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Spatial and Temporal Dynamics and Driving Factors of Vegetation in Jiangsu Province from 2002 to 2022 Based on kNDVI

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Abstract Vegetation not only plays a critical role in regulating regional climate, hydrological cycles, carbon sequestration, and oxygen release, but also is directly linked to ecosystem stability and regional sustainable development. In this study, based on the data of kNDVI in Jiangsu Province (an economically developed coastal region in eastern China) from 2002 to 2022, the spatial and temporal dynamics of vegetation in the province were systematically analyzed by using the Theil-Sen slope estimation and Mann-Kendall trend test methods. The results indicate that vegetation coverage in Jiangsu Province generally followed a trend of "fluctuation in the early period and improvement in the later period" from 2002 to 2022. Spatially, kNDVI changes exhibited clear heterogeneity, with an overall pattern of "decline in the south, increase in the north, and stability in the central region". Based on the 21-year mean of kNDVI, it is found that vegetation conditions were relatively better in northern and central Jiangsu, while lower mean of kNDVI was observed in southern Jiangsu (*e.g.*, Suzhou, Wuxi, and Changzhou), reflecting the pressure of accelerating urbanization on green space coverage. Further investigation into the driving factors of changes in vegetation reveals that social factors had the strongest influence, with a path coefficient of −0.86, followed by topographic and climatic factors. This spatial differentiation pattern and the identified driving factors highlight ongoing conflicts between the economic development and ecological conservation in Jiangsu Province. In the future, land use structure should be optimized based on local conditions, and coordinated development between ecological restoration and urban expansion should be strengthened.

Key words kNDVI; Vegetation coverage; Variation trend; Driving factors; Jiangsu Province
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With the continuous intensification of global climate change and human activities[1], the characteristics of temporal and spatial variations of vegetation as an important component of terrestrial ecosystems have increasingly become a core issue of research in ecological environment. Vegetation not only plays a crucial role in regulating regional climate, water cycle, carbon sequestration and oxygen release, but also directly affects the stability and sustainable development of regional ecosystems. China, as the most populous developing country in the world, has accelerated urbanization in its eastern coastal areas and undergone drastic changes in land use patterns, which have imposed significant pressure on the ecological environment. Jiangsu Province, located in the economically developed eastern coastal region of China, is a core component of urban agglomeration in the Yangtze River Delta. Due to its unique geographical location, diverse ecological types and complex land use patterns, it is a representative area for studying the evolution process of vegetation in typical regions. However, current studies on vegetation changes in Jiangsu Province mostly focus on local periods or specific areas, and lack a systematic analysis across long-term scales.

Kernel normalized difference vegetation index (kNDVI) is a nonlinear extension of the traditional normalized difference vegetation index (NDVI)[2]. Based on the idea of kernel function mapping, this index performs nonlinear transformation on the original NDVI, which effectively overcomes the "saturation" phenomenon of NDVI in areas with high vegetation coverage and its sensitivity to soil background[3]. In previous studies, NDVI has been widely used to monitor vegetation coverage, but its performance is limited in areas with dense canopies and complex backgrounds[4]. In contrast, kNDVI has higher stability and sensitivity in heterogeneous landscapes such as urban-rural fringe areas and subtropical forests by enhancing vegetation signal and suppressing background noise, and is suitable for long-term monitoring of vegetation dynamics.

In this paper, based on the time-series vegetation index (kNDVI), the spatial and temporal changes of vegetation in Jiangsu Province from 2002 to 2022 were systematically revealed, and their driving factors were explored, which helps deepen the understanding of regional ecological change processes. This study can provide a methodological framework and a practical case for the research on ecological evolution in typical urban agglomerations in the east, and the research results can provide basic data and decision support for local governments to optimize territorial spatial planning, promote ecological protection and restoration, and implement the "dual carbon" goals and ecological compensation policies.

1 Data and methods

1.1 General situation of the study area Located in the eastern coastal region of China, Jiangsu Province (116°18′ – 121°57′ E,

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30°45′ – 35°20′ N) borders the Yellow Sea in the east, Anhui Province in the west, Zhejiang and Shanghai in the south, and Shandong Province in the north. In therms of terrain, it is narrow and elongated from north to south and wide from east to west. The total area of the province is approximately 107 200 km^2, and it is one of the provinces with the largest population density and the most developed economy in China.

The overall terrain of Jiangsu Province slopes from northwest to southeast. The main terrain is plains, and the area of plains accounts for over 86% of the total area. The low-lying area of the Lixia River, the alluvial plain of the Yellow River and Huai River in northern Jiangsu, and the alluvial plain of the Yangtze River Delta constitute the main geographical units. Here the river network is dense, and the water system is well-developed, so it is a typical plain region with dense water network. Jiangsu Province has a transitional monsoon climate from northern subtropical to warm temperate zones, and it is characterized by distinct seasons, synchronized high temperatures and rainfall, and humid climate. The annual average temperature ranges from 13.6 to 16.1 ℃, and the annual average precipitation is 800 – 1 200 mm. It is larger in the south than the north. Precipitation is mainly concentrated during the summer Meiyu period and the typhoon season. There is some fluctuation in precipitation from year to year, and drought and floods occur occasionally.

Jiangsu Province is located in the transitional zone between evergreen broad-leaved forests and deciduous broad-leaved forests in the eastern monsoon region. The original natural vegetation was composed of evergreen broad-leaved forests, deciduous broad-leaved mixed forests and grassland vegetation, but the natural vegetation has become fragmented and severely degraded due to long-term agricultural development and urbanization processes. Currently, it is dominated by artificial vegetation and secondary vegetation, and the coverage rate of forests is approximately 24.1%. They are mainly distributed in hilly areas (such as the low mountain and hilly areas in southern Jiangsu) and riverbank and coastal protection forest areas. Typical tree species include *Pinus massoniana*, *Cunninghamia lanceolata*, *Paulownia fortunei*, *Populus* spp., *Robinia pseudoacacia*, and so forth.

1.2 Data sources The kNDVI data used in this study were the MODIS vegetation index product obtained based on the platform Google Earth Engine (GEE, https://code.earthengine.google.com)[5], and the time ranges from 2002 to 2022. The MODIS data have a high temporal resolution (16 d) and medium spatial resolution (250 m × 250 m), and are suitable for long-term monitoring of vegetation dynamics[6]. To ensure data quality, the used images have undergone filtering and quality control processing by clouds, cloud shadows, water bodies, and atmospheric aerosols, and the consistency and reliability of the time series have been significantly improved. Leveraging the advantages of MODIS images in terms of temporal continuity and regional coverage, the constructed kNDVI data set provides a stable and high-quality remote sensing input foundation for the changes in vegetation coverage in Jiangsu Province from 2002 to 2022 in this study.

1.3 Research methods

1.3.1 Calculation of kNDVI. To more sensitively reflect the changing trends of vegetation in different regions, kNDVI was introduced in this study[7]. Based on the traditional NDVI, kNDVI incorporates a spatial weight kernel function to perform a weighted average of NDVI values of pixels within the neighborhood, so as to reduce noise interference and enhance the expression ability of local vegetation change signals. Its formula is as follows:

$$kNDVI = \tanh\ (NDVI)^2$$

$$NDVI = (NIR - Red)/(NIR + Red)$$

In the formula, *NIR* is the reflectivity in the near-infrared band; *Red* means the reflectivity in the red band.

1.3.2 Theil-Sen slope estimation and Mann-Kendall trend test methods. To quantitatively assess the temporal changes of vegetation coverage (kNDVI) in Jiangsu Province from 2004 to 2024, the Theil-Sen slope estimation method and the Mann-Kendall non-parametric trend test method were introduced in this study[8 – 11]. These two methods are insensitive to abnormal values, can effectively reveal potential trend changes in long-term time series, and have been widely used to monitor climate and ecological changes.

The Theil-Sen slope estimation method is a robust trend estimation method. Its basic idea is to calculate the median of slopes between all pairs of data points to represent the overall trend direction and changing rate. The Mann-Kendall test, which is a commonly used non-parametric method, is used to test whether there is a significant monotonic trend in the time series. This method does not rely on the type of data distribution, and is suitable for non-normal distribution data.

The formula for Theil-Sen slope estimation is as follows:

$$\beta = Median\left(\frac{NPP_j - NPP_i}{j - i}\right),\ 1997 \leqslant i \leqslant j \leqslant 2017$$

In the formula, *Median* ( ) means taking the median. $\beta > 0$ indicates that kNDVI shows an increasing trend; $\beta = 0$ shows that kNDVI remains unchanged; $\beta < 0$ means that kNDVI tends to decrease.

For the Mann-Kendall test method, it is assumed that x_1, x_2, $\cdots$, x_n are time series variables, and the constructed statistic is as below:

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} sgn\ (x_i - x_j)$$

$$sgn\ (x_i - x_j) = \begin{cases} 1 & x_i - x_j > 0 \\ 0 & x_i - x_j = 0 \\ -1 & x_i - x_j < 0 \end{cases}$$

In the formulas, x_i and x_j represent the corresponding values in the i^{th} and j^{th} year, respectively, and $i > j$; n is the length of the data set. Then the statistical quantity of a normal distribution Z is obtained as follows:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var\ (S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{Var\ (S)}} & S < 0 \end{cases}$$

In the formula, $Var\ (S)$ is variance. At the given α significance level, if $|Z| \geqslant Z_{\alpha/2}$, the null hypothesis is rejected, indicating that there is a significant upward or downward trend in the time series data at the α significance level. $Z \geqslant 1.96$ means a significant increase or decrease, and $Z < 1.96$ stands for a slight increase or decrease.

In this study, the Theil-Sen method can be used to quantify the trend slope of kNDVI and clarify its changing intensity. The Mann-Kendall test can be used to determine the statistical significance of the trends. The combination of the two can comprehensively depict the dynamic change characteristics of vegetation coverage in Jiangsu Province over the past 20 years.

1.3.3 Structural equation modeling. Structural equation modeling (SEM), which is a modeling method based on the analysis of the covariance matrix of variables to study multivariate statistical relationships, can handle latent variables and observed variables simultaneously, and test the direct and indirect effects between variables[12-14]. In this study, SEM was used to explore the complex path relationships of climate factors, topographic factors, and social factors on vegetation dynamics. Among them, climate factors include average temperature, average rainfall, and solar radiation; topographic factors contain altitude and slope; social factors are land use type and nighttime light index. The data of climate factor are from WorldClim (https://www.worldclim.org/)[15], and the data of topographic factors are from Google Earth Engine, while the data of social factors are from the resource environment science and data platform (https://www.resdc.cn/)[16-17]. All three types of data were resampled spatially using ArcGIS to make their spatial resolution consistent with the data of kNDVI.

2 Results and analysis

2.1 Temporal changes of vegetation in Jiangsu Province As shown in Fig. 1, the kNDVI in Jiangsu Province fluctuated in the early stage and then increased in the later stage over the past 21 years. The average and maximum of kNDVI in Jiangsu Province showed a fluctuating upward trend overall from 2002 to 2022, indicating that the vegetation coverage in Jiangsu Province generally improved over the past two decades. The annual average kNDVI fluctuated significantly from 2002 to 2010, remaining generally between 0.26 and 0.29. It suggests that the vegetation coverage level was relatively low during this period, and the ecosystem stability was weak. The annual average was the lowest in 2009 (only 0.26), and showed a gradual upward trend after 2011. It was relatively high in 2022 (up to 0.31), reflecting the effectiveness of ecological restoration and greening efforts in Jiangsu Province.

Regarding the maximum kNDVI, its changing trend was basically consistent with that of the average, but the increase was more significant. Since 2011, the maximum significantly increased, reaching a peak of 0.61 in 2022, indicating that the vegetation condition in some local areas had significantly improved. The continuous increase in the maximum also reflects the regional effectiveness of ecological construction. For instance, the greening projects in nature reserves, wetland restoration areas, or urban-rural fringe areas may have played a positive role.

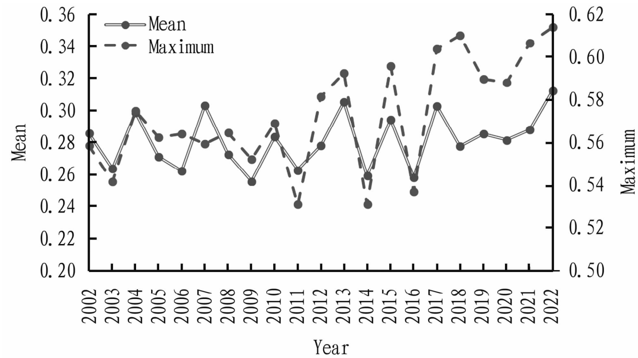

Fig. 1 Changing trends of kNDVI in Jiangsu Province from 2002 to 2022

2.2 Spatial changes of vegetation in Jiangsu Province Based on the Theil-Sen slope estimation method, the spatial changes of vegetation in Jiangsu Province from 2002 to 2022 were obtained. The spatial changes of vegetation were classified by using the Mann-Kendall (MK) non-parametric trend test method. In this study, the changes of kNDVI were divided into five grades, namely significant decrease, slight decrease, no change, slight increase, and significant increase. As shown in Fig. 2, there was obvious spatial heterogeneity in the changes of kNDVI in Jiangsu Province. That is, it declined in the south, rose in the north, and was stable in the center. kNDVI increased mainly in the northern parts of Jiangsu Province, such as Yancheng, Suqian, Huai'an, Lianyungang, and Yangzhou.

In contrast, it tended to decrease slightly or significantly in the south of Jiangsu Province (such as Suzhou, Wuxi, and Changzhou) and some areas along the river. These areas were concentrated in urban built-up areas and their surrounding areas, and were the regions with the most intensive urbanization process in Jiangsu Province. Urban expansion, infrastructure construction, and high-intensity human activities in these areas led to the fragmentation, degradation and even disappearance of natural vegetation, causing a significant decrease in coverage. Meanwhile, there was no change in the center and some hilly and plain areas, indicating that the overall vegetation coverage in these areas was relatively stable, which was possibly related to stable land use patterns.

2.3 Spatial distribution of vegetation in various cities of Jiangsu Province Based on the annual data of kNDVI in Jiangsu Province from 2002 to 2022, the average over 21 years was calculated, and the vegetation coverage in each city was analyzed (Table 2). During 2002 - 2022, the average of kNDVI in each prefecture-level cities in Jiangsu Province was moderately low. Among them, Yancheng City had the highest average of kNDVI (up to 0.32), followed by Huai'an City (0.31), Suqian City (0.31), Lianyungang City (0.31), and Xuzhou (0.30). The averages of these five cities all reached or exceeded 0.30, revealing that the overall condition of vegetation coverage in these cities was relatively good. The average of kNDVI in Suzhou City was the lowest (only 0.17), significantly lower than that of other cities.

The maximum of kNDVI in most regions was between 0.44 and 0.50, but there was some fluctuation. For example, the maximum of kNDVI in Lianyungang City and Huai'an City was both 0.50, indicating that there was a better vegetation condition in some areas within the cities. The minimum of kNDVI in Yancheng City and Lianyungang City were 0.00, showing that there was extremely sparse or degraded vegetation in some areas. The standard deviation of each city was generally between 0.08 and 0.11, reflecting the large fluctuation of kNDVI within the cities and the differences in ecosystem stability. Among them, the standard deviation of kNDVI in Huai'an City, Lianyungang City, and Wuxi City was higher (0.11), which was possibly affected by more significant land use changes.

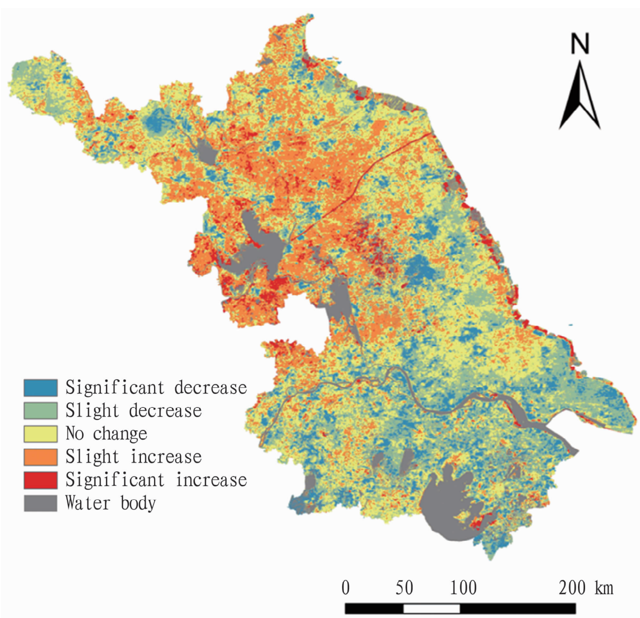

Fig. 2 Spatial changes of kNDVI in Jiangsu Province during 2002 – 2022

Table 2 Statistical situation of kNDVI in each city

City	Minimum	Maximum	Mean	Standard deviation
Yancheng	0.00	0.46	0.32	0.10
Huai'an	0.01	0.50	0.31	0.11
Suqian	0.03	0.48	0.31	0.10
Lianyungang	0.00	0.50	0.31	0.11
Xuzhou	0.01	0.46	0.30	0.07
Yangzhou	0.01	0.46	0.29	0.10
Taizhou	0.01	0.43	0.29	0.08
Zhenjiang	0.01	0.45	0.27	0.09
Nantong	0.01	0.41	0.27	0.09
Nanjing	0.01	0.49	0.26	0.10
Changzhou	0.01	0.49	0.25	0.10
Wuxi	0.01	0.48	0.22	0.11
Suzhou	0.01	0.44	0.17	0.08

In terms of spatial distribution, the cities where the average of kNDVI was higher were mostly concentrated in the northern and central regions of Jiangsu Province, such as Yancheng, Huai'an, Suqian and Lianyungang. These areas had more farmland, wetlands or ecological reserves, such as Yancheng wetland and agricultural areas of Huaihe Plain.

Over a long period, the implementation of policies on ecological restoration and returning farmland to forests has likely contributed to vegetation recovery. In contrast, the average of kNDVI in the south of Jiangsu Province (such as Suzhou, Wuxi and Changzhou) was relatively lower, reflecting the pressure brought by the accelerated urbanization process on vegetation coverage. Especially in Suzhou, which is one of the most economically active cities in Jiangsu Province, its rapid industrialization and urban expansion may lead to the fragmentation and degradation of vegetation, so that the average of kNDVI was the lowest in the province.

2.4 Driving factors of changes in vegetation The results of the structural equation modeling indicate that social factors had the most significant impact on kNDVI, and this effect was negative (path coefficient was −0.86). Among them, the influence of land use (−0.92) was stronger than that of nighttime light index (−0.59), revealing that land use changes were the main anthropogenic driving factor for the decline in vegetation coverage. This suggests that urban expansion and population concentration directly caused a decrease in kNDVI (namely vegetation coverage).

Among the climatic factors, temperature had the most prominent influence (path coefficient was −0.50), higher than that of precipitation (0.46) and solar radiation (−0.20). This shows that in this study area, temperature had a significant and clearly directional regulatory effect on vegetation changes, and its negative effect means that an increase in temperature may inhibit vegetation growth. By comparison, precipitation had a positive effect on vegetation, but the influence was weaker than that of temperature. Solar radiation also had a negative effect, but its influence was relatively lower. In comparison, terrain factors had a positive effect on kNDVI (path coefficient was 0.47). Higher altitudes and steeper slopes usually correspond to lower human disturbance intensity, which is conducive to the maintenance of vegetation coverage.

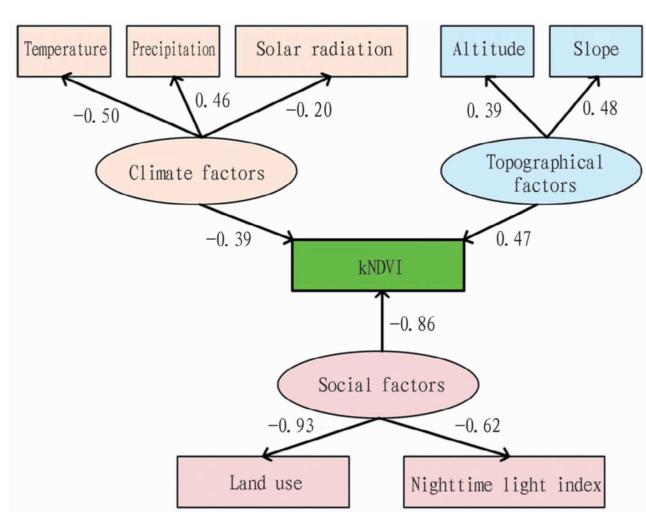

Fig. 3 Driving factors of kNDVI

3 Conclusions

The results of annual kNDVI from 2002 to 2022 show that vegetation coverage in Jiangsu Province experienced initial fluctuations followed by a later improvement. These changes exhibited significant spatial heterogeneity, with a decrease in the south, an increase in the north, and relative stability in the central region. Consequently, while the vegetation conditions of northern Jiangsu continuously improved, the urbanized southern belt faced persistent ecological pressure. The 21-year averages of kNDVI confirm this, with lower averages in southern cities like Suzhou, Wuxi, and Changzhou, reflecting the pressure of urbanization on green spaces. Furthermore, structural equation modeling reveals that social factors had the most significant impact on vegetation change, which was predominantly negative. Overall, this spatial pattern indicates an ongoing conflict between economic development and ecological protection in Jiangsu Province. Future efforts should focus on optimizing the land use structure according to local conditions to strengthen the coordinated development of ecological restoration and urban expansion.

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