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Spatial explicit management for the water sustainability of coupled human and natural systems[★]

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ABSTRACT

Linking water to research on coupled human and natural systems (CHANS) has attracted wide interest as a means of supporting human-natural sustainability. However, most current research does not focus on water environmental properties; instead, it is at the stage of holistic status assessment and measures adjustment from the point of view of the whole study region without revealing the dynamic interaction between human activities and natural processes. This paper establishes an integrated model that combines a System Dynamics model, a Cell Automaton model and a Multiagent Systems model and exploits the potential of the combined model to reveal regions' human-water interaction status during the process of urban evolution, identify the main pollution sources and spatial units, and provide the explicit space-time measurements needed to enhance local human-natural sustainability. The successful application of the integrated model in the case study of Changzhou City, China reveals the following. (1) As the city's development has progressed, the water environment status in some spatial units is still unsatisfactory and may even become more serious, especially in the urban areas of the Urban District and Liyang County. The concentration of Chemical Oxygen Demand (COD) in monitoring section 157 of the Urban District has increased from 36.90 mg/l to 40.84 mg/l. The main source of this increase is the increase in secondary industry. (2) With the application of the spatially explicit measures of the sewage treatment ratio improvement and new sewage plant construction, the water quality in the urban area has significantly improved and now satisfies the water quality standards. The measure of livestock manure utilization enhancement is adopted to improve the spatial units in which livestock is the main pollution source and achieve the goal of water quality improvement. The model can be used to support the sustainable status assessment of human-water interaction and to identify effective measures that can be used to realize human-water sustainability along with social-economic development.

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1. Introduction

Coupled human and natural systems (CHANS) are huge, nonlinear, complex systems in which human factors and natural factors interact with one another (Liu et al., 2007; Li, 2012). Conducting research on the dynamic mechanism of CHANS is a prerequisite for its sustainable operation (Wang et al., 2018). The United Nations set clean water as one of 17 sustainable development goals needed to promote prosperity while protecting the planet in 2030. Water is the limiting factor for CHANS sustainable development (Clarke, 2013). Exponentially growing populations and increasing urban expansion have resulted in severe environmental problems related to water. These problems influence the sustainability of CHANS due to the spatial distribution of water environment capacity in the natural systems and industrial sectors within social-economic systems. In the face of this challenging situation, integrated environmental management aimed at ensuring the sustainability of the human-natural system requires the use of a holistic modeling approach that combines water quality modeling and the social-economic process rather than an approach that is based only on the hydrological processes of natural systems. Currently, this is a tipping point for water research ranging from traditional research on natural processes to complex research involving CHANS (Feng et al., 2018).

In recent decades, some obvious progress has been made in research on CHANS (Binder et al., 2013). Some of this work describes the theoretical connotations of CHANS. Fu and Wei (2018) use a conceptual framework to arrive at better human choices for

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CHANS sustainability. Ison (2018) proposes systems thinking and systems praxis trajectories for interaction exploration of CHANS. Some scholars have studied the driver mechanism of human behavior and its ecological effects in CHANS (Monticino et al., 2007). Rammer and Seidl (2015) simulated the interaction between human and natural systems as it relates to adaptive forest management under climate change. Wandersee et al. (2012) modeled human perception and decision-making behaviors in CHANS. Boumans et al. (2015) established an analytical framework that describes the dynamic process through which ecosystem service functions are tied to human demands. The characteristics of CHANS, such as resilience, threshold and carrying capacity, have also been revealed. Xu et al. (2018) attempted to identify the common threshold in the Mississippi River Delta, which is a highly intertwined CHANS. Rus et al. (2018) assessed urban resilience under the influence of natural disasters. Peng et al. (2016) evaluated the urban development potential in mountain areas using ecological carrying capacity from the point of view of CHANS. Current CHANS research has developed in terms of both theory and methods. However, it still lacks a spatially explicit model that can be used to realize CHANS sustainability through spatial-temporal adjustments within specific geographical spatial entities.

Due to the basic support for human-natural sustainability, water research in CHANS has attracted broad research interest in various concepts such as human-water systems and socio-hydrological systems (Feng et al., 2018; Blair and Buytaert, 2015; Srinivasan et al., 2012). Instead of using normal hydrological models, research linking water with CHANS should consider the dynamic interactions and coevolution of social-hydrological systems (Lu et al., 2018). However, most current research only marginally considers social processes in simulating coupled human-water systems and fails to provide an explicit description of the interactions between human and water systems (Troy et al., 2015). Sanderson (2018) extends the social-hydrological research by considering social stratification, inequality, and power. The current water-related research on CHANS mainly concerns the properties of water resources and includes little consideration of water environmental properties and social functions.

Water environment research on CHANS should focus on the process through which pollutants flow between social-economic systems and biophysical systems. Although some related research is concerned with both the social and biophysical factors, these studies are often theoretical and often fail to address practical issues such as water environment carrying capacity (WECC) (Zhang et al., 2019). The spatial and temporal scale of this research is too coarse to provide more realistic guidance. It is unable to support pollutant sources identification and measurement effect assessment for specific spatial entities. Most of the current water environment research on CHANS uses administrative regions or river basins as study regions. These regions are regarded as single homogeneous entities for water environment status assessment and optimization adjustment. Current water environment assessment methods such as hierarchical multicriteria methods (Giupponi and Rosato, 2002), and water footprinting (Allocca et al., 2018) primarily involve static analyses that are conducted for a single year. The temporal interaction between different elements has been studied using the system dynamics method (Zhang et al., 2014). However, the interaction mechanism has only been analyzed on the scale of the entire study region through statistical data. Thus, the current research methods only provide information about CHANS sustainable status on a macro scale. More detailed information regarding the mechanisms of internal spatial-temporal interactions between different elements is lacking.

The spatial-temporal interaction exists in reality. Macro phenomena are always the result of micro spatial-temporal phenomena. Micro spatial objects (man-made or natural infrastructures) such as sewage outlets and sewage plants and their locations play key roles in pollution effects and water sustainability in CHANS. These parameters affect the spatial patterns and the final sustainability status of pollutants. In previous water environment research on CHANS, only the total pollution amount is taken into consideration (Guo et al., 2001); the influence of pollutant spatial patterns and spatial objects on human-water sustainable status is ignored. Due to the limitations of the methods used, the adjustment measures obtained from scenario simulation lack feasibility. They cannot provide operational schemes that can be used by local government managers as a basis for management policies for human-water environment sustainable development. The corresponding policies generally involve planning objectives such as future economy amounts (Feng and Huang, 2008) or population levels (Yang et al., 2015) that apply to the whole study region. Thus, the existing research cannot guide urban managers on how and where to apply detailed measures aimed at achieving specific planning objectives that take into account spatial features and spatial entities. The current research methods used in CHANS cannot provide information about specific spatial objects and their locations that can be used to improve the local sustainability of the study regions because all the spatial entities are generalized and homogenized as virtual planes. To make the CHANS theory more practical and permit the fine management of sustainable development, the space-time scale of research should be more detailed, and the spatial objects should be defined.

Some scholars have pointed out the importance of internal interaction mechanisms in CHANS research. Synthesis of various factors, including time, space, materials, energy, and information, will become an inevitable trend in future CHANS research (Zeng et al., 2011). Some scholars hold that the integrated water environment management for sustainability of CHANS theory should be developed into an applied discipline that can be used to guide regional sustainability and create a balance between social-economic development and water environment protection. Long and Jiang (2003) stated that the related land use pattern and industrial structure analysis should be considered when developing principles for integrated water environment management in CHANS. However, current research tools do not serve as powerful tools for satisfying such objectives.

To date, most research methods use overly simplistic algorithms with different degrees of generalization concerning space-time scales and theoretical goals. The results of current water environment research on CHANS are thus little able to provide information and guidelines for human-water environmental sustainability. The deficiencies of the current research are as follows. (1) Internal interaction mechanisms and appropriate human-water sustainable status cannot be analyzed using the current methods, nor can the influences of man-made or natural infrastructures and their locations on the sustainability of CHANS. (2) The improvement of measures based on previous methods is not feasible. The space-time research scale of such measures is too coarse to provide a basis for developing detailed guides for sustainability improvement of local CHANS.

To overcome these deficiencies, this paper attempts to develop a spatial-temporal explicit simulation framework that includes the detailed consideration of spatial objects and that can be used in water environment integrated management for the sustainability of CHANS. The main innovations of this work are as follows. (1) An integrated framework combining the System Dynamics (SD), Cell Automaton (CA) and Multiagent System (MAS) models is first established as a unified platform for sustainability research on CHANS. The input-output interfaces among the SD model, the CA model and the MAS model are clearly described. (2) The simulation framework includes pollution sources analysis for specific monitoring sections. Based on the status of pollution sources and on dynamic change analysis, the model supports fine-scale integrated river basin management for human-natural sustainability by allowing spatial-temporal adjustment for individual spatial objects.

This paper is organized as follows. Section 2 describes the methodology, including the establishment of SD, CA and MAS and construction of the SD-CA-MAS model. Section 3 presents the model calibration results, the spatial-temporal assessment results for the sustainability assessment of CHANS, and the spatial-temporal measures evaluation for sustainability enhancement and water environment improvement. The last section evaluates the significance, application range and deficiencies of the simulation framework.

2. Methods

In this study, an integrated model to reveal the spatial-temporal explicit status of water environment and sustainability of CHANS is established. This model includes spatial-temporal explicit adjustment for certain spatial objects and provides support for fine-scale integrated water environment management for sustainability enhancement of CHANS. The integrated model is named HAWS in keeping with its goal of human-water sustainability.

HAWS consists of three submodules: SD, CA and MAS. The integrated model builds interfaces between the SD, CA and MAS models and uses them to assess the water environment and the human-water sustainability status under the process of urban evolution in the study area; it also searches for effective solutions to improve the local water environment and human-water sustainability through pollution sources structure analysis. The SD and CA models are run separately and are based on different administrative districts, including one urban district and two county-level cities. The outputs of the SD and CA models serve as input data to drive MAS model simulation.

Section 3.1 describes the structure of HAWS, the establishment of detailed submodules, and the interfaces among submodules. Section 3.2 describes the methods used in model calibration and validation. Section 3.3 presents the model forecasting methods.

2.1. Model coupling based on SD-CA-MAS

HAWS, the integrated model, is established based on the coupling of SD, CA and MAS (Fig. 1). The output of the SD and CA simulations provides the input for MAS simulation. The MAS model is a key component of the integrated model. Both the SD model and the CA model provide boundary conditions for MAS simulation. The prediction results for economy, population and pollutants from the SD simulation are set as scale limitations of each agent's property value in the MAS model. The detailed property value of each agent is determined through specific processes. First, various gridded maps such as population maps and economic maps are established using gridded GIS technology. Industry maps, sewage plant maps, sewage outlet maps and maps showing large-scale livestock and poultry farms are established according to the field investigation. Then, based on R software, the RNetLogo package, NeoLogo software and ArcGIS software, the property values of most of the agents can be determined. The land use map from the CA model is used to set spatial boundary limitations for different types of agents in the MAS model. With the limitations set by the results of the CA and SD models, the property values and movement spatial boundaries for all of the agents in the MAS model are clear. In the MAS model, the interactions between human systems and the water environment can be observed and analyzed through model simulation. Finally, the future human-water sustainability status of the economy, the population and the water environment in the absence of any management measures can be assessed. The best-fit management measures for human-water sustainability improvement can then be identified by scenario simulation.

2.1.1. Establishment of the SD model

In the SD model, the human-water system in Changzhou consists of three subsystems that separately represent the Urban Districts of Changzhou, Liyang County, and Jintan County. The subsystems division fully reflects the key function of the administrative division in controlling local social-economic activities according to the social system and development form with Chinese characteristics. The administrative divisions and related policies could affect the population amount, the economic scale and the discharge intensities of water pollutants in the three districts of Changzhou. Finally, the corresponding temporal and spatial water pollution structures are expected to result in differences in the water environment and in the human-water sustainability status. Each of the three subsystems consists of four components: an economic component, a population component, a land use component and a pollutant emissions component. The Cobb-Douglas production function is adopted to predict future economic growth rate. The future population is predicted based on birth rate, mortality rate and population migration. The detailed description could be found in my previous paper (Zhou et al., 2017).

2.1.2. Establishment of the CA model

The SLEUTH model, a typical CA model, is used as a land use prediction platform. It consists of an urban growth model and a land cover transition model. It requires 6 input layers (Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade) to drive model simulation (Silva and Clarke, 2002). Then the model is calibrated through the three processes including coarse calibration, fine calibration and final calibration to determine the best fit value of the five coefficients (Fig. 2).

To better realize prediction performance, the Exclusion layer is transformed into an Exclusion/Attraction layer. The range of values in the layer is 0–100; areas of limited development, such as ecologically sensitive areas, are assigned a value of 100, indicating that no land use changes will occur in these areas. The areas are unlike to develop urban areas are assigned values more than 50 according to their relevant weights. The areas of neutral development are assigned a valve of 50. The areas that are expected to attract development are assigned values less than 50 according to their relevant weights. The areas that landuse change are most likely occurred are assigned a value of 0. Economy and population factors are set within the attraction portion in the exclusion/attraction layer. The values are set according to the expected amounts of industrial economy and population in 2025 based on the results of the SD model, and the spatial pattern of the industrial economy is represented through the process of point density in ArcGIS 10.6 according to industrial values based on spatial locations. The spatial pattern of the population is achieved through gridded GIS (Sorichetta et al., 2015). The weights of industrial economy and population are recognized as equal in the layer according to the following formula:

$$E_{ep} = 50 - \frac{\left(\frac{E_{current}-E_{min}}{E_{max}-E_{min}} + \frac{P_{current}-P_{min}}{P_{max}-P_{min}}\right) \times 50}{2} \tag{1}$$

In Equation (1), E_{ep} denotes the score of each grid cell in the exclusion/attraction layer, E_{max} denotes the maximum industrial value among all the grid cells of industrial economy map, E_{min} denotes the minimum industrial value among all the grid cells of industrial economy map, $E_{current}$ denotes the current industrial

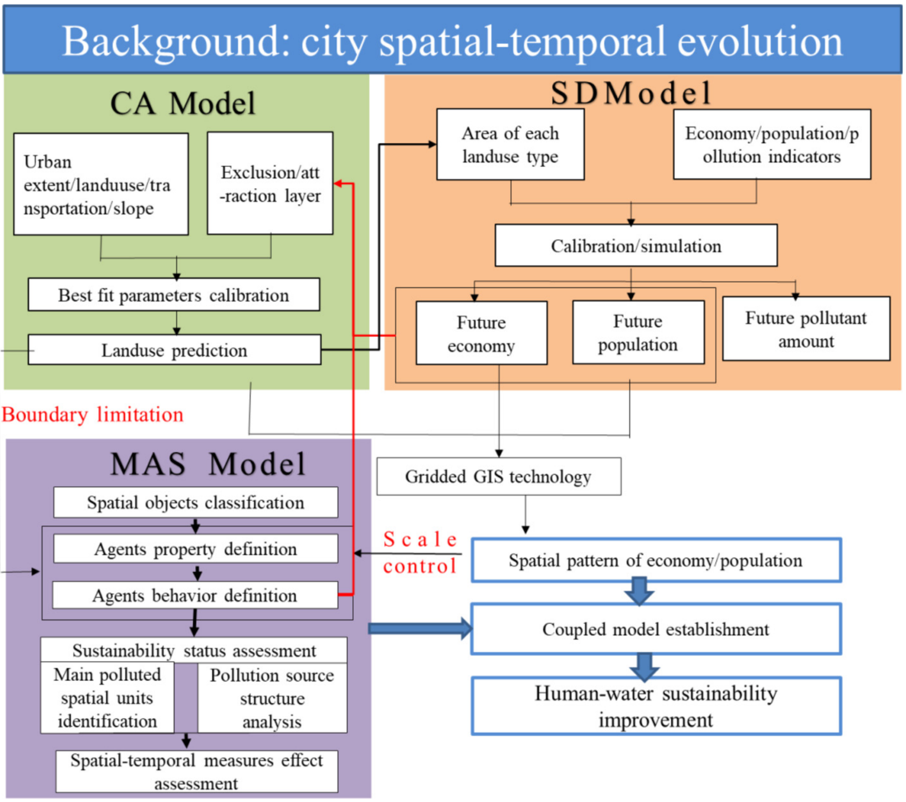

Fig. 1. Framework of the integrated SD-CA-MAC model.

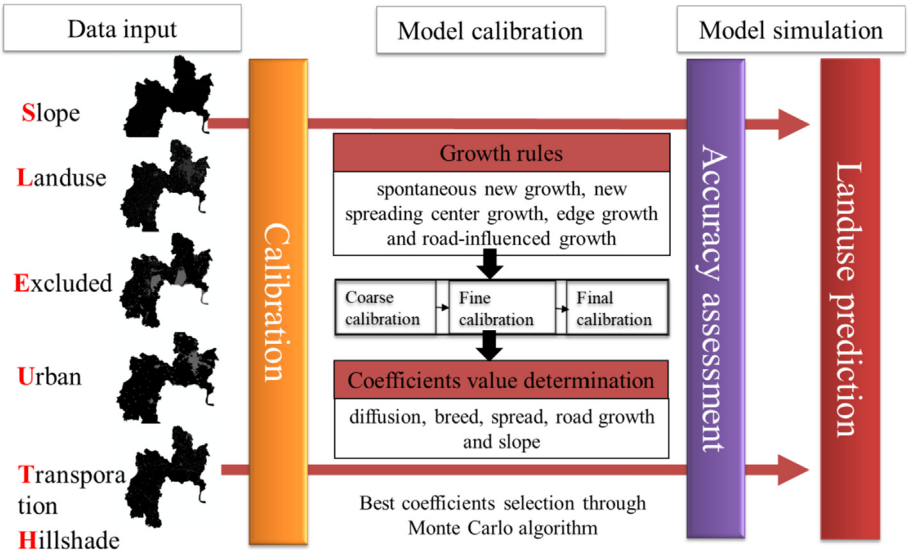

Fig. 2. Simulation process of the CA model.

value of a certain grid cell of industrial economy map, P_{max} denotes the maximum population among all the grid cells of population map, and P_{min} denotes the minimum population among all the grid cells of population map, $P_{current}$ denotes the current population of a certain grid cell of population map.

2.1.3. Establishment of the MAS model

A simulation platform for human-environment systems is established to simulate the spatial-temporal operation of human-environment systems in the real world. All the real world elements of human-environment systems are individually represented by computational agents. The elements include population, economy, landscape, river basins and pollutants. The landuse pattern from outputs of CA simulation provides the movement boundaries of each element. For example, Urban population will always live in the urban area, and industrial activities will always be carried out on the construction land. Pollutants from agricultural production will always flow within farm land. Once the pollutants flow into river, they would follow the flow of the river.

The framework represents the property value of each element and the pollutants flow process between them. Every social-economic element is considered to systematically describe a human-water system; thus, the platform can support detailed pollution sources analysis for specific monitoring sections.

The entire process of pollution, from pollutant production by human activities to pollution monitoring, can be observed in the MAS model (Fig. 3); the model shows the processes associated with social-economic activities, pollutant production, pollutant discharge, pollutant flow and pollutant monitoring. The linkage between human activities and water quality has been established. With the clear description of pollution sources, the pollution sources structure for every monitoring section can be calculated, and the main pollution source can be identified. The MAS model also provides for assessment of the effects of specific measures on water quality improvement.

2.1.4. Interface between different models

In creating a coupled model, the establishment of interfaces between different submodels using data inputs and outputs is a key process. In the integrated model based on SD-CA-MAS, the three main interfaces are the interface between the SD model and the CA model, the interface between the SD model and the MAS model, and the interface between the CA model and the MAS model.

The economic and population results of the SD model are translated into demands for cell space and used to form the input data of the exclusion/attraction layer data to drive CA simulation. The future land use area data, which were also extracted from the land use map of the CA model, are used as the driving data for the SD model to identify intensity limitation activities.

The interface between the SD model and the MAS model is realized through unidirectional data input from the SD model to the MAS model. The simulated results of the SD model, such as economy scale and population amount, control the output of the MAS model. The value of corresponding agent properties is assigned according to the input data from the SD model obtained through gridded GIS technology. For example, the property value of population amount of the urban population agents is assigned the value according the formula below.

$$IP_m = IP \times Cj \Big/ \sum_{j=1}^{n} C_m \qquad (2)$$

where IP_m refers to the urban population amount of urban population agent m, IP refers to the urban population amount value of the whole study region, Cj is the urban population coefficient of urban population agent m, n is the number of urban population agents of the whole study region.

The urban population coefficient of urban population agent m is calculated according to the formula of urban population density distribution below (Wang and Guldmann, 1996):

$$d_r = d_0 \times \exp\left[-\left({}^{r}\!/_{r_0}\right)\right]^{\sigma} \qquad (3)$$

where d_r refers to the urban population coefficient of urban population agent m with distance of r away from urban center, d_0 refers to the urban population coefficient of urban center, r_0 is the influence radius of the urban region in the study area, σ is a constraint parameter reflecting the information entropy of urban population spatial change.

The interface between the CA model and the MAS model is realized through bidirectional data input and output. The variation in location of a certain agent in the MAS model will influence the input data value of the Exclusion/Attraction layer in the SLEUTH model, and changes in the Exclusion/Attraction layer will ultimately affect the future land use pattern.

For example, once the population amount of a certain population agent is changed, according to formula (1), the value of $P_{current}$ would be changed, accordingly the value of E_{ep} of the Exclusion/Attraction layer would be changed. Finally, the value change of a certain agent in MAS model would influence the simulation results of CA model.

In return, the simulated results of the CA model will directly limit the movement boundaries of different agent types. For example, pollutants from agriculture activities will always flow within the land use type of farm land. The different land use types also determine the runoff coefficients for nonpoint pollutant sources. Thus, the interfaces between different models are established to permit data exchange and model integration. Linking the three models at both the macro- and micro-scales improves their performance.

2.2. Model calibration and validation

In the SD model, the accuracy of the simulated data is validated by comparison with actual statistical data. In the CA model, the calibration procedure includes three stages: coarse calibration, fine calibration and final calibration. One hundred Monte Carlo trials were conducted using the best-fitting parameter sets, and the simulated results were compared with the observational data

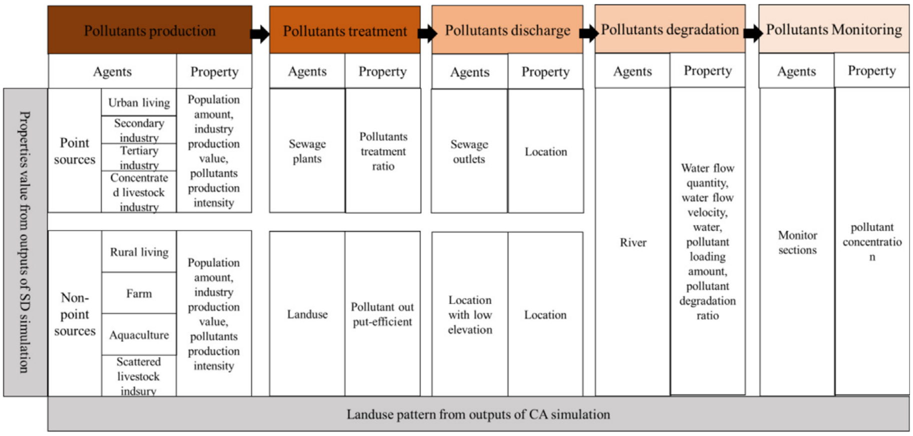

Fig. 3. The pollution process from pollutant production to pollutant monitoring.

(Berberoğlu et al., 2016). In this way, we were able to quantitatively assess the accuracy of the SLEUTH model results and distinguish the best-fitting parameter set. Finally, the unique fit parameter set for each exclusion/attraction in the three study regions was achieved.

The accuracy of the MAS model is assessed through the comparison of water quality simulated results and monitor results. The water quality monitoring data from the main water quality monitoring sections were used to verify the validity and reliability of the simulated results.

Table 1
Best fit parameter values and accuracy of CA model.

Parameter Values	Urban District	Jintan County	Liyang County
Diffusion	5	6	2
Breed	20	18	13
Spread	14	17	18
Slope resistance	71	58	50
Road gravity	55	21	46
Overall accuracy (%)	0.91	0.92	0.93
Kappa coefficients	0.73	0.75	0.76

2.3. *Forecasting*

To display the capability of forecasting the future situation of human-water sustainability along with the urban evolution according to the best-fitting growth parameters and the best performance exclusion/attraction layer in the three subregions, the coupled HAWS model is run to separately forecast tendencies in the year 2025 in the three subregions. The detailed population numbers and economic values for the three subregions in the year 2025 are forecasted according to the historical development trend as baseline scenario.

2.4. *Study area, software and data sources*

Changzhou City, located at Taihu Lake in China, is a prefecture-level city in southern Jiangsu province including three county-level cities (Urban district, Liyang county and Jintan county) (Fig. 4). A more detailed description of the study area can be found in a previous work (Zhou et al., 2017). Various types of pollutants, including heavy metals, COD, BOD, and others, are discharged into the water body. In proposing a general framework for water sustainability research of CHANS, our goal is not to analyze all pollutants. Therefore, only the prevalent pollutant, COD, is adopted as the pollutant index in the study area.

VENSIM software (http://vensim.com/vensim-software/) is used as the SD model platform to predict future economic, population and economic development. A typical CA model, SLEUTH, is used to predict future land use change (Silva and Clarke, 2002). The NetLogo software (http://ccl.northwestern.edu/netlogo/) is adopted as the MAS platform. ArcGIS software and R software are used to process the input data. The ‘RNetlogo’ package is used for data exchange between R software and NetLogo software (Thiele et al., 2012). The data for the study region is mainly collected from the local social and economic statistical yearbook and the pollution census data statistical yearbook; the land use data are obtained from remote sensing images, and water environment and resources data are obtained by field monitoring. The data input of SD model include population amount, economic amount of each industry, population and economy growth level, landuse structure, etc. The SLEUTH model is adopted as the CA tool. The basic input data include urban extent maps and transportation maps for 1995, 2000, 2005 and 2010, land use maps for 1995 and 2010, and slope and hillshade maps. The input data for the MAS model include economic production, population amount, pollutant production amount, pollutant treatment ratio of each industry type, water quality, water quantity water flow velocity, etc.

3. Results and discussion

3.1. *Model calibration*

To enhance the accuracy of the SD model results, the data from 2005 to 2010 were used to calibrate the parameters of the model, and the data from 2011 to 2012 were used to verify the validity and reliability of the simulated result. The results indicated that the majority of errors were controlled at the 10% level and that the testing error was within the allowable bounds. Hence, the SD model can be used to model the real environment.

The best fit parameters for the three subregions are shown in Table 1. The detailed spatial distribution of the subregions including

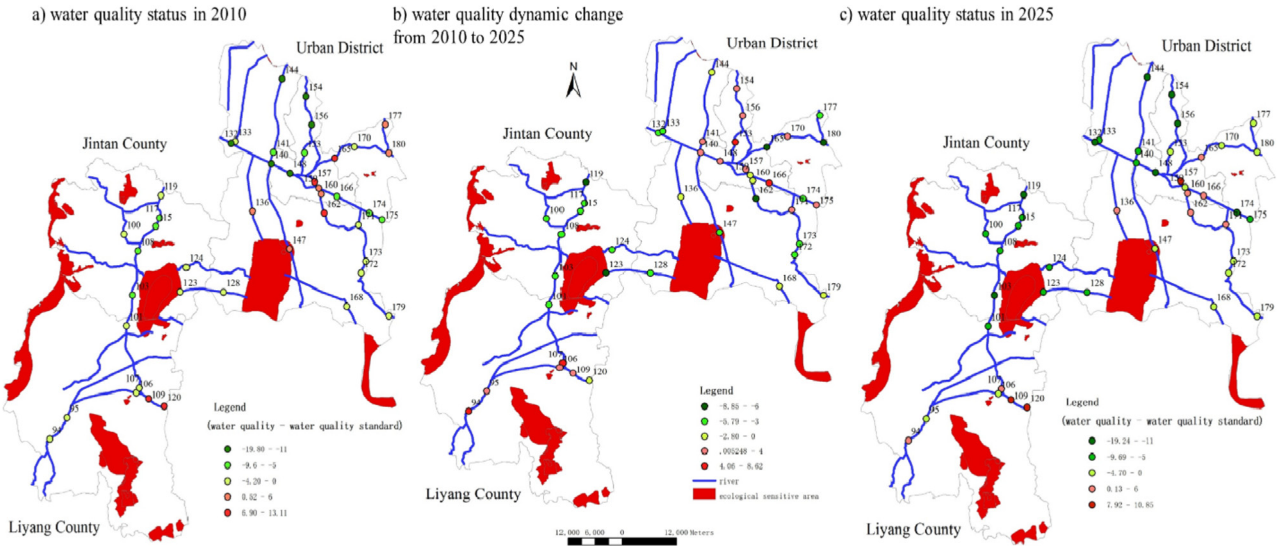

Fig. 4. a) Water quality status in 2010; b) water quality dynamic change and c) water quality status of different monitoring sections in 2025.

Urban District, Jintan County and Liyang County is presented in Fig. 4. For calibration, the model simulation results are compared with the observational data for 1995–2010. The overall accuracy and Kappa coefficients indicate that the simulation accuracy is relatively good.

To enhance the accuracy of the model, the water quality monitoring data for the main water quality monitoring sections were used to verify the validity and reliability of the simulated result. The results of this analysis are shown in Table 2. It can be seen that the simulated results for Jinghan River in the urban district are more accurate than those for the rivers in the rural districts. It may be that point sources in urban areas are easier to model. The simulated results of river upstream areas show better accuracy than the simulated results for downstream areas. It may be that the structure of the pollution sources in upstream areas is relatively simple. The model can be used to model the real environment.

3.2. Sustainability assessment using the HAWS model

According to the local baseline scenario of the study area, from 2010 to 2025, the total population in the three subareas showed an increasing trend. The population of the Urban District increased from 3.29 million to 3.89 million, while that of Jintan County increased from 0.55 million to 0.63 million and that of Liyang County increased from 0.75 million to 0.85 million. The economic scale shows a similar trend; however, the extent of increase in different industrial types is quite variable. Tertiary industry displays the most obvious increase; it was estimated 5.39-fold compared with the 2010 level in the Urban District, while the increases in Jintan County and Liyang County were estimated 4.28-fold and 3.85-fold, respectively.

In 2010, there were 14 monitoring sections with poor water quality status (Fig. 4a). The seriously polluted monitoring sections are located in the region downstream of the downtown of the Urban District and Liyang County, while the water quality status of most of the agricultural area and all of Jintan County is good. Analysis of the pollution sources structure of the most polluted monitoring sections (Table 3) showed that agriculture is the main pollution source for monitoring section 120 in Liyang County, while domestic living contributed 88.97% of the total pollution found in monitoring section 162 in the Urban District.

In 2025, 14 monitoring sections display poor water quality status (Fig. 4c). The pollution pattern is nearly the same as that for 2010. The water quality status in Jintan County shows significant improvement compared with 2010, whereas the number of polluted monitoring sections in Liyang County has increased from 2 to 4. The number of polluted monitoring sections in the Urban District has decreased. The pollution sources structures of the most polluted monitoring sections, including sections 157, 158 and 162, show significant differences. The main pollution source of monitoring section 157 is industry, accounting for 64.96%, while that of monitoring section 162 is domestic living, accounting for 74.79%. The high contribution ratio of domestic living to pollution in monitoring section 162 is mainly due to its proximity to the municipal sewage plant. Large amounts of pollutants from urban living would flow to the nearest municipal sewage plant and then to monitoring section 162.

Analysis of the water quality status in 2010 and 2020 through comparison with the local water quality standards shows that although the total number of monitoring sections with decreased water quality is the same, the spatial pattern and degree of change show some differences. It is found that 10 monitoring sections maintain poor water quality status. These sections are mainly located in the urban areas of the Urban District and Liyang County. The water quality status of 4 monitoring sections has decreased and fails to meet the local water quality standard. These are monitoring sections 166 and 171 in the Urban District and monitoring sections 94 and 107 in Liyang County. The pollution sources structure revealed that the large increase in industry resulted in standard-exceeding levels of pollutants in sections 166 and 171. Scattered livestock and poultry breeding farms are the main pollution sources that resulted in water quality degradation in monitoring sections 94 and 107. The pollution sources structure is consistent with the local industrial structure.

An analysis of the dynamic changes in water quality between 2010 and 2025 shows that water quality status improved in 28 monitoring sections and decreased in 18 monitoring sections (Fig. 4b). The monitoring sections with improved water quality are mainly located in Jintan County and upstream along the river in areas with low intensity of human activities. The monitoring sections with degraded water quality are mainly located downstream of industrial and livestock and poultry breeding activities. It can be concluded that the main reason for the degradation of water quality in the Urban District is the increase in the value of industry, although domestic living contributed most of the pollutants during the years 2010 and 2025. The main reason for water quality degradation in Liyang County is the increase in the intensity of livestock and poultry breeding industries.

3.3. Development of sustainability improvement strategies

Based on the previous analysis under the local baseline scenario of the study area, various specific measures should be adopted according to the local pollution sources structure and the extent of change. The management measures that are used to solve water-related environmental problems in the Urban District should focus on the pollutants produced by industry, tertiary and domestic living, while in Liyang County, measures related to agriculture, industry and domestic living should be implemented, with special emphasis on measures that address the treatment of pollutants

Table 2
The error test results of MAS model.

River basins	Monitor Section	COD concentration (mg/L) of 2010 year			COD concentration (mg/L) of 2011 year			COD concentration (mg/L) of 2012 year		
		Simulated	Observed	Error (%)	Simulated	Observed	Error (%)	Simulated	Observed	Error (%)
Jinghang	132	14.49	15	3.4	15.96	16.3	2.1	15.44	16.1	4.1
	159	31.8	30.4	−4.62	33.74	31.9	−5.78	32.95	30.9	−6.62
	175	24.18	22.5	−7.45	24.98	23.2	−7.69	24.29	22.4	−8.45
Danjin	119	25.45	26	2.11	26.21	26.9	2.55	25.21	26.1	3.41
	108	26.29	25	−5.17	29.88	28.2	−5.96	28.72	26.8	−7.17
	101	28.89	27.4	−5.45	30.81	29.1	−5.88	31.99	28.7	−11.45
Zhong	95	16.75	17	1.45	16.76	17.1	1.97	17.02	17.43	2.33
	109	29.89	27.8	−7.53	30.00	27.8	−7.9	27.82	25.4	−9.53
	120	30.28	28.3	−6.98	30.55	28.5	−7.21	30.20	27.9	−8.24

Table 3
Monitoring sections with obvious water quality excess and their pollution sources structure.

Monitoring sections	Water quality standard (COD: mg/L)	Water quality (COD: mg/L)		Sources Structure (%)							
				Agriculture		Industry		Tertiary		Domestic living	
		2010	2025	2010	2025	2010	2025	2010	2025	2010	2025
120	20	28.30	27.92	30.50	36.80	25.83	31.39	2.73	4.95	40.93	26.86
162	20	33.11	25.27	1.03	1.27	6.10	11.17	3.91	12.77	88.97	74.79
157	30	36.90	40.84	22.09	18.67	51.14	64.96	0.92	2.05	25.85	14.32

derived from the livestock and poultry breeding industries. The corresponding measures will be simulated and the effect will be assessed using the integrated model. Jintan County possesses relatively good water environment status and could maintain its current mode of development. The specific measures needed to achieve water environment improvement in the Urban District and Liyang County are listed in Table 4.

Because most of the monitoring sections with poorer water quality are located downstream of the urban area, measures that focus on domestic and industrial pollution should be adopted first to achieve a significant pollutant treatment effect.

According to the requirements of the 13th Five-year Plan, the sewage treatment ratio is to reach 95%; thus, the first measure to be put forward is that the treatment ratio of sewage plants in Urban District and Liyang County is set at 95%; the effect can then be observed through simulation. With the application of sewage treatment ratio improvement, 24 monitoring sections show a trend toward improvement in water quality. The COD concentration of monitoring section 162 decreased from 25.27 mg/l to 9.13 mg/l, a value far below the 20 mg/l specified in the water quality standard. The COD concentration of monitoring section 157 is 36.69 mg/l; thus, its level still exceeds the water quality standard. The COD concentration of monitoring section 120 is 22.45 mg/l.

Through the analysis of pollutant sources and of the spatial patterns of pollutants found in monitoring sections with excessive amounts of pollution, it can be found that industrial direct discharge is the main pollution source. Thus, three sewage plants and one sewage plant with a 95% sewage treatment ratio are constructed in the Urban District and Liyang County compared with the local baseline scenario of the study area. The potential location sites of sewage plants are determined according to the process of Rikalovic et al. (2014). Then the best optimal is selected according to the water quality status from the results of HAWS simulation. The service area of each sewage plant is shown in the purple region of Fig. 4. Under the scenario that includes the application of treatment ratio improvement and new added sewage plants, the Urban District finally achieves the goal of water quality attainment for the entire region. The COD concentration of monitoring section 157 is 29.59 mg/l, slightly below the water quality standard of 30 mg/l. Monitoring section 162, which currently shows a COD level of 7.72 mg/l, shows a significant decrease. Compared with the application of sewage treatment ratio improvement alone, the addition of new sewage plants would improve the water quality downstream. For example, monitoring section 171's water quality is reduced by 0.95 mg/l and that of monitoring section 175 is reduced by 0.45 mg/l; thus, the further from the location of measures application, the weaker the effect. The COD concentration of monitoring section 120, 15.05 mg/l, meets the requirement set by the water quality standard. However, some monitoring sections in Liyang County, including sections 107 and 94, were still unable to satisfy the requirement set by the water quality standard. Through pollution structure analysis of these sections, it could be found that scattered livestock and poultry breeding farming contributed large amounts of pollutant. Thus, the effect on local water quality of enhancing the livestock manure utilization level is tested. With a 30% improvement in the current livestock manure utilization level, the COD concentrations of monitoring sections 107 and 94 could reach 25.59 mg/l and 15.43 mg/l, respectively; both would then meet the water quality standard requirement (Fig. 5).

The water quality of the entire region of the Urban District in 2025 would satisfy the water quality requirements with the

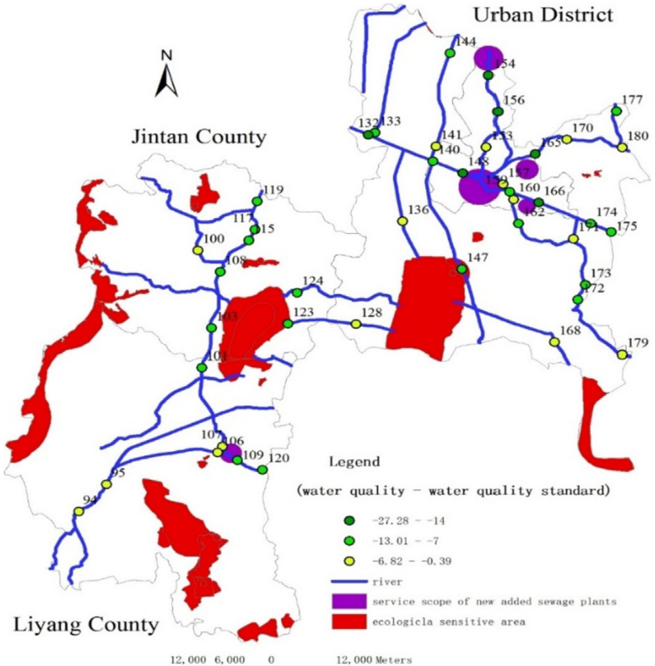

Fig. 5. Water quality status in 2025 with the application of measures for sewage treatment ratio improvement, new sewage plant construction and livestock manure utilization ratio enhancement.

Table 4
Measures for water environment improvement.

Region	Measure 1	Measure 2	Measure 3	Measure 4
Urban District	Improve treatment ratio of sewage plants	Add new sewage plants, realize centralized treatment of industrial sewage	—	—
Liyang County			Realize centralized treatment of rural sewage	Improve livestock manure utilization ratio

application of two measures, sewage treatment ratio improvement and new sewage plant construction. Due to the diversity of pollution sources in Liyang County, the approach of agriculture pollution reduction should be adopted in that area to improve the water quality of the monitoring section because agriculture is its main pollution source. Through scenario simulation of the application of different measures, it can be found that the monitoring sections that are closer to the object spatial units with measures application would show more significant improvements in water quality. This suggests that to improve the water quality of a specific monitoring section, attention should be firstly paid to management of the main pollution sources near that location. For the water quality improvement of the whole study region, the linkages between upstream and downstream should be totally concerned.

4. Conclusions

Spatial-temporal explicit assessment and improvement in the water sustainability of coupled human and natural systems is realized in the study area, and an integrated model is developed based on the SD, CA and MAS models. The model achieves spatial-temporal adjustment based on pollution sources structure analysis. The integrated model reveals the major polluted monitoring sections and the main pollution sources. It supports the simulation of various adjustment measures and allows direct observation of their effects on water quality. Finally, the best fit space-time measures set could be put forward for water environment improvement. The use of this model allows human-water sustainability along with economic-population development based on complex systems theory.

In previous research in this area, only the holistic status of the study area is taken into account, or the studied area is divided into spatial units for analysis. Taking Changzhou City as an example and comparing the results obtained in previous research with those obtained using the integrated SD-CA-MAS approach developed in this study, the significance of these limitations is revealed. Based on the existing water environmental research on CHANS, it can only be found that the study area of Changzhou in 2025 is in overloaded status, and no information about the main pollution sources for specific monitoring sections is obtained. Through the simulation proposed here using the HAWS model, specific monitoring sections with worse water quality could be recognized. In 2010, and 2025, monitoring sections 157 and 162 in the Urban District and section 120 in Liyang County are in bad water quality status; this indicates that the WECC status upstream is overloaded. Furthermore, the pollution sources structure and the main pollution sources for these monitoring sections could be identified. Thus, the measures of sewage treatment ratio improvement and new added sewage plants are adopted in Urban District and Liyang County. In addition, to further improve the water environmental status of Liyang County, measures of livestock manure utilization ratio enhancement are adopted for some specific monitoring sections. The integrated model targets the key environmental problems and proposes a feasible solution for achieving a significant water quality improvement effect. The solution can be presented in any space-time format rather than as a single developmental goal.

Once the required data for model simulation is provided, the integrated model could also be applied for human-water sustainability simulation in other administrative units or river basins. In the current situation, a county or a medium-sized city may be fit for spatial explicit management with consideration of the data availability and city complexity. The measures effects such as treatment technology level, structural upgrading, spatial patterns or network optimization on water quality and sustainability status can be directly assessed through the integrated model established in this study. For better spatial explicit management, it requires human-environmental data with higher spatial and temporal resolution such as human living, agriculture and industrial activities, Pollutants life cycle monitoring from production to degradation, and the natural condition change.

Several obstacles remain to be overcome in future research. To achieve a more accurate and dynamic simulation, a dynamic hydrological simulation model should be developed and incorporated into the integrated model presented here. The current hydrological status reflects only the static status represented by the drought period in 2010. The future hydrological status is expected to differ due to climate change and human activities. The dynamic internal interaction between hydrological status and social-economic development and their effects on the water environment could be further analyzed in future work. At the same time, more data and more varied sources of data are needed to permit more accurate simulation. Data with high space-time resolution facilitate a detailed simulation process and would be helpful in devising detailed management methods for CHANS sustainability improvement. Along with the development of the Internet of Things and Big Data, the integrated model could exhibit its power in urban evolution prediction, human-water sustainability assessment and improvement.

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