The impacts of spatio-temporal variation of natural and agricultural influences on the environmental water quality in a fluvial-lacustrine watershed in China

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Research Article

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The impacts of spatio-temporal variation of natural and agricultural influences on the environmental water quality in a fluvial-lacustrine watershed in China

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Abstract

Despite the significant impacts of natural factors such as rainfall, topography, soil type, and river network as well as agricultural activities on the environmental water quality, little is known about the influence of their temporal and spatial variations in a fluvial-lacustrine watershed. In this study, a whole process accounting method based the export coefficient model (WP-ECM) was first developed to quantify how natural factors and agricultural activities distribution influenced water quality. A case study was performed in a typical fluvial-lacustrine area – Dongting basin, China. The simulated results indicated that the natural factors can promote the migration and transformation of agricultural pollutants generated from the watershed and the spatial distribution of the natural factors displayed high variability. It should be priority to monitor the areas with greater natural impact in the basin. Moreover, the cultivated land area and the number of pig-breeding were positively correlated with the pollutant discharge, and it is an important measures to reduce and control the anthropological influence in the agricultural high-impact areas. From the perspective of the spatial distribution of comprehensive influence, the comprehensive high-impact areas are mainly distributed in the Dongting Lake district in 2005–2010 and in Xiang River watershed in 2010–2020. A key strategy for controlling or reducing the cultivated land area and the intensity of livestock breeding in these high-impacts areas, especially in Dongting Lake district and Xiang River watershed, is to reduce the impact of the environmental water quality for the entire basin.

Keywords: Spatio-temporal variation, Natural influence, Agricultural influence, WP-ECM model, Dongting basin
1. Introduction

High-intensity agricultural activities and population growth have led to the discharge of a large number of non-point source (NPS) pollutants into rivers and other water bodies worldwide, resulting in water quality deterioration in the world (Sinha and Michalak, 2016). The process of NPS pollutant generation, migration, and transformation is affected by natural conditions and is wide-ranging and extremely complicated. As a result, the harmful impacts of NPS pollution are great and prevention is hard (Shrestha et al., 2021; Wang et al., 2019; Varekar et al., 2021).

Based on the source-sink theory, the NPS pollutants generated from the rural life, livestock and poultry breeding, and agricultural planting merge into water bodies through natural ecological processes including transport via rainfall (Carpenter et al., 1998), the migration of surface runoff or groundwater (Schoumsnd et al., 2014), soil adsorption (Howarth et al., 2011), and biogeochemical transformations (Billen et al., 2009; Seitzinger et al., 2002). Natural factors and human activities exert significant influence on the NPS pollution. Previous studies have extensively discussed the intensity of the impact on water quality based on the mechanism model or the statistical model (Zhang et al., 2022; Epele et al., 2018; Rodrigues et al., 2021; Mainali and Chang, 2018; Han et al., 2020; Alvarez-Cabria et al., 2016). However, few studies have investigated the spatial distribution pattern of the impact, which will contribute to identify the critical areas affecting environmental water quality and develop spatial differentiation management measures in the basin.

Natural factors, such as regional meteorology, physical geography, hydrology and river network data, make the spatial pattern of pollutant emissions heterogeneous, especially for large-scale watersheds (Xiong et al., 2022; Varekar et al., 2021; Byrne et al., 2020; Cheng et al., 2019; Grizzetti et al., 2015). The erosion and scouring of
rainfall promote pollutants entering the river with soil particles and other suspended solids, which leads to the NPS pollution. Since the slope of the land has a profound impact on the runoff flux and velocity, topography further affects the generation and transportation of the pollutants (Ding et al., 2010). NPS pollutants are transported from the producing unit and migrate to the receiving water body via rainfall runoff, soil erosion, and underground runoff. The spatial distribution of surface runoff affects the transport of pollutant and reflects the possibility of runoff contamination at a certain point in the region (Rao et al., 2022; Miralha et al., 2021; Zhou et al., 2021). For most areas, the transport of adsorbed pollutants takes the soil erosion as a carrier (Udayakumara et al., 2021; Li et al., 2022). Soil leaching is another important path of the pollutant transport. Soluble matter, such as the negatively charged nitrate nitrogen and fine soil particles, easily permeates through the vadose zone, rather than being adsorbed by soil (Kiese et al., 2011). Despite a series of terrestrial processes, NPS pollutants are also affected by biochemical transformation of the river network when the water flows into the watershed inlet (Peterson et al., 2001). Remarkably, nutrient retention in rivers controls its distribution pattern in the land–freshwater continuum, reducing the magnitude of riverine export of pollutants from land to water body (Cheng et al., 2021; Bao et al., 2018).

Model simulation is a major way to evaluate and visualize the temporal and spatial variation of the natural and agricultural impact on the environmental water quality. Models can be divided into empirical models and physical mechanism models. The export coefficient model (ECM), which is an empirical model, considers the process of pollution generation from the source of the human activities. It requires fewer parameters, compared with the process model, and operates easily, guaranteeing the accuracy of the result (Wang et al., 2020; Cai et al., 2018). ECM is
one of the most classical empirical models and is widely used in some meso-scale and large-scale regions (Johnes, 1996). In addition, many scholars have made some small improvements based on the ECM model (Hua et al., 2019; Burke et al., 2018; Ding et al., 2017). However, the previous studies only partially considered the process of the NPS pollutant generation and migration. Few studies have quantified the whole process of the pollutants generation, transport and biogeochemical transformation after they enter the river. SCS-CN model is also an empirical model based on statistics from experimental observation data, representing the natural law of rainfall runoff to simulate surface runoff that promotes the pollutant transportation (Caletka et al., 2020; Jung et al., 2012). The Universal Soil Loss Equation (USLE) is a famous empirical model to predict the annual average soil loss caused by surface erosion and gully erosion according to the experimental data of nearly 10,000 runoff plots, it considers rainfall, soil erodibility, crop management, slope length and soil and water conservation measures (Wang et al., 2021; Pijl et al., 2020). The mechanism model, represented by the soil water assessment tool (SWAT) model, can simulate some detailed process, included the hydrological process and the nutrient transfer into rivers, and provide accurate results on a small- or large-scale (Zhang et al., 2022; Athira, R.P., 2021; Baijrcharya et al, 2018). The combination of ECM, SCS-CN, USLE, and SWAT makes the model process more complete compared with the ECM. In contrast to the previous research, the model considers the migration and transformation processes which has a significant effect on the pollutant load. Thus, the whole process model of natural and agricultural influence based on ECM (WP-ECM) affords the possibility of simulating detailed analysis of the process and improving the accuracy of the result (Guo et al., 2022).
Due to the consistency principle of spatial units, the basic unit of agricultural activities is transformed from county administrative unit to grid scale which is the minimum unit of the natural factors influence by revising the export coefficient of cultivated land. In this study, a whole process model was used to estimate the natural and agricultural impacts on the water quality on the grid scale in a fluvial-lacustrine basin in China. The main objectives of the study were to separately quantify the temporal and spatial variation of natural and agricultural impacts on the water quality and to identify the critical impact area in the watershed.

2. Materials and methods

2.1. Study watershed

The Dongting basin is located in the middle course of the Yangtze River (111°40'E to 113°10'E; 28°30'N to 30°20'N) with a total area of 263,000 km², accounting for 14.6% of the Yangtze River basin (Feng et al., 2021) (Fig. 1). Dongting Lake is the second largest freshwater lake in China and a typical river-connected lake (Yu et al., 2018). There are seven water systems in the basin: Ouchi River, Songzi River and Hudu River diverting the Yangtze River water in the north, Xiang River, Zi River and Yuan River in the south and Li River in the west, which are stored through the river network of Dongting Lake, and finally flow enters the Yangtze River from the outlet of Chenglingji. Therefore, the basin bears the important function of regulating and storing the Yangtze River, as well as connecting the four rivers, Xiang, Zi, Yuan and Li (Yin et al., 2017). The watershed has a subtropical monsoon climate with an annual average temperature of 16.6°C and an annual average rainfall of 1429 mm. In addition, 70% of the annual rainfall occurs between April and September. It is surrounded by mountains to the southeast and west,
with a hilly basin in the middle and Dongting Lake plain in the north. The terrain gradually inclines from south to central and northeast.

Owing to its geographical advantages, the basin is an important production base for bulk agricultural products in China (Feng et al., 2021). However, long-term agricultural development has led to water quality deterioration, with a gradual decreased from Class III to Class IV in Dongting Lake (Geng et al., 2021b). The agricultural nitrogen is the main stress factor affecting the water quality in the Dongting basin (Feng et al., 2021). Thus, the agricultural nitrogen discharge into the water body was selected to characterize the agricultural impact on the environmental water quality in this study.

Fig. 1. Location of the Dongting basin and its five sub-basins.
The entire watershed includes parts of Guizhou, Guangxi, Chongqing, Hubei, Jiangxi and Guangdong Provinces, as well as the entirety of Hunan Province. Hunan Province covers an area of $2.18 \times 10^4$ km$^2$, accounting for 80.61% of the total basin area. For the sake of data availability, only the watersheds in Hunan Province were considered in this study.

DEM data and land use data for the Dongting basin from 2005 to 2020 were obtained from Chinese Academy of Sciences Resource and Environmental Science Data Center. Soil type and physical and physicochemical properties data were acquired from Nanjing Institute of Soil Science. From 2005 to 2020, weather data including rainfall, temperature, sunshine hours, wind speed, and relative humidity was collected daily accessing to China Meteorological Data Sharing Network. The monitored data involving stream discharge and water quality at the outlets of the entire basin and its five sub-basins were gained from Hydrological Yearbook of the People's Republic of China and Ecological Environment Monitoring Center in Hunan Province, respectively, which were used for calibrating and validating the WP-ECM model. And in order to quantify the agricultural influences on the environmental water quality in the basin, we collected the socioeconomic data including population, the number of livestock breeding, and the intensity of fertilizer application.

2.2. Methodology

2.2.1. WP-ECM model

The WP-ECM is established by incorporating the SCS-CN, USLE, and SWAT to the ECM model and modifies the original ECM model that adding the natural driving process, natural transportation and transformation processes. The input factors of the WP-ECM model include the natural influence factors, such as the rainfall, slope,
soil erosion, surface runoff, underground infiltration and the river transfer coefficient, as well as agricultural influence factors, like the land use, rural population, chemical fertilizer application, and livestock and poultry breeding. Soil erosion was quantified by the USLE and SCS-CN model was used to evaluate the surface runoff and underground infiltration. The river transfer coefficient was calculated by the SWAT model using the pollutant load from the upstream to the river channel, the pollutant load from the sub-basin to the river channel, and the pollutant load from the river channel. Based on the coefficient of the natural factors and the intensity of agricultural influence, the natural and agricultural spatial distribution form 2005 to 2020 were obtained. The WP-ECM model can be described as:

\[
LI = \sum_{i=1}^{n} AC_i \cdot (\alpha_i \cdot \beta_l \cdot TI_i \cdot AI_i + \gamma_i) \cdot \sum_{j=1}^{m} E_{ij} A_{ij} (I_{ij}),
\]

where \( LI \) is the comprehensive impact on the environmental water quality (kg); \( n \) represents the number of sub-watersheds; \( m \) represents the number of pollution sources; \( AC_i \) is the river transfer coefficient; \( \alpha_i \) is the rainfall factor; \( \beta_i \) is the terrain factor; \( TI_i \) is the surface runoff factor; \( AI_i \) is the soil erosion factor; \( \gamma_i \) is the soil moisture leaching factor; \( E_i \) is the export coefficient of the pollution source (kg·ha\(^{-1}\)·yr\(^{-1}\) or kg·head (person)\(^{-1}\)·yr\(^{-1}\)); \( A_i \) is the area of land-use type, or number of livestock or population; and \( I_i \) is the pollutant inputs all of these for source \( i \) (kg).

2.2.2. Calculation of the comprehensive natural influence coefficient (NIC)

In the WP-ECM model, the natural influence module considers the driving effect of rainfall and terrain, the transportation effect of surface runoff, soil erosion and underground infiltration, and the transformation effect of river network on the agricultural NPS pollutants. NIC can be described by the following formula:

\[
NIC = \sum_{i=1}^{n} AC_i \cdot (\alpha_i \cdot \beta_l \cdot TI_i \cdot AI_i + \gamma_i)
\]

(2)
The specific calculation methods are shown in Table 1.

Table 1. Natural factors calculation method.

<table>
<thead>
<tr>
<th>Natural factors</th>
<th>Calculation method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>Using the product of time and spatial difference factors of rainfall. See formulas (2) and (3) for details.</td>
</tr>
<tr>
<td>Slope</td>
<td>Translated into the relationship between slope and runoff. See formula (4) for details.</td>
</tr>
<tr>
<td>Surface runoff</td>
<td>Using SCS-CN runoff model and correcting the slope gradient and rainfall initial loss rate. See formulas (5)–(9) for details.</td>
</tr>
<tr>
<td>Soil erosion</td>
<td>Using the universal soil loss equation (USLE) to evaluate the soil erosion. See formulas (10)–(19) for details.</td>
</tr>
<tr>
<td>Underground infiltration</td>
<td>Using the product of seasonal and spatial distribution index of rainfall. See formulas (20)–(23) for details.</td>
</tr>
<tr>
<td>River transformation</td>
<td>Using the output files of SWAT model. See formulas (25) for details.</td>
</tr>
</tbody>
</table>

The rainfall impact factor is jointly determined by the influence factors of temporal heterogeneity and spatial heterogeneity (Ding et al., 2010). \( \alpha \) can be described by the following formula:

\[
\alpha = \alpha_t \cdot \alpha_s = \frac{f(\overline{r})}{f(\bar{r})} \cdot \frac{R_u}{\overline{R}}
\]

(3)

where \( \alpha_t \) is the interannual rainfall variation impact factor; \( \alpha_s \) is the rainfall spatial heterogeneity factor; \( \bar{r} \) is the multi-year average rainfall (mm); \( R_u \) is the annual
rainfall of space unit u during the study period (mm); and $R$ is the average rainfall of the entire basin during the study period (mm).

It should be emphasized that the time unevenness impact factor can be expressed by the interannual variation of agricultural NPS pollutants. According to the data of rainfall and agricultural pollutant load in the basin, the correlation between the annual average precipitation and the annual water inflow of agricultural NPS pollutants in the entire basin was established as follows:

$$L_{TN} = 2.576r^2 + 447.96r - 4234 \quad R^2=0.8468 \quad (4)$$

where $r$ is the annual rainfall (mm), and $R^2$ is the coefficient of determination of the regression equation.

Slope affects the transport of pollutants on the slope surface, which in turn affects the nutrients loss due to carried by surface runoff (Liu and Singh., 2004). It has been demonstrated that there is a positive correlation between slope gradient and slope runoff, which can be expressed as the product of the power function of the slope gradient and constant. The terrain impact factor $\beta$ can be defined as:

$$\beta = \left( \frac{S_u}{10.06} \right)^{0.61} \quad (5)$$

where $S_u$ is the gradient of space unit u in the watershed; 10.06 represents the average gradient of the watershed; 0.61 is the correlation coefficient between the slope and runoff.

Considering the topographic features and soil properties of the study area, the SCS-CN runoff model is commonly used to calculate the surface runoff (Mishra et al., 2006). The formula of the SCS-CN model is as follows:

$$Q = \begin{cases} \frac{(P-I_a)^2}{(P-I_a+S)^2}, & P > I_a, \\ 0, & P \leq I_a, \end{cases}$$

$$ (6)$$
where $P$ is rainfall (mm); $I_a$ is the initial rainfall loss (mm); and $S$ is the maximum water storage capacity (mm), which is related to the underlying surface factors. In order to calculate $S$, the parameter-runoff curve number (CN) is introduced, and the relation between $S$ and CN is as follows:

$$S = \frac{25400}{C_N} - 254$$ (7)

where CN is a dimensionless parameter, which comprehensively reflects the characteristics of the underlying surface of the basin, and its value ranges from 1 to 100. The larger its value, the smaller its water storage capacity. According to the organic matter parameters in soil data, the saturated hydraulic conductivity coefficient was obtained by SPAW software, and then hydrological grouping was carried out to identify the corresponding soil types. The CN values of different land use types and soil types are shown in Table S1, and the CN values under slope adjustment were calculated according to the following formulas:

$$CN_{2s} = \frac{CN_3 - CN_2}{3} (1 - 2e^{-13.86SLP}) + CN_2$$ (8)

$$CN_3 = CN_2 \times e^{0.00673(100-CN_2)}$$ (9)

$$CN_{0.05} = \frac{100}{1.879(\frac{100}{CN_{0.20}} - 1)^{1.15}} + 1$$ (10)

where $CN_{2s}$ is the curve number of slope adjusted water condition II; $CN_3$ is the curve number of default 5% slope water condition III; $CN_2$ is the curve number of default 5% slope water condition II; SLP is the average slope of the basin; and $CN_{0.20}$ is the runoff curve number when the initial rainfall loss rate is 0.20.

Due to the fact that the transport of adsorbed pollutants takes soil erosion as the carrier, the universal soil loss equation (USLE) was used to assess the risk of soil erosion in the study area (Hailu et al., 2015). The formula is as follows:
\[ AI = \text{Norm}(A) \]  
\[ A = R \times K \times L \times S \times C \times P \]

where Norm is a normalized function; A is the annual amount of soil erosion \((t \cdot \text{hm}^{-2} \cdot \text{a}^{-1})\); R is the factor of rainfall erosivity; K is the soil erodible factor \((t \cdot \text{hm}^2 \cdot \text{h}^{-1} \cdot \text{MJ}^{-1} \cdot \text{mm}^{-1} \cdot \text{hm}^{-2})\); L is the slope length factor; S is the slope factor; C is the vegetation cover and management factor; P is the factor of soil and water conservation measures. The calculation methods of soil erosion factors were conducted according to previously published studies (Wischmeier et al., 1971; Van, R.R.D et al., 2001; Karaburun, 2010), and the P values of different land use types can be assigned in Table S2. The rainfall erosivity, R, is calculated as follows:

\[ R = \sum_{i=1}^{12} 1.735 \times 10^{1.5\lg P_{i}^{2} - 0.8188} \]

where i is the ith month; \(P_{i}\) is monthly rainfall (mm); \(P\) is annual rainfall (mm); R is the annual rainfall erosivity \(((\text{MJ} \cdot \text{mm})/(\text{hm}^2 \cdot \text{h} \cdot \text{a})))\). The soil erodible factor, K, is calculated according to the following formula:

\[ K = 0.1317 \left\{ 0.2 + 0.3\exp[-0.0256\text{SAN}(1 - \frac{\text{SIL}}{100})] \right\} \times \left( \frac{\text{SIL}}{\text{CLA} - \text{SIL}} \right)^{0.3} \times (1 - \frac{0.25C}{C + \exp(3.72 - 2.95C)}) \times (1 - \frac{0.7SN1}{SN1 + \exp(-5.51 + 22.9SN1)}) \]

where K is the unit of soil erodibility value in the American system \(((t \cdot \text{acre} \cdot \text{h})/(100 \cdot \text{acre} \cdot \text{ft} \cdot \text{tan} \cdot \text{in})))\). Since the international system unit is \(((t \cdot \text{km}^2 \cdot \text{h}) \cdot \text{(km}^2 \cdot \text{MJ} \cdot \text{mm})))\), it was multiplied by the conversion coefficient of 0.1317; SAN, SIL, CLA and C are sand \((0.050 \sim 2.000 \text{ mm})\), silt \((0.002 \sim 0.050 \text{ mm})\), clay \((< 0.002 \text{ mm})\) and organic matter (%), respectively; and SN1 = 1 - SN/100.

\[ S = \begin{cases} 
10.8\sin\theta + 0.03, & \theta < 5^\circ \\
16.8\sin\theta - 0.05, & 5^\circ \leq \theta < 14^\circ \\
21.91\sin\theta - 0.96, & \theta \geq 14^\circ 
\end{cases} \]
\[ L = \left(\frac{\lambda}{22.13}\right)^\alpha \]  
\[ \alpha = \frac{\beta}{\beta + 1} \]  
\[ \beta = \frac{\sin\theta/0.0896}{3.0\sin^{0.8}\theta + 0.56} \]  

where \( S \) is the slope factor; \( \theta \) is the slope value extracted by DEM; \( L \) is the slope length factor; \( \lambda \) is the slope length value extracted by DEM; 22.13 m is the slope length of the standard plot; \( \alpha \) is the slope length factor; and \( \beta \) is the ratio of rill erosion to surface erosion.

\[ FVC = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \]  
\[ C = \begin{cases} 
1 & \text{FVC} \leq 0.095 \\
0.6508 - 0.3436\lg FVC & 0.095 < \text{FVC} < 0.783 \\
0 & \text{FVC} > 0.783 
\end{cases} \]  

where \( FVC \) is the fractional vegetation coverage; and \( NDVI \) is the normalized difference vegetation index.

During pollutant migration, underground infiltration/groundwater runoff is an important transport mechanism of the agricultural NPS pollutant. In this paper, the underground storage/groundwater runoff factor only considers the influence of soil water infiltration on pollutant transport, and the actual infiltration amount of pollutants in runoff is approximately calculated by the product of soil–water infiltration capacity and pollutant load intensity (Follett et al., 1991). The underground infiltration (LI) can be determined through the spatial distribution index (PI) of rainfall and the seasonal distribution index (SI). These parameters are calculated as follows:

\[ \gamma = \text{Norm}(PI \cdot SI) \]
$$PI = \frac{(r-0.4S)^2}{r+0.6S}$$  \hspace{1cm} (22)$$

$$SI = \left(\frac{2\times \text{prec}(Is)}{r}\right)^2$$  \hspace{1cm} (23)$$

$$S = \frac{25400}{CN} - 254$$  \hspace{1cm} (24)$$

where Norm is a normalized function; PI is the rainfall spatial distribution index which represents the maximum theoretical rainfall that can be used for infiltration in a basin unit; SI is the seasonal distribution index, which represents the influence of seasonal changes in rainfall on soil moisture infiltration; prec(Is) is the total rainfall during the non-flood season (October to April of the following year).

In the river transfer module, the pollutant transfer in each sub-basin is estimated by QUAL2E, which has been incorporated in SWAT. Considering the area of the research basin and the accuracy of the model, the minimum confluence area threshold was set to $10^5$ ha and the basin was divided into 121 sub-basins. The transfer coefficient (AC) is calculated based on the SUB_OUT file and RCH_OUT file of the SWAT model (Guo et al., 2022). The calculation formula can be expressed as:

$$AC_i = \prod_{j=1}^{n} \frac{RCH_{j, out}}{RCH_{j, in} + SUB_{j, source}} (i = 1, 2, 3 \ldots n)$$  \hspace{1cm} (25)$$

where $RCH_{j, out}$ is the pollutant load transported from each sub-basin $j$; $RCH_{j, in}$ is the pollutant load transported upstream into the main river reach of each sub-basin $j$; and $SUB_{j, source}$ is the pollutant load of all local inputs into the river channel in sub-basin $j$.

2.2.3. Spatial distribution of agricultural influence on the grid scale

As for the spatial distribution of agricultural influence, the spatial distribution of the planting pollution was determined based on the cultivated land pattern. In this
model, a portion of the pollutants from rural life and livestock and poultry breeding
are applied as organic fertilizers into cultivated land in order to obtain the spatial
expression of rural life and livestock and poultry breeding pollution. It is worth noting
that optimizing the spatial distribution of pollution sources does not change the total
amount of the pollutants, but only rationally distributes pollutants generated from
different sources in space. The spatial expression rule of agricultural NPS pollutants is
as follows:

\[ M_i = \sum_{j=1}^{b} \left( \frac{CR_i}{\sum_{i=1}^{CR_i} \times \rho_j \times PE_j} \right) \]

(26)

where \( M \) is the total amount (kg) of organic fertilizer from livestock, poultry, and
rural life applied to the farmland; \( PE \) is the discharge of these pollutants (kg); \( b \) is the
number of counties represented in the pollution source; \( n \) is the number of farmland
blocks covered by pollutants returning to the field; \( CR \) is farmland area (hm\(^2\)); \( \rho \) is the
proportion of pollutants returning to the field; \( i \) is the \( i \)-th farmland; and \( j \) is the \( j \)-th
county.

It is worth noting that the pollutant emission intensity of cultivated land is
revised by the distribution, the area of cultivated land and the total amount of organic
fertilizer applied to cultivated land in each region.

\[ E_i' = \frac{M_i}{CR_i} \times \delta + E_i \]

(27)

where \( E_i' \) is the modified farmland pollutant emission intensity (kg·hm\(^{-2}\)·a\(^{-1}\)); \( E_i \) is the
emission intensity of original land use pollutants (kg·hm\(^{-2}\)·a\(^{-1}\)); \( M \) is the total amount
of organic fertilizer applied to livestock, poultry, and rural life (kg); \( CR \) is farmland
area (hm\(^2\)); \( \delta \) is the fertilizer loss coefficient after the applying of these pollutants to
the farmland.
3. Results

3.1. Comparative analysis of simulated and observed values

WP-ECM simulation results show that the relative error of the agricultural pollutant simulations of the entire watershed was 5.21%, 4.17%, 4.55%, and 1.37% in 2005, 2010, 2015, and 2020, respectively. Compared with the ECM simulation method, the relative error was reduced by 12.16%, 9.9%, 8.97%, and 6.87% in 2005, 2010, 2015, and 2020, respectively (Table 2). Similarly, the simulated load accuracy analysis of TN in Xiang River watershed, Zi River watershed, Yuan River watershed and Li River watershed in 2005, 2010, 2015, and 2020 was obtained (Table 3, Table 4, Table 5, and Table 6). The relative error all reduced in each basin, indicating that the model was suitable for natural and agricultural influence estimation in these large-scale basins.

Table 2. Simulated load accuracy analysis of TN in the Dongting Lake basin.

<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2005</td>
</tr>
<tr>
<td>ECM</td>
<td>Measured value</td>
<td>176211.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(t/yr)</td>
</tr>
<tr>
<td></td>
<td>Simulated value</td>
<td>192980.83</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(t/yr)</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>17.37%</td>
</tr>
<tr>
<td>WP-ECM</td>
<td>Simulated value</td>
<td>172980.83</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(t/yr)</td>
</tr>
</tbody>
</table>
Table 3. Simulated load accuracy analysis of TN in Xiang River watershed.

<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2005</td>
</tr>
<tr>
<td>ECM</td>
<td>Measured value (t/yr)</td>
<td>46747.72</td>
</tr>
<tr>
<td></td>
<td>Simulated value (t/yr)</td>
<td>53842.34</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>25.43%</td>
</tr>
<tr>
<td>WP-ECM</td>
<td>Simulated value (t/yr)</td>
<td>48312.34</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>12.55%</td>
</tr>
</tbody>
</table>

Table 4. Simulated load accuracy analysis of TN in Zi River watershed.

<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2005</td>
</tr>
<tr>
<td>ECM</td>
<td>Measured value (t/yr)</td>
<td>13247.21</td>
</tr>
<tr>
<td></td>
<td>Simulated value (t/yr)</td>
<td>15041.30</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>18.68%</td>
</tr>
<tr>
<td>WP-ECM</td>
<td>Simulated value (t/yr)</td>
<td>13841.30</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>9.21%</td>
</tr>
</tbody>
</table>

Table 5. Simulated load accuracy analysis of TN in Yuan River watershed.
<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2005</td>
<td>2010</td>
</tr>
<tr>
<td>ECM</td>
<td>Measured value (t/yr)</td>
<td>19878.04</td>
</tr>
<tr>
<td></td>
<td>Simulated value (t/yr)</td>
<td>18142.48</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>27.43%</td>
</tr>
<tr>
<td>WP-ECM</td>
<td>Simulated value (t/yr)</td>
<td>16284.60</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>14.38%</td>
</tr>
</tbody>
</table>

Table 6. Simulated load accuracy analysis of TN in Li River watershed.

<table>
<thead>
<tr>
<th>Model</th>
<th>Index</th>
<th>TN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2005</td>
<td>2010</td>
</tr>
<tr>
<td>ECM</td>
<td>Measured value (t/yr)</td>
<td>4716.11</td>
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<tr>
<td></td>
<td>Simulated value (t/yr)</td>
<td>5001.85</td>
</tr>
<tr>
<td></td>
<td>Relative error</td>
<td>18.10%</td>
</tr>
<tr>
<td>WP-ECM</td>
<td>Simulated value (t/yr)</td>
<td>4708.49</td>
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<tr>
<td></td>
<td>Relative error</td>
<td>11.18%</td>
</tr>
</tbody>
</table>

3.2. Spatio-temporal variation of natural influence on the environmental water quality in the watershed

The average NIC of Dongting basin in 2005, 2010, 2015 and 2020 was 0.37, 0.44, 0.31, and 0.42, respectively. As for its five watersheds, the average NIC of the
Dongting Lake district and Xiang River watershed was higher than other watersheds, whereas that of Li River watershed was the lowest (Fig. 2, Fig. 3). This may because the natural spatial characteristics are complex in the Dongting Lake district and Xiang River watershed where the elevation, rainfall and land use types have higher spatial heterogeneity, compared to in Li River watershed. Notably, the average NIC was higher in 2010, which as due to more rainfall and a higher impact of surface runoff, underground seepage, and soil erosion that year. It can be obtained from the following single factor analysis.

Fig.2. Natural influence coefficient (NIC) in Dongting Lake basin and its five sub-basins in 2005, 2010, 2015 and 2020.
Fig. 3. Spatial distribution of comprehensive natural influence coefficient (NIC) in the entire watershed in 2005, 2010, 2015 and 2020.

The influence coefficient of rainfall on the pollutant load was 0.61–1.27, 0.84–1.88, 0.82–1.51, 1.05–1.91 in 2005, 2010, 2015, and 2020, respectively (Fig. 4a). Additionally, it was higher in the north and lower in the south. The terrain impact factor ranged from 0 to 3.10 (Fig. 4b). Surface runoff is mainly affected by the distribution of rainfall and the type of land use type, and its distribution varies greatly from year to year in the range of 0–1 (Fig. 4c). The soil erosion factor also ranged from 0–1 (Fig. 4d). Since the transport of adsorbed pollutants takes soil erosion as the carrier, more severe soil erosion leads to a greater the impact factor is. In terms of time distribution, the soil erosion factor in 2015 and 2020 is smaller than that in 2005 and 2010. Soil moisture and its distribution varied from year to year in the range of 0–1 (Fig. 4e). The average river transport ratio was 0.90, 0.89, 0.88, and 0.88 in 2005, 2010, 2015, and 2020, respectively (Fig. 4f). It decreased regularly from the upstream
to the downstream of the basin and it was relatively higher along the mainstream than that of the sub-basins along the tributaries. The river transfer efficiency has changed slightly in the basin from 2005 to 2020.
Fig. 4. Spatial distribution of natural impact factors in the watershed in 2005, 2010, 2015 and 2020. (a) rainfall factor, (b) terrain impact factor, (c) surface runoff factor, (d) soil erosion factor, (e) soil leaching factor, and (f) river transfer efficient.
3.3. Spatio-temporal variation of agricultural influence on the environmental water quality in the watershed

The intensity of agricultural influence (AI) is affected by the intensity of fertilization, the amount of livestock and poultry activities, and the rural population. The AI of the Dongting basin was 1.47 t/km$^2$, 1.46 t/km$^2$, 1.45 t/km$^2$, 1.27 t/km$^2$ in 2005, 2010, 2015, and 2020, respectively (Fig. 5). As for its five sub-basins, the average AI of the Dongting Lake district was higher than other watersheds. Interestingly, the influential intensity of the agricultural activities gradually decreased from 2005 to 2020 in each basin and decreased dramatically in the most recent five years. It has declined by 13.61%, 11.17%, 17.18%, 14.20%, 5.49%, and 8.26% in the entire watershed, Dongting Lake district, Xiang River watershed, Zi River watershed, Yuan River watershed, and Li River watershed, respectively over the past 15 years. This is because the government has encouraged the application of organic fertilizer instead of the synthetic fertilizer, limited the intensity of livestock and poultry breeding, and improved the utilization rate of rural manure treatment facilities in the Dongting basin. As for the entire basin, the high-impact areas were mainly distributed in the Dongting Lake district (Fig. 6).
Fig. 5. The intensity of agricultural influence (AI) in Dongting Lake basin and its five sub-basins in 2005, 2010, 2015 and 2020.

Fig. 6. Spatial distribution of agricultural influence intensity (AI) in the entire watershed in 2005, 2010, 2015 and 2020.
4. Discussion

4.1. Spatio-temporal variation of natural influence on the environmental water quality in the watershed

The process of nitrogen loading into the water body is that nitrogen pollutants enter the water after soil erosion, surface runoff, underground infiltration and river transport attenuation under the action of rainfall and gravity (Rao et al., 2022; Han et al., 2018). Accumulation process of nitrogen in water is actually a process in which nitrogen load is transported into water under the external driving effect. Nitrogen load transport process shows that natural environment factors such as rainfall characteristics, topographic characteristics, soil physical and chemical properties, river network structure and so on affect the material flow and energy flow state of NPS process (Wang et al., 2021). The influence of these factors is shown by the spatial variation of natural driving forces, which is the reason for the different influence patterns.

In this study, the rainfall drives the agricultural nitrogen discharge, which can promote nutrients to be transported quickly (Fig. 7). This result is consistent with the previous studies (Wang et al., 2022; Li et al., 2020). Slope has great influence on the process of confluence. Meanwhile, the process of the agricultural pollutants discharge is also related to the geographical conditions of the spatial location of the pollutants generating units, specifically affected by the process of surface runoff, soil erosion and underground infiltration. It can be found there are all positive correlation between the amount of soil erosion, surface runoff, and underground infiltration and agricultural nitrogen discharge in 2005, 2010, 2015, 2020 in the Dongting basin (Fig. 8, Fig. 9, Fig. 10). Pollutants reach the estuary through the above process, and finally
flow out of the basin outlet through the migration and transformation of rivers. The spatial heterogeneity of river transport is mainly manifested by the distance from sub-basin to the outlet of the basin. It can be found that the farther the sub-basin is from the outlet of the basin, the smaller the river transport is (Fig. 11). Accordingly, the natural factors can promote the migration and transformation of agricultural pollutants generated from the watershed. In terms of the watershed spatial management, it should be priority to monitor the areas with greater natural impact in the basin.

**Fig. 7.** Relationship between the average annual rainfall of sub-basins and nitrogen pollutant discharge into water body.
Fig. 8. Relationship between the soil erosion amount of sub-basins and nitrogen pollutant discharge into water body.
**Fig. 9.** Relationship between the surface rainfall amount of sub-basins and nitrogen pollutant discharge into water body.

**Fig. 10.** Relationship between the underground infiltration amount of sub-basins and nitrogen pollutant discharge into water body.
Fig. 11. Relationship between the distance from the sub-basins to the outlet of the whole basin and river transfer coefficient.

4.2. Spatio-temporal variation of agricultural influence on the environmental water quality in the watershed

Many research have demonstrated that there is a positive relationship between pollutant loss and cropland area (Qu et al., 2022; Chen et al., 2017). Positive relationships occur as a result of excessive anthropogenic inputs such as fertilizer application associated with alterations in soil surface conditions and lower hydraulic conductivity that increase runoff and erosion rates (Jordan, 1997; Zhou et al., 2017). In this study, agricultural influence was positively correlated with cultivated land area.
within its sub-basins (Fig. 12). This may because the cultivated land is easy to have the excessive nitrogen inputs associated with high manure applications to soils. The high-impact areas were mainly distributed in the Dongting Lake district because the highest percentage of the cultivated land is distributed in the lakeside zone, especially in the east of the district (Fig. 13). In addition, many studies have shown that livestock and poultry breeding has an important impact on the amount of pollutants entering the lake (Chen et al., 2023; Foley et al., 2011; Garnett et al., 2013). There is a strong correlation between the number of pig and the pollutants discharge in the watershed from 2005 to 2020 (Fig. 14).

Fig. 12. Relationship between the cultivated land area of sub-basins and nitrogen pollutant discharge into water body.
Fig. 13. Spatial distribution of cultivated land in the entire watershed in 2005, 2010, 2015 and 2020.
Fig. 14. Relationship between the number of pig breeding of sub-basins and nitrogen pollutant discharge into water body.

From the perspective of the spatial distribution of comprehensive influence (CI), controlling the intensity of the agricultural activities in the high-impact areas in the watershed is a key strategy to reduce the impact of environmental water quality for the entire watershed. In this study, the high-impact areas were mainly distributed in the Dongting Lake district in 2005-2010 and in the Xiang River watershed in 2010–2020 (Fig. 15). Thus, it is an important measures to reduce and control the anthropological influence in the Dongting Lake district and the Xiang River watershed for the entire Dongting Lake watershed management.
4.3. Limitations

Although WP-ECM model is suitable for natural and agricultural influences simulation, we calibrated and validated the model only using the measured data at the mouth of the watershed. Thus, long-term observed data at the headwaters should be conducted in order to obtain more accurate simulations. Moreover, the results can only provide a critical monitor and governance area for the natural and agricultural influences in the recent 15 years, and have not predicted the impacts in future, which is an essential prerequisite for eco-economic planning measures in the watershed.
5. Conclusion

A whole process calculating method based ECM model was first constructed to evaluate the temporal and spatial variation of the natural and agricultural influences in a fluvial-lacustrine watershed in China. The results show that the model was suitable for NPS discharge estimation in this region. The natural factors can promote the agricultural influence on lake water quality. In addition, the cultivated area and the number of pig-breeding are the critical factors influencing the environmental water quality, and the agricultural high-impact areas were mainly distributed in the Dongting Lake district, especially in the east of the district. Moreover, from the perspective of the spatial distribution of CI, the comprehensive high-impact areas were mainly distributed in the Dongting Lake district in 2005–2010 and in the Xiang River watershed in 2010–2020. These findings provide important information for guiding watershed planning, especially for the large watershed, by controlling the cultivated land area and/or reducing the intensity of livestock breeding in these high-impact areas, in order to reduce the influence on the environmental water quality.

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Author contribution

Yu Feng: conceptualization, methodology, investigation, data curation, writing - original draft, writing - review & editing, visualization, project administration.

Binghui Zheng: resources, supervision.

Haifeng Jia: reviewing & editing.

Bing-bing Song: data curation.

Yang Liu: writing - reviewing & editing.

Jun-ping Bi: resources.

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Data availability

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval The work did not involve Human Participants and/or Animals. To the best of our knowledge and belief, this manuscript has not been considered for publication elsewhere.
Consent to participate  All the authors approved to participate.

Consent for publication  The authors have reviewed the manuscript and approved it for publication.

Competing interests  The authors declare no competing interests.

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Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M.,


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