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Spatiotemporal dynamics of wetlands and their driving factors based on PLS-SEM: A case study in Wuhan

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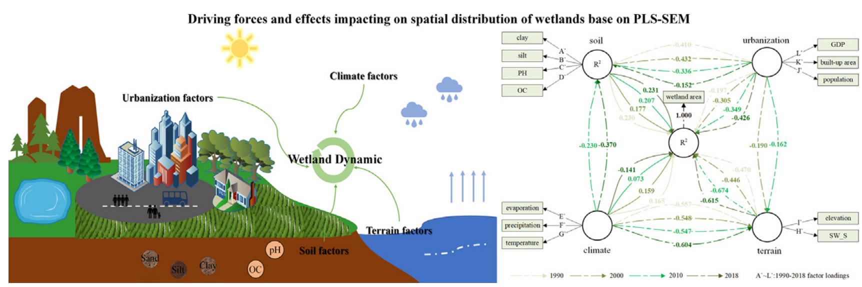
HIGHLIGHTS

- A framework was proposed to explore the interaction between natural environment and human activities on wetland changes.
- Four potential indirect impact pathways from latent variables to wetlands changes was discover.
- Climate change threatens wetlands.
- The study provides theoretical support to protect wetlands under different conditions.

GRAPHICAL ABSTRACT



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ABSTRACT

Globally, wetlands have been severely damaged due to natural environment and human activities. Understanding the spatiotemporal dynamics of wetlands and their driving forces is essential for their effective protection. This study proposes a research framework to explore the interaction between the natural environment and human activities and its impact on wetland changes, by introducing Partial Least Squares Structural Equation Modeling (PLS-SEM) and Geographically Weighted Regression (GWR) model, then applying the methodology in Wuhan, a typical wetland city in China. The validity and reliability evaluation indicated that the PLS-SEM model is reasonable. The results showed that the area of wetlands in Wuhan decreased by 10.98% in 1990–2018 and four obvious direct pathways of influence were found. Positive soil and terrain conditions are conducive to maintaining wetlands, while rapid urbanization drastically reduce the distribution of wetlands. It is remarkable that the impact of climate on wetlands is gradually shifting from positive to negative. Furthermore, four potential indirect impact pathways affecting wetland distribution shown that urbanization and climate enhance the negative impact of terrain on wetland distribution, while their impacts on soil weaken soil's direct positive impact. This study provides a quantitative methodology for determining the causes of wetland loss; it can also be applied to other cities or regions, which is essential for applying more effective measures to protect wetlands.

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1. Introduction

Wetland ecosystems are an important part of aquatic and terrestrial ecosystems and play an important role in hydrological regulation, biodiversity conservation and the maintenance of regional ecological balance (Kumari et al., 2020; Meng et al., 2017). Meanwhile, the wetland and ecosystem has the highest ecosystem services values of all types of

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ecosystems (Davidson et al., 2019). However, in the context of global climate change and rapid urbanization, wetlands are being severely damaged. It is estimated that, in the past 150 years, more than 50% of the world's wetlands have changed, been degraded, or disappeared (Ramsar Convention on Wetlands, 2018). The existing wetlands are still deteriorating, and the loss of urban wetlands is particularly serious due to the long-term extraction of groundwater, industrial pollution, population growth, aquaculture, and other urbanization processes (Davidson, 2014; Xu et al., 2019; Yu et al., 2017). Therefore, it is essential to understand the evolutionary trends of wetland and to further explore the driving factors of wetland degradation, which can help policy makers to formulate effective protection policies and management plans.

The natural environment and human activities are generally considered the main driving factors leading to structural changes in wetland ecosystems (Asselen et al., 2013). First, climate is the basis for the formation and development of wetlands (Neubauer and Verhoeven, 2019), in which precipitation has a direct impact on changes, and temperature and evapotranspiration regulate the distribution of wetlands by affecting the hydrological cycle (Havril et al., 2018; Hirmas et al., 2018). In addition, snow and glacier melt can also affect wetland systems (Baltaci et al., 2020; Ray et al., 2019). Second, wetland ecosystems often contain abundant shallow groundwater resources, and the fluctuation in surface water also affects the distribution of wetlands to some extent (Li et al., 2019). The distribution of wetlands can also be influenced by elevation and slope (Liu et al., 2013). In addition, the structure and elements of the soil affect the survival of the microbial community and therefore impact on the wetlands, e.g., the abundance of organic matter in the soil is beneficial to the distribution of wetlands (Hinson et al., 2017). Rapid urbanization increases the risk of wetland degradation (Mao et al., 2018b), and brings about local climate change (Baltacı et al., 2017). Urban expansion, suburban development, and the replacement of natural wetlands by agricultural and other landscapes increases wetland vulnerability (Liu et al., 2013). The factors that affect wetland distribution are often synergistic, and the degree of influence will change in different periods.

The continuous degradation of wetlands and the decline or loss in ecological environment service function has led to a greater awareness of the importance of wetland ecosystems (Xu et al., 2019). In general, existing research on wetland changes is focused on several aspects. The first is analyzing wetland degradation from a microscopic perspective. At the mechanism level, changes in soil structure and elements, biological and ecological mechanisms, and biogeochemical processes were analyzed. In this process, the changes in plant and animal populations caused by wetland degradation are analyzed (An et al., 2019; Bansal et al., 2019; Ma et al., 2020). However, this method relies on the selection of samples, which involves the selection of experimental regions, and there is uncertainty to some extent. The results of the study can only have reference value and significance for the region at this time, and it is difficult to adapt to different study areas. The second is using statistical and mechanical models to evaluate wetland degradation, such as partial least squares regression, correlation analysis, gray correlation, and multiple linear regression (Jia et al., 2017; Li et al., 2020b; Lin et al., 2018; Zheng et al., 2017), to quantify the relationships between wetland destruction and a single independent variable, such as climate, urbanization, or terrain. This method is relatively simple, and the evaluation results are often one-sided. It is gradually being replaced by more sophisticated methods (Wang et al., 2021b; Ye and Qiu, 2021). The third is using remote sensing images to monitor land use/cover changes (Abdullah et al., 2019; Adnan et al., 2020; Cong et al., 2019; Jia et al., 2021; Zhang et al., 2021), and to study the spatiotemporal evolution of wetlands in a large area or at a large scale. These studies are mainly to explore dynamic changes in wetland area, and cannot further explore the causes of wetland degradation. The last is to explore the driving forces of wetland change using wetland ecological risk assessment methods, such as quantitative analysis of the driving mechanisms of wetland degradation considering political, economic, and social factors (Guo and Zhang, 2019; Li et al., 2020a; Song et al., 2021). This evaluation method focuses more on the main risks to wetlands, such as natural hazards and anthropogenic factors. However, the causes and their interactions affecting wetlands have been still unknown. Wetland degradation occurs under the long-term integrated influence of the natural environment and human activities. It is necessary to make a scientific assessment of wetland degradation from a comprehensive perspective, rather than just based on the decline of a specific aspect.

Compared with the above methods, Structural Equation Modeling (SEM) is a quantitative research method based on statistical analysis techniques to deal with multifactor causal relationships (Hayes et al., 2017). On the basis of integrated path analysis, factor analysis, regression analysis, and analysis of variance, by establishing a link between empirical data and theoretical analysis, the relationships between multiple causes and consequences can be determined. SEM is used to perform the estimation of latent variables and create a complex variables prediction model (Cepeda-Carrion et al., 2019). This method provides a better understanding of the direct and indirect interactions between the factors, in addition to the results of a traditional multivariate statistical analysis (Ren et al., 2021; Schweiger et al., 2016). Considering that wetland degradation is the result of the interaction between the natural environment and human activities, SEM model was used to explore the compound factors and interactions affecting wetland changes in this study. In addition, Geographically Weighted Regression (GWR) was introduced to determine the local spatial variation in the driving factors.

Wuhan, as one of the megacities with the richest inland wetland resources in China, is also one of the leading cities in the world for inland urban wetland resources. Wuhan is located in central China and has abundant water resources and wetland resources; it is known as the "City of Hundred Lakes" (Luo et al., 2018). Due to its special geographical location and hydrological conditions, it not only requires flood control, but is a gathering place for migratory birds and other endangered species (*Aythya baeri, Acipenser sinensis, Neophocaena asiaeorientalis,* etc.) (Mei et al., 2019; Wang et al., 2021a; Weerasinghe et al., 2021). With the rapid urbanization and industrial development of recent decades, the reclamation of lakes for farmland, the reduction or even disappearance of lakes, frequent waterlogging and the decline of endangered animals have become extremely serious. Consequently, wetland protection is particularly important. A study of the factors affecting the change of wetland in Wuhan can reflect the actual situation of urban wetlands and provide reference prices for other wetland cities. Therefore, this study analyzes wetland changes and explores the effects of the natural environment, human activities, and their interaction on the long-term spatial distribution of wetlands. The three objectives of this study were to (1) construct an analysis framework to identify the driving factors of wetland changes; (2) quantify the direct and indirect effects and the interaction of natural environment and human activities on wetland changes; and (3) explore the spatial heterogeneity in the influential factors of wetland distribution.

2. Materials and methods

2.1. The study area

The city of Wuhan (113°41′–115° 05′E, 29°58′–31°22′N) in central China is rich in wetland resources and is a typical lake wetland city in the middle and lower reaches of the Yangtze River (Fig. 1). Wuhan has 1.627×10^5 hectares of wetlands, accounting for 18.9% of the city's total land area. Wuhan consists of seven central districts (includes Jiang'an, Jianghan, Qiaokou, Hanyang, Wuchang, Qingshan, and Hongshan districts) and six suburban districts (includes Huangpi, Dongxihu, Caidian, Hannan, Jiangxia, and Xinzhou districts). The city has a humid continental subtropical monsoon climate, with an average annual temperature of 16 °C and annual precipitation of 1200 mm (Fang et al., 2019). It hardly ever snows in winter. In 2018, the permanent population grew to 13.64

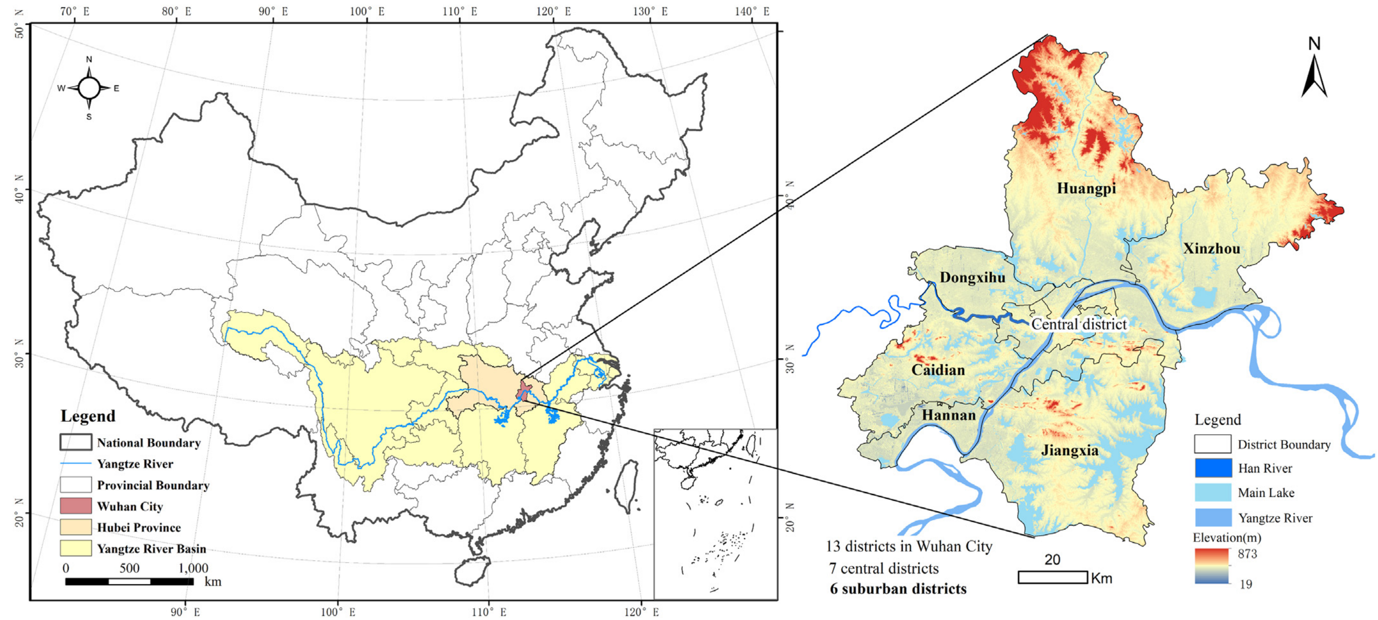

Fig. 1. The location of Wuhan City.

million, and the GDP reached 1.48 trillion RMB (Wuhan Statistics Bureau, 2020). Meanwhile, rapid urbanization and industrialization have become a serious threat to the wetlands. Balancing economic and social development with healthy ecological development of wetlands is a necessary and comprehensive task. Understanding the main driving forces and effects of wetland loss is a priority for achieving this goal (Gao et al., 2020; Hu et al., 2017).

2.2. Data sources

The study used land-use, socioeconomic, terrain, soil, and meteorological datasets. The land-use datasets were obtained from the Institute of Geographic Sciences and Natural Resources Research, China (http://www.resdc.cn/), including data from 1990, 1995, 2000, 2005, 2010, 2015, and 2018, with a spatial resolution of 30 m. The accuracy of the classification was in excess of 94.3%. These data were interpreted based on the Landsat 5 MSS, Landsat 7 ETM/TM, and Landsat 8 OLI remote sensing satellite data, and the classification results were verified by unmanned aerial vehicle images and field investigations. The first-level classification of land-use data includes cropland, grassland, woodland, water bodies, built-up land, and unused land, and there are 24 specific types (Table 1). Among them, paddy fields of cropland, natural water, reservoirs and ponds, tidal flats of water bodies, and marshes were considered as wetlands in this study. During this study, meteorological data were obtained from the National Meteorological Information Centre (http://data.cma.cn/), including the annual average temperature, precipitation, and evaporation. The operations of reading, merging, checking, counting, and generation of spatial interpolation batch codes were performed, and 1-km spatial raster data were interpolated by ANUSPLINE 4.4 software (Price et al., 2000). Soil data included the proportion of clay, sand, silt, organic carbon (OC), and soil pH. Soil property data were collected from the Resource and Environment Science and Data Centre (http://www.resdc.cn/), and soil pH and organic carbon were obtained from the Harmonized World Soil Database (http://www.fao.org/soils-portal/soil-survey/). Elevation was generated using ASTER DEM (http://www.gscloud.cn). Socio-economic data included the annual average population density, Gross Domestic Product (GDP), and built-up areas. Population density data were derived from LandScan Global Population Data (https://landscan.ornl.gov/landscan-datasets) and the Resource and Environment Science and Data Center (http://www.resdc.cn/). The GDP data are the product of the GDP statistical value of the county administrative region where the grid unit is located and the GDP weight ratio of the standardized land use type and inhabitant density (Xiangdi et al., 2011).

Table 1
The land use classification system and its description.

Categories	Types	Description
Cropland	Paddy field, dry land	Land for growing crops.
Woodland	Closed forest, shrub, sparse wood, other woodland	Forestry land for growing trees, shrubs, bamboo, etc.
Grassland	High-coverage grassland, medium-coverage grassland, low-coverage grassland	Land mainly grows various types of herbaceous plants, with a coverage of more than 5%.
Waterbody	Natural water, reservoirs and ponds, permanent glacial snow, tidal flats, beaches	Land for natural inland waters and water conservancy facilities.
Built-up land	Urban areas, rural residential areas, other built-up land	Includes urban and rural residential areas, industrial and mining land, traffic land, among others.
Unused land	Sand, Gobi, saline alkali land, marshes, barren land, bare rock, other unused land	Land has not been used.

2.3. Methodology

The study proposed a research framework to explore the interaction between natural environment and human activities on wetland changes. Human activities have accelerated the degradation of wetlands, and the natural environment (including climate, soil, terrain, etc.) is an important part of construction and maintenance of wetlands. The spatiotemporal evolution of wetlands was analyzed macroscopically by spatial statistical methods. The Partial Least Squares Structural Equation Model (PLS-SEM) and GWR were introduced to explore the composite factors affecting wetland changes and their interactions, and to understand the local spatial variation of driving factors. This study takes Wuhan as a case to analyze, as is shown in Fig. 2. Since 1990, China's industry and economy have developed rapidly, and the damage to wetlands has been significant. However, the changes in wetland area and patterns driven by multiple factors have been slow and gradual. After China's accession to the Ramsar Convention in 1992, more attention has been paid to wetland

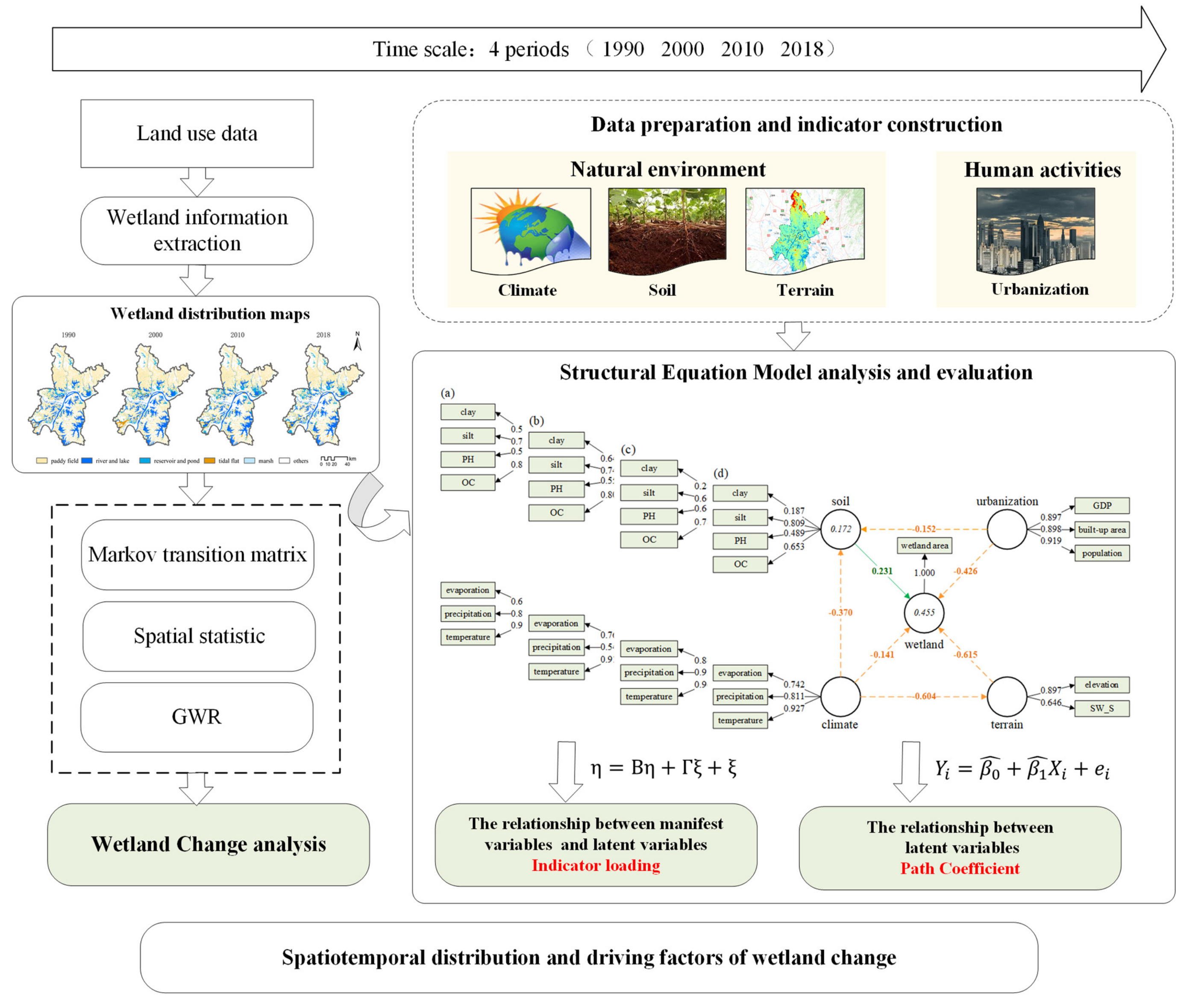

Fig. 2. Overall framework of the wetland changes assessment.

protection (Sun et al., 2015). The spatial distribution of wetlands in Wuhan for 1990, 2000, 2010, and 2018 was investigated to explore the evolution of wetlands and the driving factors affecting these changes in the past 30 years. First, five wetland types of multitemporal mappings were performed, and the spatial and temporal evolution of wetlands were determined using spatial statistical methods. Furthermore, a land-use transition matrix was used to analyze changes in wetland landscape types over the past 30 years, according to the spatiotemporal transformation among different wetland types and between wetlands and non-wetlands. At the grid scale, correlation analysis of manifest variables was used to explore the correlation between variables in PLS-SEM preliminarily. Wetland distribution data, urbanization data, soil data, meteorological data, and terrain data were used as latent variables to construct the PLS-SEM collectively. Subsequently, the indicator loadings for latent variables were established, and the hypothesized relationships between exogenous variables (urbanization, soil, climate, and terrain) and endogenous variables (wetland distribution) were calculated as path coefficients. As a result, the main driving forces and effects on wetland changes were evaluated using the path coefficient and indicator loadings. The changes in driving paths and driving effects in 1990, 2000, 2010, and 2018 were also discussed. Finally, the GWR model was used to determine the sensitivity and spatial heterogeneity of the wetland distribution's response to various factors.

2.3.1. Identifying the degree of changes in wetlands

Various wetlands provide different levels of ecosystem services. Natural water, marshes, and beaches, as natural wetlands, can provide habitats for many animals and plants. Reservoirs can conserve water resources and withstand natural disasters such as floods and droughts. Paddy fields, as human-made wetlands, have lost many of the ecological functions of other wetlands because they are relatively independent of the external environment. Therefore, the transition from other wetlands to paddy fields, similar to the transition from paddy fields to non-wetlands, should also be considered a type of damage (Mao et al., 2018a; Peng et al., 2020). We categorized wetlands as either functional or non-functional to identify the degree of wetland change; the latter included paddy fields, whereas other wetlands were considered functional (Table 2). The transitions among functional wetlands, non-functional wetlands, and non-wetlands were defined to describe the degree of wetland change, as shown in Table 3.

Table 2
The wetland classification system and its description.

Level 1	Level 2	Description
Non-functional wetlands	Paddy fields	Land with irrigation facilities and for growing aquatic crops.
Functional wetlands	Natural water	Linear water bodies formed naturally or excavated manually, and natural impoundment areas.
	Reservoirs and Ponds	Artificial impoundment areas.
	Tidal flats	The tidal zone between the water level in normal and flooding periods in a river or lake.
	Marshes	Land with long-term humid, seasonal, or perennial water accumulation and moist plants.

2.3.2. Land-use transition matrix

The variation in wetlands was analyzed using the transition matrix proposed by Markov (Zhang et al., 2011). A Markov chain can be described as a series of states, and the model is the dynamic evolution of land-use types in different periods by generating a land-use area transition matrix. The expression is:

$$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \cdots & \vdots & \cdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \tag{1}$$

$$\sum_{j=1}^{N} P_{ij} = 1, i, j - 1, 2, \ldots, n \text{ and } 0 \le P_{ij} < 1 \tag{2}$$

In this study, P_{ij} is the transition probability from the ith to the jth state; n represents the number of land-use types. Four states were analyzed in the periods 1990–2000, 2000–2010, 2010–2018, and 1990–2018.

The Markov chain model is a random process in which the state of the land use type at time $t+1$ depends only on the current time t, independent of any time before t. The state transition of the land use type S_t between the start time t and the end time $t+1(S_{t+1})$ can be expressed as follows:

$$S_{t+1} = P_{ij} \times S_t \tag{3}$$

2.3.3. The PLS-SEM model specification

PLS-SEM is used to estimate the causal network among latent variables. The latent variables can be expressed by a set of manifest variables. The manifest variables are quantities that can be directly observed or measured, and are also called observed variables. Latent variables are those that cannot be directly observed but can be constructed with one or more manifest variables through a certain theory or hypothesis. PLS-SEM usually includes measurement models and structural models. The measurement model (or external model) is an explanatory model consisting of latent variables and manifest variables (Ullman and Bentler, 2012). The following formulas can express this:

$$X = \Lambda_x \xi + \delta \tag{4}$$

$$Y = \Lambda_y \eta + \varepsilon \tag{5}$$

Eqs. (4) and (5) are exogenous and endogenous indicators, respectively. Λ refers to the relationship between the manifest and latent variables; δ and ε refer to the measurement error.

The structural model (or inner model) is a path diagram reflecting the relationship between the effects of latent variables (Hoyle, 1995; Kline, 2015):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{6}$$

where η is the endogenous latent variable, ξ is the exogenous latent variable, and B represents the effect of the exogenous latent variables on the endogenous latent variables. Γ represents the effect of some endogenous latent variables on other endogenous latent variables. ζ is the regression residuals.

In this study, PLS-SEM was used to evaluate the essential factors affecting wetland distribution. Compared to Covariance Based Structural Equation Modeling (CB-SEM) (Hair et al., 2011), PLS-SEM relaxes the assumption of multivariate normal distribution in the parameter estimation process (Shen et al., 2016). The wetland ecosystem examined in this study, the CB-SEM model, cannot guarantee this assumption of normality. Furthermore, PLS-SEM is more suitable for exploratory research on small samples and can effectively evaluate the interaction between variables (Fan et al., 2016; Tenenhaus et al., 2005).

Many factors influence wetland change, including climate, soil structure, characteristics of terrain, economics, policy, urbanization, and more. These factors vary over time and from region to region. This study takes Wuhan as a case; 14 evaluation indicators were compiled and calculated using temperature, precipitation, evaporation, clay, sand, silt, OC, pH, elevation, surface water scarcity, GDP, population, and built-up areas as manifest variables, and climate, soil, terrain, and urbanization as latent variables in PLS-SEM. An integrated raster dataset with a cell size of 1 km × 1 km was utilized in the PLS-SEM model (Table 4). The climate, soil, population, GDP, and elevation data were rasterized into grid layers, and the average pixel value for each grid was taken as a sample set. In addition, the proportions of built-up area, surface water, and wetlands in each cell of the grid were calculated. The surface water scarcity (SW_S) index was calculated by taking negative values for the total proportion of surface water. Table S1 presents the datasets from 1990, 2000, 2010, and 2018 in more detail. The value of each variable was a logarithmic transformation to reduce the difference by an order of magnitude.

Some studies have shown that changes in wetlands are influenced by terrain, soil, urbanization, and climate change. Moreover, recent studies have suggested that urban development and climate change

Table 3
The degree of change and definition of wetland types.

Degree of change in wetlands	Definition
Severely damaged	Functional wetland → Non-wetland
Slightly damaged	Functional wetland → Non-functional wetland
	Non-functional wetland → Non-wetland
Unchanged	Functional wetland → Functional wetland
	Non-functional wetland → Non-functional wetland
Slight recovery	Non-wetland → Non-functional wetland
	Non-wetland → Functional wetland
Significant recovery	Non-wetland → Functional wetland

Table 4
Modeling indicators.

Latent Variable	Manifest Variable	Year
Climate	Temperature (°C)	1990; 2000; 2010; 2018
	Precipitation (mm)	1990; 2000; 2010; 2018
	Evaporation (mm)	1990; 2000; 2010; 2018
Soil	Clay (%)	1990
	Sand (%)	1990
	Silt (%)	1990
	OC (%)	1990
	pH	1990
Terrain	Elevation (m)	2000
	Surface water scarcity (proportion)	1990; 2000; 2010; 2018
Urbanization	GDP (billion yuan)	1990; 2000; 2010; 2018
	Population (10,000 people)	1990; 2000; 2010; 2018
	Built-up area (proportion)	1990; 2000; 2010; 2018
Wetland area	Wetland area (proportion)	1990; 2000; 2010; 2018

Note: 1990 ; 2000 ; 2010 ; 2018

impact terrain and soil, and have comprehensive effects on wetland change (Moomaw et al., 2018). Thus, their interactions, such as the coupled impacts of urbanization–soil factors, urbanization–terrain factors, climate–terrain factors, and climate–soil factors, should be considered when assessing ecological changes. PLS-SEM was initialized based on the above assumptions and established indicators.

2.3.4. Spatial heterogeneity of wetland dynamics to driving factors based on GWR

GWR is usually used to quantify spatial heterogeneity by establishing relationships between dependent and independent variables with spatial attributes. A prerequisite for applying the GWR model to analyze is the existence of spatial correlation between the spatial distribution of wetlands and the driving factors. In this study, each independent variable in GWR either promoted or resisted wetland changes. GWR can be given by

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \tag{7}$$

where y_i is a dependent variable representing the wetland proportion in the *ith* cell, x_{ij} is the *jth* independent variable (driving factor) at position (u_i, v_i), and $\beta_j(u_i, v_i)$ is the intercept at location (u_i, v_i), which is usually used for local estimation by the weighted least square method. k is the total number of factors, and ε_i denotes the random error term.

3. Results and analysis

3.1. The spatiotemporal evolution of wetland landscape

From 1990 to 2018, the distribution of wetlands changed significantly in Wuhan (Fig. 3). Wetlands showed an overall trend of degradation, and the wetland area was smallest in 2018, 565.22 km^2 less than in 1990. Among human-made wetlands, the paddy field area decreased by 638.43 km^2. The area of reservoirs and ponds areas initially increased and then decreased, but the area in 2018 was 155.98 km^2 larger compared with 1990. In natural wetlands, the tidal flat area increased by 93.01 km^2, and natural water and marsh areas decreased by 156.42 km^2 and 19.36 km^2, respectively, over the same period. The results show that the degradation of wetlands mainly manifested as reductions in paddy fields and natural water. By 2018, human-made wetlands accounted for 71.13% of the total wetland area, while natural wetlands accounted for 28.87%.

There were also differences in spatial distribution among the various wetland types (Fig. 4). Wetlands were dominated by paddy fields, accounting for 60.3% of the total wetland area in 2018. They were mostly distributed in the suburban districts of Wuhan. The proportion of natural water was ranked second. Wuhan is located at the confluence of the Yangtze River and Han River, and has 187 lakes and abundant natural water resources. In addition, tidal flats and marshes are primarily distributed around rivers and lakes. In general, the wetlands in Wuhan are widely distributed. In 2018, wetlands accounted for 53.01% of the administrative area of Wuhan.

3.2. Identification and analysis of wetland dynamic types in Wuhan City

The spatial distribution of wetland destruction and restoration types over the last 30 years is shown in Fig. 5. The main types of wetland changes were slight damage and slight recovery. Slightly damaged regions were mainly distributed in the suburban districts, while severely damaged areas were relatively small, mainly in the central districts. The slight recovery areas were widely distributed, but the recovery areas were small and mostly distributed along rivers and lakes. From 1990 to 2018, wetland destruction extended from central districts to suburban districts, and the degree of destruction became increasingly severe.

The degree of wetland changes in Wuhan is shown in Fig. 6, and the transfer destination for the loss of wetlands is shown in Fig. 7. From 1990 to 2000, wetlands showed an increasing trend. The area of recovered wetlands was 14.25 km^2 more than the damaged area. From 2000 to 2010, the status of wetlands showed a degradation trend, and wetland loss was 94.07 km^2 more than that recovered, primarily due to paddy fields' conversion to built-up land, reservoirs, and ponds, with 198.94 km^2 and 99.57 km^2, respectively, and most natural water was converted to reservoirs and ponds, totaling 69.48 km^2. Wetlands changed dramatically from 2010 to 2018, up to 471.22 km^2 of wetlands was severely damaged, and the slightly recovered area increased to 360.30 km^2. During this period, the area of paddy fields decreased significantly, primarily being converted to built-up land and dry farmland (237.18 km^2 and 193.14 km^2, respectively). Natural water, reservoirs, and ponds were invaded by paddy fields, comprising 40.24 km^2 and 57.4 km^2, respectively. In general, wetlands in Wuhan changed greatly from 1990 to 2018, and the damaged area was greater than the recovered area (approximately 414.96 km^2). While wetlands degraded, wetland recovery was enhanced, especially from 2010 to 2018, indicating that policies protecting the wetland environment have an obvious effect and have been gradually strengthened over the past 30 years in Wuhan. It is necessary to further strengthen protection measures and continue wetland reserve construction in the future.

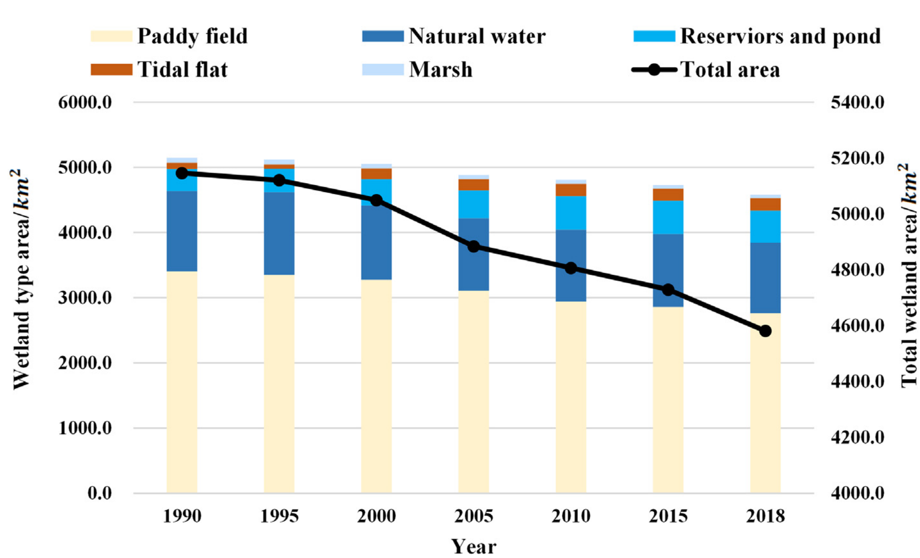

Fig. 3. Changes in wetland areas in Wuhan, 1990–2018.

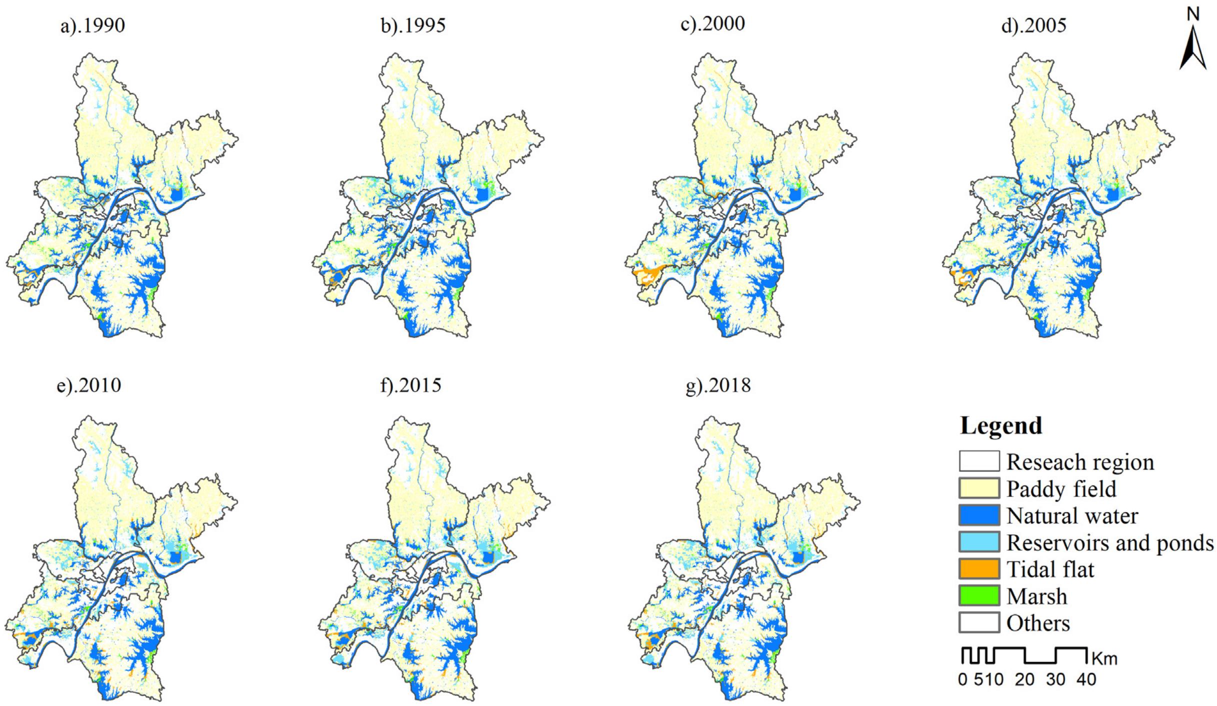

Fig. 4. Spatial distribution of wetlands in Wuhan during 1990–2018.

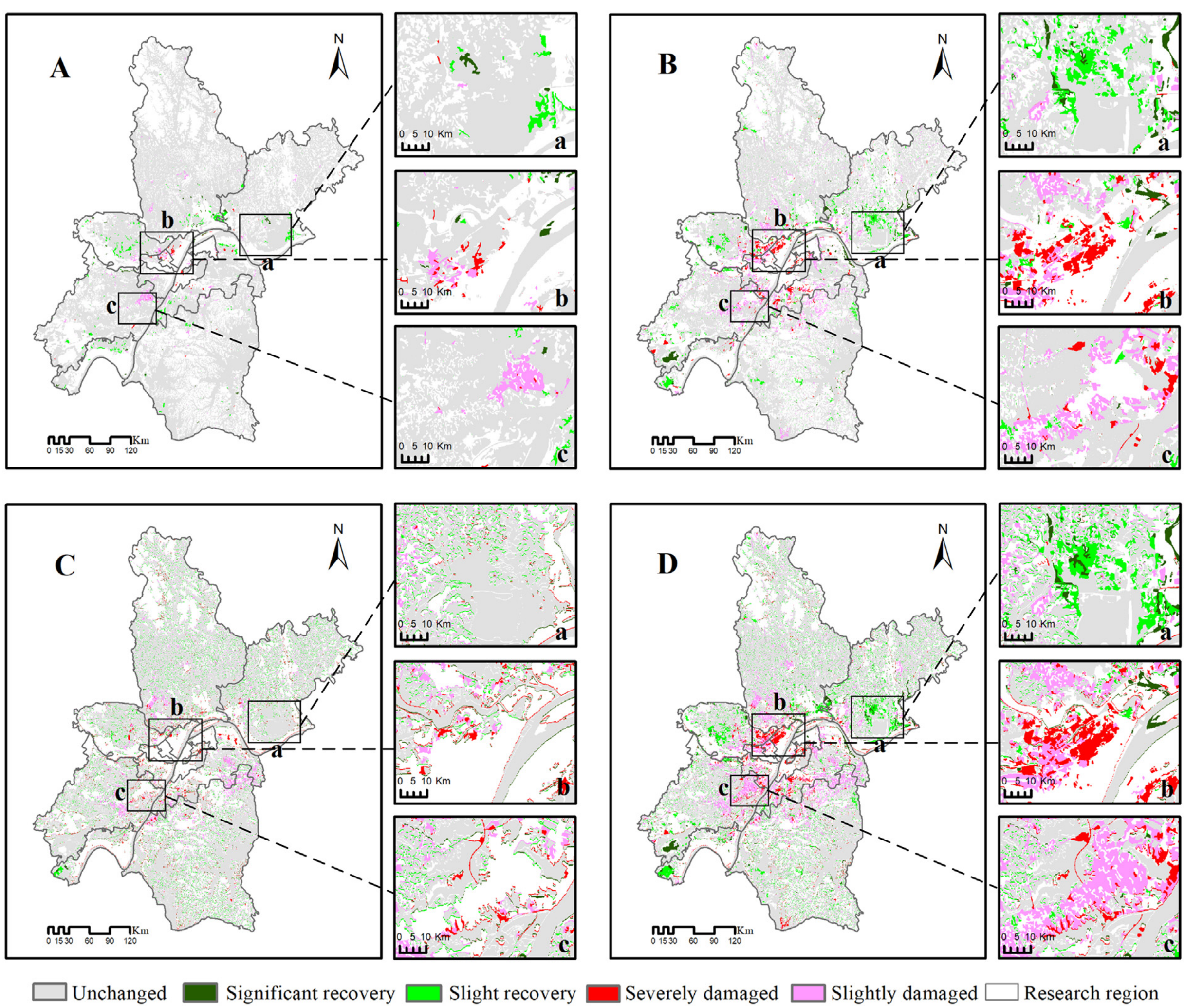

Fig. 5. The spatial distribution maps of wetland change in 1990–2000 (**A**), 2000–2010 (**B**), 2010–2018 (**C**), and 1990–2018 (**D**).

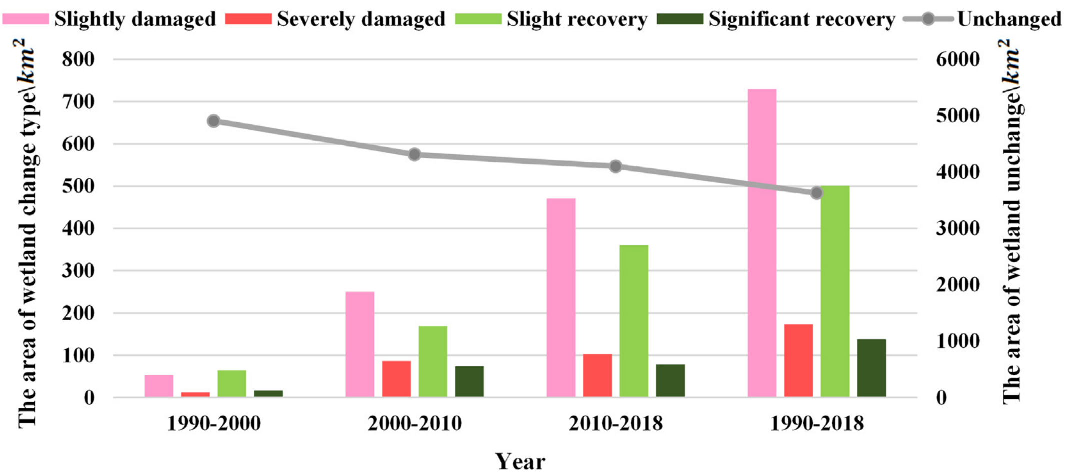

Fig. 6. Area of each type of wetland change (1990–2018).

3.3. The Main driving forces and driving effects of wetland distribution

3.3.1. Correlation analysis between driving factors and wetland distribution

In this section, the relationship between the wetland area and the other 13 variables is explored. As shown in Fig. 8, there were correlation coefficients for the four periods from 1990 to 2018. The results confirmed that wetland area was significantly and positively correlated with temperature (tem), evaporation (eva), silt, surface water (SW), and OC, but negatively correlated with precipitation (pre), elevation (ele), population (pop), GDP, and built-up area (build). In addition, we found: (1) At a confidence level of $p = 0.05$, the proportion of clay, OC, and pH in the soil were positively correlated with wetland distribution. (2) The confidence level of urbanization increased from $p = 0.5$ to $p = 0.001$ in the past 30 years, with the continuous increase in population, built-up area, and the value of GDP gradually exacerbating wetland loss. From 1990 to 2018, the correlation coefficient of built-up area, GDP, and population to wetland distribution decreased from −0.23 to −0.48, from −0.1 to −0.29, and from −0.11 to −0.3, respectively. (3) The low elevation and wide surface water area are beneficial for the distribution of wetlands.

3.3.2. PLS-SEM models

Reliability and validity were assessed to effectively evaluate the credibility of the PLS-SEM model (Chen et al., 2015; Hair et al., 2019). The reliability of internal coherence was evaluated using Composite Reliability (CR) (Jöreskog, 1969), which is generally expected to be greater than 0.7 and no less than 0.6. The Average Variance Extracted (AVE) is used to verify convergent validity, which is required to be greater than 0.5 (Nasution et al., 2020).

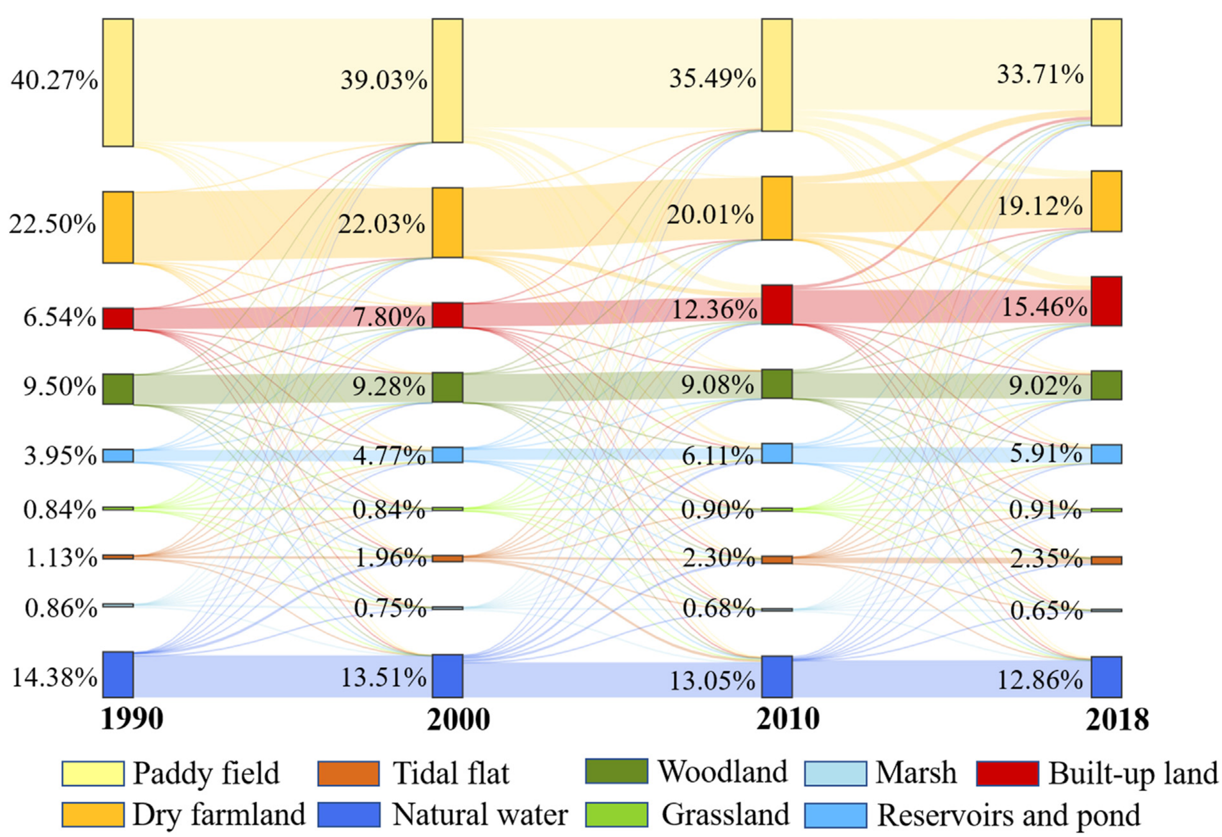

Fig. 7. A Sankey diagram of land-use type conversions from 1990 to 2018. The percentage values on each side indicate the land-use type of the total area.

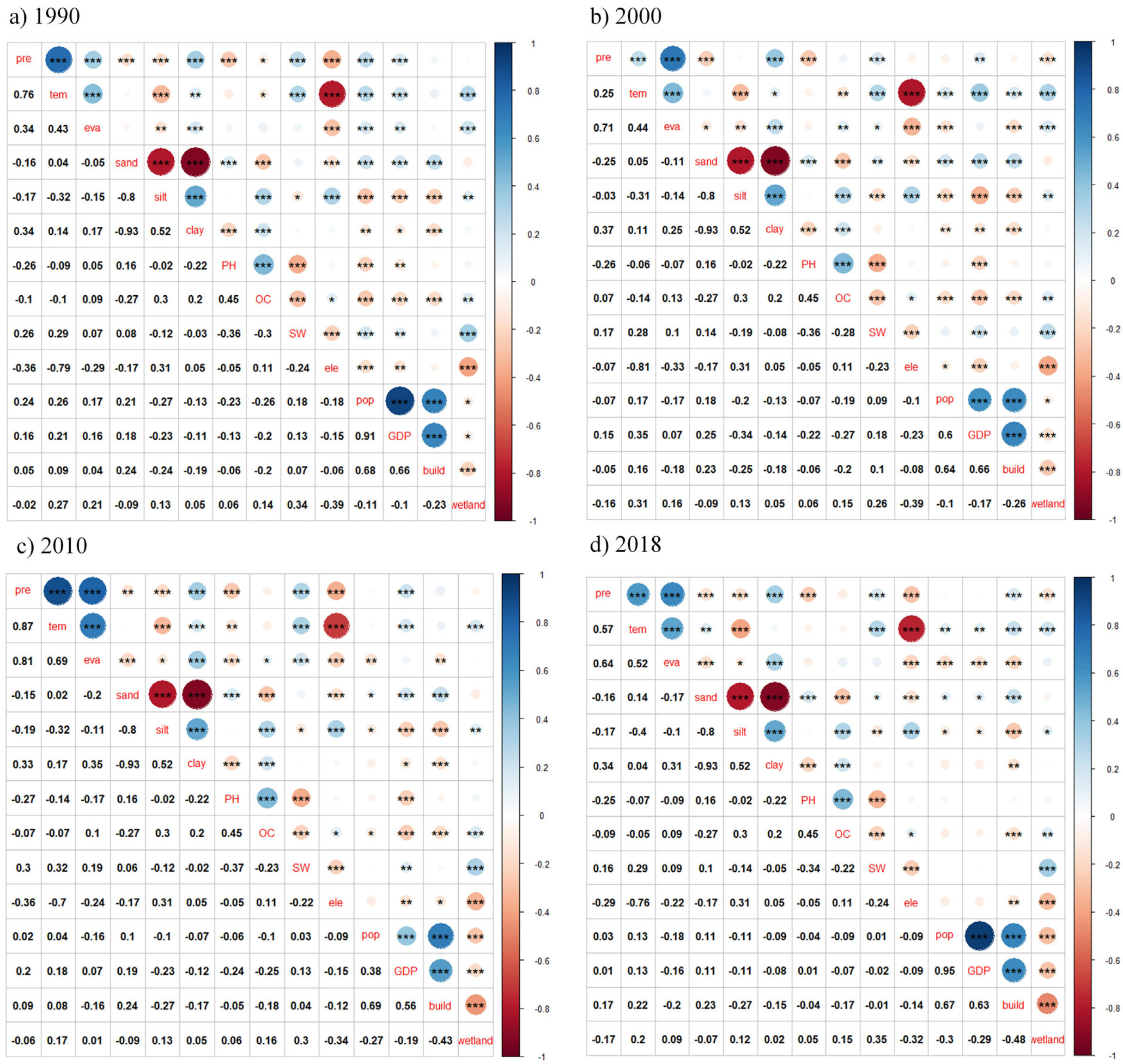

Fig. 8. Variable correlations and interactions from 1990 to 2018 (*$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$).

As the data in this study satisfied the above conditions well, all factor loadings for all indicators were between 0.489 and 0.961 in Table 5. This indicates that all the factor loadings satisfy the requirement for structural validity (Moeinaddini et al., 2020). The Variance Inflation Factor (VIF) was used to detect the multicollinearity of the 13 variables, and the results showed that the VIF values of the main manifest variables were from 1 to 5 (Table S2), indicating that there was no severe covariance among the elements (Thompson et al., 2017). The path coefficients between the latent variables are given in Table S3. Both the model external and internal loadings are significant ($P < 0.01$), and a T-statistic of greater than 1.96 was similarly confirmed. The β values of urbanization, climate, soil, and terrain factors and their interactions are also statistically significant. In summary, all the above indicators essentially meet the ideal values, proving that the evaluation model is reasonable and reliable.

3.3.3. Effects of latent variables and manifest variables on wetland distribution

The PLS-SEM models of the relationships between latent variables and manifest variables on wetland distribution from 1990 to 2018 are shown in Fig. 9. The PLS-SEM models explained 27.2%, 31.7%, 40.3%, and 45.5% of the variance occurring in 1990, 2000, 2010, and 2018, respectively. This finding reflects the increasing explanatory power of these factors for wetland changes. The results indicate that urbanization and terrain always had negative effects on wetland distribution, with path coefficients of −0.197, −0.305, −0.349, −0.426, and −0.470, −0.446, −0.674, and −0.615 from 1990, 2000, and 2018, respectively. Soil had a positive effect from 1990 to 2018, with path coefficients of 0.230, 0.177, 0.207, and 0.231, respectively. Notably, the path coefficient of climate has changed, and the impact of climate on wetland distribution was positive in 1990, 2000, and 2010 (β=0.165, 0.159, 0.073 respectively), and negative in 2018 (β = − 0.141).

The results of PLS-SEM model showed in Fig. 9. In 1990, in addition to the four direct pathways affecting wetland distribution, urbanization had an indirect and negative effect on wetland distribution through its effect on soils, and climate had a positive and indirect impact on wetland distribution through its effect on terrain (Fig. 9a). In 2000, an indirect and positive pathway through urbanization impacted the terrain and altered wetland distribution (Fig. 9b). In 2010, four indirect pathways were identified. The negative impact of urbanization and climate on soil indirectly weakened the positive impact of soils on wetlands. Climate and urbanization positively indirect affected wetlands through their effect on the terrain (Fig. 9c). In 2018, urbanization did not indirectly affect wetland distribution through its impact on the terrain (Fig. 9d).

Table 5
Reliability and validity assessment of the PLS-SEM model.

gep	1990			2000			2010			2018		
Construct	Loading	AVE	CR	Loading	AVE	CR	Loading	AVE	CR	Loading	AVE	CR
Climate		***0.679***	***0.861***		***0.569***	***0.792***		***0.850***	***0.944***		***0.690***	***0.869***
Temperature	0.953			0.911			0.961			0.927		
Precipitation	0.864			0.540			0.959			0.811		
Evaporation	0.620			0.766			0.841			0.742		
Soil		***0.477***	***0.781***		***0.475***	***0.778***		***0.490***	***0.700***		***0.439***	***0.633***
Clay	0.575			0.642			Delete*			Delete*		
Sand	Delete*			Delete*			Delete*			Delete*		
Silt	0.747			0.748			0.665			0.809		
OC	0.821			0.806			0.787			0.653		
pH	0.589			0.551			0.648			0.489		
Terrain		***0.669***	***0.798***		***0.670***	***0.798***		***0.610***	***0.756***		***0.611***	***0.754***
Elevation	0.922			0.927			0.843			0.897		
Surface water	0.698			0.703			0.714			0.646		
Urbanization		***0.744***	***0.895***		***0.629***	***0.835***		***0.880***	***0.711***		***0.819***	***0.931***
GDP	0.939			0.771			0.784			0.897		
Population	0.947			0.789			0.708			0.919		
Built-up area	0.674			0.684			0.791			0.898		
Wetland area		1.000	1.000					1.000	1.000		1.000	1.000

Note: CR > 0.65; AVE > 0.45; Outer loadings > 0.55. Values that do not satisfy the conditional hypothesis or are not significant are omitted.

3.4. Influential factors of wetlands distribution from spatial heterogeneity

The results depicted in Fig. 10 show that the regression coefficients of GWR in 2018 showed significant spatial differences in terms of the degree of influence of different factors on wetland distribution. The regression coefficient of the built-up area (Fig. 10a) ranged from −0.300 to 0.294, with an overall negative influence, and was the strongest in the central districts. The positive influence was mainly in the northern part of Huangpi District, the eastern and northern parts of Xinzhou District, and the southern part of Jiangxia District. The regression coefficient of GDP (Fig. 10b) ranged from −0.155 to 0.064. The regression coefficient of the population (Fig. 10c) was −0.464 to 0.040, with the negative impact gradually weakening from the central to suburban districts. The regression coefficient of the proportion of OC (Fig. 10d) in soil was −0.703 to 0.279, negatively correlated in Huangpi districts and positively correlated in other districts. In contrast, the distribution of

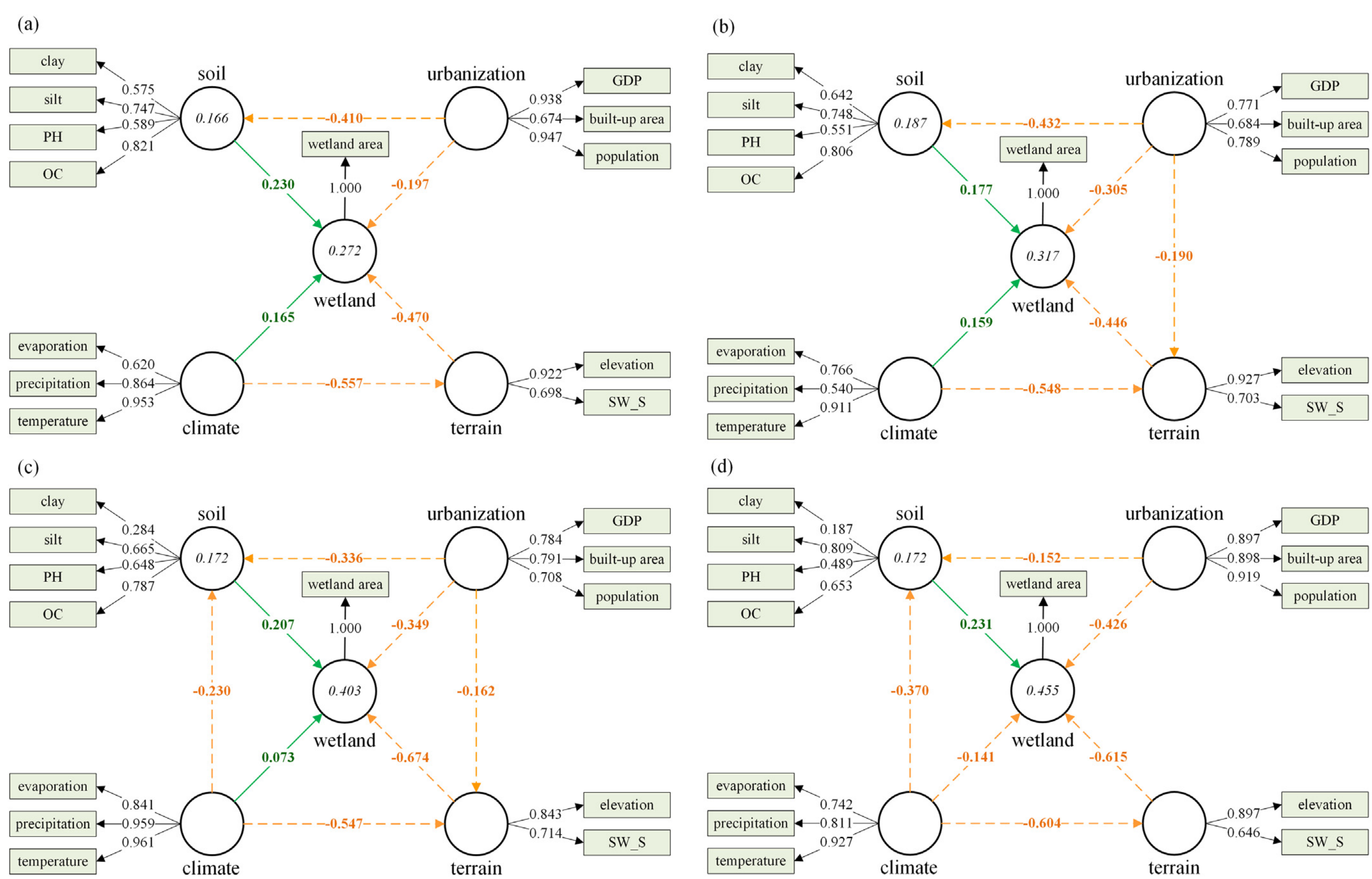

Fig. 9. The PLS-SEM model diagram shows the relationship between each variable and the distribution of wetlands in 1990 (**a**), 2000 (**b**), 2010 (**c**), and 2018 (**d**). The circles represent latent variables and the rectangles represent manifest variables. The arrows represent the link between them. The dotted orange lines indicate negative correlations and solid dotted green lines indicate positive correlations.

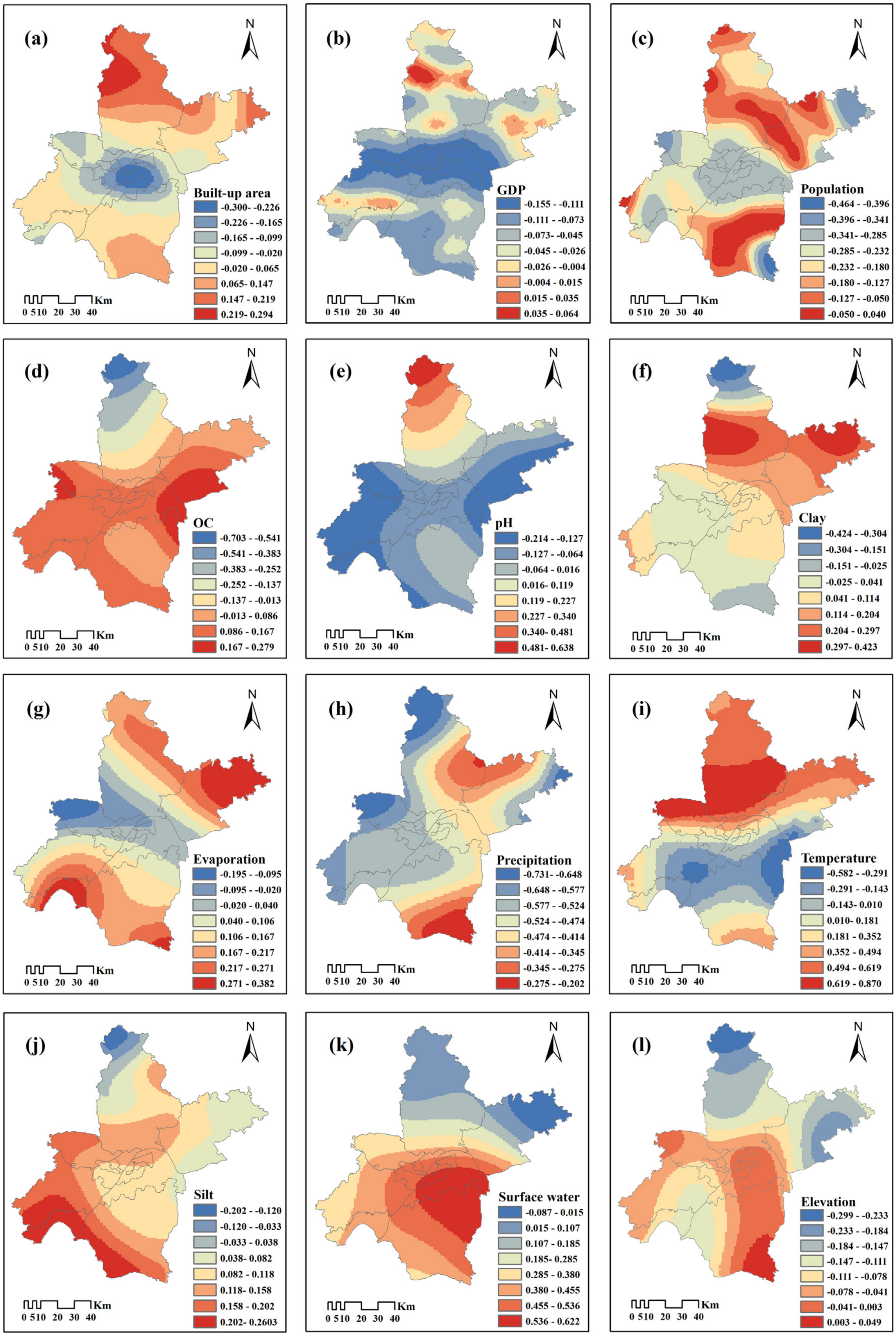

Fig. 10. Spatial distribution regression coefficients and corresponding factor scores from GWR. Input factor scores: (**a**) Built-up area; (**b**) GDP; (**c**) population; (**d**) surface water; (**e**) OC; (**f**) pH; (**g**) Clay; (**h**) silt; (**i**) evaporation; (**j**) precipitation; (**k**) temperature; (**l**) elevation.

the pH regression coefficient (Fig. 10e) was contrary to the OC. The amount of clay in the soil (Fig. 10f) showed a positive correlation in the northeast and a negative trend in the southwest. The amount of silt (Fig. 10j) had mainly positive effects, and the influence in the north of Huangpi District was negative. The regression coefficient of precipitation (Fig. 10h) ranged from −0.300 to 0.294, decreasing from northwest to southeast along the gradient, with high values reached at the junction of Jiangxia and Huangpi districts and Xinzhou district. The regression coefficient of temperature (Fig. 10i) ranged from −0.582 to 0.870, and decreased from north to south. Evaporation (Fig. 10g) in the central region of Wuhan was negatively correlated and positively correlated to the north and south. The regression coefficient of the surface water area (Fig. 10k) was −0.087 to 0.622, increasing along the direction from the northwest to the southeast. The elevation (Fig. 10l) indicated that the higher the elevation, the less suitable for the distribution of wetlands, and was thus negatively correlated. It is worth pointing out that surface water, OC in soil, and climate factors were the dominant factors affecting wetland distribution.

4. Discussion

4.1. Direct impact of factors on wetlands distribution

Our results demonstrated that the more rapid urbanization, as indicated by the higher density of population, GDP, and built-up area, the more severe the damage to wetlands (Fig. 8). This trend can also be seen in the weaker impact of peripheral areas, such as suburban districts (Fig. 10a–c). Therefore, human activities are the main factors driving wetland loss. The expansion of built-up land has led to the destruction of many wetlands. The development of agriculture and aquaculture has led to the expansion of villages and damaged wetland resources.

It was also found that temperature and evaporation were positively correlated with wetland distribution and area during 1990–2018, whereas precipitation showed a negative correlation (Fig. 8) due to the destruction of the ecosystem by rainstorms and floods. This finding was consistent with the results of Lemke and Michael (Lemke et al., 2017). It is remarkable that the positive impact of climate factors on wetlands gradually weakened from 1990 to 2010 and turned into a negative impact in 2018 (Fig. 9). This shows that the current climate is becoming increasingly unfriendly to wetland distribution. The conclusions obtained in the relevant studies are generally consistent: global warming and extreme weather may pose a threat to wetlands (Xu et al., 2019).

According to the analysis, we found that abundant surface water resources were beneficial to the distribution of wetlands and played an important role in breeding wetland ecology (Fig. 8). Adequate water resources contributed to the number of wetland reserves in Wuhan during rapid urbanization. In addition, the results showed that a higher proportion of organic carbon and silt in the soil was beneficial to the distribution of wetlands (Fig. 8). In addition, the soil property, organic carbon, pH value, and water content affect the diversity of microbial communities and jointly affect the ecological regulation capacity of wetlands (Ma et al., 2020). Based on the above analysis, the protection of water resources should be further strengthened, and biological invasion should be prevented to maintain organic matter in the soil to achieve sustainable development of wetland resources.

4.2. Indirect impact of latent variables on wetlands distribution

The complex interaction between the natural environment and human activities on wetlands is difficult to understand. This study innovatively found the influence of the interaction between terrain, urbanization, climate, and soil on wetlands by using PLS-SEM. The interaction impact pathways were particularly complex in 2010 and 2000, closely related to accelerated urbanization in this period (Fig. 9). Among them, urbanization factors play a dominant role in the interdecadal scale wetland changes. This study deepens our understanding of the driving forces and effects of wetland changes, and has promotion and application value for wetland protection.

From 1990 to 2018, the negative impact of urbanization on wetlands became increasingly apparent. Besides the direct effects, the negative impact of urbanization on soil diminished the direct positive impact of soil on wetland distribution, attributed to land use related to human activities. Some studies have explained that human-made stress, such as large-scale soil disturbance activities (land reclamation or road construction, etc.), results in nutrient loss, changes in the composition of biological communities, and a reduction in biodiversity (Orimoloye et al., 2020; Zhang et al., 2016). Economic activities, such as aquaculture, industry, agriculture, and urban wastewater, change the water cycle and soil structure by decreasing the water quality. As a result, the positive impact on wetlands is weakened, and the habitat quality decreases. Therefore, in the development of land use and economic activities, we should not only build wetland protection areas, prohibit the occupation of wetlands, and put in place other protection measures, but also pay attention to the damage to soil environment, changes in microbial community, changes in the content of trace elements that are beneficial to the environment, and so on.

The models from 2000 and 2010 showed that the effects of urbanization on terrain exacerbated the negative impact of the terrain on wetlands (Fig. 9b, c). This finding may be related to the acceleration of economic construction and urbanization during this period. Human development and other activities have caused excessive consumption of water resources, which exacerbates the process of wetland degradation. The reclamation of lakes and the occupation of lake wetlands have damaged the structural integrity of wetlands. This has inspired us to protect the wetlands by maintaining the content and sustaining the quality of surface water and groundwater. The fragmentation of wetland landscapes has increased, and the ecological health of wetlands has declined. In 2018, the influence of urbanization on terrain disappeared from the model. It has been shown that wetland protection and ecological restoration policies were promoted accordingly, and the interactions between latent variables affecting wetland distribution gradually stabilized.

The response of wetland distribution to climate change was highlighted in this study. The results showed that climate has a favorable effect on wetland distribution by regulating surface water content. This was because climate change alters hydrological cycles, especially altering surface water supply, runoff, evapotranspiration, and precipitation interception (Havril et al., 2018). We thus conclude that the loss of wetlands can be alleviated by improving the regulation of climate on surface water and enhancing water purification capacity. In 2010, climate change began to alter wetland distribution by affecting the soil (Fig. 9c), and the negative impact increased in 2018 (Fig. 9d). This finding indicates that factors conducive to wetland distribution in soil are weakened in the current climate. Coupled with the gradual deterioration of the direct impact of climate on wetlands, the negative impact of climate on wetlands has intensified. Therefore, this phenomenon must be considered in future studies. We need to pay attention to the impact of global warming on the environment, and look for breakthroughs in the research on how climate conditions affect wetland changes, to further analyze the principles and mechanisms of the influence process.

4.3. Limitations and implications

Different from existing research on wetland changes, we innovatively proposed a research framework to explore the interaction between the natural environment and human activities in terms of the impact on wetland changes, which makes up for the lack of quantitative analyses in the existing research. This study focused on the importance of quantitative driving factors of wetland change, thus providing a new perspective on wetland change. Secondly, this study incorporated natural environment and human activities into the comprehensive analysis framework, and established a framework for evaluating the complex causal relationship between wetland distribution and driving factors. Some indirect pathways affecting changes in wetland distribution were discovered in the model that affected the distribution of wetlands to some extent. By constructing a balanced system between economic and social development and wetland ecosystem health, the impact of human activities on wetland ecosystems can be controlled in a reasonable range to achieve sustainable development of the environment and society. This study also provides theoretical support for wetland conservation in the 17 specific Indicators of the SDGs, such as SDG 6.6 (protect and restore water-related ecosystems), SDG 15.1 (ensure the conservation, restoration, and sustainable use of terrestrial and inland freshwater ecosystems and their services), and so on.

The causes of wetland changes often vary in different regions. By introducing manifest and latent variables appropriate to the study areas, the framework can be extended to different study areas to provide targeted guidance on wetland conservation. Nevertheless, the factors affecting wetland distribution should be considered more comprehensively, especially factors related to biodiversity and water level. Moreover, although SEM has the capacity to analyze a finite number of samples, obtaining more effective samples can improve the model's accuracy. In addition, more multisource data should be considered for joint use in the future, to facilitate a more comprehensive assessment of wetland changes.

5. Conclusions

This study innovatively constructs a research framework to explore interactions between the natural environment and human activities on the wetland changes by introducing PLS-SEM and GWR model. The interactions of the driving factors and the magnitude of the forces are systematically explored from the perspective of the spatial and temporal dynamics of wetlands. Taking Wuhan as a case study, the degree and compound driving factors of wetland change from 1990 to 2018 were analyzed. The results showed that the area of wetland decreased from 1990 to 2018 by 565.22 km or 10.98%, while restored area increased, especially during 2010–2018. Focusing on the driving factors of wetland changes, we indicated that rapid urbanization and a lack of water resources threatened wetland distribution, while a higher proportion of silt or organic carbon promoted wetland distribution. Meanwhile, the climate has become increasingly unfriendly to wetland distribution. More importantly, the PLS-SEM model detected some indirect pathways that affect the distribution of wetlands. Urbanization increased the negative impact on wetland distribution through its impact on the terrain, while the impact of urbanization on the soil weakened the directly positive effect of soil on wetlands. The negative effects of terrain on wetlands are enhanced by climate. In addition, the negative impact of climate on wetlands is also exacerbated by the impact of climate on soil.

Overall, this study proposed an innovative method to effectively enhance our understanding of the driving forces and effects of wetland change. These findings have important implications for the application of more effective measures to protect wetlands under different conditions and can promote the achievement of the ecological and environmental indicators in the UN SDGs 2030.

CRediT authorship contribution statement

Chao Wang: Methodology, Writing – review & editing, Funding acquisition. **Le Ma:** Methodology, Writing – original draft, Writing – review & editing, Visualization. **Yan Zhang:** Writing – review & editing, Formal analysis. **Nengcheng Chen:** Supervision, Writing – review & editing. **Wei Wang:** 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.151310.

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