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Quantifying influences of natural and anthropogenic factors on vegetation changes using structural equation modeling: A case study in Jiangsu Province, China

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Vegetation coverage in highly developed areas has been significantly altered in response to multiple disturbances over recent decades. However, the major driving factor of vegetation coverage change in these areas remains unclear, with climate change and anthropogenic factors playing interactive roles under different soil and terrain conditions. Comprehensively understanding the underlying drivers of vegetation change can provide references for regulating environmental management and prevention of vegetation degradation. In this paper, a structural equation modeling (SEM) method was employed to quantify the effects of fundamental natural environment (i.e. the relative stable variables including soil and topography), climate change and human activity change on vegetation coverage change in Jiangsu province, China from 2000 to 2015. Four variables including land use, population density, road impact and night lights were used to indicate human activities. The results showed that the increase of NDVI smaller than 0.10 covered 39.13% of the study area while the decrease of NDVI larger than 0.10 accounted for 20.23%. Areas with NDVI increase mainly distributed in croplands in northern Jiangsu. This could be explained by the increase of crop yield due to the development of modern agriculture. The decrease of NDVI was mainly observed in southern Jiangsu with higher urbanization level and city centers in northern Jiangsu, indicating the effect of rapid urbanization on vegetation degradation. The constructed SEM model suggested that the total effects (influential coefficients) of fundamental natural environment, climate change, and human activity change on NDVI change in Jiangsu were −0.24, 0.17, and −0.74, respectively. Although the fundamental natural environment didn't have a direct effect on NDVI change, but it had an indirect effect through interactions with human activities. We also constructed SEM models for northern and southern Jiangsu separately, due to their different natural environment and changing patterns of climate change. The results indicated the different driving mechanisms of NDVI change in northern and southern Jiangsu. Furthermore, the results suggested night light as the best indicator of human activity change, followed by the road impact index. We concluded that our study offered a framework to better understand and explain the complex interrelationships behind the spatial temporal change of NDVI.

1. Introduction

Vegetation, as a natural link between soil, atmosphere, and water, plays a fundamental role in terrestrial ecosystems by regulating energy exchange and carbon cycles (Piao et al., 2003; Bégué et al., 2011; Liu et al., 2018). Vegetation change are usually considered as an indicator of environmental changes, ecosystem function evolution and human activities (Pettorelli et al., 2005).

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Satellite-derived Normalized Difference Vegetation Index (NDVI) has often been taken as a proxy for terrestrial vegetation growth in recent years (Zhang et al., 2013; Sun et al., 2015; Tao et al., 2019). Thanks to the easy accessibility of high resolution remote sensing data in the worldwide extent, long-term NDVI datasets have been widely used for monitoring vegetation dynamics (Piao et al., 2011; Leroux et al., 2017).

Vegetation change can be affected by climatic factors, land use change, and other human-induced factors (Qu et al., 2018). Studies showed that the change of precipitation as well as temperature over a time period significantly impact NDVI variations (Liu and Menzel, 2016; Zhang et al., 2020). And the climatic influences on NDVI vary across topographic conditions and soil types (Muradyan et al., 2019). Over the past decades, human activities become more intensive and diverse, exerting greater pressures on ecosystems at both local and regional scales (Rounsevell et al., 2012; Motesharrei et al., 2016; Diaz et al., 2018). The anthropogenic factors thus have become non-negligible drivers affecting the spatial-temporal variations of vegetation. Furthermore, the complicated interactions between natural and anthropogenic factors make the vegetation dynamics a more complex process. Due to the complex mechanisms of vegetation change, quantifying the contributions of main drivers to vegetation changes is still a challenging.

Numerous studies have been conducted to understand the underlying drivers of vegetation change in the past decades. Many studies focused on the impacts of climatic factors (mainly temperature and precipitation) on vegetation change, in which regression or correlation analysis has been commonly adopted. For example, Mao et al. (2012) analyzed the effects of regional climates on seasonal NDVI during 1982–2009 in Northeast China based on a correlation analysis. Zhang et al. (2013) employed regression analyses to detect the NDVI-based vegetation changes and their responses to climate change from 1982 to 2011 in a Basin in the middle Himalayas. Lamchin et al. (2018) carried out correlation and regression analyses to detect correlations between vegetation greenness and climate variables in Asia. Gu et al. (2018) identified the relationship between vegetation NDVI and climatic factors based on linear regression and partial correlation for the 2000–2014 period in a Basin in southwest China. Pang et al. (2017) used Pearson correlation coefficients to examine the relationships between the NDVI and the two climatic variables (temperature and precipitation) in Tibet plateau from 1982 to 2012. Sun et al. (2019) conducted a partial correlation analysis to examine the relationships between NDVI variation and elevation, precipitation, and temperature based on satellite observations of the Yarlung Zangbo River Basin in the Tibetan Plateau.

In recent years, more studies have been developed to distinguish the human-induced effects on vegetation dynamics from the effects of climatic factors (Zhang et al., 2016; Yin et al., 2020). Wen et al. (2017) first evaluated the total effects of climate factors on NDVI variations using the adjusted coefficient of determination of a multiple linear regression, and took the remaining fraction (i.e. one minus adj-R^2) as the effects of anthropogenic factors on NDVI variations. Jiang et al. (2017) built the regression relationships between the mean NDVI and climatic factors in Central Asia, then the NDVI residuals (defined as differences between the predicted and observed NDVI values) were considered as the consequence affecting by human activities. Similarly, Qu et al. (2018) adopted the residual analysis method to distinguish the impacts between climate change and ecological restoration projects on vegetation.

Except for the residual analysis on assessing the total effect of anthropogenic factors, other statistical and machine learning methods have been used to identify the effects of natural and anthropogenic driving factors individually. Leroux et al. (2017) calculated the variable importance of rainfall, soil, topography, land cover changes, population density, and accessibility for vegetation trend from 2000 to 2015 in the Sahel using the random forest algorithm. Han et al. (2019) examined the NDVI trend and its dependency on elevation and land cover in the Hexi region, northwest China for the period 1982–2015 based on statistical tests. Zhang et al. (2020) explored the effects of natural and anthropogenic driving factors (including land use changes and population density) on vegetation dynamics based on a multiple linear regression analysis in a large dam-reservoir-river system.

Many of the previous studies focused on only climatic factors, and others basically took climatic factors and anthropogenic factors as independent variables. However, there is few studies concerning the complex interactions between natural factors and anthropogenic factors on vegetation change. Peng et al. (2019) quantified influences of natural factors on vegetation changes based on geographical detector in Sichuan, western China, in which effects of individual natural factor and interactions between each two factors were calculated. However, geographical detector can only examine the interactive effect of two factors. The vegetation change system is driven by multiple factors and their interactions. Although there are statistical methods to quantify the interactions between two variables, most models (such as correlation analysis) cannot effectively quantify the impact of a variable by removing the influence from other variables and thus lead to biased results (Sugihara et al., 2012; Chen et al., 2018; 2020a). Some causation models (e.g. Convergent Cross Mapping (CCM) and Granger Causality (GC)) that can remove the influence from other influencing factors, have been employed (Chen et al., 2019, 2020b). However, these models are advantageous in extracting reliable interaction between just two variables, and fails to reliably quantify the overall effects of multiple influencing factors on the target variable. Compared with other models, structural equation modeling (SEM) can not only quantify the impact of a variable by removing the influence from other variables, but also effectively quantify the combined effects of multiple influencing factors on the target variables by considering the interactions between independent variables (Grace and Keeley, 2006). It was first applied in social sciences (Sobel, 1982; Pearl, 1998), and recently has been applied in agriculture (Bayard and Jolly, 2007), soil (Brahim et al., 2011; Angelini et al., 2016), environmental science (Sparrevik et al., 2011; Wang et al., 2019; Hao et al., 2020), and ecology (Grace et al., 2014, 2016; Lamb et al., 2014). SEM quantitatively identifies direct and indirect causal effects, and the indirect effect is caused by interactions between factors (Sobel, 1987). Therefore, SEM can be a potential tool to analyze the complicated interactions between factors affecting vegetation change.

Vegetation coverage in highly developed areas has been significantly altered in response to multiple disturbances over recent years (Zhong et al., 2019; Kowe et al., 2020). Understanding the underlying drivers of vegetation change and their interactions can provide references for regulating environmental management and prevention of vegetation degradation in developed areas. However, there is limited studies on how the driving factors interact with each other when impacting vegetation change in these areas. Without consideration of interactions between driving factors, the extracted influence of specific drivers on vegetation changes are probably biased. The relative contribution of different natural and anthropogenic drivers to vegetation changes in the developed areas remains unclear. Jiangsu province is a highly developed and influential province in China. Intense urbanization and agricultural modernization, especially since 2000, have exerted great influences on vegetation changes in this area. This study attempts to quantify the influences of natural and anthropogenic drivers on vegetation changes indicated by NDVI in Jiangsu province using the SEM approach. In addition to the climatic factors (i.e.

annual average temperature and annual precipitation), we also included topography and soil as fundamental environment factors, which determine the vegetation distribution. Furthermore, we used four human pressure variables (land use, road impact, population density and night-time lights) in the concept of the human footprint (Sanderson et al., 2002) to represent anthropogenic factors in this study. The objectives of this study are, 1) to examine the contributions and interactions of natural and anthropogenic drivers to vegetation changes in Jiangsu province from 2000 to 2015, China with Structural Equation Modeling, 2) to identify the main factors affecting NDVI change in Jiangsu province. Our findings will provide an important scientific foundation for revealing the interactions mechanism of natural and anthropogenic drivers for vegetation change in developed areas.

2. Materials and methods

2.1. Study area

Jiangsu Province is located in the Yangtze River Delta of eastern China (30°45′ to 35°20′N, and 116°18′ to 121°57′E) (Fig. 1). This area has an eastern Asian monsoon climate with an annual average temperature of 13.6–16.1 °C and an average annual precipitation of 1, 000 mm. The elevation ranges from −163 to 633 m, with the flat plains in north and middle of the province account for 85% of the total area. Due to natural conditions suitable for agriculture, Jiangsu Province has been one of most important grain producing province in China. Furthermore, Jiangsu has experienced a rapid urbanization and industrialization, becoming one of the richest provinces in China. Yet the development of southern Jiangsu (including Nanjing, Changzhou, Wuxi, Suzhou, yangzhou, Taizhou, and Nantong) has a higher level of urbanization than northern Jiangsu (including Xuzhou, Lianyungang, Suqian, Huai'an and Yancheng). Due to the urbanization, the area of cultivated land decreased from 67.8% to 64.2% from 2000 to 2015, and urban land area increased from 2.7% to 4.5% of the province. The socioeconomic development and climate change over the past decades have changed the land surface and ecosystem functions of Jiangsu (Huang et al., 2015).

2.2. Data

The normalized difference vegetation index (NDVI) data of Jiangsu in 2000 and 2015 with a resolution of 1 km*1 km were downloaded from RESDC (http://www.resdc.cn). The annual NDVI

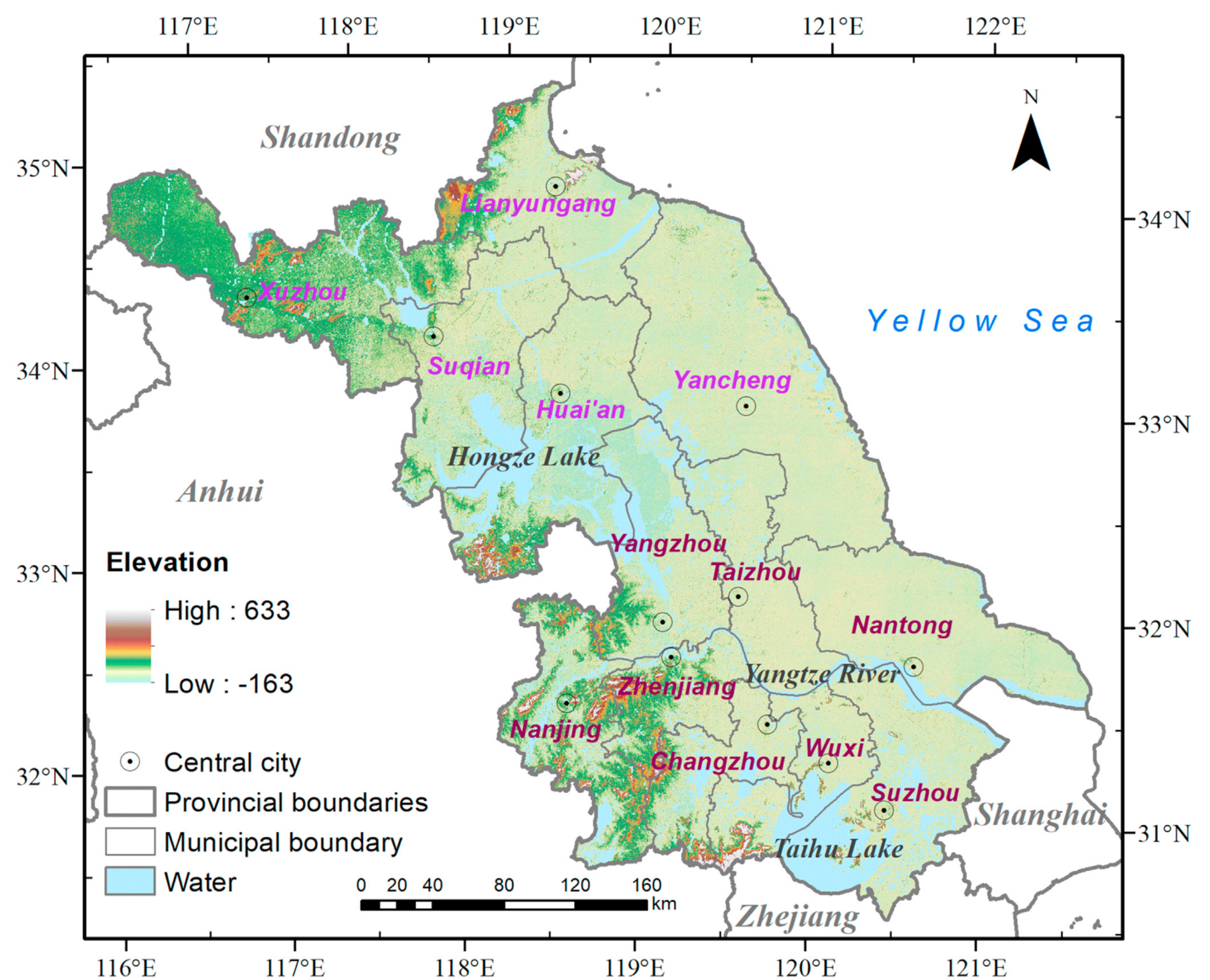


Fig. 1. The location and digital elevation model (DEM) of the study area, the municipal districts with purplish red texts belong to southern Jiangsu, and those with purple texts belong to northern Jiangsu.

data were generated using the maximum value composite (MVC) method based on the ten-day SPOT/VGTATION NDVI data. In other words, the maximum value in the ten-day composites was regarded as the annual NDVI value at each pixel. The MVC method is established based on the principle that low-values are either erroneous or have less vegetation vigor, and thus minimizes cloud contamination, atmospheric effects and scan angle effects (Holben, 1986). In this case, this dataset was a reliable source for our research.

Both climate change and human activities were the main driving factors for vegetation change in Jiangsu. Besides, the impact of climate and human activities were usually varying with different soils and topography. Soil and topography are relatively stable compared with climate and human activities. Thus, we called soil and topography as fundamental natural environment factors in this study. The combinations of climate, human activities and fundamental natural environment conditions would have different affects on NDVI change. Thus, ten variables representing natural environmental condition, climate and human activities were generated, as listed in Table 1. All the variables were projected into the UTM coordinates for further processing. The reason why we chose these variables and the production procedure of all the data were illustrated as follows.

2.2.1. Fundamental natural environmental variables

In this study, the relatively stable factors, soil and terrain, were called the fundamental natural environment. Although the impact of soil and terrain on vegetation change depends, soil and terrain determine the vegetation distribution. Soil type is correlated with the vegetation type to some extent, and the nutrient availability and water retention capability of different soils are highly related to vegetation growth status (Leroux et al., 2017). The soil type of Jiangsu Province was extracted from the 1:100 Million Soil Map of the People's Republic of China (http://www.resdc.cn). This soil map was compiled by the Chinese Soil Census Office and published in 1995. The soil system adopted was genetic classification system. There were mainly 8 soil types in Jiangsu, including *Anthrosols*, *Semi-hydromorphic soil*, *Semi-argosol*, *Argosols*, *Hydromorphic soil*, *Ferralosols*, *Solonchak and Solonetz*, *Primosols*.

The topographic condition would also influence the vegetation growth of a location (Okou et al., 2016; Liu et al., 2018; Raduła et al., 2018). Furthermore, it would affect the way and intensity of human activities, thus indirectly affect vegetation change. In this study, we generated three commonly-used topographic variables, including elevation, slope, and topographic wetness index. The three variables were derived from the 30 m SRTM DEM of this study area using the Spatial Analyst Tools in ArcGIS 10.6. Topographic wetness index was calculated according to the following equation (Beven and Kirkby, 1979): $twi = \ln (a/\tan\beta)$, where a is the cumulative upslope area draining through a point (per unit contour length), β is the slope gradient at the point.

2.2.2. Climatic variables

Many researches have examined the significant response of vegetation to precipitation and temperature change. We obtained the annual average temperature and annual precipitation of Jiangsu in 2000 and 2015 from the national meteorological data set of China on platform of RESDC (http://www.resdc.cn/). Based on daily observation data collected from more than 2400 meteorological stations in China, the ANUSPLIN interpolation software (Hutchinson M F, 1998) was used for the interpolation of annual average temperature and annual precipitation of China at a resolution of 1 km.

2.2.3. Human activity variables

Following the concept of "human footprint" (Sanderson et al., 2002), four variables measuring the direct and indirect human pressures were generated for Jiangsu in 2000 and 2015. The four variables included population density, land use/cover, night-time lights and road impact.

The number of people in an area is frequently used as a primary underlying cause of human activity intensity (Cincotta et al., 2000).

Table 1
The potential driving factors for vegetation change.

Factors	Variables	Year	Data set	Original spatial resolution	Data Sources
Fundamental natural environment	Soil type	-	1: 1 Million Soil Map of the People's Republic of China	-	*Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)* (http://www.resdc.cn)
	Elevation	-	Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM)	30 m	*Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences* (http://www.gscloud.cn)
	Slope	-	Derived from SRTM DEM of Jiangsu	30 m	-
	Topographic wetness index	-		30 m	-
Human activity change	Road impacts index	1995*	Calculated based on the National road data, the detailed procedure was in Section 2.1.3.	-	*Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)* (http://www.resdc.cn)
		2015		-	*Geographical Information Monitoring Cloud Platform of China* (http://www.dsac.cn/)
	Population	2000/2015	Gridded Population density of the World (GPW), Version 4	1 km	*Socioeconomic Data and Applications Center (SEDAC)* (http://sedac.ciesin.columbia.edu)
	Night-time Lights	2000/2013**	Global DMSP-OLS Night-time Lights Time Series 1992–2013, Version 4	1 km	*Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)* (http://www.resdc.cn)
	Land use	2000/2015	National land use database for China	1 km	*Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)* (http://www.resdc.cn)
Climate change	Annual average temperature Annual precipitation	2000/2015	National meteorological data set of China	1 km	*Data Center for Resources and Environmental Sciences Chinese Academy of Sciences (RESDC)* (http://www.resdc.cn)

* Note that the road data in 2000 was not available, thus the road data in 1995 was downloaded as an alternative source, assuming that the changing of roads in Jiangsu from 1995 to 2000 was few.
** Note that night-time lights data in 2015 was not available, the night-time lights data in 2013 was then downloaded as an alternative source.

Human population density used in this study was the Gridded Population of the World, Version 4 (GPWv4) data sets (Center for International Earth Science Information Network, 2016).

Land use/cover represents how people use land, such as for settlements, growing food, or producing economic goods (Foley et al., 2005; Geist and Lambin, 2002). Change of land use is related to change of vegetation cover type or vegetation greenness (Milà i Canals et al., 2007). The land use data was obtained from the China's land use database developed by Environmental Sciences Chinese Academy of Sciences (RESDC) (H. Liu et al., 2018). The original data was at a resolution of 1 km with 6 primary classes (including cropland, forest land, grassland, water, residential, industrial and mining land, and unused land) and 26 secondary classes.

Night-time Lights is an effective data for capturing flowing and unobtrusive human activities (Elvidge et al., 1997). The Night-time Lights data for Jiangsu in 2000 and 2015 were the DMSP-OLS (Defense Meteorological Satellite Program-Operational Linescan System) data with a resolution of 30 arc-seconds downloaded from RESDC. The DMSP-OLS sensors detect the gleam visible-near infrared (VNIR) radiance on the earth surface, which represent the night lights with intensity degree from the urban lights and even small-scale residential areas, traffic, etc.

Roads shrink the distance of human from nature (Trombulak and Frissell, 2000; Assis et al., 2019), and can indicate the development level of an area. Usually, the closer distance from a location to a road, the greater the impact of human activities on the environment of this location. Furthermore, the difference of the impact with distance varies among the road types. For example, the impact of a railway on a location would be larger than that of a country road with the same distance. Therefore, we calculated the road impact (*RII*) index by taking both the distance to a road and the road type into account. The vector data of roads for Jiangsu in 1995 and 2015 was first downloaded as shown in Table 1. Roads in each year were categorized into the following six types: expressway, railway, national roads, provincial roads, country roads, and other roads. For roads of type i, the shortest distance between each pixel and roads of this type (D_i) was calculated using the Path Distance tool in ArcGIS 10.6. If the shortest distance of one pixel to a type of roads was beyond 15 km, then the shortest distance of this pixel was assigned to 15 km due to the assumption that the road would have rare impact on a pixel when the distance of the pixel to the road was larger than 15 km (Sanderson et al., 2002). The total impact of all types of roads on one pixel was calculated base on the following weighted sum formula.

$$RII = \sum_{i=1}^{6} w_i * (1 - D_i / 15) \quad (1)$$

where *RII* represent the total impact value of all type of roads for one pixel. The larger the *RII* value, the greater the impact of roads. i is the i_{th} type of roads. w_i is the weight for different road types. In this study, we determined the weights according to the study of Li et al. (2018), i.e. the weights for expressway, railway, national road, provincial road, county road, primary urban roads, secondary urban roads, and other roads equaled to 0.23, 0.21, 0.18, 0.12, 0.09, 0.07, 0.06 and 0.04 respectively.

2.3. Structural equation modeling for NDVI change

Structural equation modeling (SEM) is a method for developing and testing hypotheses about the relationships in a system (Grace, 2006; Van Acker and Witlox, 2010). SEM 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 causal analysis. First, a variable can be a dependent variable in one set of relationships, and can be an independent variable in another set of relationships meanwhile. Second, it can manage observed variables and the so-called latent variables which cannot be measured directly. In general, latent variables are a combination of observed variables (Sheykhfard and Haghighi, 2020). For example, the human activity factor cannot be observed but can be indicated by several observed variables (such as population, road impact, etc.), thus can be defined as a latent variable. Third, SEM identifies direct and indirect causal effects quantitatively, and the indirect effect is caused due to the interactions between latent variables. If causal relationships are indirectly connected, for instance soil and terrain could affect NDVI change through their influence on human activities (Teferi et al., 2013; Asselen and Verburg, 2012), SEM could identify the indirect effect of the fundamental natural environment on NDVI change. Due to the above advantages, SEM is highly suitable for detecting the influences of driving factors on vegetation coverage change.

To obtain the relationship network, the application of SEM includes the following steps. First, several hypotheses on the relationships between variables are developed based on literature review or prior knowledge, and a graphical conceptual model is constructed according to these hypotheses. Then the conceptual model is converted to a mathematical model through SEM. The mathematical model is calibrated based on either experimental or observational data. Poor model fitting could suggest revision of the conceptual model and re-specification of the mathematical model. When model fitting is satisfactory, the final SEM model is constructed. The flow chart for development of a SEM model for NDVI change is shown in Fig. 2.

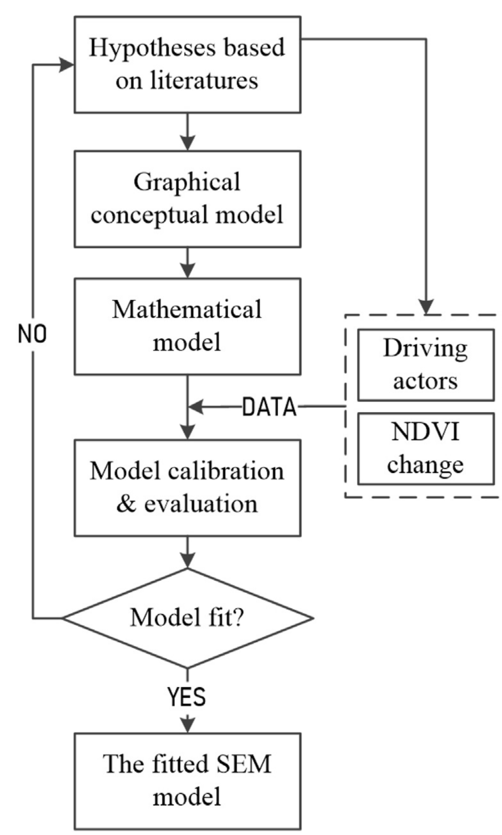


Fig. 2. A schematic diagram of SEM modeling for detecting the driving mechanism of NDVI change in Jiangsu.

2.3.1. Graphical conceptual model establishment

The target variable of our study is the NDVI change of Jiangsu from 2000 to 2015. Based on the knowledge on driving mechanism of NDVI change through literature review, the main hypotheses of our study were as follows. We took NDVI of Jiangsu in 2000 as a starting point, and assumed either successive climate change or change of human activities would cause change of vegetation coverage since then. At the same time, human activities would also affect climate change. The fundamental natural environment might have a direct impact on NDVI change. Besides, it would affect the change patterns of human activities in different locations, for instance high elevation and steep slopes would hinder the exploration of natural resources. This indicated that fundamental natural environment had an indirect effect on NDVI change. These general hypotheses were converted into a graphical conceptual model describing the interactive relationships between driving factors and NDVI change in Jiangsu (Fig. 3).

In the conceptual model, fundamental natural environment, climate change and human activity were the latent variables which cannot be observed directly. Soil type (St), elevation (Ele), slope (Slp) and topographic wetness index (TWI) were the observed variables to indicate the fundamental natural environment. The change of annual precipitation (Ap), annual average temperature (Aat) from 2000 to 2015 were the observed variables to indicate climate change. The change of road impact index (Rii), population density (Pd), night-time lights (Ntl) and land use (Lu) from 2000 to 2015 were the observed variables to indicate the human activity change.

2.3.2. Data processing

In this study, 20456 calibration points were generated using a systematic sampling strategy with a grid of 2000 m $\times$ 2000 m from the study area. For each sample point, its elevation, slope, TWI and soil type were extracted from the data of elevation, slope, TWI and soil type shown in Table 1, respectively. The change of road impact index (Rii), population density (Pd), night-time lights (Ntl), annual precipitation (Ap), and annual average temperature (Aat) from 2000 to 2015 were calculated for each sample point as subtracting the value in 2000 from that in 2015. The soil types were coded according to its suitability for vegetation growth. As for land use change, pixels with land use change were labeled as 0, and others with no land use change were labeled as 1. The above processing of the observed variables were conducted in ArcGIS 10.6.

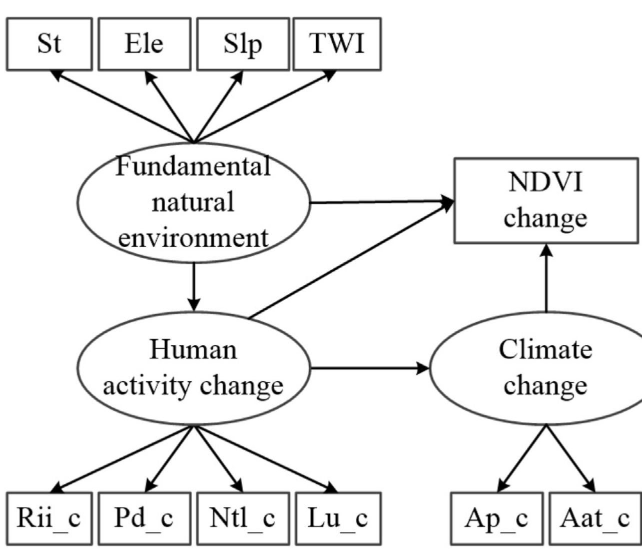


Fig. 3. The conceptual structural equation model of NDVI change from 2000 to 2015 in Jiangsu, boxes represents observed variables, and ellipses the latent variables. Arrows between latent variables and arrows from latent variables to NDVI change identified the cause and effect relations, while arrows from latent variables to observed variables represented the correlation relationships between them. The abbreviations of the observed variables were as follows, St, soil type, Ele, elevation, Slp, Slope, Ap_c, change of annual precipitation, Aat_c, change of annual average of temperature, Rii_c, change of road impact idex, Pd_c, change of population density, Ntl_c, change of night lights, Lu_c, change of land use.

2.3.3. Model calibration and revision

A maximum likelihood estimation method was adopted for SEM modeling. The model fit was assessed using several goodness-of-fit indices, including CFI (Comparative Fit Index), RMSEA (Root Squared Mean Error of Approximation) and root mean square residual (SRMR) (Byrne, 2001). If the original model fitted poorly, it was revised for several rounds by deleting or changing the non-significant ($p > 0.05$) paths (Xie et al., 2020; Yang et al., 2019). A lower SRMR than 0.05, lower RMSEA than 0.08, and CFI approximating 1 indicated a good fit of modeling (Hooper et al., 2008). If several models passed the criterion, a best model was determined by comparing the goodness-of-fit indices of the SEM models. The 'lavaan' package (Rosseel, Y., 2012) in the R statistical language (R Core Team, 2014) was used to conduct SEM based on the calibration sample points.

Due to the different patterns of climate and human activities in northern and southern Jiangsu, SEM models were also constructed for northern and southern Jiangsu to examine the different driving mechanisms of NDVI change.

2.3.4. Analysis of the direct and indirect effects of driving factors

When the model and all variables passed the statistical test, the path diagram and standardized coefficients were provided. The path coefficients between the latent variables and NDVI change were standardized regression coefficients. A larger path coefficient indicated a larger effect of a latent variable on NDVI change. The total standardized effects of a latent variable on NDVI change consisted of both direct and indirect effects (Grace et al., 2016; Grace and Bollen, 2005). The direct effect of one latent variable (such as human activity change to NDVI change) was the path coefficient on the arrow which directly pointed to NDVI change from the latent variable of human activity change. And the indirect effect was measured as the product of the coefficient on the arrows from human activity change to a mediator variable (such as, climate change) and the coefficient on the arrow from the mediator variable to NDVI change. Moreover, in a SEM, there might be more than one mediator variable from one driving factor to NDVI change, thus the indirect effects were the sum of all indirect coefficients of every indirect path.

3. Results

3.1. Spatial and temporal variations of NDVI in Jiangsu

The spatial distribution of NDVI in Jiangsu Province in 2000 and 2015 and its change are shown in Fig. 4. It showed that most parts of the province had a high or an extremely high vegetation coverage in both 2000 and 2015. Areas of NDVI larger than 0.6 accounted for 94.43% of the total area in 2000 and 81.60% in 2015 (Table 2), respectively. This indicated a good vegetation coverage in Jiangsu. However, the proportions of high and extremely high NDVI changed from 2000 to 2015. Specifically, high vegetation coverage decreased from 75.67% in 2000 to 44.87% in 2015, while extremely high vegetation coverage increased from 18.75% in 2000 to 36.72% in 2015. A notable extremely low NDVI distributed in narrow strips in Lianyungang and Yancheng municipal districts along the

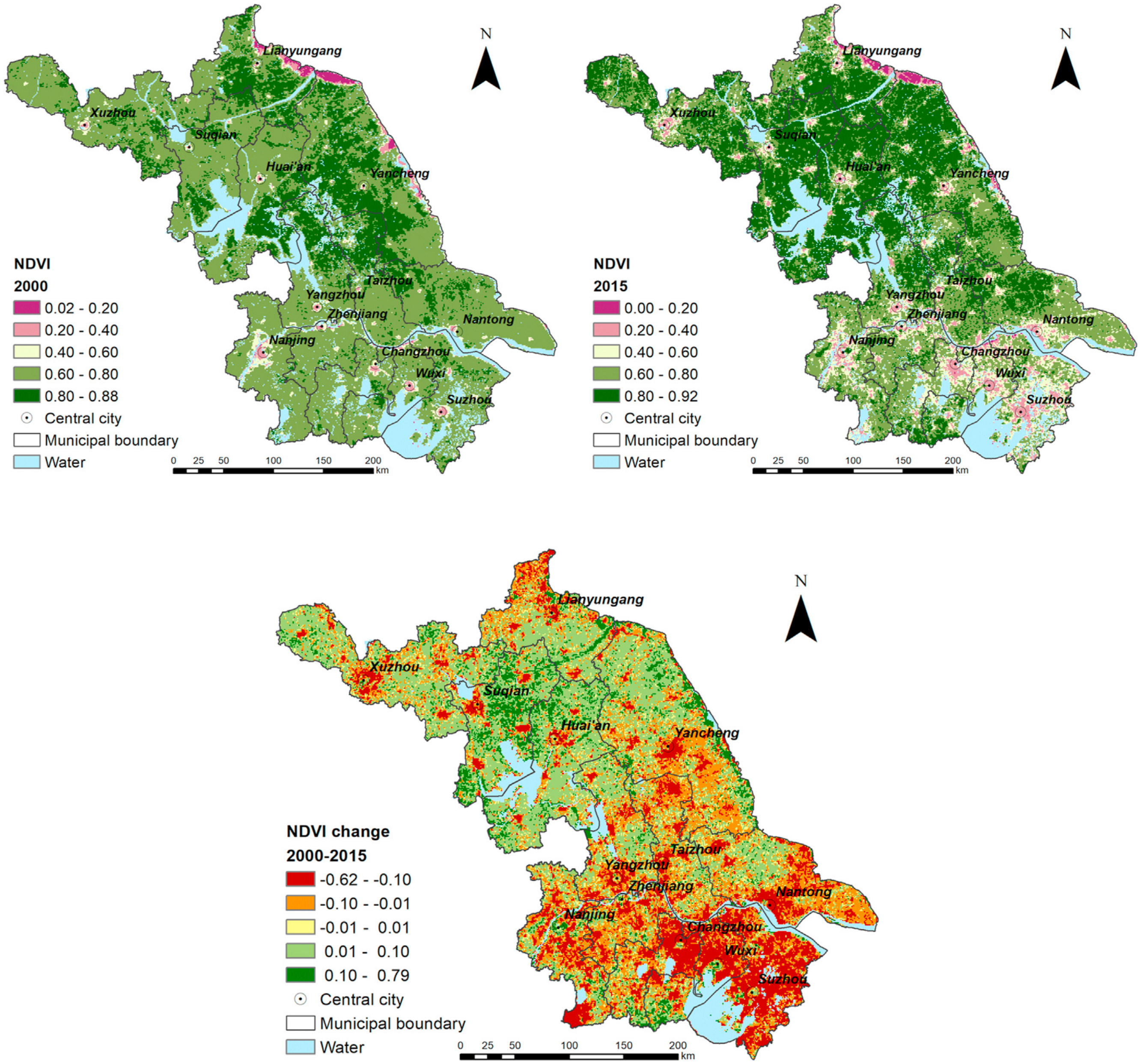


Fig. 4. NDVI of Jiangsu Province in 2000 and 2015 and its change.

Table 2
NDVI characteristics in Jiangsu and its change from 2000 to 2015.

	2000		2015		2000–2015	
NDVI	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area change (km^2)	Proportion (%)
[0.0–0.2]	601.56	0.69	569.43	0.65	−32.14	−0.04
(0.2–0.4]	1209.15	1.38	4349.54	4.96	3140.39	3.58
(0.4–0.6]	3078.12	3.51	11,233.89	12.80	8155.77	9.29
(0.6–0.8]	66,399.06	75.67	39,367.82	44.87	−27031.23	−30.81
(0.8–1.0]	16,456.15	18.75	32,223.37	36.72	15,767.22	17.97

coastline. The land use of these areas were mainly salt pans. Furthermore, NDVI in 2015 had a larger heterogeneity than in 2000. The differences in NDVI between north and south Jiangsu became very obvious in 2015. In specific, NDVI in south Jiangsu in 2015 was generally much lower than that in north Jiangsu. Yet most of north Jiangsu had a higher NDVI in 2015 than that in 2000.

As shown in Table 3, the total area of NDVI increase was close to that of NDVI decrease. The increase of NDVI was mainly slight increase (increase smaller than 0.10), the proportion of which was 39.13%. Meanwhile, the slight decrease (decrease smaller than 0.10) and remarkable decrease (decrease larger than 0.10) of NDVI accounted for 25.10% and 20.23% of the study area, respectively.

Table 3
The areas and proportions of NDVI change in Jiangsu from 2000 to 2015.

NDVI change	Area (10^2 km^2)	Proportion (%)	Northern Jiangsu (%)	Southern Jiangsu (%)
Remarkable decrease [-0.62−0.10]	177.52	20.23	4.98	15.25
Slight decrease (−0.10−0.01]	220.27	25.10	10.54	14.56
No change (−0.01-0.01]	72.72	8.29	4.42	3.87
Slight increase (0.01−0.10]	343.35	39.13	27.58	11.55
Remarkable increase (0.10−0.79]	63.58	7.25	5.77	1.48

NDVI in most of southen Jiangsu decreased obviously, as we can also see in Fig. 4. Extremely decrease of NDVI mainly distributed in the 'Suzhou-Wuxi-Changzhou' urban agglomeration, where almost all the decrease area connected together. The main reason for the NDVI decrease was due to the rapid urbanization, especially for areas around Yangtze River. NDVI in areas surrounding northern city centers also decreased to different extent. This is consistent with the urban development in Jiangsu. In comparison, areas with NDVI increase most distributed in non-urban areas of north Jiangsu, especially in Suqian, Huai'an, and Xuzhou municipal districts. The land use of these areas were mainly cultivated land, and a larger crop yield of these areas probably explained the NDVI increase.

3.2. The constructed SEM model of NDVI change in Jiangsu Province

The final fitted SEM model for Jiangsu Province is shown in Fig. 5. It can be seen that the interactions among variables were well supported in SEM. The Goodness-of-fit (GOF) measures of the final SEM were as follows, CFI = 0.94, RMSEA = 0.077, and SRMR = 0.04, indicating a good fit of the model. The paths between slope/TWI and fundamental natural environment didn't pass the significance test, thus were deleted.

It showed that NDVI change was impacted by climate change, human activity change, and fundamental natural environment in different ways. Climate change only had a direct impact on NDVI change with an influential coefficient of 0.17. Human activity change not only had a direct impact with an influential coefficient of −0.86, but also had a positive indirect effect on NDVI change through its positive effect on climate change. Yet the fundamental natural environment had nearly no direct impact on the change of NDVI. However, it indirectly impacted the change of NDVI through its influences on human activities. There were two indirect paths from fundamental natural environment to NDVI change. One was through human activities change to NDVI change, the other was through human activities change and then climate change. The two indirect effects of fundamental natural environment were −0.28 and 0.04, respectively.

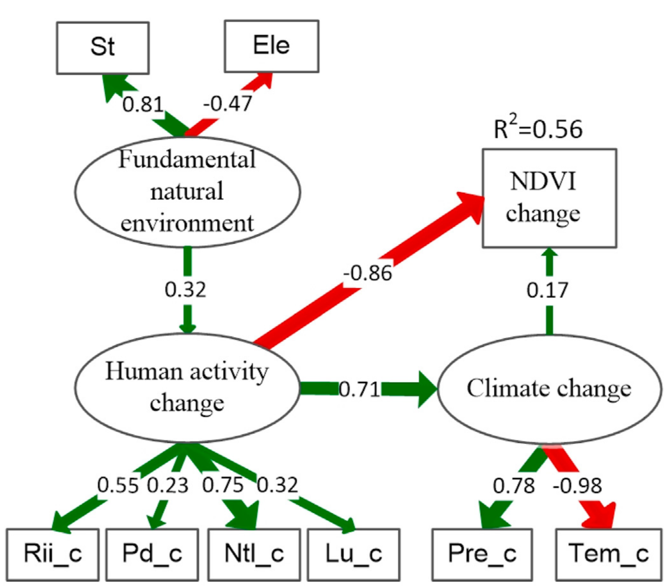


Fig. 5. The final graphical fitted SEM model showing the multivariate relationships of NDVI change and its driving factors. The thickness of the arrows was proportional to the standardized path coefficients shown on each arrow. Green lines showed statistically significant positive paths, while red lines represented statistically significant negative paths. Variables in circles were latent variables and variables in boxes were observed variables.

The direct and indirect paths of fundamental natural environment, human activity change, climate change on NDVI change based on the SEM model is shown in Table 4. By adding up the direct and indirect effects of the latent variables on NDVI change, the total effects of fundamental natural environment, climate change, and human activity change on NDVI change were −0.24, 0.17, and −0.74, respectively.

Among the natural variables, soil type was the variable best indicating fundamental natural environment, followed by elevation. A soil type with higher suitability for vegetation growth indicated a larger decrease of NDVI, while a higher elevation indicated a lower decrease of NDVI. Both annual average temperature and annual precipitation were good indicators for climate change. Night light was the best indicator for human activities, followed by the road impact index. And a larger increase of night light and road impact caused a larger decrease of NDVI.

3.3. The constructed SEM models of NDVI change in northern and southern Jiangsu

The fitted SEM models with estimated coefficients for northern and southern Jiangsu are shown in Fig. 6. The two SEM models indicated different driving mechanisms of NDVI change in northern and southern Jiangsu. For northern Jiangsu (CFI = 0.99, RMSEA = 0.04, and SRMR = 0.019), the fundamental natural environment showed no direct effect on human activity or NDVI change. This was mainly due to the flat terrain of northern Jiangsu. The other difference was that the effect of climate change on NDVI change was negative in northern Jiangsu, while the effect of climate change on NDVI change was positive for either the entire province or southern Jiangsu. This was due to the different changing patterns of climate in northern and southern Jiangsu. For example, the annual precipitation in 2015 in northern Jiangsu districts decreased or slightly increased compared with that in 2000, while the annual precipitation in southern Jiangsu increased. Besides, human activity change had a very small effect on climate change, and the indirect effect of human activity change through climate change was thus very small. The total effects of climate change and human activity change were −0.11 and −0.62, respectively.

The fitted SEM model for southern Jiangsu (CFI = 0.917, RMSEA = 0.075, and SRMR = 0.044) was similar with that for the whole province, but climate change had a lager effect on NDVI change in southern Jiangsu than in the entire province. Besides, elevation had a higher loading coefficient to the fundamental natural environment, showing its higher indicative effect than in the

Table 4
The direct, indirect and total effects among fundamental natural environment (FNE), climate change (CC), human activity change (HAC) and NDVI change based on the statistically significant SEM paths.

Paths	Effects on human activity change	Paths	Effects on climate change	Paths	Effects on NDVI change
Direct		Direct		Direct	
FNE→HAC	0.32	HAC→CC	0.71	HAC→NDVI CC→NDVI	−0.86 0.17
Indirect		**Indirect**		**Indirect**	
		FNE→HAC→CC	0.23	FNE→HAC→NDVI FNE→HAC→CC→NDVI HAC→CC→NDVI	−0.28 0.04 0.12
Total		**Total**		**Total**	
FNE ~ HAC	0.32	FNE ~ CC HAC ~ CC	0.23 0.71	**FNE ~ NDVI** **CC ~ NDVI** **HAC ~ NDVI**	**−0.24** **0.17** **−0.74**

entire province. The total effects of fundamental natural environment, climate change and human activity change on NDVI change were −0.21, 0.32, and −0.71, respectively. Although the effects for the three driving factors were different for northern and southern Jiangsu, human activity change played the most important role in driving NDVI change.

4. Discussions

4.1. Applicability and limitation of the SEM method

In recent studies on vegetation dynamics and its driving mechanism, the complex interactions between the driving factors have been rarely studied. SEM is an efficient method to examine the networks of causal relationships among factors by taking all the variables into account. In this study, we defined three driving factors, including fundamental natural environment, climate change and human activity change, as latent variables. By using the latent variables, the quantified relationships of how the three driving factors impacted each other were estimated. Furthermore, SEM partitioned direct from indirect effects of the driving factors on NDVI change. The indirect effects were mainly caused by the interrelationships between the latent variables. In our case, fundamental natural environment impacted human activities, meanwhile human activities had an effect on climate change. Thus, fundamental natural environment had an indirect effect on NDVI change. This is consistent with our understanding on the mechanism of NDVI change.

The spatial pattern of climate change in northern and southern Jiangsu was different, leading to different effects of climate change on NDVI change. It can be also seen from the opposite directions of the effects of climate change on NDVI change in SEM models for northern and southern Jiangsu. This was one reason causing the smaller effect of climate change compared with that of fundamental natural environment in the entire province. It also shows that partitioning the areas with different patterns for SEM modeling is helpful to better understand the different casual relationships in those areas.

The correlation analysis between different variables and NDVI change was shown in Fig. 7. It showed that night light were negatively correlated with NDVI change with the highest coefficient, followed by annual average temperature (with a positive coefficient), annual precipitation, and road impact index. The annual average temperature and annual precipitation showed high correlations with NDVI change. However, the total effect of climate change based on SEM was not high, compared with that of human activity change and even natural environment. This is mainly due to the different calculation mechanism for correlation analysis and SEM model. The correlation analysis only estimated how relevant one variable is to the other variable without considering other variables. Due to interactions between different driving factors, the value of correlation coefficients may not interpret the quantitative influence of individual variable on NDVI change (Chen et al., 2017). Instead, the path coefficients from SEM method is designed to understand the coupling between two variables by excluding influences from other factors. Furthermore, SEM could estimate the total effect of driving factors (i.e. climate change and human activities) by measuring both direct and indirect effects.

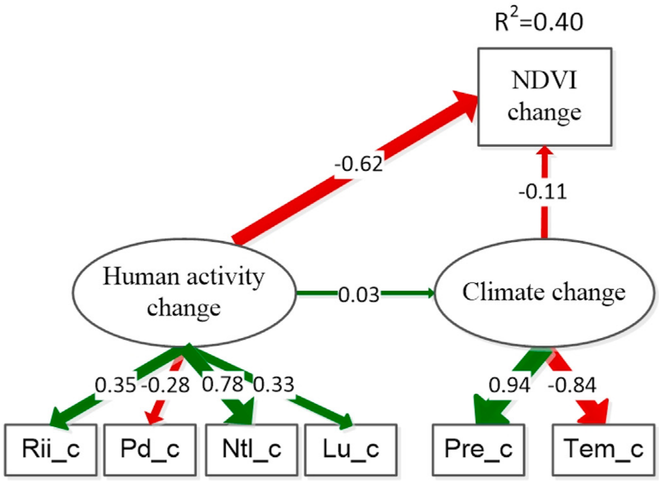
Although some limitations exist, correlation analysis provides valuable reference for understanding the relationship between NDVI change and its driving factors. Furthermore, the correlation coefficients could provide important reference for SEM model revision or variable selection for causality analysis.

To our knowledge, the approach built for this study is the first attempt to examine the driving mechanism of NDVI change in a developed region. The concept of the SEM model can be further refined for similar areas highly interfered by human activities, where the model may include more complex drivers representing human activity intensities such as variables indicating degree of agricultural mechanization and urban electricity consumption, etc..

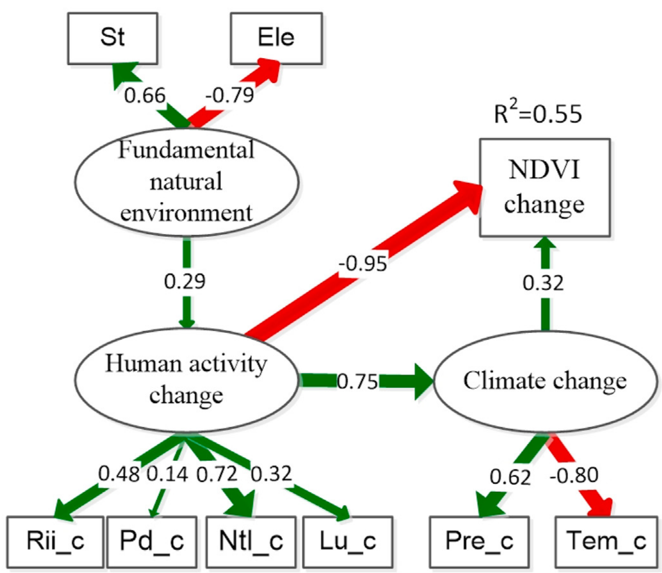
The present SEM study has some limitations. First, the sample data for model calibration was not measured data but rather interpolated data. The climate change was represented by subtraction of two years data. Variables representing long-term climate change could added in future work. Second, the relationships between the driving factors and NDVI change are usually not linear. However, it is not easy to quantity the non-linear complex relationships, the estimation of SEM in our study was linear. More study on possible non-linear relationships between the driving factors and NDVI change should be conducted in future. Finally, the fitted model didn't fully explained the variances present in NDVI change. This may due to the unmeasured factors which require further investigation. However, the R^2 of the fitted models and the fitness indices showed a good explanation ability of the constructed models.

4.2. Comparison with other related studies in Jiangsu

The results of our study showed that most of the degraded vegetation from 2000 to 2015 occurred in areas around cities, especially in south Jiangsu. And the greening of vegetation was mainly in cultivated land in north Jiangsu. The results were consist with the studies of Yao et al. (2017) and Zhang et al. (2020). The degradation of vegetation in Jiangsu is mainly due to the rapid



(a) The fitted model for northern Jiangsu



(b) The fitted model for southern Jiangsu

Fig. 6. The fitted SEM models for northern and southern Jiangsu.

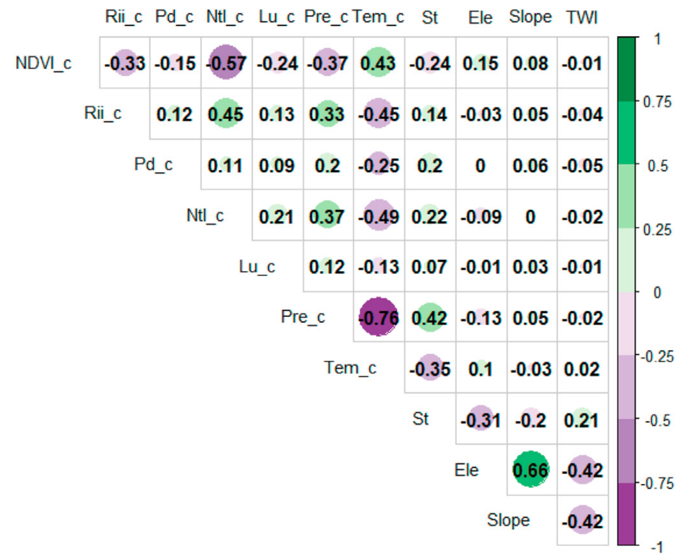


Fig. 7. The correlations between different variables and NDVI change. The Pearson correlation was adopted to measure the correlation between continuous variables and NDVI change. The Spearman correlation was adopted for the categorical variables including land use change and soil type.

urbanization and economic development of Jiangsu resulting in transferring from cultivated land to urban land use. And the greening of vegetation was mainly because of the development of modern agriculture including fertilization, breeding and mechanization (Wang et al., 2019). For example, the total agricultural mechanical power and grain yield for northern Jiangsu from 2000 to 2015 increased by 1718.74 $\times$ 10^4 kW and 794.77 $\times$ 10^4 ton, respectively (Table 5).

4.3. Patterns of the coupling between human activity change and NDVI change

Fig. 8 shows patterns of the coupling between human activity change (predicted by SEM) and NDVI change. Area with the pattern of human-activity-decrease and NDVI-increase occupied 43.1% of the total area. This pattern was mainly distributed in non-urban areas in northern Jiangsu. 78.0% of this pattern was cropland, followed by rural area of 13.2% and forest of 5.1% in 2000. Land use slightly changed in 2015, with cropland occupying 77.8% and rural area occupying 13.4%. The increase of NDVI was owing to the increase of crop yield (Table 5) and greening in rural areas. Agriculture modernization caused the increase of crop yield. At the same time, many villagers left villages to go to work in cities. The decrease of population was the main reason for decrease of human activities.

Area with the pattern of human-activity-increase and NDVI-decrease occupied 30.4% of the total area. This pattern was mainly distributed in the highly urbanized southern areas and areas around northern city centers. This indicated the influences of urbanization on land surface. From 2000 to 2015, the increasing area of urban, rural land and industrial & traffic land in this pattern occupied 6.1%, 3.99% and 1.58% of Jiangsu, respectively. This increase was mainly transferred from cropland, especially from paddy field. In addition, yielding losses in cropland in this pattern have reported (Pan et al., 2013; Wang et al., 2019), resulting in the decrease of NDVI. Furthermore, the requisition-compensation balance of cropland policy started in 1999 in China, which means that arable land should be compensated for construction land use. It may happens that some cropland with not-good land quality were compensated (Song and Pijanowski, 2014). This can be also a reason of NDVI decrease.

There were 6.2% of the total area with simultaneous increase of NDVI and human activities, which mainly distributed in southern Jiangsu. This indicates that some human activities improved ecosystem functions for those areas. For example, the urban greenness rate from 33.2% up to 42.8% due to the demonstration of vegetation recovery projects (http://tj.jiangsu.gov.cn/). This indicates that policy play a role in protecting natural environment from human pressures (Feng et al., 2020). These areas may provide references for mitigating degrading of ecosystem functions for other areas.

There were 17.7% of the total area where human activity decreased but NDVI also decreased, mainly distributed in croplands

Table 5
The change of agricultural indices for northern and southern Jiangsu from 2000 to 2015 according to the statistical yearbooks.

	Total planting area of crops (10^3 ha)	Planting area of grain crops (10^3 ha)	Total agricultural mechanical power (10^4 kW)	The amount of fertilizer applied for agriculture (10^4 ton)	Grain yield (10^4 ton)
Northern Jiangsu	518.39	648	1718.74	31.95	794.77
Southern Jiangsu	−546.88	−333.83	183.50	−47.43	−45.93

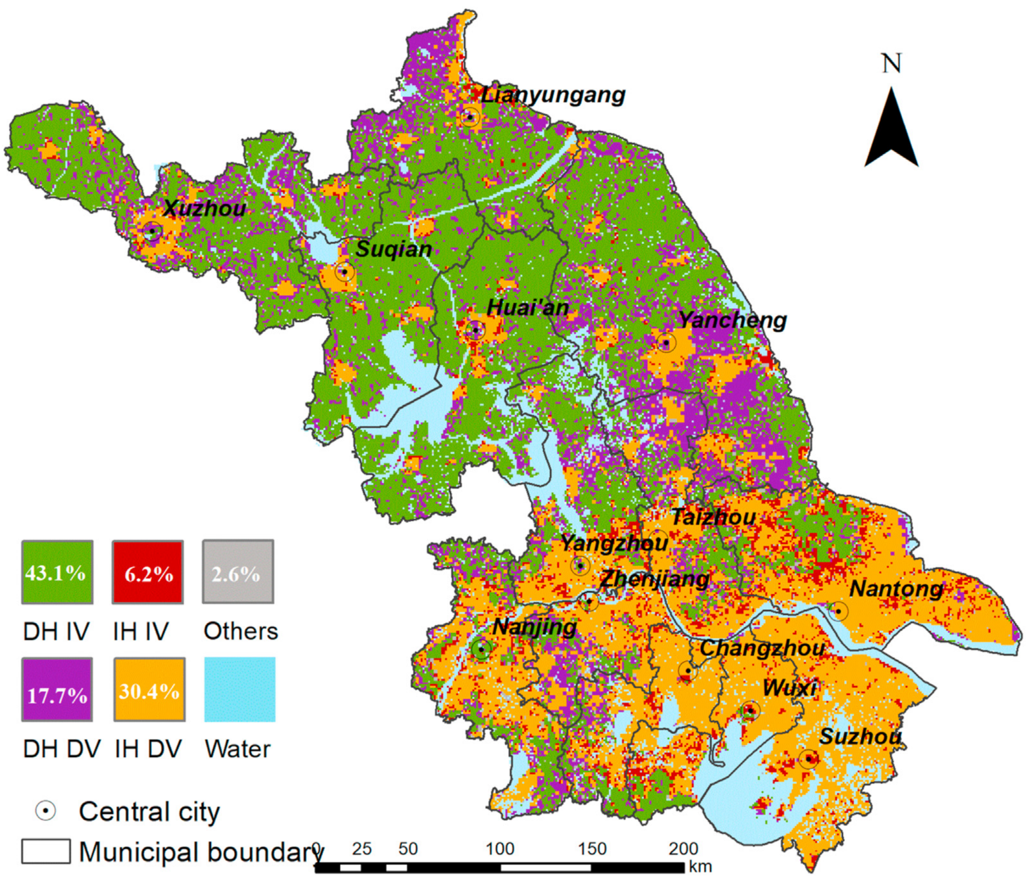


Fig. 8. Patterns of the coupling between human activity change and NDVI change, DH: decrease of human activities (value < −0.001), IH: increase of human activities (value ≥ 0.001), DV: decrease of NDVI (value < −0.001), IV: increase of NDVI (value ≥ 0.001).

in Yancheng, Taizhou and north Lianyungang. This indicates that government should pay attention on those areas to improve the ecosystem functions.

5. Conclusions

This study adopted SEM modeling to quantify the influences of the fundamental natural environment (soil and terrain), climate change and anthropogenic drivers on NDVI change in Jiangsu Province from 2000 to 2015. The results showed that the total effects of the fundamental natural environment, climate change, and human activity change on NDVI change in Jiangsu Province were −0.24, 0.17, and −0.74, respectively. The fundamental natural environment indirectly impacted NDVI change through its interactive relationship with human activities. We also constructed SEM models for northern and southern Jiangsu, indicating the different driving mechanisms of NDVI change. This was mainly due to their different natural environment and changing patterns of climate change. Although the effects for the three driving factors were different for northern and southern Jiangsu, human activity change played the most important role in driving NDVI change. Furthermore, the results suggested night light as the best indicator of human activity change in Jiangsu, followed by the road impact index. Soil type was the best indicator for natural environment in Jiangsu.

Our results showed that SEM is supportive of hypotheses on the causal relationships of driving factors on NDVI change. SEM provides a perspective by partitioning direct from indirect effects and thereby revealing a variety of mechanisms behind the NDVI change patterns. Partitioning areas based on their different changing patterns of driving factors for SEM modeling is necessary to better understand the complex mechanisms of NDVI change. We conclude that our study offers a framework to better understand and explain the complex interrelationships behind the spatial temporal change of NDVI. The work of the study can improve monitoring of vegetation degradation as well as land-use planning.

CRediT authorship contribution statement

Lin Yang: Conceptualization, Methodology, Writing - original draft. **Feixue Shen:** Data curation, Software, Investigation, Visualization. **Lei Zhang:** Software. **Yanyan Cai:** Validation. **Fangxin Yi:** Conceptualization, Writing - review & editing. **Chenghu Zhou:** Supervision.

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.

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