying	0.37	4.70	71.05
Dezhou	0.51	5.01	74.76
Weihai	0.52	5.39	76.94
Rizhao	0.48	7.22	67.27
Qingdao	0.53	5.76	74.12
Weifang	0.43	5.37	65.99
Taian	0.36	5.23	51.28
Liaocheng	0.55	3.80	76.35
Zaozhuang	0.53	4.78	73.17
Linyi	0.60	3.54	84.21

Zibo	0.57	3.15	77.30
Heze	0.45	5.23	64.90
Yantai	0.47	4.64	75.39
Binzhou	0.43	5.19	71.04

3.2 The impact of CC and HA on vegetation recovery in Shandong province's growing season

From 2002 to 2023, approximately 94.18% in Shandong Province exhibited an increasing trend in vegetation NDVI during the growing season. Of this, 91.56% of the area experienced a joint promotion from both climate change and human activities, while 4.78% was influenced solely by human activities, primarily in Liaocheng, Jining, and Zibo cities. A small portion, 0.33%, showed a positive influence from climate change alone.

Conversely, about 3.42% of the area displayed a decreasing trend in vegetation NDVI during the growing season. Of this, 2.41% experienced joint suppression from CC and HA, mainly located at the boundaries of Qingdao, Rizhao, and Zaozhuang cities, as well as in a few urban centres. An additional 0.56% of the area was solely affected by human activities, while 0.42% was influenced exclusively by climate change (Figure 4).

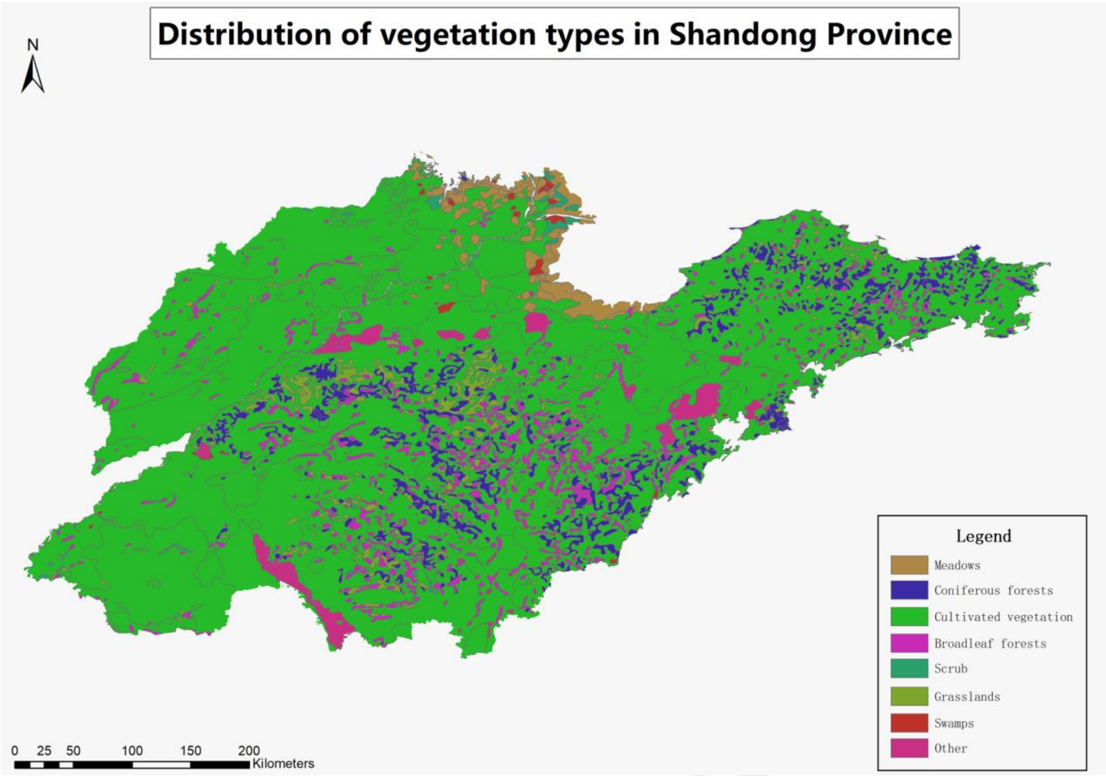

Figure 4. Spatial distribution of vegetation recovery status due to different drivers

Overall, CC and HA primarily had a positive impact on vegetation recovery during the growing season in Shandong Province (Cui et al.,2022). Among these, climate change exerted a moderate positive influence, while HA had a significant positive impact. The area proportions of vegetation recovery in the growing season due to climate change were 84.57% for promotion, 11.56% for no significant effect, and 3.49% for suppression. The areas where climate change had a significant promoting effect were concentrated in the central and western parts of Shandong Province; moderate and slight promoting effects were mainly observed in the northern and southern areas; and suppression was primarily found at the boundaries of Jinan, Rizhao, and Zaozhuang cities, as well as in Changzhi, Jining, and Zibo cities (Figure 5).

Human activities promoted vegetation recovery during the growing season in 96.43% of the region, had no significant effect in 1.10%, and suppressed vegetation recovery in 2.65%. Except for the urban centres of Qingdao, Jinan, and a few other cities, areas where human activities promoted vegetation recovery were evenly distributed across the province. The areas where human activities suppressed vegetation recovery were located at the boundaries of Qingdao, Rizhao, and Zaozhuang cities, as well as in some urban centres (Figure 6).

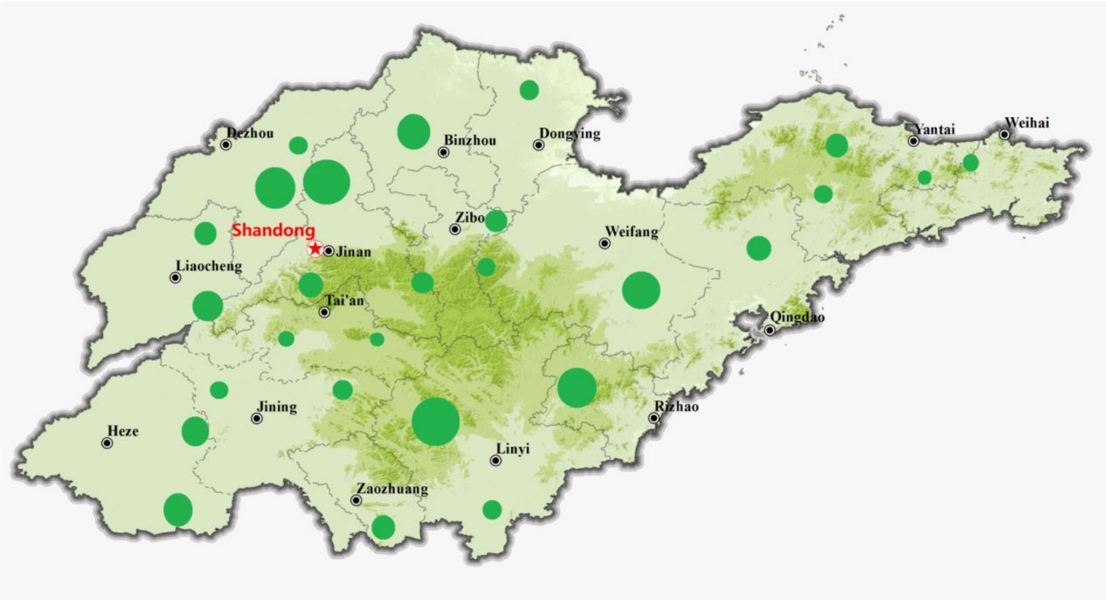

Figure 5. Spatial distribution of CC impacts on vegetation restoration

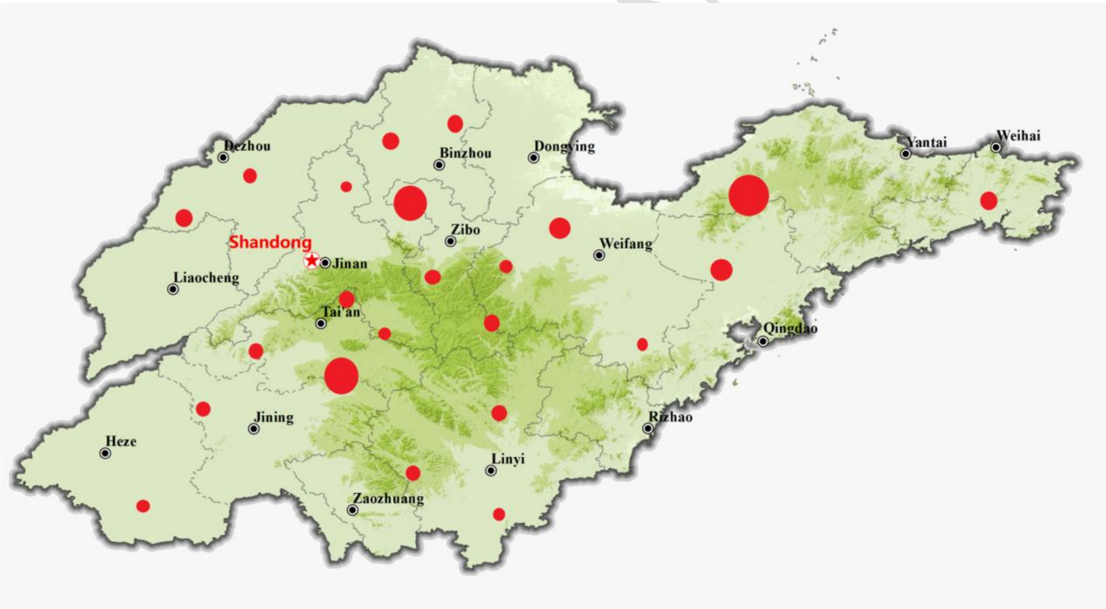

Figure 6. Spatial distribution of anthropogenic impacts on vegetation recovery

3.3 The relative contribution of CC and HA to vegetation recovery in Shandong province during the growing season

From 2002 to 2023, human activities and climate change contributed 71.56% and 20.38%, respectively, to vegetation recovery during the growing season in Shandong Province. The relative contribution of CC ranged from 0%-40%, with areas where the contribution was between 0%–20% and 20%–40% accounting for 33.52% and 42.27%, respectively. Spatially, CC had a higher relative contribution in the central and northern regions of Shandong, with an average contribution exceeding 20%. The relative contribution of CC was lower in Weifang, Dezhou, Jining, and Tai'an cities, with an average contribution not exceeding 20%. Very few areas experienced a negative relative contribution from climate change, mainly located at the boundaries of Qingdao, Rizhao, and Zaozhuang cities, as well as in the central areas of Dezhou, Jining, and Linyi cities, with an average relative contribution of approximately -20%.

The relative contribution of HA was concentrated between 60% and 100%, with areas where the contribution ranged from 60%–80% and 80%–100% accounting for 42.34% and 41.17%, respectively. Spatially, HA had the highest relative contribution in the southern regions of Shandong, with an average contribution exceeding 70%. Very few areas experienced a negative contribution from human activities, which were mainly located at the boundaries of Qingdao, Rizhao, and Zaozhuang cities, as well as in a few urban centres, with a relative contribution of approximately -80%.

In all 16 prefecture-level cities, vegetation recovery during the growing season was influenced by both CC and HA. Climate change had a significant positive impact on vegetation recovery in Rizhao, a low positive impact in Liaocheng, Jining, and Dezhou, and a moderate positive impact in the remaining cities. Human activities significantly promoted vegetation recovery in all 16 cities, with relative contributions exceeding 60%. Notably, human activities contributed more than 90% to vegetation recovery in Dezhou, Jining, and Zibo cities (Table 2).

Table 2. Impacts and relative contributions of NDVI drivers during the growing season in 16 prefecture-level cities in Shandong Province

Region	Climate change		Human activity		
	Impact degree	Relative contribution rate/%	Impact degree	Relative contribution rate/%	Driving force
Jining	Mild promotion	7.28	Clear promotion	91.98	CC&HA

Jinan	Clear promotion	29.04	Clear promotion	89.26	CC&HA
Dongying	Clear promotion	21.26	Clear promotion	78.15	CC&HA
Dezhou	Mild promotion	8.45	Clear promotion	82.43	CC&HA
Weihai	Mild promotion	4.19	Clear promotion	89.69	CC&HA
Rizhao	Modest promotion	14.81	Clear promotion	91.20	CC&HA
Qingdao	Modest promotion	11.60	Clear promotion	77.46	CC&HA
Weifang	Clear promotion	28.37	Clear promotion	68.88	CC&HA
Taian	Mild promotion	6.53	Clear promotion	79.34	CC&HA
Liaocheng	Clear promotion	19.80	Clear promotion	93.93	CC&HA
Zaozhuang	Modest promotion	16.24	Clear promotion	72.11	CC&HA
Linyi	Clear promotion	21.26	Clear promotion	69.30	CC&HA
Zibo	Clear promotion	23.58	Clear promotion	97.22	CC&HA
Heze	Modest promotion	19.77	Clear promotion	80.46	CC&HA
Yantai	Modest promotion	15.50	Clear promotion	82.35	CC&HA
Binzhou	Contribute	6.10	Clear	75.50	CC&HA

slightly	promotion

CC: Climate change; HA: Human activity

4. Discussion

The study data in this paper cover the vegetation cover changes in Shandong Province and its 16 prefectural-level cities during the period from 2002 to 2023, and are mainly based on monthly Normalised Vegetation Index (NDVI) data at 1-km resolution, as well as monthly mean temperature and monthly cumulative precipitation data for the same period. These data were derived from the National Earth System Science Data Centre (NESDC) and were used to analyse the spatial and temporal changes in vegetation cover and the direct influence of climatic factors on vegetation. The study also used administrative boundaries and elevation data of Shandong Province provided by the Resource and Environmental Science Data Centre to support the spatial analysis and presentation of results. In addition, through the literature review and relevant ecological project reports, the study integrated information on major ecological restoration projects implemented in Shandong Province since 2002, which were used to assess the contribution of HA to vegetation restoration. After format conversion, coordinate unification and cropping, all data were used to comprehensively analyse the relative contributions of CC and HA to changes in vegetation cover, providing a scientific basis for regional ecological conservation.

4.1 The combined impact of CC and HA

To differentiate the combined effects of CC and HA on vegetation recovery, this study employed several analytical methods, which are outlined below:

Firstly, multiple regression residual analysis was utilised. By constructing a regression model, the relationship between climate factors (such as temperature and precipitation) and vegetation change was quantified. This analysis enabled the extraction of the direct effects of CC, resulting in residuals that reflected the impact of climate elements on vegetation. Based on these residuals, the study further examined their relationship with HA (such as land-use changes and ecological restoration programs) to quantify the contribution of HA to vegetation recovery. For example, the findings showed that climate change contributed to a vegetation NDVI increase of 0.21 (21.2%) across Shandong Province, while human activities accounted for a larger portion of the NDVI increase at 0.73 (73.4%).

Secondly, the pixel dichotomy method was used to divide the changes in vegetation recovery into two components: climate-driven and human activity-driven. These two factors were modelled separately to simulate their roles in vegetation recovery. By comparing the potential vegetation NDVI (Normalized Difference Vegetation Index) with the actual vegetation NDVI in different regions, the study was able to identify the comparative contributions of CC and HA to vegetation recovery. For instance, in Liaocheng, Jining, and Zibo, HA contributed over 90% to vegetation recovery, while in Rizhao, CC had a more significant impact, contributing to 40% of the NDVI increase.

Finally, lag effect analysis was conducted to address the traditional oversight of the long-term and cumulative effects of CC in vegetation change studies. This article considered the accumulating effects of climate change, revealing that while climate change may not have had an immediate impact on vegetation in certain periods, its effects gradually accumulated over time. By conducting lag analysis, the study distinguished between the cumulative effects of CC and the immediate impacts of HA, enabling a more accurate assessment of the combined influence of both factors on vegetation recovery. The findings indicated that the cumulative effects of CC contributed to a 15% increase in NDVI over the 21-year study period, highlighting the importance of considering long-term impacts.

Additionally, the study analysed the spatial and temporal variation in vegetation recovery across 16 cities in Shandong Province, highlighting the differences in vegetation recovery under the influence of HA and CC. By conducting city-level analysis, the study clearly identified the predominant influences of either CC or HA in specific regions. For example, the contributions of human activities in Liaocheng, Jining, and Zibo exceeded 90%, while the promotion of vegetation recovery by climate change was particularly evident in Rizhao. In Rizhao, climate change contributed to a vegetation NDVI increase of 0.15 (14.8%), while human activities accounted for 0.76

(76.4%) of the NDVI increase.

In conclusion, this study utilised various methods to differentiate the combined effects of CC and HA on vegetation recovery, quantifying their respective contributions. Throughout this process, the lag effects of CC, as well as the interactions between climate factors and HA, were thoroughly considered, ensuring a clear distinction and analysis of the influencing factors.

4.2 Discussion of findings

Between 2002 and 2023, the NDVI of vegetation in Shandong Province increased rapidly at a rate of $5.36 \times 10^{-3} \cdot a^{-1}$, with areas of vegetation improvement far exceeding areas of degradation or stability. Vegetation showed a dynamic greening trend, and the quality of vegetation progressively improved. This trend was closely linked to the warming and wetting climate trend in Shandong Province, as well as to the execution of ecological restoration programmes since the 1990s, such as the Grain-for-Green Programme, the Three-North Shelterbelt Project, and the Taihang Mountain Ecological Protection and Restoration Project. The vegetation cover index used in this article mitigated the risk of NDVI failure in areas with extremely low or high vegetation coverage (Hmimina et al., 2013), and the results indicated that vegetation coverage across the province was generally in good condition. The average vegetation coverage across Shandong Province was 84.21%, with high coverage (⩾75%) accounting for 37.4% of the area.

Affected by water and thermal conditions, vegetation coverage in Shandong Province increased from the northwest to the southeast and displayed a distinct strip-like pattern based on topographical features (Chen et al., 2021; Du et al., 2023; Shi et al., 2022). High vegetation coverage was observed in mountainous regions such as Rizhao, Taishan, and the Zhongtiao Mountains. Between 2002 and 2023, the vegetation recovery rate was high across all 16 prefecture-level cities in Shandong Province. Among these, Rizhao experienced the most significant promotion of vegetation recovery due to both CC and HA, resulting in the most pronounced ecological improvement. Rizhao's NDVI rise at a rate of $7.22 \times 10^{-3} \cdot a^{-1}$, the highest among all cities. In terms of vegetation coverage, the majority of prefecture-level cities were classified as having medium-high or high levels of coverage. Liaocheng and Tai'an, located in the northern part of the Loess Plateau, experienced lower annual temperatures and precipitation, with poor soil conditions, resulting in lower vegetation coverage at a moderate level. Tai'an had the lowest vegetation coverage at 51.28%, while Zibo had the highest at 77.30%. A study of the temporal and spatial distribution of vegetation coverage in Shandong Province from 2000-2020 indicated that Tai'an exhibited significant fluctuations in vegetation coverage due to long-term mining subsidence, with the lowest coverage recorded. The findings of this article also indicated that Tai'an had the lowest vegetation coverage, which could be attributed to recent economic transformation and active ecological restoration efforts in Jining.

The combined influence of CC and HA was the primary factor driving the rapid overall increase in vegetation NDVI in Shandong Province from 2002 to 2023. CC had a positive overall impact on vegetation recovery in the province, with an average contribution rate of 24.32%. However, the effects of CC on vegetation recovery exhibited spatial heterogeneity (Liu et al., 2018). Regions with significant, moderate, and slight positive contributions were distributed across central, northern, and southern Shandong, respectively, which may be related to the recent increases and precipitation in the Yellow River region. Regions with minimal or slight negative effects were mainly located in western prefecture-level cities such as Liaocheng, Jining, and Dezhou, which may be attributed to the limited correlation between precipitation and vegetation recovery in the western areas, as well as the suppressive effect of rising temperatures on vegetation growth (Anderson-Teixeira et al., 2013).

Compared to CC, HA played a more prominent role in improving vegetation in Shandong Province, with an average contribution rate of 74.56%. On the one hand, large-scale vegetation restoration reduced the sensitivity of regional vegetation recovery to climate change; on the other hand, there was some delay in the effectiveness of ecological engineering projects (Wang et al., 2018). The combined effects of these factors likely explain the increasing influence of human activities on vegetation NDVI in Shandong Province in recent years.

Spatially, the driving forces of CC and HA on vegetation conditions in Shandong Province were similar, with both factors being widespread across the province. HA were the main driver of vegetation NDVI growth in Shandong, with areas influenced by human activities accounting for as much as 96.3% of the provincial area. This finding is consistent with analyses of the driving forces behind vegetation greening on the Loess Plateau. The role of climate change in driving vegetation NDVI growth was also significant, with the area influenced by climate change contributing to 84.7% of the provincial area. However, such as the central urban areas of Qingdao and Jinan, both CC and HA had a suppressive effect on vegetation cover. In these areas, expansive urban construction and frequent changes in land use types may have inhibited vegetation recovery and growth (Hasan et al., 2019), while the heat island effect induced by climate change could also have a potentially negative impact on vegetation (Mohajerani et al., 2017).

Currently, Shandong Province has largely achieved widespread greening, with vegetation NDVI and coverage at relatively high levels. In this context, differentiated greening strategies tailored to local conditions are required. These strategies should be designed according to the region’s current ecological situation to avoid ecological degradation caused by improper afforestation. In regions with significant potential for vegetation restoration in central Shandong, the implementation of greening projects should be strengthened. In rapidly urbanising areas such as Qingdao and Jinan, attention should be given to vegetation restoration to balance economic development with improvements in ecosystem quality. In regions with more challenging growing conditions, such as Datong and Tai’an, attention should be given to the region's climatic resources, focusing on low-growing vegetation planting and appropriate extension of the nurturing and maintenance period to improve vegetation quality. Furthermore, such as Dezhou and Jining, an ecological engineering monitoring and adjustment mechanism should be established, based on vegetation condition monitoring, to prevent resource waste.

This article employed a linear model to fit the effects of CC and HA on vegetation dynamics, focusing on temperature and precipitation as the main climate factors.

However, other elements, such as solar radiation and relative humidity, were not considered, which could potentially lead to an overestimation or underestimation of the impact of CC on the temporal and spatial variation of vegetation. Additionally, the use of different NDVI products could lead to variations in the research results and may not perfectly align with field survey and monitoring data. Therefore, future research should incorporate additional climate factors to more accurately capture the impacts of CC. Moreover, efforts should be made to strengthen the consistency between vegetation data sets, establish a numerical relationship between NDVI products and ground-truth data, and enhance the robustness and reliability of the research outcomes.

5. Discussion and conclusion

5.1 Discussion

First, previous studies have focused on qualitatively analyzing the impacts of climate change (CC) and human activities (HA) on vegetation cover, such as assessing the contributions of CC and HA to vegetation cover through simple correlation or trend analyses (Li et al., 2019; Wang et al., 2024). These studies, while providing preliminary insights, have limitations in quantifying the specific contributions of CC and HA. In this paper, we quantitatively assessed the joint effects of CC and HA on vegetation restoration by employing pixel dichotomy, trend analysis, and multiple regression residual analysis. This method not only separates the contributions of CC and HA more precisely, but also provides specific relative contributions (73.4% from HA and 21.2% from CC), thus providing a more scientific basis for the development of ecological conservation strategies.

Second, most of the existing studies only considered the effects of climatic factors on vegetation cover in the current month, ignoring the cumulative and lagged effects of these factors (Luo et al., 2023). This simplified approach may lead to an underestimation of the long-term impacts of climate change. In this paper, we assessed the long-term impacts of climate change on vegetation cover more comprehensively by introducing a cumulative lag effect analysis. This approach not only considers shortterm climate fluctuations, but also long-term cumulative effects, thus providing more accurate assessment results. For example, in Rizhao City, the significant contribution of climate change to vegetation recovery may be related to long-term temperature and precipitation changes.

Although some studies have pointed out the joint effect of CC and HA on vegetation recovery, few studies have been able to quantify the specific proportion of contribution of these two factors (Ren et al., 2024). This lack of quantitative analysis makes it difficult to assess the relative importance of different factors in vegetation restoration. In this paper, the relative contributions of CC and HA to vegetation restoration were explicitly quantified through multiple regression residual analysis. This quantitative analysis not only reveals the dominant role of human activities in vegetation restoration, but also emphasizes the significant impact of climate change in some areas. For example, in Rizhao City, the contribution of climate change to vegetation restoration is significantly higher than that in other cities, which provides a new perspective for understanding the response mechanism of regional ecosystems.

This paper provides a more accurate quantitative assessment tool by comparing with previous studies, using pixel dichotomy, trend analysis and multiple regression residual analysis. The cumulative and lagged effects of climate change are taken into account, providing more comprehensive assessment results. The detailed analysis of 16 cities reveals the specific dynamics of different regions in the process of vegetation restoration, providing an important reference for the formulation of targeted ecological protection measures. The relative contributions of CC and HA to vegetation restoration were explicitly quantified, providing new perspectives for understanding the response mechanisms of regional ecosystems. These innovations and contributions not only enrich the research methodology in the field of vegetation restoration, but also provide a more scientific basis for ecological conservation and sustainable governance.

5.2 Conclusion

First, between 2002 and 2023, the overall vegetation coverage in Shandong Province remained relatively high, with an average vegetation coverage of 84.21%. Spatially, vegetation coverage exhibited a clear increasing trend from the northwest to the southeast, displaying distinct strip-like patterns.

Secondly, at the city level, high and medium-high vegetation coverage dominated. Among the cities, Linyi had the highest vegetation coverage at 84.21%, while Yantai and Jining exhibited relatively lower levels, with vegetation coverage of 75.39% and 54.76%, respectively.

Thirdly, during the study period, under the combined influence of CC and HA, the NDVI of vegetation during the growing season in Shandong Province increased rapidly at a rate of $5.36\times10^{-3}\cdot a^{-1}$, with significant improvements in vegetation coverage. Rizhao city experienced the most significant positive impact from both CC and HA, with an NDVI trend rate of $7.22\times10^{-3}\cdot a^{-1}$.

Fourth, in contrast, areas such as the junction between Qingdao, Rizhao, and Zaozhuang, along with certain city centres, experienced a decline in vegetation coverage due to the suppressive effects of both CC and HA. These areas accounted for 3.2% of the total area, mainly located at the urban boundaries and centres where human activities had a moderate suppressive effect.

Overall, the positive impact of HA on vegetation improvement in Shandong Province exceeded that of climate change, with respective contribution rates of 73.46% for human activities and 21.32% for climate change. At the city level, HA had a clearly positive effect on vegetation restoration in all 16 prefecture-level cities. For example, in Liaocheng, Jining, and Zibo, human activities accounted for over 90% of the vegetation recovery, while in Rizhao, climate change contributed to 14.81% of the NDVI increase. The combined efforts of ecological restoration projects and favourable climatic conditions led to substantial vegetation greening across the province, highlighting the importance of continued sustainable land management practices.

Although the above studies have achieved important results in analyzing vegetation cover changes and their drivers in Shandong Province, there are still some limitations, mainly in the following aspects:

Firstly, in terms of data and methodology, the data of the study spans the period 2002-2023, which, although it can reflect the trend of vegetation cover change in the past period of time, has a limited ability to predict and assess the future vegetation cover.

With accelerating global climate change and changing human activities, future changes in vegetation cover may differ from the past, and more timely data are needed to update the study results. Although various methods such as pixel dichotomy, trend analysis and multiple regression residual analysis were used, these methods may have certain assumptions and limitations. For example, multiple regression residual analysis may not be able to completely exclude the interference of other unconsidered factors when separating the contribution of climate change and human activities to vegetation cover, thus affecting the accuracy of the results. In addition, pixel dichotomization may have some errors when dealing with vegetation and non-vegetation information, especially in areas with low vegetation cover or complex vegetation types.

Secondly, in terms of factor consideration, the study mainly considered the effects of two key climatic factors, temperature and precipitation, on vegetation cover, but did not fully consider the role of other climatic factors (e.g., solar radiation, wind speed, humidity, etc.). These factors may also have important effects on vegetation growth and cover, especially under certain specific climatic conditions. Changes in vegetation cover are not only influenced by external climate and human activities, but are also closely related to biotic and abiotic processes within the ecosystem, such as species competition, succession, pests and diseases. However, the study has not deeply explored the contribution of these internal ecosystem processes to vegetation cover change, and may not be able to fully reveal the internal mechanism of vegetation cover change.

Again, the interaction between human activities and climate change has not been thoroughly explored. There may be complex interactions between climate change and human activities, and the impacts of such interactions on vegetation cover change may be more complex than the impacts of a single factor. However, the study did not explore in depth the specific mechanisms and extent of this interaction, and may not be able to fully understand the combined effects of the two on vegetation cover change.

Finally, although the study points out that there are significant regional differences in vegetation cover change among different cities in Shandong Province, the analysis of vegetation cover change and its drivers in different areas within each city (e.g., urban centers, suburbs, mountainous areas, etc.) is not deep enough. There are large differences in land use, human activity intensity and ecological conditions in different areas within cities, which may lead to different driving mechanisms of vegetation cover change, and more detailed spatial analysis is needed to reveal these differences. The study mentions the decline of vegetation cover in the border areas of Qingdao, Rizhao, and Zaozhuang, but does not analyze in depth the special causes and mechanisms of the decline of vegetation cover in these border areas. Border areas may be affected by the ecological environment, climatic conditions and human activities in the neighboring areas, and their changes in vegetation cover may have unique characteristics and drivers, which need to be further investigated in order to formulate targeted ecological protection and restoration measures.

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