Journal of Environmental Management 325 (2023) 116562

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Quantifying the direct effects of long-term dynamic land use intensity on vegetation change and its interacted effects with economic development and climate change in jiangsu, China

Feixue Shen [a], Lin Yang [a,b,*], Lei Zhang [a], Mao Guo [a], Haili Huang [a], Chenghu Zhou [a,b]

[a] School of Geography and Ocean Science, Nanjing University, Nanjing, 210023, China
[b] State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, 100101, China

ARTICLE INFO

Keywords:
Vegetation change
Land use intensity
Climate change
Structural equation models
Sustainable land management

ABSTRACT

Vegetation change reflects sensitive responses of ecosystem environment to global climate change as well as land use. It is well known that land use type and its transformation affect vegetation change. However, how the changes in land use intensity (LUI) within different land use types impact vegetation and the interactions with other drivers remain poorly understood. We measured the LUI of Jiangsu Province, China, within the main land use types in 1995, 2000, 2005, 2010, 2015 and 2018 by combining remote sensing-based land use data with representative county scale economic and social indicators. Structural equation models (SEMs) were built to quantify the influences of long term LUI on vegetation change interacting with economic development, climate change and topographical conditions in transformed land, cropland, rural settlements and urbanized land, respectively. Seventy percent of significant vegetation change existed in non-transformed land use types. Although the area with a vegetation greening trend is larger than that with a vegetation browning trend, the vegetation browning areas is prominent in urbanized lands and some croplands in south basins. The constructed SEMs suggested the dominant negative effect of fast economic development regardless of land use types, while LUI played important and different direct and indirect effects on affecting vegetation change significantly interacting with economic development and climate change in different land use types. The LUI increasing led a vegetation greening in cropland, and stronger than climate warming with both positive direct and indirect effects for influencing climate change. The LUI change took negative effects on vegetation change in rural and urban areas, while a positive indirect effect of LUI increasing in urbanized land signaled the positive results of human managements. We then provided some land use-specific suggestions on basin scale for land management in Jiangsu. Our results highlight the necessity of long-term LUI quantification and promote the understanding of its effects on vegetation change interacted with other drivers within different land use types. This can be very helpful for sustainable land use and managements in regions with fast economic development.

1. Introduction

Vegetation is a key element in the global biogeochemical cycles that provide water, carbon, and nitrogen to all livings. Vegetation change is a sensitive indicator of environment responses to global climate change as well as human activities (Haberl et al., 2007; Myneni et al., 1997; Piao et al., 2020). Numerous studies have explored into how climate change influences vegetation change, and increasingly into the effect of human activities. Land use type and its transformation have been widely adopted as anthropogenic drivers of vegetation change (Yang et al., 2021; Zhu et al., 2016). Yet, due to various managements or policies, land use intensity (LUI) is heterogeneous within single land use type, such as various agricultural intensification level in cropland or urbanization level in urban (Erb et al., 2013; Parihar et al., 2018; Zhang L. et al., 2022). The changes in LUI directly disturbs vegetation growth by affecting the plant community or interfering the nutrient cycling (Gossner et al., 2016; Tamm, 1995). Meanwhile, it may indirectly influence vegetation change through interacting with other drivers, such

* Corresponding author. School of Geography and Ocean Science, Nanjing University, Nanjing, 210023, China.
E-mail addresses: shenfx@smail.nju.edu.cn (F. Shen), yanglin@nju.edu.cn (L. Yang), zhanglei@smail.nju.edu.cn (L. Zhang), guomao@smail.nju.edu.cn (M. Guo), helenhuang@smail.nju.edu.cn (H. Huang), zhouch@lreis.ac.cn (C. Zhou).

https://doi.org/10.1016/j.jenvman.2022.116562
Received 17 May 2022; Received in revised form 13 October 2022; Accepted 16 October 2022

as climate change (Choi et al., 2021; Zeng et al., 2020). Therefore, examining these direct and indirect effects of dynamic LUI on vegetation change helps comprehensively understanding the consequences of land use for ecosystem, thereby projecting strategies for sustainable land use and management (Chen et al., 2019; Mueller et al., 2014).

Recently, how the changes in LUI affect environment attracts increasing attentions (Allan et al., 2014; Gossner et al., 2016; Verburg et al., 2015). The LUI was mostly quantified using indices indicating the intensity of human activities within single land use via field surveys or experiments on site or plot (Blüthgen et al., 2012; Parihar et al., 2018). For instances, Felipe-Lucia et al. (2020) generated a LUI dataset by integrating field surveyed mowing frequency, livestock density and fertilization level in 150 grassland plots, and proportions of harvested volume, nonnative tree species and deadwood with saw cuts in 150 forest plots in German, and proved that LUI altered ecosystem network. Hisse et al. (2022) found that intensified management (e.g., higher plant densities and fertilization levels) increased annual crop yield at sites in a five-year field experiment. Those studies, usually at plot scales, revealed the environmental effects of various LUI mainly during a short period. On a regional scale, a few LUI dataset were quantified using the regional administrative statistical data, such as county-level crop yield in cropland (Ye et al., 2022) or regional harvest statistics ranging from the national to provincial or forestry district level in forest (Kuemmerle et al., 2016). However, it is still rarely known how LUI affects vegetation change on large scales. Especially, the interacted effects between long-term LUI and other drivers of vegetation change in different land use types on vegetation change are poorly understood.

To disentangle the interactive effects of natural and anthropogenic drivers in vegetation dynamics, different methods have been adopted, such as the residual analysis using multiple linear regression (Wen et al., 2017), the random forest algorithm and linear trend analysis (Leroux et al., 2017), the geographical detector (Peng W. et al., 2019a,b), the correlation networks analysis (Kleyer et al., 2019) and the structural equation model (SEM) (Yang et al., 2021). Among these methods, SEM is powerful for the study of multivariate interacting systems (Grace and Keeley, 2006), and has been applied to quantify the interactions among drivers of the ecological process, such as water quality change (Wang et al., 2021), soil organic carbon change (Luo et al., 2017), and vegetation change (Yang et al., 2021). Compare to other methods, the SEM can quantify not only the direct effect of a driver on the objective variable by removing the influence of other drivers, but also the indirect effects of a driver by providing an insight into the underlying mechanism for the objective variable through influencing the other drivers named as mediated factors.

Vegetation in highly developed areas has been significantly altered in transformed land undergoing land transformations, but also within one land use type with a great range of LUI change due to rapid urbanization (Zhang L. et al., 2022) and agricultural advancement (Huang and Wang, 2021). Jiangsu Province, China, a developed region, has both rapid urbanization and long agriculture history with increasingly intensification (Liang et al., 2021). It is a typical area to understand how the long-term dynamic LUI affects vegetation growth interacted with economic development and climate change. The objectives of this study are (1) to quantify LUI of cropland, urban and rural settlements by combining remote-sensing based land use types with county-level economic and social indicators, and generate a LUI dataset of Jiangsu Province in 1995, 2000, 2005, 2010, 2015 and 2018, (2) to analyze the spatial-temporal change of vegetation and LUI, and (3) to generate the influencing paths of anthropocentric drivers (LUI, economic development) and natural drivers (temperature, precipitation, elevation, slope) on vegetation change for (a) transformed, (b) cropland, (c) rural settlements and (d) urbanized land, respectively using SEM models. Our findings will extend the understandings of the interacted effects of natural environment and human activities on vegetation change within different land use types on regional scale.

2. Study area and data

2.1. Study area

Jiangsu Province, China, located between 116°18′-121°57′E and 30°45′-35°20′N (Fig. 1), has an eastern Asian monsoon climate with annual temperature of 13.6–16.1 °C and annual precipitation of 1000 mm. Jiangsu Province lies in the downstream of Yangtze River Basin (YZRB) and Huaihe River Basin (HRB) with rich water supply but fragile ecological environment on the eastern coast. Besides, two relatively isolated water systems (sub-basin) existed within the two basins: Yishusi River Basin (YSRB) to the northeast of Huaihe River Basin, and Taihu Lake Basin (TLB) to the southeast of YZRB (http://jsslt.jiangsu.gov.cn/art/2020/9/10/art_80216_9499025.html). Because of the large-area plains and high-quality soils, Jiangsu Province is an important grain-producing area and part of the Yangtze River Delta Economic Zone in China. Since China's reform and opening-up policy started in 1978, with increased economic development level from northwest to southeast, land use in Jiangsu has experienced obvious changes (Qu et al., 2019). In 2018, the urbanization rate surpassed national average level, reaching ~69.6% (http://www.jiangsu.gov.cn/). Of all land areas (excluding water systems) in Jiangsu, only ~5% are forest, grassland and bare land; the cropland and built-up land accounted ~71% and ~24% respectively.

2.2. Data

2.2.1. Land use types

The land use type data at 1 km resolution was extracted from the dataset of land use developed by the Resource and Environment Science Data Center (RESDC, http://www.resdc.cn/). This dataset is one of the most accurate land use products generated through remote sensing in China (Liu et al., 2014), and includes national land use type data in 1980, 1990, 1995, 2000, 2005, 2010, 2015, 2018 and 2020, thus suitable for a long time series analysis. The land use types in this dataset are divided into six primary/first classes (cropland, forest, grassland, water, built-up land and bare land) and 26 secondary classes. With an interpretation with human-computer interaction and field survey data onsite verification, the evaluation accuracy of the first level of land use is >93% and that of the second level is >90% (Ning et al., 2018).

We derived the cropland and built-up land covering 95% of Jiangsu Province for LUI calculation in each year, and not too intensified land use practices exists in the remaining land use types. We excluded pixels with water and bare land in any year and pixels with grassland or forest in every year. Further, the primary class of built-up land was subdivided into rural settlements and urbanized land to identify the LUI disparity between rural and urban areas. Specifically, the rural settlements, as a secondary class, belonged to the primary class of built-up land. And the secondary classes including urban and built-up land for industry, transportation or some special usage in the dataset were labeled as the urbanized land.

2.2.2. Economic and social indicators

Considering the scientific merit, completeness and accessibility of data, LUI was assessed via typical human activities in different land use types by nine county-scale economic and social indicators (Table 1). These indicators were collected from the Statistical Yearbook and agricultural census of Jiangsu Province from 1995 to 2018.

The typical human activities in cropland are relate to agricultural management for increasing food production, including tillage system, agricultural mechanization, fertilizer management and water management (Jiang et al., 2020; Liu et al., 2020; Temme and Verburg, 2011). Accordingly, we collected total sown area, consumption of chemical fertilizer and total power of agricultural machinery, respectively. Note that the total sown area in 1995 was not available, so we adopt that in 1997 provided by the agricultural census of China as a substitute.

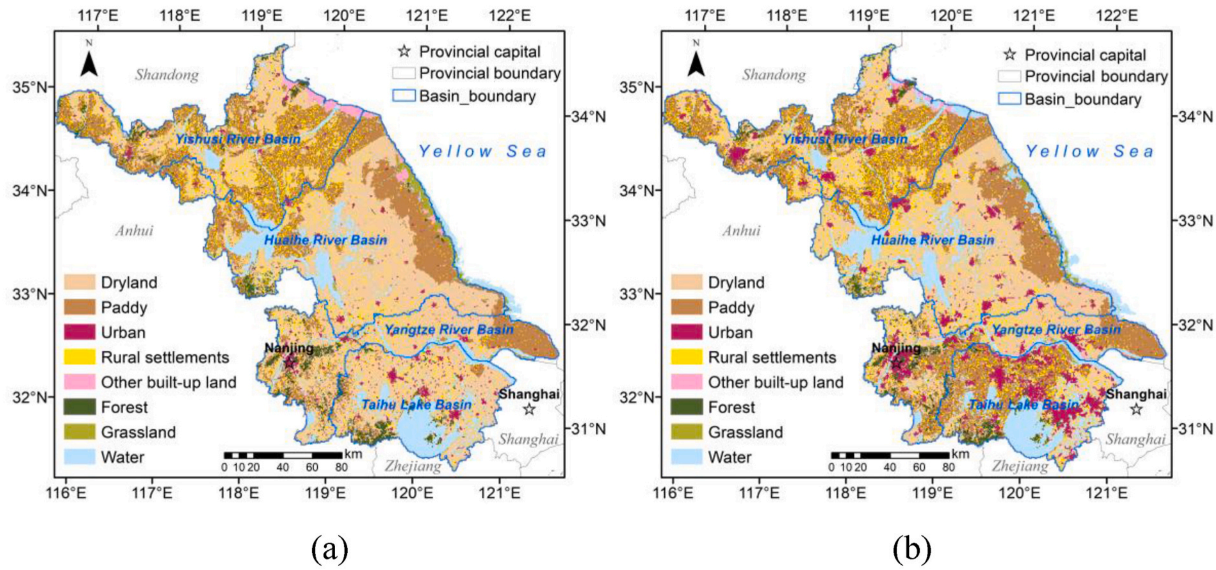


Fig. 1. Land use types of Jiangsu Province in 1995 (a) and 2018 (b).

Table 1
Economic and social indicators and their weights for calculating the land use intensity.

Main land use types	Economic and social indicators	Weight
Cropland	Total Sown Area	0.5
	Consumption of Chemical Fertilizer	0.3
	Total Power of Agricultural Machinery	0.2
Rural settlements	Electricity Consumed in Rural Area	0.6
	Employed Persons for Primary Industry	0.4
Urbanized land	Total Consumption of Electricity of the Year & Electricity Consumed in Rural Area[a]	0.4
	Employed Persons for Secondary Industry & Tertiary Industry[a]	0.3
	Freight Traffic of Highways	0.3

Note, the sum of weights of all indicators in each land use type equals to 1, detailed information on the weight's calculation can be seen in section 3.1.

[a] Assuming that the consumption of electricity in urbanized land is about the remains of total consumption of electricity of the year minus electricity consumed in rural area, and the employed persons in urbanized land is about the sum of employed persons for secondary industry and tertiary industry.

The typical human activities in built-up land are residential activities (e.g., industrial, commercial and daily living activities) for improving economic growth and life quality (Xia et al., 2020; Yin et al., 2020). Six representative economic and social indicators were selected, namely freight traffic of highways, employed persons for primary, secondary and tertiary industries, total consumption of electricity of the year, and electricity consumed in rural areas. The specific indicators for calculating LUI on rural settlements and urbanized land were in Table 1.

2.2.3. County boundaries

The vector data of county boundaries in 1995 (75 counties) and 2015 (55 counties) were downloaded from RESDC. Then we generated county boundaries in 2000, 2005, 2010 and 2018 according to the official released articles of county-level administrative division adjustment (http://jssdfz.jiangsu.gov.cn/art/2019/11/12/art_57470_8810959.html) for the data unavailability.

2.2.4. Vegetation index

Normalized difference vegetation index (NDVI) has been seen widely for representing vegetation growth and observing vegetation change over a long spell (Bégué et al., 2011; Liu and Menzel, 2016). The annual NDVI data from 1998 to 2018 with a 1 km resolution were downloaded from RESDC. The maximum value composite method was applied to generate this yearly dataset based on the SPOT/VEGETATION products (http://www.vito-eodata.be) for minimizing cloud contamination, atmospheric effects and scan angle effects (Holben, 1986).

2.2.5. Climate and topography

Annual mean temperature (AMT) and annual gross precipitation (AGP) from 1998 to 2018 were produced with the monthly temperature and precipitation on software ArcGIS 10.2. The monthly temperature and precipitation dataset with 0.5 arc-minute (~1 km) resolution was generated by Peng S. et al., 2019, which is reliable based on 496 national weather stations across China.

Two topographic indices, elevation and slope, were derived from the SRTM (Shuttle Radar Topography Mission) digital elevation model (DEM) v4.1. The original resolution is 90 m and we used a resampled DEM with 1 km resolution produced by RESDC.

2.2.6. Night-time light

As an important trigger of intensive human activities, the accelerated economic development tends to result in increased human disturbance to vegetation growth directly and indirectly by influencing LUI (Kou et al., 2021). Night-time light (NTL) is an available high-resolution data closely related to the economic development level (Liu et al., 2021). We used an annual harmonized global nighttime light dataset from 1992 to 2018 with 30 arc-seconds (~1 km) resolution (Li et al., 2020).

3. Methodology

3.1. Quantification of land use intensity of jiangsu

We quantified the LUI of Jiangsu Province in 1995, 2000, 2005, 2010, 2015 and 2018. In our study, the calculation unit for LUI was generated by overlying county boundaries and land use types using ArcGIS 10.2. For each unit, we calculated the LUI with three steps as follows.

Firstly, the intensity (density or frequency) of economic and social indicators in each unit of each year were generated. Then, the zero-mean normalization method was used to eliminate measurement units among indicators (Reverter et al., 2005). We finally added a constant number to all the standardized indicators for the negative values after standardization. Secondly, the LUI was calculated in each calculation unit using the above standardized indicators with the weighted stacking method. The formula is as follows:

$$LUI_{ijy} = \sum_{1}^{m} (u_{ijym} * w_{jm}) \quad (1)$$

where LUI_{ijy} is the LUI of the land use type j of county i *in year* y; u_{ijym} is the mth standardized indicator of j at i in y; w_{jm} represents their weights as shown in Table 1.

We determined the indices weights in cropland by reviewing the relative importance of each indicator in several published studies about the agricultural management intensity quantification in China (Jiang et al., 2013; Li et al., 2018; Liu et al., 2020). However, with limited effective information found in built-up land, we determined the weights on urbanized land and rural settlements referring to an objective method of coefficient of variation (CV) (Ren and Fan, 2011):

$$w_{jm} = \frac{CV_m}{\sum_{1}^{m} CV_m} \quad (2)$$

where w_{jm} and CV_m are the weight and variation coefficient of mth intensity of economic and social indicator in each land use type j (Table 1).

Finally, considering the coefficients of LUI assigned to different land use types in the previous studies listed in Table 2, we assigned coefficients of one, two and three for cropland, rural settlements and urbanized land when integrating LUI for the whole study area, respectively. When there is grassland/forest (natural land) transformed from/to the targeted three land use types along the time series, we assigned a value of 0.01 to LUI of natural land assuming a very small LUI with few human interferences in those grassland/forest.

3.2. Quantification of effects of driving factors for vegetation change using structural equation modeling

Structural equation modeling, a causality analysis method (Pearl, 1998), has been increasingly developed in exploring complex influence networks in ecosystems recently (Chen et al., 2022; Lian et al., 2021). This approach encompasses a set of multivariate statistical techniques, including factor analysis, regression, path analysis and simultaneous equation modeling (Hou et al., 2014). SEM has several advantages for detecting the influences of driving factors on vegetation change. First, a variable can be dependent in one set of relationships while independent in another set of relationships. Second, the SEM separates the direct and indirect causal effects based on the mediation theory of path analysis.

Changes in climate (AMT and AGP), terrain conditions (elevation and slope), economic development (NTL change) and LUI change were taken as drivers to build an SEM of vegetation change. The NDVI trend from 1998 to 2018 was calculated through linear regression on each pixel with the NDVI value as the independent variable and the according year of NDVI as the dependent variables (Bégué et al., 2011). The slope of the function was defined as the trend of NDVI per year. A larger positive slope represents a faster increase in NDVI. Additionally, we assumed a linear change in intervals of LUI dataset. Thus similarly, slopes of AMT, AGP, LUI and NTL were also calculated as the trends.

We focused on areas with significant vegetation change examined by F-test, so pixels with significant slope ($p < 0.05$) of NDVI trend were selected as the target samples for building the SEM. Then, these pixels were labeled by four land use types, i.e., a) transformed land, b) cropland, c) rural settlements and d) urbanized land. The transformed land consists of areas once labeled by different land use types before 2018. SEMs were constructed for the four land use types, respectively. The specific procedure is as follows.

3.2.1. Building a graphical conceptual model

The hypotheses in the graphical conceptual model in Fig. 2 are based on knowledges about the driving mechanism of vegetation change through a literature review (Liu and Menzel, 2016; Liu et al., 2019; Zhu et al., 2016). First, natural and anthropogenic drivers directly influenced vegetation change. Meanwhile, the vegetation change had feedback on the changes of the two climatic drivers. Second, the slope and elevation may influence vegetation change indirectly by affecting all the other drivers. Economic development (NTL trend) may indirectly influence vegetation change by altering the LUI trend. And the LUI change could influence vegetation change by affecting regional climate (AMT and AGP trends). The climatic drivers change might also have indirect effects on vegetation change through influencing economic development. Moreover, two correlations were assumed: One is between the change of

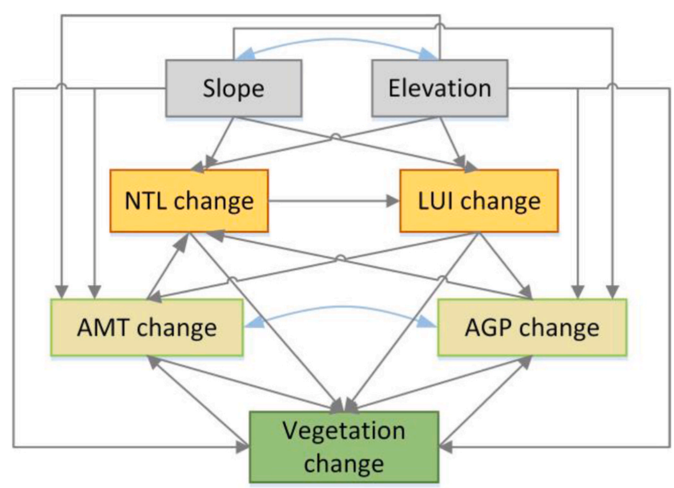


Fig. 2. Graphical conceptual model of vegetation change from 1998 to 2018 in Jiangsu. Boxes represent the observed variables; the gray arrows between variables identify the potential cause-and-effect relations; the blue double arrow means the correlation. NTL, night-time light; LUI, land use intensity; AMT, annual mean temperature; AGP, annual gross precipitation. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Reviews of coefficients of human activities intensity assigned to different land use types.

	Forest/Grassland	Cropland	Built-up land		Reference
			Rural settlements	Urbanized land	
Land use intensity comprehensive index	1,2	3	4		Zhuang and Liu (1997)
Landscape development intensity	1, 1.58, 1.83, 2.02, 2.77, 3.41, 3.68, 3.74	4.54, 7	6.9, 6.92, 7.47, 7.55, 7.7	7.81,8,8.07,8.28,8.29,8.32,8.66,9.18,9.19,9.42,10	Brown and Vivas (2005)
Human activity intensity of Land surface	0,0.067,0.133	0.2	0.6	0.6 , 1	Xu et al. (2015)
Human interference index	0	0.2–0.4	0.6–1		Chi et al. (2018)
Human footprint	0	6,7,8	8,10		Sanderson et al. (2002); Venter et al. (2016)

AMT and AGP; the other is between the elevation and slope.

3.2.2. Mathematical SEM construction and revision

On basis of the target pixels with significant vegetation change, we extracted the trends of NDVI, NTL, LUI, AMT and AGP and the values of elevation and slope as the input data in a mathematical SEM according to the graphical conceptual model. Maximum likelihood estimation was adopted for structural equation modeling using the *sem* function of the 'lavaan' package in the R.3.5.0 (Rosseel, 2012). In general, a good fit of SEM model satisfies most of the assessment indices including a lower root mean square error of approximation (RSMEA) than 0.05, lower standardized root mean square residual (SRMR) than 0.08, higher comparative fit index (CFI) than 0.95, higher Ttucker-Lewis index (TLI) than 0.9 (Hu and Bentler, 1998), lower chi-square/df ratio than 2 or 5 (Schumacker and Lomax, 2004), and bigger *p* value of the *t*-test than 0.05 (Marsh and Hocevar, 1985). If the model fitted with poor goodness-of-fit indices or physical significance, it was revised by deleting non-significant path ($p > 0.05$) or changing the paths by the 'modify' function of 'lavaan'. Finally, we built the SEMs by satisfying indices including CFI, TLI, SRMR, RMSEA, chi-square/df ratio and *p* value.

3.2.3. Quantifying direct and indirect effects of driving factors on vegetation change

The standardized path coefficients between variables in the final SEM were adopted for quantifying the effects of the driving factors on vegetation change. A larger path coefficient indicated a larger effect. The total effect (TE) of a variable on the target variable consisted of both direct and indirect effects (Grace et al., 2016). The direct effect (DE) of a variable (such as the effect of LUI change on vegetation change) was the path coefficient on the arrow which directly pointed to vegetation

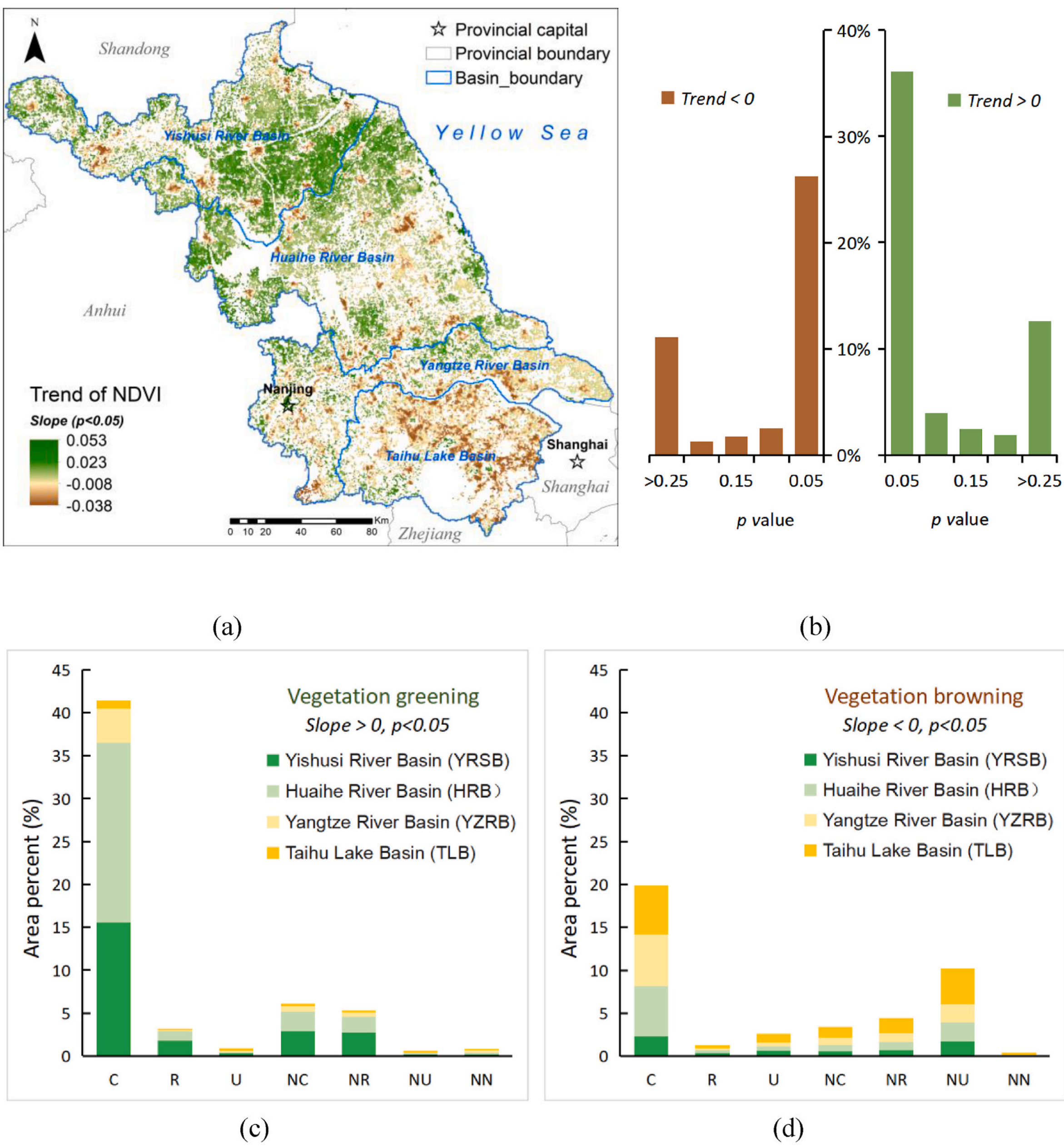


Fig. 3. Spatial distribution of significant NDVI trends ($p < 0.05$) from 1998 to 2018 (a) and frequency distribution of the significance level (p value) of the trends (b). The area percent of each basin of each land use type in total areas of significant vegetation changes including vegetation browning trends (c) and vegetation greening trends (d). C, cropland, R, rural settlements, U, urbanized land, NC, new cropland, NR, new rural settlements, NU, newly urbanized land, NN, new natural land. The p value of the trend in vegetation for each pixel is estimated based on *t*-test.

change from the variable. The indirect effect was measured by the multiplication of coefficients from LUI change to a mediator variable (such as AMT change) and the coefficients from the mediator variable to vegetation change. Moreover, the indirect effect was the sum of all indirect coefficients of every indirect path between one driving factor and vegetation change.

4. Results

4.1. Spatial-temporal variation of vegetation in Jiangsu Province

The NDVI trend in Fig. 3a shows the significant vegetation change ($p < 0.05$) ranging from −0.038 yr^{-1} to 0.053 yr^{-1} with high spatial heterogeneity in recent two decades. The total area of significant vegetation greening is 37.5% larger than the browning area as shown in Fig. 3b, but vegetation browning is also significant enlarging from northwest to southeast. We further find that about 70% of significant vegetation change existed within non-transformed land use. Cropland has the largest area with both vegetation greening (mostly in YSRB and HRB, Fig. 3c) and browning (mainly in HRB, YZRB and TLB, Fig. 3d). Rural settlements in northern two basins mainly have vegetation greening trends, while most rural settlements in southern basins have vegetation browning trends. Besides, most urbanized land and new urbanized land in the whole province show an obvious browning trend. Besides, new cropland and rural settlements both show the larger greening areas (mostly in YSRB and HRB) than browning areas.

4.2. Spatial-temporal variation of LUI in Jiangsu Province

The LUI from 1995 to 2018 is mapped in Fig. 4a to f. The spatial LUI change over years and the trends in each land use type on a basin scale is shown in Fig. 5a and b. In 1995 and 2000, the LUI was evenly distributed, except high LUI in some cities of southern Jiangsu (Fig. 4a and b). From 2005 to 2018, the dynamic LUI gradually exhibited a large spatial and temporal variability from northwestern to southeastern basins (Fig. 4c-f). This is mainly due to the dynamic LUI within C and NU for urban expansion (Fig. 5b). In cropland, the LUI increased quickly in YSRB, while slowly in HRB, but it decreased in southern Jiangsu (Figs. 1 and 5b). The NU manifested the largest increasing trend overall Jiangsu. A large variation of LUI trends (a wider box in Fig. 5b) in southern basins indicates diverse LUI changes under rapid urbanization. As for U, the LUI in YSRB and TLB increased faster than that in the other two basins (Fig. 5b). Yet, the LUI of R remained almost unchanged except that in TLB. The LUI consistently increased in NR but decreased in NC and NN in all basins. The dynamic LUI indicates an overall increase but spatially and temporally different patterns, especially within C, R and U, which highly addresses the necessity of basin and land dependent management in LUI.

4.3. SEMs for vegetation change

The four fitted SEMs for (a) transformed land, (b) cropland, (c) rural settlements and (d) urbanized land are presented in Fig. 6, with their model evaluation indices in Table 3. These models indicate that the fast economic development represented by the NTL change was the main driver of vegetation browning regardless of land use types in Jiangsu. The LUI change is also a contributing factor, but its relative importance and impacts were diverse in driving vegetation change across land use types. In addition, the SEM for urbanized land indicates a quite different mechanism compared to those for other land use types. The details of each SEM are as follows.

4.3.1. SEM for transformed land

The NTL change has the largest total effects (TE = −0.67) on vegetation change, followed by LUI change (TE = −0.25), elevation (TE = 0.25), AMT change (TE = 0.23), AGP change (TE = −0.13) and slope (TE = −0.04). Both faster economic development (larger positive NTL slope) and larger LUI increase for land transformation (e.g., cropland transforming into urbanized land indicates a larger LUI increase than rural settlements transforming into urbanized land) lead to vegetation browning directly with little interaction with climate change. The negative direct effect of NTL change (DE = −0.57) is larger than that of LUI change (DE = −0.23). Meanwhile, accelerated economic development indirectly exacerbates the vegetation browning by hastening the LUI increasing (Fig. 6a). Among the natural drivers, both higher elevation and faster warming (a faster AMT increase) directly lead to vegetation greening, and this positive DE is strengthened by negatively influencing the economic development. The vegetation greening preferred a lower slope due to indirect effects. Additionally, with only negative indirect effect of AGP change on vegetation change, the vegetation enhancement prevents a higher rise in AGP with a coefficient of −0.19.

4.3.2. SEM for cropland

The total effects of NTL change, LUI change, elevation, AGP change, AMT change, and slope on vegetation change are −0.63, 0.27, 0.17, −0.13, 0.12 and −0.04 respectively (Fig. 6b). The faster economic development produces direct negative effects on vegetation change, and it also brings indirect negative effects through influencing the LUI change. The increasing LUI in cropland directly leads to vegetation greening (DE = 0.13). Meanwhile, increasing LUI indirectly positively influences vegetation change through accelerating regional warming (IE = 0.06) and preventing AGP increasing (IE = 0.08). As for the natural drivers, similarly, the AMT change and elevation are both directly and indirectly enhancing the vegetation growth but slope has negative indirect effects. Besides, it shows a significant direct negative effect of AGP increasing on vegetation greening.

4.3.3. SEM for rural settlements

Economic development is still with the largest TE of −0.65 for aggravating vegetation browning directly and indirectly, and both the change of two climatic drivers have larger effects than LUI change. The AGP change (TE = −0.42) is a more important driver than AMT change (TE = 0.23) due to its role in accelerating economic development. The LUI increase exerts a total effect (−0.20) by indirectly preventing vegetation greening through influencing two climatic factors (Fig. 6c). Similarly, the effects of elevation and slope are the smallest with TE of 0.13 and −0.03.

4.3.4. SEM for urbanized land

The effects of each driver in urbanized land are greatly different from those in other models. The change of NTL and AGP has the same biggest total effects on vegetation change (TE = −0.33), followed by the AMT change (TE = −0.17), LUI change (TE = −0.14), slope (TE = 0.06) and elevation (TE = −0.03) (Fig. 6d). Faster economic development still, directly and indirectly, causes vegetation browning, but the relative importance is smaller than that in other models. The changes of two climatic drivers are more important than LUI change in driving vegetation change. Both the higher rise in AGP and AMT leads to vegetation browning directly. However, although a faster LUI increase has a direct negative effect on vegetation greening, 18% of the negative effects are offset indirectly by preventing regional warming. The total effects of slope or elevation are also small but the direction of effects is contrary to that in other models.

5. Discussions

5.1. Divergent direct and indirect effects of LUI change on vegetation change

The SEM models of different land use types have a similar structure with different directions and influencing coefficients of effects of each

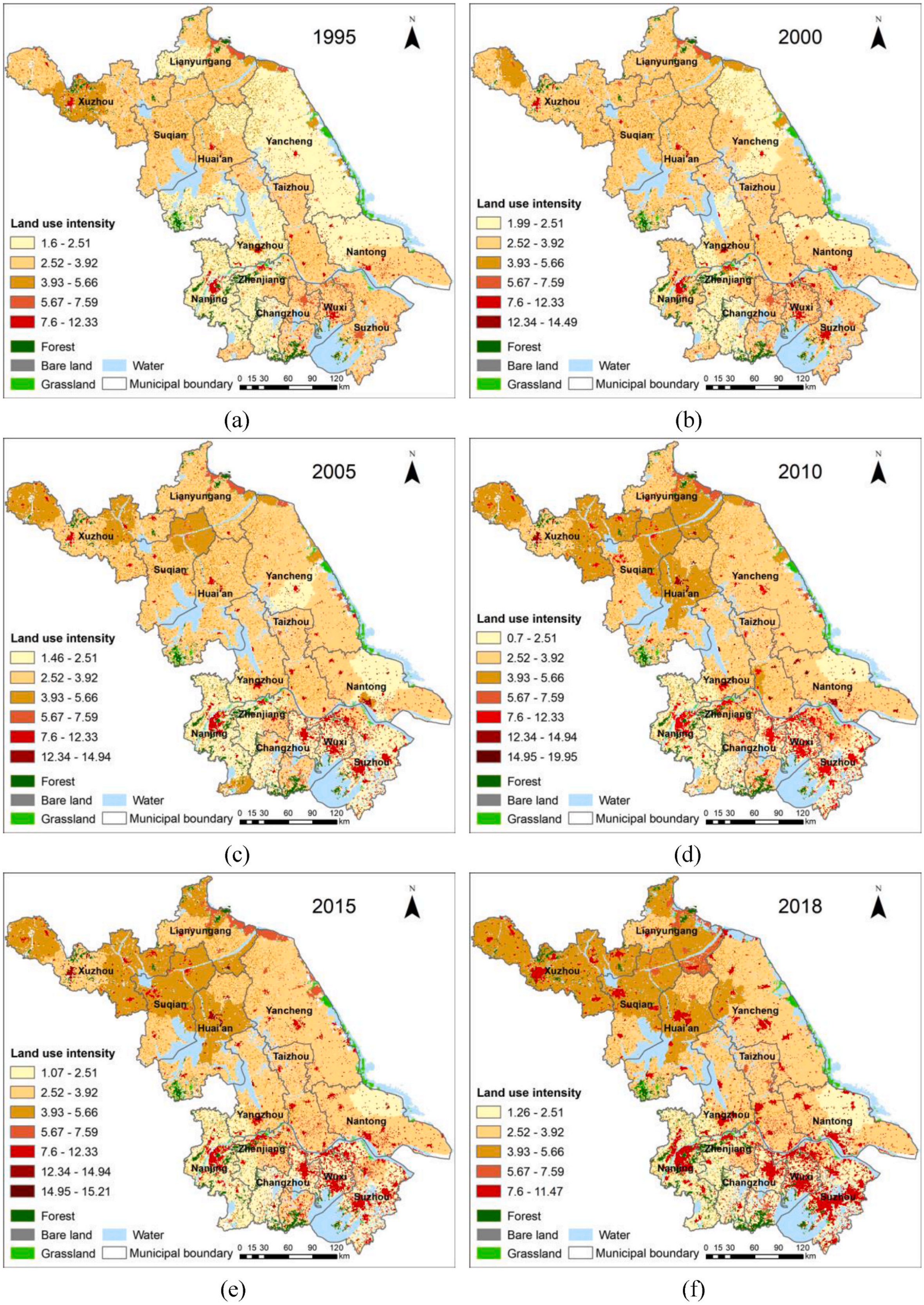


Fig. 4. The land use intensity of Jiangsu Province in 1995 (a), 2000 (b), 2005 (c), 2010 (d), 2015 (e) and 2018 (f). The five class breaks of LUI in 1995 were generated with the classification method of Natural Breaks (Jenks) in ArcGIS 10.2, and the breaks of the five classes were then taken as the standard for LUI in the other years so that the intervals are comparable with different maximum or minimum values.

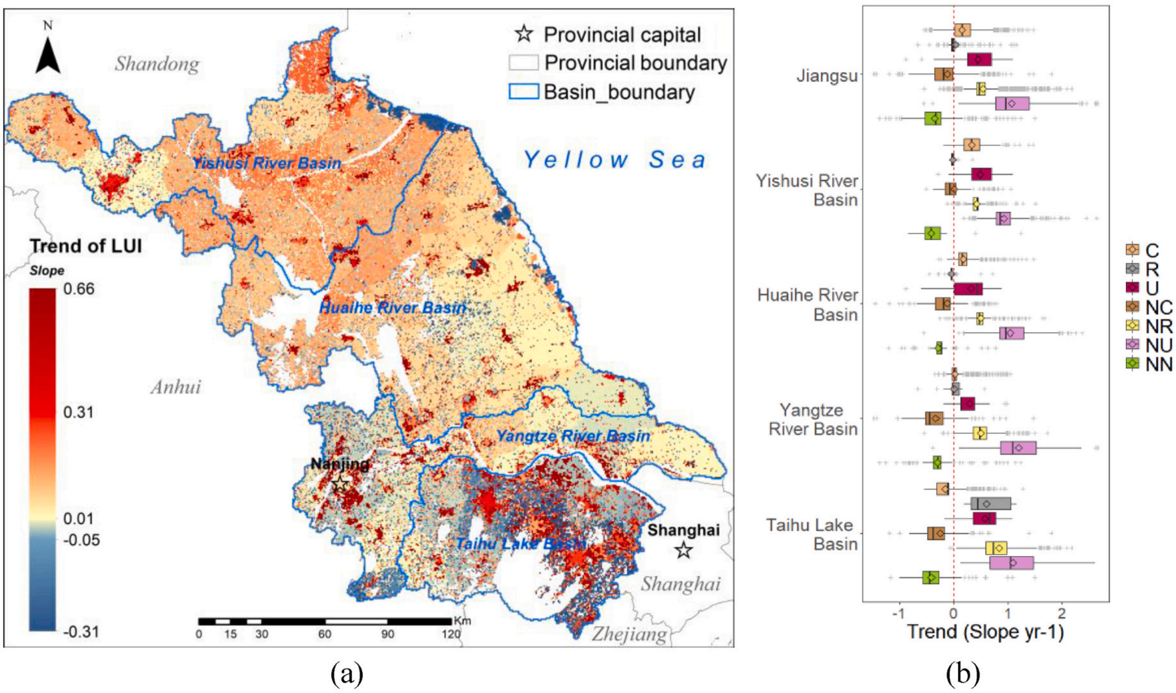


Fig. 5. Trends (slopes) of LUI from 1995 to 2018 (a) and boxplot of land use intensity trends in each land use type of each basin (b). The red dashed line is the baseline of 0. C, cropland; R, rural settlements; U, urbanized land; NC, new cropland; NR, new rural settlements; NU, newly urbanized land; NN, new natural vegetated land. The new land use types represent those transformed from other types before 2018. The new natural vegetated land represents the new grassland and new forest. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

factor. Although the economic development shows the dominate negative effects on vegetation change regardless of land use types, LUI has a divergent important effect on vegetation change interacted with economic development, climate change and topography in different land use types. This indicates the importance of understanding the effects of the long-term dynamic LUI interacted with other drivers on vegetation change.

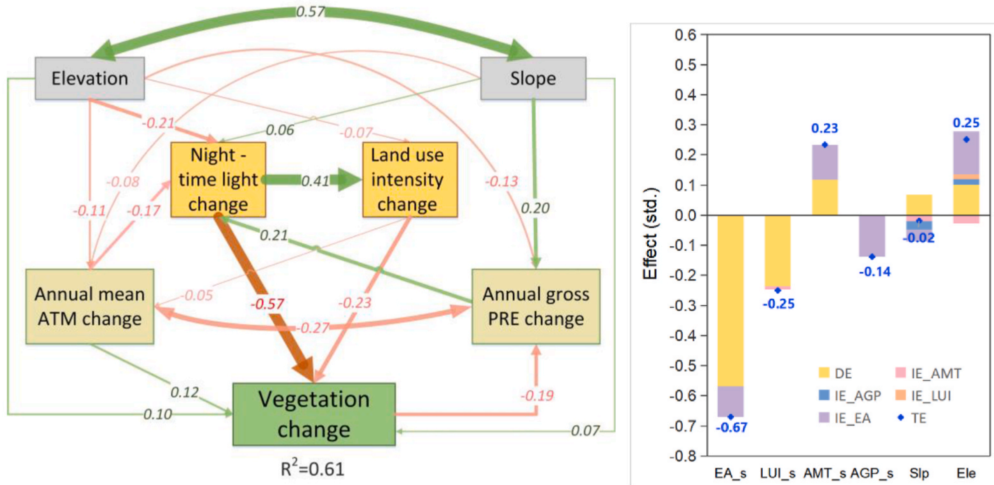
The SEM of cropland supports that the vegetation greening was mainly because of intensified agricultural management (LUI increasing) and regional climate warming (AMT increasing). Which is similar with the studies of Feng et al. (2021) and Piao et al. (2020). Furthermore, we found the strong interactions between long-term LUI change and climate change. The LUI increasing has a positive effect on climate warming, and climate warming enhances vegetation greening for generally extending the growing season of plants (Keenan and Riley, 2018). At meantime, LUI change has a negative effect on AGP change, and the AGP increasing is negative for crop growth (IE = 0.08). This might be because Jiangsu has adequate precipitation, and more precipitation in south Jiangsu could damage plants growth, but less precipitation in north Jiangsu did not influence the plant growth with the sufficient irrigation system (Huang and Wang, 2021). Besides, the SEM supports that an anti-intensification (LUI decreasing) threatened the crop growth of two southern basins under faster economic development (NTL increasing). This anti-intensification might result from the cropland abandonment for labors decreasing in rural settlements (Liang et al., 2021).

In regard to rural settlements and urbanized land, the LUI change has both negative total effects on vegetation change with the intensified land use. But for rural settlements, LUI has no significant direct effects, which is might because LUI in most rural settlements changed not much (except Taihu Lake Basin as shown in Fig. 5b). Meanwhile, the SEMs suggest different indirect effects of LUI in rural and urban areas. In rural settlements, LUI has negative indirect effects through influencing climate (Fig. 6c). Yet, interestingly, a positive indirect effect of LUI increasing is significant through influencing climate warming in urbanized lands when the climate warming heightened the vegetation browning only in urbanized land (Weng et al., 2004) (Fig. 6d), such as the vegetation greening trends are found in few cores of cities in southern Jiangsu under increasing LUI (Figs. 3a and 5a). This finding is consistent with some new recent findings on enhanced vegetation greening in cities under human management (Jia et al., 2018; Zhang L. et al., 2022). Besides, LUI increasing is also accelerated by economic development within built-up lands, but only limited by the high elevation in rural for the intensive human activities of recreation and tourism on mountain of cities (Pickering and Hill, 2007).

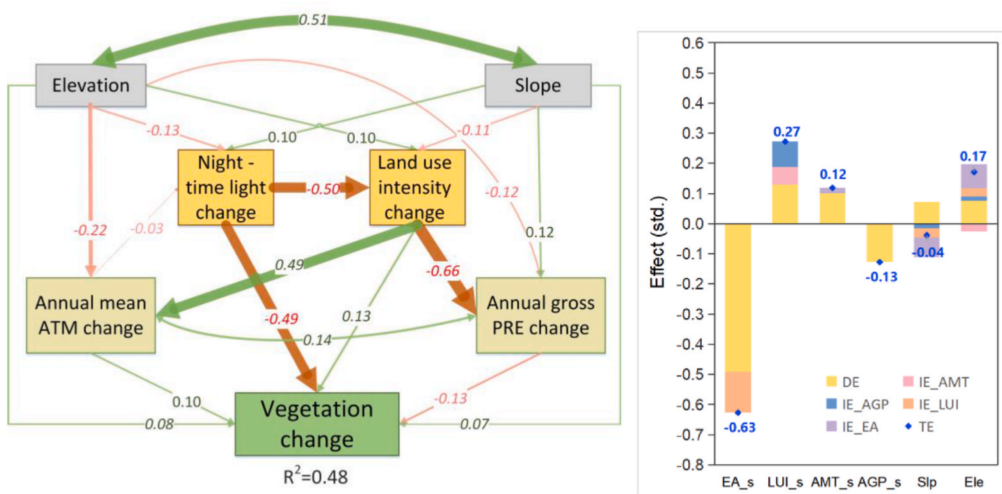
The constructed SEM in transformed land is consistent with previous studies. Those studies suggested that the vegetation growth is directly threatened by land transformations with an increasing of LUI, such as other land use transformed to NU in all basins (Fig. 3d) (Yang et al., 2021; Zheng et al., 2021; Zhong et al., 2019). Furthermore, the SEM model addressed that this LUI increasing is accelerated by economic development without limitations of elevation, which is an alarming for the economic induced land transformation ignoring the environment protection in developed region. Unexpectedly, the LUI change in terms of land transformations shows the very less interaction with climate change in our model. This may due to the land transformations with large influences on climate change, like deforestation, less happen in developed region. Besides, the stronger interaction between LUI and climate change within land use type indicates the influences of land use on climate change might depend more on the LUI within land use type rather the land transformations in Jiangsu which have been dominated by humans with a long history.

5.2. Implications for land management in sustainable land use intensification

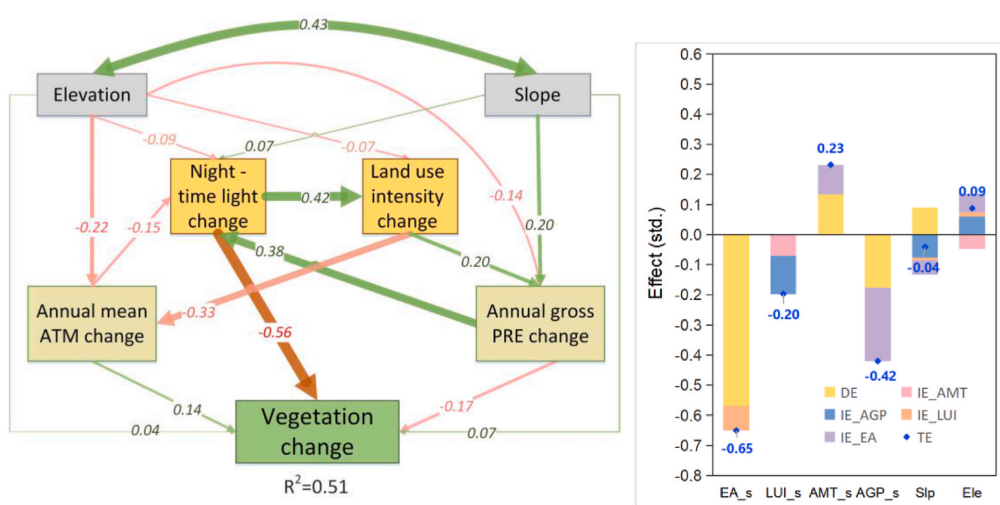
The diverse direct and indirect effects of LUI on vegetation change in different land use types suggest the necessity of land management for sustain development (Fig. 6). As one of the vital food base of China, the key to sustain managements in cropland of Yishusi River Basin and Huaihe Basin is to keep the steady food production while minimize the



(a) Transformed land



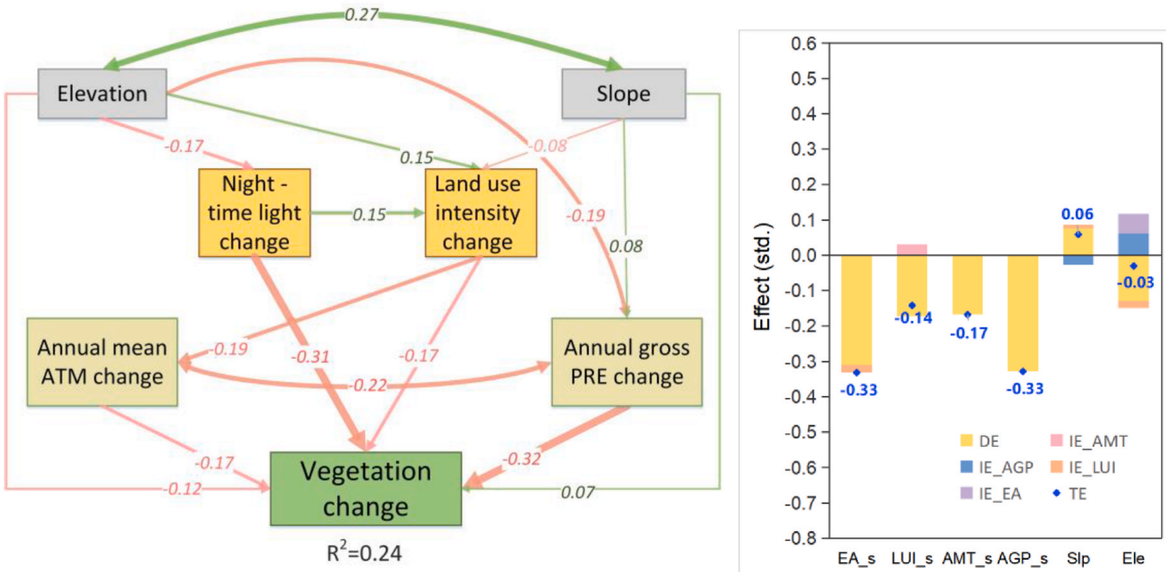
(b) Cropland



(c) Rural settlements

Fig. 6. Path diagrams of the fitted SEMs and the total effect (TE), direct effect (DE) and IE_*x* (indirect effects of one driver on vegetation change through another driver *x* (mediated factors)) of these anthropocentric and natural drivers on NDVI_s in the transformed land use types (a), cropland (b), rural settlements (c) and

urbanized land (d). Path diagrams contain rectangles for observed variables, curves with double arrows for correlations, and straight lines with single arrows for linking a driver to point a predicted variable. The values on the arrows were the effect sizes. The thickness of the arrows was proportional to the effect size. Green and red lines represent the significant positive and negative paths ($p < 0.05$). For the stack column charts, the abscissa labels of 6 bars are the vegetation change drivers (EA_s (s means slope), LUI_s, AMT_s, AGP_s, Slp and Ele), and the diamond on each bar is the TE by summing the DE and all IE_x on this bar. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



(d) Urbanized land

Fig. 6. (*continued*).

Table 3
The evaluation indices of the SEM models.

		Transformed land	Cropland	Rural settlements	Urbanized land
Relative Goodness-of-Fit Indices	CFI	1	1	0.999	0.998
	TLI	0.999	1	0.993	0.995
Absolute Goodness-of-Fit Indices	RMSEA	0.008	0.000	0.024	0.011
	SRMR	0.002	0.000	0.010	0.013
The Chi-Square test Statistic	Chi-Square	4.151	0.427	9.206	7.268
	Chi-Square/df	2.076	0.214	2.302	1.211
	p	0.126	0.808	0.056	0.297
Sample number	n	15,450	30,935	2196	1634

possible negative consequences of climate change (Zhang et al., 2022) and economic-induced unreasonable managements. The Climate-Smart Agriculture (CSA, https://www.fao.org/climate-smart-agriculture/overview/en/) can be recommended as one potential management mode for containing greenhouse gas and supporting crop growth while increasing organic matter storage in soils (Silva et al., 2021). Meanwhile, the promotion of the agricultural scale management can be considered to control vegetation degradation in southern Jiangsu and some central area of Huaihe River Basin for avoiding the cropland mismanagement. As for in urban and rural, due to the larger influences of climate change on vegetation growth, more policy supports are demanded to improve the adaptability of vegetation to regional climate change, such as the selection of vegetation species (Norton et al., 2015). Meanwhile, due to the negative effect of LUI on vegetation change in urban and rural under fast economic development, policies could guide land use with low-carbon life and industrial production in those areas, such as the greener daily commute, recreation and cleaner industrial production. In addition, policy on Smart Growth for controlling urban sprawl (Downs, 2005) is also needed in rural areas of southern Jiangsu.

5.3. *Research significance, limitations and prospects*

The environmental effects of LUI change within different land use types on a regional scale are poorly understood so far. We first obtained the LUI change based on the representative county-scale economic and social indicators from 1995 to 2018 in Jiangsu Province, and then explored the effect of LUI change and its interactions with other drivers on vegetation change in different land use types. Our study helps recognize vegetation change patterns and its complex underlying mechanisms under increasingly intensive land use to provide comprehensive views in policy-making for regional sustainable land use and management.

There are still some limitations of our study. The statistical data on the county scale were limited with their spatial resolution, though they are the most detailed and longest records of human activities on land on a regional scale. Besides, the weight assignment of each land use type for LUI calculation is also a challenge at present. Thus, in the future, more innovative methods are needed for producing the long-term LUI dataset on a regional and global scale to understand the environmental effects of land use intensification.

6. Conclusion

This study quantified the direct and indirect effects of LUI trends on vegetation change interacting with ecological development, climate change and topographic condition in transformed land, cropland, rural settlements and urbanized land in Jiangsu Province, China from 1998 to 2018 using SEM. With the vegetation browning area expanding from northwest to southeast, Jiangsu showed a 70% of significant vegetation change in C, R and U indicating the importance of mechanisms of vegetation change within land use types for environment managements. The SEMs suggested the dominant total negative effect of economic development on vegetation change in all land use types. Meanwhile, the LUI change produced significant diverse direct and indirect effects on vegetation change indicating the potentials of environment protection through managing LUI. The LUI increasing in cropland (mainly due to agriculture intensification) directly promotes vegetation greening, and it also indirectly enhances vegetation growth due to the strong interactions with climate change. Thus, the total effects LUI in cropland ranks the second behind the economic development. Yet, the vegetation change in both rural settlement and urbanized land are negatively influenced by LUI increasing and shows more sensitivity to climate change than LUI change, while the LUI increasing in urbanized land takes a distinctive positive indirect effect through influencing climate warming. Our study highlighted the importance of long-term LUI quantification and promoted the understanding of its effects on vegetation change in different land use types for regional land managements.

Author contribution

Shen Feixue: Conceptualization, Visualization, Software, Data curation, Methodology, Writing - original draft; Yang Lin: Conceptualization, Resources, Writing - review & editing, Supervision, Funding acquisition. Zhang Lei, Guo Mao & Huang Haili: Formal analysis, Validation; Zhou Chenghu : Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 41971054), and the Leading Funds for the First-Class Universities (020914912203 and 020914902302). We are very grateful to reviewers and editor for the constructive suggestions for this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.116562.

References

Allan, E., Bossdorf, O., Dormann, C.F., et al., 2014. Interannual variation in land-use intensity enhances grassland multidiversity. Proc. Natl. Acad. Sci. USA 111 (1), 308. https://doi.org/10.1073/pnas.1312213111.

Bégué, A., Vintrou, E., Ruelland, D., et al., 2011. Can a 25-year trend in Soudano-Sahelian vegetation dynamics be interpreted in terms of land use change? A remote sensing approach. Global Environ. Change 21 (2), 413–420. https://doi.org/10.1016/j.gloenvcha.2011.02.002.

Blüthgen, N., Dormann, C.F., Prati, D., et al., 2012. A quantitative index of land-use intensity in grasslands: integrating mowing, grazing and fertilization. Basic Appl. Ecol. 13 (3), 207–220. https://doi.org/10.1016/j.baae.2012.04.001.

Brown, M.T., Vivas, M.B., 2005. Landscape development intensity index. Environ. Monit. Assess. 101 (1), 289–309. https://doi.org/10.1007/s10661-005-0296-6.

Choi, Y., Lim, C.-H., Chung, H.I., et al., 2021. Forest management can mitigate negative impacts of climate and land-use change on plant biodiversity: insights from the Republic of Korea. J. Environ. Manag. 288, 112400 https://doi.org/10.1016/j.jenvman.2021.112400.

Chen, C., Park, T., Wang, X., et al., 2019. China and India lead in greening of the world through land-use management. Nat. Sustain. 2 (2), 122–129. https://doi.org/10.1038/s41893-019-0220-7.

Chen, Z., Xu, M., Gao, B., et al., 2022. Causation inference in complicated atmospheric environment. Environ. Pollut. 303, 119057 https://doi.org/10.1016/j.envpol.2022.119057.

Chi, Y., Shi, H., Zheng, W., et al., 2018. Spatiotemporal characteristics and ecological effects of the human interference index of the Yellow River Delta in the last 30 years. Ecol. Indicat. 89, 880–892. https://doi.org/10.1016/j.ecolind.2017.12.025.

Downs, A., 2005. Smart growth: why we discuss it more than we do it. J. Am. Plann. Assoc. 71 (4), 367–378. https://doi.org/10.1080/01944360508976707.

Erb, K.-H., Haberl, H., Jepsen, M.R., et al., 2013. A conceptual framework for analysing and measuring land-use intensity. Curr. Opin. Environ. Sustain. 5 (5), 464–470. https://doi.org/10.1016/j.cosust.2013.07.010.

Felipe-Lucia, M.R., Soliveres, S., Penone, C., et al., 2020. Land-use intensity alters networks between biodiversity, ecosystem functions, and services. Proc. Natl. Acad. Sci. USA 117 (45), 28140–28149. https://doi.org/10.1073/pnas.2016210117.

Feng, D., Bao, W., Yang, Y., et al., 2021. How do government policies promote greening? Evidence from China. Land Use Pol. 104, 105389 https://doi.org/10.1016/j.landusepol.2021.105389.

Gossner, M.M., Lewinsohn, T.M., Kahl, T., et al., 2016. Land-use intensification causes multitrophic homogenization of grassland communities. Nature 540 (7632), 266–269. https://doi.org/10.1038/nature20575.

Grace, J.B., Keeley, J.E., 2006. A structural equation model analysis of postfire plant diversity in California shrublands. Ecol. Appl. 16 (2), 503–514. https://doi.org/10.1890/1051-0761(2006)016[0503:ASEMAO]2.0.CO;2.

Grace, J.B., Anderson, T.M., Seabloom, E.W., et al., 2016. Integrative modelling reveals mechanisms linking productivity and plant species richness. Nature 529 (7586), 390–393. https://doi.org/10.1038/nature16524.

Haberl, H., Erb, K.H., Krausmann, F., et al., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. USA 104 (31), 12942. https://doi.org/10.1073/pnas.0704243104.

Hisse, I.R., Biganzoli, F., Peper, A.M., et al., 2022. Annual productivity of cropping sequences: responses to increased intensification levels. Eur. J. Agron. 137, 126506 https://doi.org/10.1016/j.eja.2022.126506.

Huang, W., Wang, H., 2021. Drought and intensified agriculture enhanced vegetation growth in the central Pearl River Basin of China. Agric. Water Manag. 256, 107077 https://doi.org/10.1016/j.agwat.2021.107077.

Holben, B.N., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Rem. Sens. 7 (11), 1417–1434. https://doi.org/10.1080/01431168608948945.

Hou, D., Al-Tabbaa, A., Chen, H., et al., 2014. Factor analysis and structural equation modelling of sustainable behaviour in contaminated land remediation. J. Clean. Prod. 84, 439–449. https://doi.org/10.1016/j.jclepro.2014.01.054.

Hu, L.-t., Bentler, P.M., 1998. Fit indices in covariance structure modeling: sensitivity to underparameterized model misspecification. Psychol. Methods 3 (4), 424–453. https://doi.org/10.1037/1082-989X.3.4.424.

Jia, W., Zhao, S., Liu, S., 2018. Vegetation growth enhancement in urban environments of the Conterminous United States. Global Change Biol. 24 (9), 4084–4094. https://doi.org/10.1111/gcb.14317.

Jiang, L., Deng, X., Seto, K.C., 2013. The impact of urban expansion on agricultural land use intensity in China. Land Use Pol. 35, 33–39. https://doi.org/10.1016/j.landusepol.2013.04.011.

Jiang, M., Hu, X., Chunga, J., et al., 2020. Does the popularization of agricultural mechanization improve energy-environment performance in China's agricultural sector? J. Clean. Prod. 276, 124210 https://doi.org/10.1016/j.jclepro.2020.124210.

Keenan, T.F., Riley, W.J., 2018. Greening of the land surface in the world's cold regions consistent with recent warming. Nat. Clim. Change 8 (9), 825–828. https://doi.org/10.1038/s41558-018-0258-y.

Kleyer, M., Trinogga, J., Cebrián-Piqueras, M.A., et al., 2019. Trait correlation network analysis identifies biomass allocation traits and stem specific length as hub traits in herbaceous perennial plants. J. Ecol. 107 (2), 829–842. https://doi.org/10.1111/1365-2745.13066.

Kou, P., Xu, Q., Jin, Z., et al., 2021. Complex anthropogenic interaction on vegetation greening in the Chinese Loess Plateau. Sci. Total Environ. 778, 146065 https://doi.org/10.1016/j.scitotenv.2021.146065.

Kuemmerle, T., Levers, C., Erb, K., et al., 2016. Hotspots of land use change in Europe. Environ. Res. Lett. 11 (6) https://doi.org/10.1088/1748-9326/11/6/064020.

Leroux, L., Begue, A., Lo Seen, D., et al., 2017. Driving forces of recent vegetation changes in the Sahel: lessons learned from regional and local level analyses. Rem. Sens. Environ. 191, 38–54. https://doi.org/10.1016/j.rse.2017.01.014.

Li, M., Wang, Y., Fu, B., et al., 2018. Cropland disturbance intensity: plot-scale measurements, multilevel determinants and applications in rural environmental protection. Ecol. Indicat. 88, 393–401. https://doi.org/10.1016/j.ecolind.2018.01.014.

Li, X., Zhou, Y., Zhao, M., et al., 2020. A harmonized global nighttime light dataset 1992–2018. Sci. Data 7 (1), 168. https://doi.org/10.1038/s41597-020-0510-y.

Lian, X., Piao, S., Chen, A., et al., 2021. Seasonal biological carryover dominates northern vegetation growth. Nat. Commun. 12 (1), 983. https://doi.org/10.1038/s41467-021-21223-2.

Liang, X., Jin, X., Sun, R., et al., 2021. A typical phenomenon of cultivated land use in China's economically developed areas: anti-intensification in Jiangsu Province. Land Use Pol. 102, 105223 https://doi.org/10.1016/j.landusepol.2020.105223.

Liu, J., Kuang, W., Zhang, Z., et al., 2014. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. J. Geogr. Sci. 24 (2), 195–210. https://doi.org/10.1007/s11442-014-1082-6.

Liu, L., Wang, Y., Wang, Z., et al., 2019. Elevation-dependent decline in vegetation greening rate driven by increasing dryness based on three satellite NDVI datasets on the Tibetan Plateau. Ecol. Indicat. 107, 105569 https://doi.org/10.1016/j.ecolind.2019.105569.

Liu, L., Xiao, X., Qin, Y., et al., 2020. Mapping cropping intensity in China using time series Landsat and Sentinel-2 images and Google Earth Engine. Rem. Sens. Environ. 239 https://doi.org/10.1016/j.rse.2019.111624. Article 111624.

Liu, S., Shi, K., Wu, Y., et al., 2021. Remotely sensed nighttime lights reveal China's urbanization process restricted by haze pollution. Build. Environ. 206, 108350 https://doi.org/10.1016/j.buildenv.2021.108350.

Liu, Z., Menzel, L., 2016. Identifying long-term variations in vegetation and climatic variables and their scale-dependent relationships: a case study in Southwest Germany. Global Planet. Change 147, 54–66. https://doi.org/10.1016/j.gloplacha.2016.10.019.

Luo, Z., Feng, W., Luo, Y., et al., 2017. Soil organic carbon dynamics jointly controlled by climate, carbon inputs, soil properties and soil carbon fractions. Global Change Biol. 23 (10), 4430–4439. https://doi.org/10.1111/gcb.13767.

Marsh, H.W., Hocevar, D., 1985. Application of confirmatory factor analysis to the study of self-concept: first- and higher order factor models and their invariance across groups. Psychol. Bull. 97 (3), 562–582. https://doi.org/10.1037/0033-2909.97.3.562.

Mueller, T., Dressler, G., Tucker, C.J., et al., 2014. Human land-use practices lead to global long-term increases in photosynthetic capacity. Rem. Sens. 6 (6) https://doi.org/10.3390/rs6065717.

Myneni, R.B., Keeling, C.D., Tucker, C.J., et al., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. Nature 386 (6626), 698–702. https://doi.org/10.1038/386698a0.

Ning, J., Liu, J., Kuang, W., et al., 2018. Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. J. Geogr. Sci. 28 (5), 547–562. https://doi.org/10.1007/s11442-018-1490-0.

Norton, B.A., Coutts, A.M., Livesley, S.J., et al., 2015. Planning for cooler cities: a framework to prioritise green infrastructure to mitigate high temperatures in urban landscapes. Landsc. Urban Plann. 134, 127–138. https://doi.org/10.1016/j.landurbplan.2014.10.018.

Parihar, C.M., Yadav, M.R., Jat, S.L., et al., 2018. Long-term conservation agriculture and intensified cropping systems: effects on growth, yield, water, and energy-use efficiency of maize in northwestern India. Pedosphere 28 (6), 952–963. https://doi.org/10.1016/S1002-0160(17)60468-5.

Pearl, J., 1998. Graphs, causality, and structural equation models. Sociological Methods &amp Research 27. https://doi.org/10.1177/0049124198027002004.

Peng, S., Ding, Y., Liu, W., et al., 2019. 1km monthly temperature and precipitation dataset for China from 1901 to 2017. Earth Syst. Sci. Data 11 (4), 1931–1946. https://doi.org/10.5194/essd-11-1931-2019.

Peng, W., Kuang, T., Tao, S., 2019. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China. J. Clean. Prod. 233, 353–367. https://doi.org/10.1016/j.jclepro.2019.05.355.

Piao, S., Wang, X., Park, T., et al., 2020. Characteristics, drivers and feedbacks of global greening. Nat. Rev. Earth Environ. 1 (1), 14–27. https://doi.org/10.1038/s43017-019-0001-x.

Pickering, C.M., Hill, W., 2007. Impacts of recreation and tourism on plant biodiversity and vegetation in protected areas in Australia. J. Environ. Manag. 85 (4), 791–800. https://doi.org/10.1016/j.jenvman.2006.11.021.

Qu, L.a., Chen, Z., Li, M., 2019. CART-RF classification with multifilter for monitoring land use changes based on modis time-series data: a case study from Jiangsu province, China. Sustainability 11 (20), 5657. https://doi.org/10.3390/su11205657.

Ren, S., Fan, A., 2011. K-Means Clustering Algorithm Based on Coefficient of Variation *2011 4th International Congress on Image And Signal Processing*, pp. 2076–2079. https://doi.org/10.1109/CISP.2011.6100578.

Reverter, A., Barris, W., McWilliam, S., et al., 2005. Validation of alternative methods of data normalization in gene co-expression studies. Bioinformatics 21 (7), 1112–1120. https://doi.org/10.1093/bioinformatics/bti124.

Rosseel, Y., 2012. lavaan: An R Package for Structural Equation Modeling 48 (2), 36. https://doi.org/10.18637/jss.v048.i02, 2012.

Sanderson, E.W., Jaiteh, M., Levy, M.A., et al., 2002. The human footprint and the last of the wild. Bioscience 52 (10), 891–904. https://doi.org/10.1641/0006-3568(2002)052[0891:Thfatl]2.0.Co;2.

Schumacker, R.E., Lomax, R.G., 2004. A Beginner's Guide to Structural Equation Modeling, second ed. Psychology Press. https://doi.org/10.4324/9781410610904.

Silva, T.A., Ferreira, J., Calijuri, M.L., et al., 2021. Efficiency of technologies to live with drought in agricultural development in Brazil's semi-arid regions. J. Arid Environ. 192, 104538 https://doi.org/10.1016/j.jaridenv.2021.104538.

Tamm, C.O., 1995. Towards an understanding of the relations between tree nutrition, nutrient cycling and environment. Plant Soil 168 (1), 21–27. https://doi.org/10.1007/BF00029310.

Temme, A.J.A.M., Verburg, P.H., 2011. Mapping and modelling of changes in agricultural intensity in Europe. Agric. Ecosyst. Environ. 140 (1), 46–56. https://doi.org/10.1016/j.agee.2010.11.010.

Verburg, P.H., Crossman, N., Ellis, E.C., et al., 2015. Land system science and sustainable development of the earth system: a global land project perspective. Anthropocene 12, 29–41. https://doi.org/10.1016/j.ancene.2015.09.004.

Venter, O., Sanderson, E.W., Magrach, A., et al., 2016. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nat. Commun. 7 (1), 12558 https://doi.org/10.1038/ncomms12558.

Wang, Y., Liu, X., Wang, T., et al., 2021. Relating land-use/land-cover patterns to water quality in watersheds based on the structural equation modeling. Catena 206, 105566. https://doi.org/10.1016/j.catena.2021.105566.

Wen, Z.F., Wu, S.J., Chen, J.L., et al., 2017. NDVI indicated long-term interannual changes in vegetation activities and their responses to climatic and anthropogenic factors in the Three Gorges Reservoir Region, China. Sci. Total Environ. 574, 947–959. https://doi.org/10.1016/j.scitotenv.2016.09.049.

Weng, Q., Lu, D., Schubring, J., 2004. Estimation of land surface temperature–vegetation abundance relationship for urban heat island studies. Rem. Sens. Environ. 89 (4), 467–483. https://doi.org/10.1016/j.rse.2003.11.005.

Xia, C., Yeh, A.G.O., Zhang, A.Q., 2020. Analyzing spatial relationships between urban land use intensity and urban vitality at street block level: a case study of five Chinese megacities. Landsc. Urban Plann. 193 https://doi.org/10.1016/j.landurbplan.2019.103669.

Xu, Y., Sum, X., Tang, Q., 2015. Human activity intensity of land surface: concept, method and application in China. Acta Geograph. Sin. 70 (7), 1068–1079. https://doi.org/10.11821/dlxb201507004.

Yang, L., Shen, F., Zhang, L., et al., 2021. Quantifying influences of natural and anthropogenic factors on vegetation changes using structural equation modeling: a case study in Jiangsu Province, China. J. Clean. Prod. 280, 124330 https://doi.org/10.1016/j.jclepro.2020.124330.

Ye, S., Ren, S., Song, C., et al., 2022. Spatial patterns of county-level arable land productive-capacity and its coordination with land-use intensity in mainland China. Agric. Ecosyst. Environ. 326 https://doi.org/10.1016/j.agee.2021.107757, 107757.

Yin, G., Lin, Z., Jiang, X., et al., 2020. How do the industrial land use intensity and dominant industries guide the urban land use? Evidences from 19 industrial land categories in ten cities of China. Sustain. Cities Soc. 53, 101978 https://doi.org/10.1016/j.scs.2019.101978.

Zeng, Y., Sarira, T.V., Carrasco, L.R., et al., 2020. Economic and social constraints on reforestation for climate mitigation in Southeast Asia. Nat. Clim. Change 10 (9), 842–844. https://doi.org/10.1038/s41558-020-0856-3.

Zhang, L., Yang, L., Zohner, C.M., et al., 2022. Direct and indirect impacts of urbanization on vegetation growth across the world's cities. Sci. Adv. 8 (27), eabo0095 https://doi.org/10.1126/sciadv.abo0095.

Zhang, Y., Piao, S., Sun, Y., et al., 2022. Future reversal of warming-enhanced vegetation productivity in the Northern Hemisphere. Nat. Clim. Change 12 (6), 581–586. https://doi.org/10.1038/s41558-022-01374-w.

Zheng, K., Tan, L., Sun, Y., et al., 2021. Impacts of climate change and anthropogenic activities on vegetation change: evidence from typical areas in China. Ecol. Indicat. 126, 107648 https://doi.org/10.1016/j.ecolind.2021.107648.

Zhong, Q., Ma, J., Zhao, B., et al., 2019. Assessing spatial-temporal dynamics of urban expansion, vegetation greenness and photosynthesis in megacity Shanghai, China during 2000–2016. Rem. Sens. Environ. 233, 111374 https://doi.org/10.1016/j.rse.2019.111374.

Zhu, Z., Piao, S., Myneni, R., et al., 2016. Greening of the earth and its drivers. Nat. Clim. Change 6. https://doi.org/10.1038/nclimate3004.

Zhuang, D., Liu, J., 1997. Study on the model of regional differentiation of land use degree in China. J. Nat. Resour. 12 (2), 105–111. https://doi.org/10.11849/zrzyxb.1997.02.002.