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THEMATIC ISSUE

Design and key techniques of a collaborative virtual flood experiment that integrates cellular automata and dynamic observations

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Abstract With the development of computer science, communications technology and environmental modeling, virtual geographic environments (VGEs) have been linked with field observations and geographic modeling. VGEs enable researchers in various fields to collaboratively perform computer-aided geographic experiments. This study proposes a collaborative environment to conduct a virtual flood experiment that integrates cellular automata and dynamic observations. Some of the key techniques, including a cellular automata flood modeling method, a real-time parameter similarity evaluation method, and a collaborative visualization and operation method, are explored. The proposed techniques are tested with a prototype system as part of a flood simulation case study of the Hunhe River in Liaoning Province. We conclude that a virtual experiment environment can provide effective technical support for flood research.

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Introduction

A geographic environment system is huge, open and complex; geographic research originates from field observations (Chen and Liu 2004), and physical and numerical models are based on observations and assumptions. Both simulations and observations are important means of generating and validating scientific knowledge (Chiggiato et al. 2012; Bever et al. 2013). However, when only relying on simulations in virtual space, errors are continuously augmented during the modeling process due to the lack of accurate parameters (Zhang et al. 2011). Therefore, geographic analysis and decision-making must combine the power of replicable experiments with field observations (Fiore et al. 2009).

Flooding is a typical geographic phenomenon, and the implementation of open-channel flow models plays an important role in floodplain management (Rinaldi et al. 2007). “Three Yellow Rivers” is a conceptual framework proposed by the Yellow River Hydro-Conservancy Committee of China to manage the Yellow River (Li 2002) and it includes “a real Yellow River”, “a model Yellow River” and “a digital Yellow River”. The modeling and experiment of natural rivers are mostly accord with the thought of “Three Yellow Rivers”. With the development of information technology, the integration of geographic information system (GIS) with hydrological and hydraulic models has been widely investigated (Bates and De Roo 2000; Al-Fuagara et al. 2008; Van Der Knijff et al. 2010; Ernst et al. 2009; Soulis 2013; Li et al. 2012, 2013; Formetta et al. 2014). However, GIS usually has no dedicated model for the processes that govern system dynamics, adaptation, and evolution (Torrens 2009; Kulkarni et al. 2014).

The goal of geographic experimentation as an integrated research method was to simulate the natural and social worlds under one explanatory umbrella (Mackinder 1987; Matthews and Herbert 2008; Lin et al. 2012). The construction of virtual geographic experimentation (Ramasundaram et al. 2005; Lin et al. 2009; Lu 2011; Li et al. 2015) can be an effective way to enhance the efficacy of experimental geography. Virtual geographic experimentation supports geovisualization (Rink et al. 2014; Helbig et al. 2014), geosimulation, geocollaboration, and human participation, it serves as a workspace that is suitable for model and data integration and collaborative flood analyses (Chen et al. 2012; Lin et al. 2013). In addition, a cellular automaton (CA) model can be defined with flexible and adjustable transition rules (Wang et al. 2000; Evensen 2003; Zhang et al. 2011). When combined with collaborative operations and analyses, CA can serve as an experimental platform to improve model predictions by integrating observations.

In this study, we design a virtual geographic environment for a collaborative flood experiment that consists of a cellular automaton for calibrating and sequentially updating a coupled hydrologic-hydraulic model using dynamic observational information. Several key techniques are introduced, including cellular automata modeling in virtual flood experiments, parameter similarity evaluation, and the construction of collaborative experimental environments. A flood routine experiment of the Hunhe River in Liaoning Province is used as a case study to develop the prototype system.

System framework

The design of the collaborative virtual experiment environment should meet the following requirements: the basic physical behavior of flood should be well simulated and some important user-defined parameters can be adjusted during the experiment; the dynamic observation data should be imported into the experiment environment and real-time similarity can be performed; meanwhile the environment should support collaborative work and expressions of experiment elements. The system framework is shown in Fig. 1.

The numerical simulation of the flood adopts a CA framework, which mainly includes the mechanism for simulating the physical flood, the parameter adjustment mechanism, and the model status assimilation mechanism. The detailed techniques of CA framework will be introduced in "Adjustable cellular automata model for observation-coupled flood simulations". The dynamic observations are processed at the same spatial and temporal scales as the numerical simulations. The dynamic

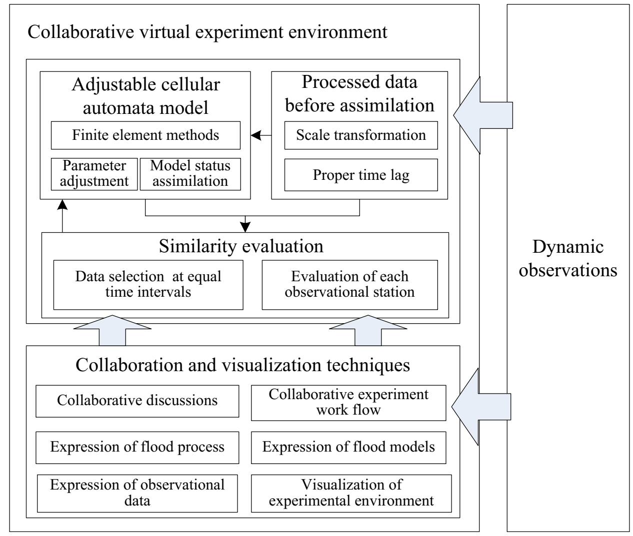

Fig. 1 The framework of the collaborative flood experiment environment

observations are integrated with the numerical simulations in asynchronous steps so that the simulations can run ahead of the actual flood events and generate predictions. The similarity analyses are performed to find the degree of accordance between the numerical simulations and the observations (introduced in "Similarity evaluation method of the dynamic flood process"). In addition, the virtual experiment environment provides a platform for collaborative discussions and operations and supports the expression of flood processes, flood models and observational data, which will be discussed in "Collaborative flood visualization and experimental techniques".

The collaborative experiment mainly follows such a workflow: (1) confirm the aim and boundary conditions of flood experiment; (2) process flood model input data and make it standardized; (3) setup flood simulation model and spatial/temporal unit; (4) evaluate similarity and calibrate flood model; (5) simulation results analysis and discussions. During this workflow GIS experts and hydrologists can collaboratively setup models and calibrate them, while policy-makers and researchers in other fields can also make comments through discussions.

Key techniques

Adjustable cellular automata model for observation-coupled flood simulations

In this study, an adjustable cellular automata model that performs flood simulations using finite element methods is introduced. The model is also designed to integrate the observed attributes of river floods and to make adjustments when the flood attributes of the observed data and numerical models differ.

CA model structure and parameters

The Von Neumann neighbor structure is adopted in the CA model, and the entire simulated region is divided into several river sections along the direction of flow according to the distribution of the observation points (Fig. 2). The application of the hydraulic model requires accurate roughness parameters, which are indirect coefficients that cannot be measured; thus, we adopted uniform roughness parameters for each section. The observation stations record continuous measurements of water depth to calibrate the flood simulation model.

The parameters of CA model can be divided into three types: (1) attributes of single cell, which include $\mu_{i,j}$ (flow velocity in the x direction), $v_{i,j}$ (flow velocity in the y direction), $h_{i,j}$ (water depth), $zc_{i,j}$ (water stage), $M_{i,j}$ (single width fluxes in the x direction), $N_{i,j}$ (single width fluxes in the y direction), Dem, $D_{i,j}$ (cumulative distance from section origin), $zm_{i,j}$ (observed water stage); (2) attributes of river section, which include n_N (roughness coefficient), L_N (length of section); (3) attributes of CA model, which include j (iterations that simulation ahead of the observation), T_{span} (change interval parameter), α (roughness adjustment coefficient), Δt (temporal unit), Δx (spatial unit in the x direction)and Δy (spatial unit in the y direction).

CA transition rules

The simulations are only sensible when the predictions occur ahead of the actual flood events, so the flood simulations are asynchronous with the observation data. Formulas (1–3) describe the physical behavior of flood routine, while Formulas (4, 5) describe how the CA model integrates dynamic observations to adjust the roughness coefficients and water depth.

First, the hydrodynamic and water mass conservation mechanisms were used to model the physical behavior of the floods. The Saint–Venant equations were discretized using the finite difference method (Liu et al. 1991) and were added to the CA framework using the appropriate conversion laws (Li et al. 2013).

$$M_{i,j}^{t+1} = M_{i,j}^{t} - g\frac{\Delta t(h_{i+1,j}^{t} + h_{i,j}^{t})(zc_{i+1,j}^{t} - zc_{i,j}^{t})}{\Delta x} - gn_{i,j}^{2}\frac{\bar{u}_{i,j}\Delta t\sqrt{(u_{i,j}^{t})^{2} + (v_{i,j}^{t})^{2}}}{\left[(h_{i+1,j}^{t} + h_{i,j}^{t})/2\right]^{1/3}} \quad (1)$$

$$N_{i,j}^{t+1} = N_{i,j}^{t} - g\frac{\Delta t(h_{i,j+1}^{t} + h_{i,j}^{t})(zc_{i,j+1}^{t} - zc_{i,j}^{t})}{\Delta y} - gn_{i,j}^{2}\frac{\bar{v}_{i,j}\Delta t\sqrt{(u_{i,j}^{t})^{2} + (v_{i,j}^{t})^{2}}}{\left[(h_{i,j+1}^{t} + h_{i,j}^{t})/2\right]^{1/3}} \quad (2)$$

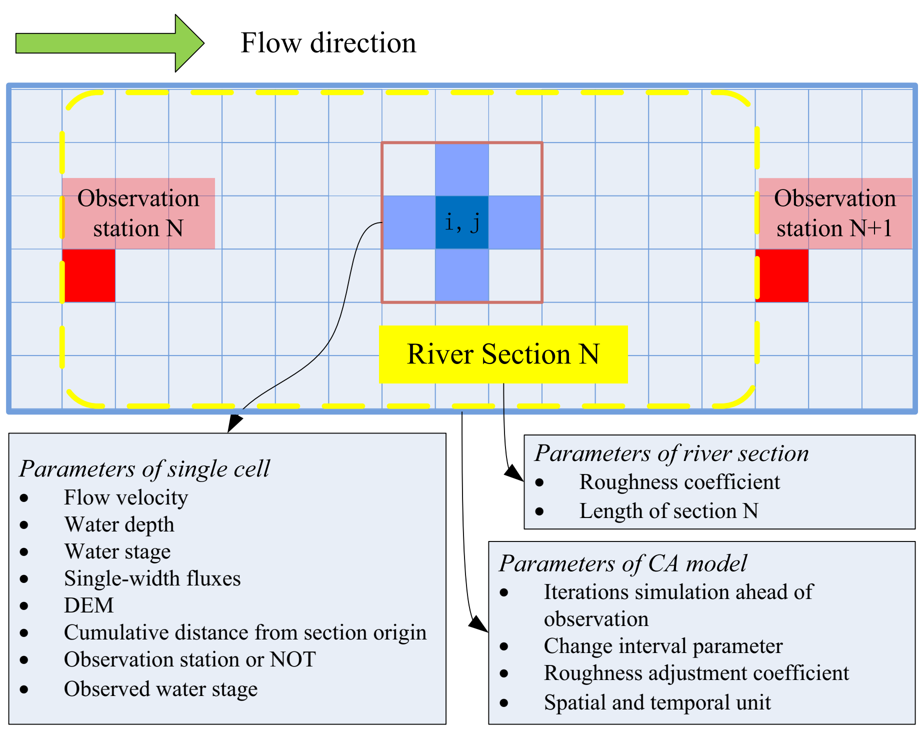

Fig. 2 CA model structure and parameters

$$h_{i,j}^{t+1} = \max\left(h_{i,j}^{t} - \frac{\Delta t(M_{i+1,j}^{t+1} - M_{i,j}^{t+1})}{\Delta x} - \frac{\Delta t(N_{i,j+1}^{t+1} - N_{i,j}^{t+1})}{\Delta y} - I_{i,j} \times \Delta t, 0\right) \tag{3}$$

In Eqs. (1), (2), and (3), $h_{i,j}^t$ represents the average water depth (m) of CA cell (i, j) at time t; $M_{i,j}^t$ and $N_{i,j}^t$ are the single-width fluxes ($\mathrm{m}^2\ \mathrm{s}^{-1}$) of CA cell ($i$, j) at time t in the x and y directions, respectively. The terms $\mu_{i,j}^t$ and $v_{i,j}^t$ represent the average horizontal water speeds ($\mathrm{m\ s}^{-1}$) in CA cell (i, j) at time t in the x and y directions, respectively, where $\mu_{i,j}^t = M_{i,j}^t / h_{i,j}^t$ and $v_{i,j}^t = N_{i,j}^t / h_{i,j}^t$. $\mathrm{zc}_{i,j}^t$ is the average water stage (m) of CA cell (i, j) at time t. $I_{i,j}$ is the infiltration value ($\mathrm{m\ s}^{-1}$) of CA cell (i, j) (omitted in this study); $n_{i,j}$ is the hydraulic roughness coefficient ($\mathrm{m}^{-1/3}$ s) of CA cell (i, j). Δt, Δx, and Δy represent the temporal unit (s), the spatial unit (m) in the x direction, and the spatial unit (m) in the y direction, respectively.

Second, because of the accumulated simulation error from the finite difference method, we integrated the dynamic observed water depth values to adjust the roughness coefficients according to Formula (4), and to modify the water depth according to Formula (5).

We used the difference in the water stages between the two closest observation stations, N and $N+1$, to compute a perturbation value to rectify the roughness coefficients and flood depth values of the CA cells in river section N, assuming that the simulation was j iterations ahead of the observation. One cell in river section N was labeled (i, j) at a cumulative distance of $D_{i,j}$ from the origin of the section (station N).

$$n_N^{\prime(k)} = \frac{\alpha(\mathrm{zm}_{N+1}^{(k-j)} - \mathrm{zm}_N^{(k-j)}) + (1-\alpha)(\mathrm{zc}_{N+1}^{(k-j)} - \mathrm{zc}_N^{(k-j)})}{(\mathrm{zc}_{N+1}^{(k-j)} - \mathrm{zc}_N^{(k-j)})} \times n_N^{(k)} (\alpha \in (0,1)) \tag{4}$$

$$h_{i,j}^{\prime(k)} = h_{i,j}^{(k)} + \frac{(\mathrm{zm}_{N+1}^{(k-j)} - \mathrm{zc}_{N+1}^{(k-j)}) \times (D_{i,j}) + (\mathrm{zm}_N^{(k-j)} - \mathrm{zc}_N^{(k-j)}) \times (L_n - D_{i,j})}{L_N} \tag{5}$$

In Eqs. (4) and (5), the simulated water stage of station N at $k-j$ iterations was defined as $\mathrm{zc}_N^{(k-j)}$ (m); the corresponding observed water stage was defined as $\mathrm{zm}_N^{(k-j)}$ (m); $n_N^{(k)}$ is the $k+j$ iterations of the roughness coefficient of river section N, and $n_N^{\prime(k)}$ is the adjusted value. $h_{i,j}^{(k)}$ is the $k+j$ iterations of the water depth at cell (i, j); $h_{i,j}^{\prime(k)}$ is the adjusted value, and L_N is the length of section N.

The change in the trend of the water stages lags behind the adjusted roughness coefficients; therefore, frequently changing roughness coefficients are likely to result in over-adjustment. We also used coefficient α and a suitable change interval parameter, T_{span}, to avoid over-adjustment.

Similarity evaluation method of the dynamic flood process

We determined the model parameter optimization approach through a similarity evaluation of the numerical model and the physical model for a given time series. Euclidean distance (ED) and dynamic time warping (DTW) (Berndt and Clifford 1994) are two classic methods for measuring time sequence similarity. The Euclidean distance method cannot reflect the dynamic characteristics of the flood time series because it is very sensitive to small changes in the timeline. Compared with the Euclidean distance, the dynamic time warping distance is more suitable for the coupled flood similarity evaluation process described in this study.

The DTW method was adopted for the similarity calculation. The coupled calculation of the water depth time series at station N between two neighboring stations (time span is T_{span}) is $\mathrm{zc}_N^{k\in[k_1,k_m]} = \{\mathrm{zc}_N^{k_1}, \mathrm{zc}_N^{k_2}, \ldots, \mathrm{zc}_N^{k_m}\}$, while the corresponding time series for the observed water depth is $\mathrm{zm}_N^{k\in[k_1,k_m]} = \{\mathrm{zm}_N^{k_1}, \mathrm{zm}_N^{k_2}, \ldots, \mathrm{zm}_N^{k_m}\}$. Therefore, the similarity index obtained by the DTW method at station N can be iteratively calculated by Eq. (6):

$$\begin{aligned} &\mathrm{DTW}(\mathrm{zc}_N^{k\in[k_1,k_m]},\ \mathrm{zm}_N^{k\in[k_1,k_m]}) = D_{\mathrm{dtw}}(\mathrm{zc}_N^{k_m}, \mathrm{zm}_N^{k_m}) \\ &= d(\mathrm{zc}_N^{k_m}, \mathrm{zm}_N^{k_m}) + \min \begin{cases} D_{\mathrm{dtw}}(\mathrm{zc}_N^{k_{m-1}}, \mathrm{zm}_N^{k_m}) \\ D_{\mathrm{dtw}}(\mathrm{zc}_N^{k_{m-1}}, \mathrm{zm}_N^{k_{m-1}}) \\ D_{\mathrm{dtw}}(\mathrm{zc}_N^{k_m}, \mathrm{zm}_N^{k_{m-1}}) \end{cases} \end{aligned} \tag{6}$$

In Eq. (6), $d(\mathrm{zc}_N^{k_m}, \mathrm{zm}_N^{k_m})$ represents the Euclidean distance between $\mathrm{zc}_N^{k_m}$ and $\mathrm{zm}_N^{k_m}$. The similarity index for the entire river, D, was measured using the average value for each station. We found that a smaller value of D implies that the flood simulation is more similar to the dynamic observations.

Collaborative flood visualization and experimental techniques

A collaborative flood experiment environment can help participants in different locations visualize and analyze hydrological data and models in the same virtual workspace. Hydrological experts and technical staff can act as 3D avatars while logged into a virtual workspace for cooperative research and for communicating in real time by exchanging video, audio, text, etc. Electronic sand tables, geographic images and 3D models can be dynamically updated to enhance the collaborative visualization of a flood event and the calibration of flood simulation models. The adjustment of flood model parameters can be simultaneously forwarded to the server so that every participant can visualize the modified flood simulations.

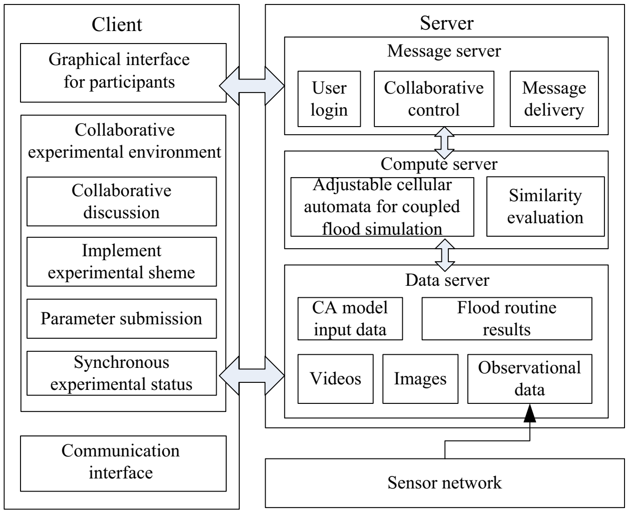

Fig. 3 Construction of a collaborative flood experiment environment system

The construction of a collaborative flood experiment environment involves a server and a client (Fig. 3). The server consists of a message server, a compute server and a data server. The message server handles the event-driven messages to the experiment participants and transfers experiment control messages and submitted parameters to the compute server. The data server stores the CA model input data and the corresponding reference materials for the flood experiment while receiving real-time observational data from the sensor network and delivering the necessary data to the compute server. The compute server runs the adjustable coupled flood CA simulation model and evaluates the similarity between the simulation and the observational data.

During the collaborative experiment, the real-time computational results and dynamic observational results are saved on server. When there are emergency network obstacles, the server can keep the experiment data in its local disk, and deliver them to clients when the network recovers. So the reliability of collaborative experiments can be ensured.

Implementation of a prototype system

Case study

The Hunhe River originates in the Changbai Mountains in Qingyuan County, Liaoning Province, China, and passes through Fushun, Shenyang, and other major cities. Flood prevention efforts in Shenyang focus on the Hunhe River. To research the effects of floods and flood prevention planning projects, the Liaoning Water Resources Department created a physical model (Fig. 4) of the Shenyang section of the Hunhe River.

The physical model was constructed based on the *Test Regulation for River Models* (Ministry of Water Resources of China 1995a) and the *Test Regulation for Normal Hydraulic Models* (Ministry of Water Resources of China 1995b). This model can be used to simulate real floods and to observe the hydraulic properties of floods of different magnitudes (e.g., water level, flow velocity, flow pattern, and extent of flooding). Here, we used observational data from the physical model as a substitute for observations from the Hunhe River.

To obtain these observations, water depth sensors were placed in different sections of the physical model, and the data were collected at 5-s intervals with a depth accuracy of 5 mm. The locations of the sensors are shown in Fig. 5. The coordinates were measured with a Topcon total station instrument and were mapped onto the cell matrix. Nine sensors were used to adjust the CA flood model, and four were used for the validation. The CA model was constructed using a digital elevation model (DEM) of the Hunhe River, and the water depth time series was input into the CA model after performing the time-scale ($\lambda_t = 41.8$) and vertical-scale ($\lambda_h = 70$) transformations.

Prototype system

The collaborative prototype system supports multiple participants such that collaborative visualization of physical model observations and numerical Hunhe River flood dynamics can be achieved. Participants can set the experimental parameters of the flood simulations and send their parameters and control messages to the compute server. The compute server performs the flood simulations using the CA model coupled with the dynamic observations obtained by the water depth sensors. The simulation results are then sent back to each client for collaborative visualization and discussion. The collaborative virtual flood experiment prototype system, which integrates cellular automata and dynamic observations, is shown in Fig. 6.

The participants in the experiment can determine the CA model parameters (T_{span}, j, Δt, and α) through the evolution of the similarity between the simulation results and dynamic observations. For example, Fig. 7 illustrates the similarity evaluation function for the simulation results and the dynamic observations using different values for parameter j (the other parameters are held constant at $T_{span} = 1000$ s, $\Delta t = 2$ s, and $\alpha = 0.02$).

The collaborative experiments were conducted with different sets of parameters, as detailed in "Adjustable cellular automata model for observation-coupled flood simulations" (T_{span}, j, Δt, and α). Through collaborative experimental

Fig. 4 The physical model of the Hunhe River

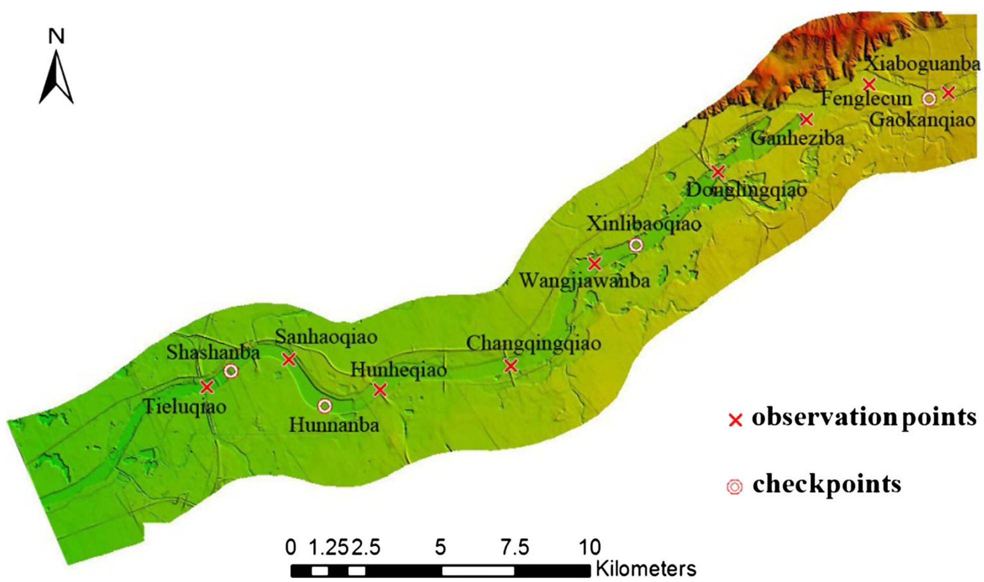

Fig. 5 Distribution of the observation points in the physical model

analysis and comparisons of the results, the experiment participants found that the coupled flood simulations can achieve results that are similar to the physical model observations when the time delay is long and when the chosen parameters are $T_{\text{span}} = 1000$ s, $j = 900$, $\Delta t = 2$ s, and $\alpha = 0.02$ (the time delay between the numerical and physical models is $j \times \Delta t = 1800$ s). A comparison of the inundated area predicted by the numerical flood simulation only and the numerical solution coupled with the dynamic observations ($T_{\text{span}} = 1000$, $j = 900$, $\Delta t = 2$ s, and $\alpha = 0.02$) is shown in Fig. 8. We find that the accuracy of the simulation improves after it is coupled with the dynamic observations.

Discussion

Geographic Science, similarly to other experimental disciplines (physics, chemistry, etc.), requires multiple observational and experimental methods for validating theoretical models. Geographic Science is also complex, and computer and communication technologies should be used to support multiple participants in collaborative experiments. Although the thought of experiment is widely adopted by geographers who performs hypothesis-testing in their researches, the virtual geographic experiment is more inclined to build an environment that can customize the necessary elements of geographic experiments, and can integrate geographic models, data analysis tools, geographic researchers and dynamic observational data to collaboratively solve geographic problems and discover new knowledge.

Similarity evaluation between simulation information flow and observation information flow is important in the experimental analysis. Characteristic parameter should be determined according to the aim of experiment before similarity analysis. In future study, the similarity analysis should be a quick evaluation tool that can judge the similarity between simulation and observations comprehensively.

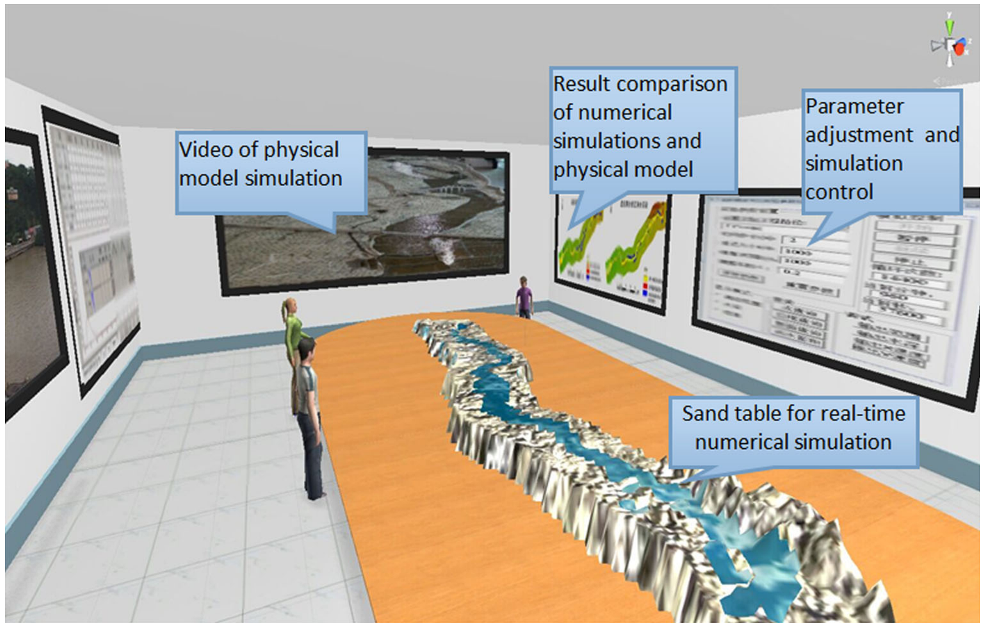

Fig. 6 Prototype system of the collaborative virtual flood experiment

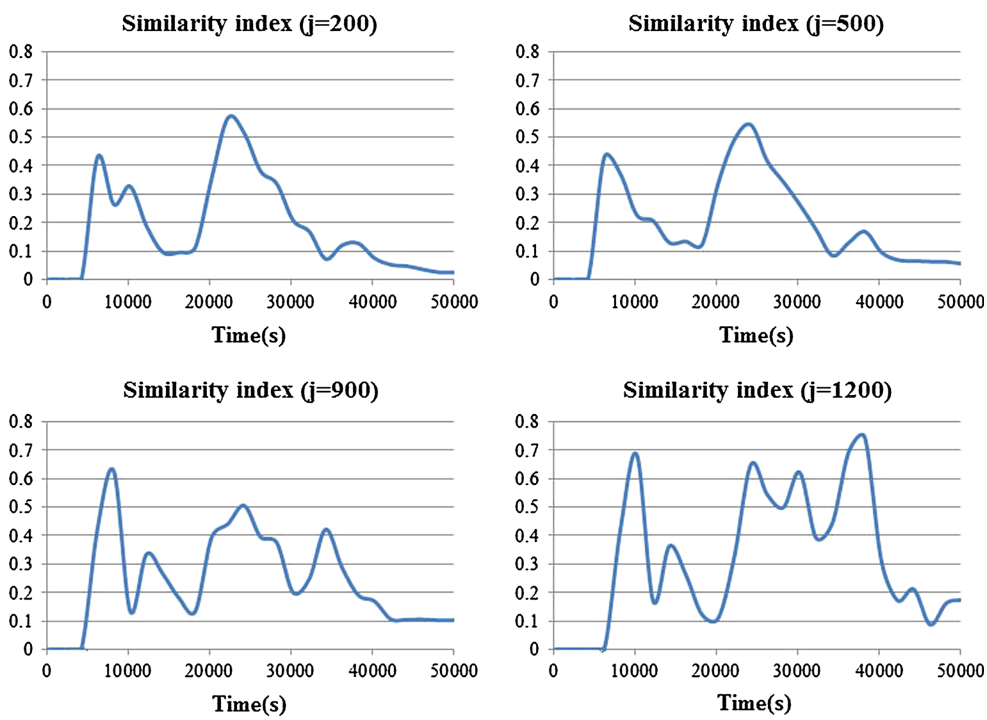

Fig. 7 Similarity between the simulation results and dynamic observations using *different values* for parameter *j*

Flooding is a typical geographic process for which a hydrological model is used as a simplified representation of a complex system. However, existing models must be calibrated to the specific conditions of each landscape and to the goals of each study (Rinaldi et al. 2007). A data-driven flood simulation framework, which supports the incorporation of dynamic observational data and information processing, can achieve more accurate modeling and simulation of flood events. In this study, we describe a collaborative virtual flood experiment that integrates cellular automata and dynamic observations. Through an experiment with the prototype system, we found that the collaborative flood experiment can combine the advantages of numerical simulations, dynamic observations and collaborative visualizations to generate accurate predictions of flood events.

With the rapid development of networking and big data, flood simulations and predictions can be supported by

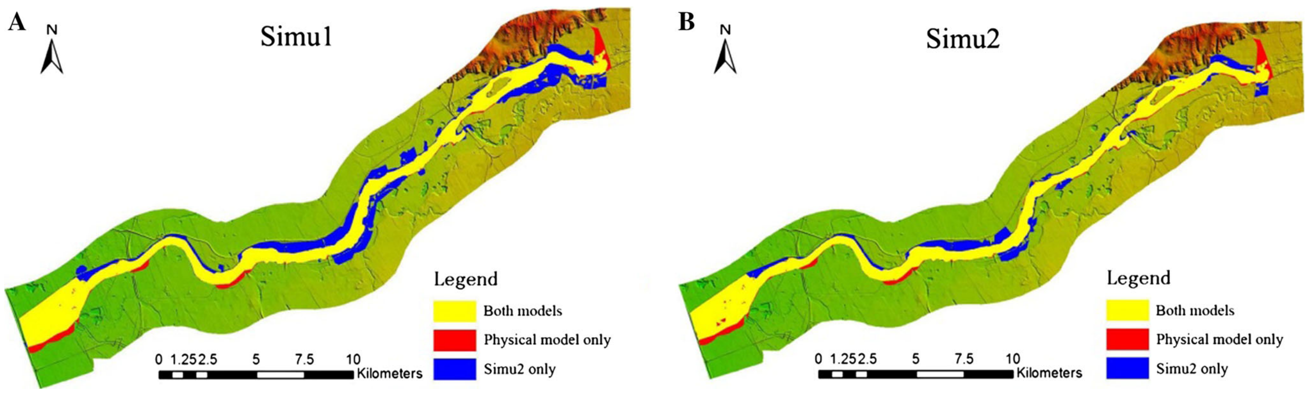

Fig. 8 Comparison of the inundation areas

cellular automata with adjustable parameters and collaborative experimental analysis. In future work, dynamic flow velocity observation data are also needed to rectify CA model; the flood model library and parameter database should be improved to support the virtual flood experiment such that participants can customize flood models and parameters for specific landscape conditions and study goals. Additionally, how human perception affects group decisions in the virtual flood experiment environment should be more thoroughly studied.

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References

Al-Fuagara A, Ahmed T, Ghazali AH, Zakaria S, Mahmud AR, Mansor S, Al-Mattarneh HMA (2008) The application of hydraulic model with GIS for visual floodplain mapping: a case study of Kuala Lumpur City, Malaysia. In: international conference on construction and building technologies (ICCBT), 2008-D, pp 273–282

Bates PD, de Roo APJ (2000) A simple raster-based model for flood inundation simulation. J Hydrol 236(1–2):54–77

Berndt D, Clifford J (1994) Using dynamic time warping to find patterns in time series. In: Fayyad UM (ed) UTHUR USA: MYR. AAAI-94 Workshop on Knowledge Discovery in Databases (KDD-94). Menlo Park, AAAI Press, pp 229–248

Bever AJ, Friedrichs MAM, Friedrichs CT et al (2013) Combining observations and numerical model results to improve estimates of hypoxic volume within the Chesapeake Bay, USA. J Geophys Res Oceans 118(10):4924–4944

Chen YG, Liu JS (2004) Main tasks and methods of geography. SCIENTIA GEOGRAPHICA SINICA 24(3):257–263

Chen M, Lin M, Wen YN, He L, Hu MY (2012) Sino-VirtualMoon: a 3D web platform using Chang'e-1 data for collaborative research. Planet Space Sci 65(1):130–136

Chiggiato J, Jarosz E, Book JW et al (2012) Dynamics of the circulation in the Sea of Marmara: numerical modeling experiments and observations from the Turkish straits system experiment. Ocean Dyn 62(1):139–159

Ernst J, Coninx I, Dewals BJ, Detrembleur S, Erpicum S, Bachus K, Pirotton M (2009) Social flood impacts in urban areas: integration of detailed flow modelling and social analysis. In: Proceedings 33rd IAHR congress—water engineering for a sustainable environment. Vancouver, British Columbia, IAHR, pp 6820–6827

Evensen G (2003) The ensemble kalman filter: theoretical formulation and practical implementation. Ocean Dyn 53(4):343–367

Fiore SM, Harrison GW, Hughes CE, Rutström EE (2009) Virtual experiments and environmental policy. J Environ Econ Manag 57(1):65–86

Formetta G, Antonello A, Franceschi S (2014) Hydrological modelling with components: a GIS-based open-source framework. Environ Model Softw 55:190–200

Helbig C, Bauer HS, Rink K et al (2014) Concept and workflow for 3D visualization of atmospheric data in a virtual reality environment for analytical approaches. Environ Earth Sci 72(10):3767–3780

Kulkarni AT, Mohanty J, Eldho TI et al (2014) A web GIS based integrated flood assessment modeling tool for coastal urban watersheds. Comput Geosci 64:7–14

Li GY (2002) Construction of "Three Yellow Rivers". Yellow River 24(7):1–3

Li Y, Gong JH, Zhu J et al (2012) Efficient dam break flood simulation methods for developing a preliminary evacuation plan after the Wenchuan Earthquake. Nat Hazards Earth Syst Sci 12(1):97–106

Li Y, Gong JH, Zhu J et al (2013) Spatial-temporal simulation and risk analysis of dam-break flooding based on cellular automata. Int J Geogr Inf Sci 27(10):2043–2059

Li Y, Gong JH, Liu H et al (2015) Real-time flood simulations using CA model driven by dynamic observation data. Int J Geogr Inf Sci 29(4):523–535

Lin H, Huang FR, Lu GN (2009) Development of virtual geographic environments and the new initiative in experimental geography. Scientia Geographica Sinica 64(1):7–20

Lin H, Chen M, Lu GN (2012) Virtual Geographic Environments—a workspace for computer-aided geographic experiments. Ann Assoc Am Geogr 103(3):465–482

Lin H, Chen M, Lu GN et al (2013) Virtual Geographic Environments (VGEs): a New Generation of Geographic Analysis Tool. Earth Sci Rev 126:74–84

Liu SK, Li XP, Li SG, Yu TY (1991) Numerical simulation of flood routing in the Xiaoqinghe flood plain. Adv Water Sci 2(3):188–193 **(in Chinese)**

Lu GN (2011) Geographic analysis-oriented virtual geographic environment: framework, structure and functions. Sci China Ser D Earth Sci 54(5):733–743

Mackinder HJ (1987) On the scope and methods of geography. Proc R Geogr Soc Mon Rec Geogr 9(3):141–174

Matthews JA, Herbert DT (2008) Geography: a very short introduction. Oxford University Press, New York

Ministry of water Resources of China (1995a) Test regulation for model of river (SL 99-95). China Water Power Press, Beijing **(in Chinese)**

Ministry of water Resources of China (1995b) Test regulation for normal hydraulic model (SL 156-165-95). China Water Power Press, Beijing **(in Chinese)**

Ramasundaram V, Grunwald S, Mangeot A, Comerford N, Bliss C (2005) Development of an environmental virtual field laboratory. Comput Educ 45(1):21–34

Rinaldi PR, Dalponte DD, Vénere MJ, Clausse A (2007) Cellular automata algorithm for simulation of surface flows in large plains. Simul Model Pract Theory 15(3):315–327

Rink K, Scheuermann G, Kolditz O (2014) Visualisation in environmental sciences. Environ Earth Sci 72(10):3749–3751

Soulis KX (2013) Development of a simplified grid cells ordering method facilitating GIS-based spatially distributed hydrological modeling. Comput Geosci 54:160–163

Torrens PM (2009) Process models and next-generation geographic information technology (GIS best practices: essays on geography and GIS, vol 2, pp 63–75). ESRI Press, Redlands

Van Der Knijff JM, Younis J, De Roo APJ (2010) LISFLOOD: a GIS-based distributed model for river basin scale water balance and flood simulation. Int J Geogr Inf Sci 24(2):189–212

Wang B, Zhou X, Zhu J (2000) Data assimilation and its applications. Proc Nat Acad Sci 97(21):11143–11144

Zhang Y, Li X, Liu X, Qiao J (2011) The CA model based on data assimilation. J Remote Sens 15(3):475–491