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Resilient planning optimization through spatially explicit, Bi-directional sociohydrological modeling

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ABSTRACT

Stormwater runoff is one critical urban issue that exemplifies the complexity in coupling human and natural systems. Innumerable studies have described and assessed the hydrological responses that result from land-use changes through a 'post land use change' hydrological analysis. Complex systems theory, however, suggests that the urban and ecological systems operate as an intertwined whole. This means that typical one-directional analysis can miss critical components of a bi-directional sociohydrological process. In addition, there is a difference in physical scales between hydrological analysis and policymaking that is often left unresolved. Typical hydrological models are limited to a watershed and are not easily applied to policymaking that is generally demarcated by a political boundary. These types of models also lack the spatial explicitness needed for physical design responses. To address these issues, we develop an integrated, finely scaled, spatially explicit socio-hydrological modeling system. The coupled land use/stormwater model projects and assesses bi-directional sociohydrological impacts to changing land uses. We apply and test the system in McHenry County, Illinois, by modeling three scenarios to the year 2045. The results show that residential and commercial developments exhibit different responses to hydrological variables, resulting in varying patterns of land use locational choices. We also find that there is a conflict between developmental preferences that prefer to be located near water (housing) and those that prefer to be located away from runoff-prone water areas (commercial land uses). Our bi-directional modeling system simulates cell-to-cell interactions to produce quantifiable and practically useful outputs. The output for McHenry County, Illinois, includes specific, locational information on how to optimize developmental regulations in response to the contradictory developmental preferences and, more importantly, how to live with runoff in the context of resilience. This research supports the need for cell-based forward-looking modeling to better understand complex urban systems and strategically establish a resilient built environment.

1. Introduction

One of the major challenges in plan-making for urban resilience is dealing with the deep uncertainty inherent in urban systems (Alberti, 2017; Comfort et al., 2001). While growth plans are intended to manage or abate a wide array of negative impacts on the built environment, such as loss of biodiversity, air pollution, or social inequity, once implemented, they many times fail to achieve their intended goals due to an inability to assess the complex interactions in urban systems. These complex interactions evolve as cities grow over both time and space with dynamic forces that contribute to an uncertain future and a slew of unintended consequences that challenge the resilience of both ecological and human systems. In order to achieve some semblance of resilience (defined as "the capacity of a system to absorb disturbance and reorganize while undergoing change" by Walker et al., 2004), it is critical that these system uncertainties be addressed. One approach is to encourage multi-scalar and multi-disciplinary decision-making that can help promote a broader dialogue and engage a broader understanding of resilient (sustainable) urban management (Deal et al., 2017). Such efforts need support from by novel analytical methods that can assess and evaluate the dynamic interactions between human and natural functions. These complex approaches however, must also be accessible to stakeholders and practitioners (Alberti, 2017; Deal et al., 2017; Kwak et al., 2021). This study attempts to link the complex interactions in

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urban and ecological systems to planning and policymaking in order to affect more resilient outcomes.

Stormwater runoff is one critical urban issue that exemplifies the complexity of human and natural systems coupling. Intensive urbanization across the globe has had great impacts on our watershed environments. The land-use changes (LUC) inherent in this urbanization have significantly altered hydrological processes, such as infiltration and evapotranspiration. The literature on the impacts of LUC on hydrological processes suggests that it plays an important role in assessing and projecting the consequences of anthropogenic activities (Kalantari et al., 2019; Li et al., 2018). Innumerable studies have conducted simulated hydrological responses to urban LUC due to economic activity or societal interactions (Islam et al., 2018; Stefanova et al., 2019). For example, Sunde et al. (2016) forecast streamflow responses for three urban development scenarios in the Hinkson Creek watershed in Missouri, U.S. They first project future urbanization patterns using the Imperviousness Change Analysis Tool (I-CAT) and estimate hydrological responses of the scenarios by using the Soil Water Assessment Tool (SWAT). Similarly, Akhter et al. (2016) investigate the hydrological responses in the Myponga watershed, Australia, as results of LUC scenarios by running Personal Computer Stormwater Management Model (PCSWMM). Kalantari et al. (2019) develop an integrated model that accounts for socioeconomic changes (e.g., population and employment growth) and hydrological responses for the Tyresån watershed in Stockholm, Sweden. They claim the importance of model integration to reveal the impacts of urbanization on hydrological conditions and the importance of feedback processes in modeling to support decision making. Similarly, Islam et al. (2018) emphasize testing multiple socioeconomic scenarios to simulate hydrological impacts and assess future risks. Most of these sociohydrology studies however, focus on one-directional impacts – the effects of changing land use on hydrological systems, and many of them conduct simulations and explore the impacts at a watershed scale.

We contend that one-directional sociohydrological analysis can miss critical components of the interrelations between LUC and hydrology. Complex systems theory suggests that these urban/eco - systems are interconnected and operate as an intertwined whole (Alberti, 2017; Batty, 2007). Especially in the context of resilience, understanding their dynamics is critical to a sensible and adaptive response (Deal et al., 2017). Paradoxically, a proximity to water is generally appreciated by households (Doss and Taff, 1996; Orford, 2002), even though this proximity may have negative effects during times of high volume runoff (especially along streams and rivers). It is, therefore, likely to expect that runoff will not only be affected by LUC, but that the spatial patterns of LUC will also be affected by runoff. To date, there is little evidence of these 'bi-directional' impacts in the literature. We suggest that understanding the bidirectionality of sociohydrology both spatially and temporally can support resilient water resource management planning and policy.

Another issue in policymaking stems from the difference in physical scales between modeling and decision-making. While most hydrological simulations are conducted at a watershed scale, development policies are demarcated by political boundaries – which very rarely follow watershed divisions. Simulations limited to an urban area therefore, cannot be easily applied to watershed scales and likewise, simulations of watershed scales are difficult to transpose to real-world collaborative, political decision-making practices. In addition, if the outputs lack spatial explicitness and produce only non-spatial data (hydrographs for example), turning the findings into physical design applications may become a challenging task; the identification of specific locations to intervene for example. The scale dichotomy can also cause difficulty in correctly applying the resulting information to planning and policymaking (Boongaling et al., 2018). Ward (2009) notes that such difficulty weakens policymakers' confidence in watershed-scaled assessments. Margerum and Whitall (2004) raise concerns about potential dilemmas in water management decision-making between different interests and different scales of analysis. They note that local stakeholder groups may not consider watershed-wide effects but look only at the fine scales within their community boundary. This gap between modeling and real-world applications suggests scalable, spatially explicit analytical approaches may be needed to demonstrate the dynamic interactions in sociohydrological systems and at the same time, produce information useful and applicable across multiple scales.

In this paper, we examine the bi-directional impacts of land development location-choices and changes in surface runoff. We analyze multiple scenario simulations that can be used for comparisons and explore their physical applications for policymaking. To do this, an integrated, spatially explicit sociohydrological modeling system that couples the Gridded Surface Subsurface Hydrologic Analysis (GSSHA) and the Land-use Evaluation and impact Assessment Model (LEAM) is applied to McHenry County, Illinois. The aim of this integration is not accurate predictions of urban environmental changes nor the testing of model performance but is focused on illustrating the missed opportunities for (re)development when sociohydrological resilience is taken into account.

The results of our integrated modeling system are simulation outcomes in cell-based raster maps at a 30m $\times$ 30m scale and demarcated by a political boundary (McHenry County). We use this region as our case study area to examine the following questions: Q1) What are the bi-directional impacts of runoff and LUC? And what are some of the complex and nonlinear interrelations for forecasting potential futures using this bi-directional approach? Q2) What are the novel findings produced by the approach? Q3) How can spatially explicit outcomes be utilized to practically optimize design or developmental regulations for resilient outcomes?

To address these questions, this paper is organized as follows. First, we review the existing literature to discuss the relations between runoff and urban growth. We use this review to introduce the models. We then outline our methods for developing a coupled modeling system and its application to three scenarios. We examine their bi-directional interrelationship with a focus on location-choices of land development in McHenry County. In this process, model validation and calibration approaches are also discussed. We present hydrological simulation and LUC projection results under the different scenarios and compare the outcomes. We discuss the implications of the modeling outcomes in terms of growth and runoff management and the benefits of spatially explicit outcomes for physical design and policy applications. The limitations of this study are also presented. Finally, we conclude this paper by summarizing its contributions to the sociohydrology literature.

2. Literature review and model selection

2.1. Relationships between urban growth and runoff quantity

Current projections show that unfavorable consequences from urban growth are being exacerbated by an incremental increase in urban population (United Nations, 2018). These increasing population trends have accelerated the intensive conversion of natural land to built-up, urbanized lands that have exponentially more mass and less perviousness (Kwak et al., 2020; Xu, 2010). Stormwater runoff is influenced by a number of interconnected biophysical factors (e.g., precipitation trends and land-use change) that are hard to predict due to their uncertainty, complexity, and dynamic nature (Abdulkareem et al., 2019). In urban areas where growth trends continue to accelerate the increase in surface roughness, decrease in surface imperviousness, and removal of vegetation with nonlinear patterning, there is a great need to generate adequate information on long-term runoff dynamics for sustainable management (Abdul-Aziz and Al-Amin, 2016).

The key advantages of technological advances in modeling have led to a broad discussion of the dynamic relationships between LUC and stormwater runoff. Many studies have examined the impact of urbanization on stormwater runoff by using various models and found important implications (Kalantari et al., 2019; Paule-Mercado et al., 2017; Saleh et al., 2019). Abdul-Aziz and Al-Amin (2016) conduct sensitivity analyses of potential hydrological responses in the Miami River Basin of Florida by using SWMM (Storm Water Management Model). Their findings show that surface imperviousness and roughness have a more dominant influence on runoff than slope and that LUC from open lands to commercial land-uses have the largest change in runoff volume, followed by LUC to industrials and to residentials. Zhang et al. (2015) examine the spatiotemporal correlations between surface run-off coefficient and LUC in the process of urbanization by utilizing the L-THIA (Long-term Hydrologic Impact Assessment) model. They compare runoff across 32 towns in Dongguan, China and find that runoff severity can be varied by different socioeconomic contexts. Li et al. (2018) similarly use the curve number method to assess the impact of urbanization on runoff in the Shenyang urban area, China. They further investigate the (auto)correlations by applying the Moran's I method and demonstrate that flooding hazards (high-high clusters) were concentrated in the urban center.

Many studies have stressed the significance of the impacts of urban growth (LUC) on hydrological systems by employing various simulation models and methods (Choi and Deal, 2008; Sharif et al., 2017; Suribabu and Bhaskar, 2015; Zhang et al., 2015). These one-directional impacts have been well documented in the sociohydrology literature (Kalantari et al., 2019; Li et al., 2018; Stefanova et al., 2019). The general focus of these studies are speedy recovery, damage prevention, and system control, targeting a runoff-controlled state as optimal (Liao, 2012). Communities that are dependent on such approaches cannot be resilient to runoff but resistant to it (Liao, 2012). When systems are suppressed to promote stability, they lose resilience (Holling and Meffe, 1996). Runoff is a dynamic process, especially when considered in dynamically changing urban areas so that the target state for stormwater management is likely to change over time. Therefore, building resilience in urban runoff systems should essentially be a process of adaptation for "living with" changes rather than controlling or fighting to maintain the status quo (Folke, 2006; Liao, 2012). To our knowledge, few studies have examined the spatiotemporal bi-directional impacts concerning "how we live with" changes in development and hydrology. This study argues the necessity for exploring the opposite directional impacts (hydrological impact on LUC) and the bi-directional impacts (between runoff and LUC) for resilient growth management.

2.2. Cell-based scalable models

The Gridded Surface Subsurface Hydrologic Analysis (GSSHA). A number of hydrological models have been developed for different purposes and scales and have been widely applied to various urban and natural contexts (Akhter et al., 2016; Boongaling et al., 2018; Marsik and Waylen, 2006; Sharif et al., 2017). The important ability in hydrological modeling is to assess the full range of potential runoff responses to a number of scenarios for extended periods (Frakes and Yu, 1999; Mohamed et al., 2020). The models available for this ability can be broadly classified into two categories: 1) lumped models and 2) distributed models. Lumped models produce hydrological average variations within an individual (sub)watershed as a single unit, whereas distributed models subdivide a (sub)watershed into particular spatial grids (cells). While currently lumped models are more widely used because of their simpler setting and low computational cost, fully distributed models, such as GSSHA, are gaining much attention with the growing availability and accessibility of data (Moore et al., 2017; Sharif et al., 2017). Distributed models have the ability not to be spatially limited in gauged watersheds but to spatially predict runoff variability responding to spatiotemporal dynamics (Chintalapudi et al., 2017; Ocio et al., 2019; Smith et al., 2004).

The selection of an appropriate model among the numerous existing ones should be made carefully. GSSHA, which is capable of illustrating hydrological impacts spatially at multiple scales (Downer and Ogden, 2006), is chosen for this study because we explore the spatiotemporal dynamics of LUC and runoff conditions and produce scalable spatially-explicit outputs. GSSHA is known for the highest performance in accuracy (Borah and Weist, 2008), and its comprehensive abilities make it applicable to long-term simulations taking account into urban growth (Downer and Ogden, 2004; Moore et al., 2017). Also, since the physical attributes of land-use, topography, and soil are greatly determinant factors in hydrological responses, GSSHA, which allows input of spatial datasets at a fine-scale, better performs than lumped models especially when it comes to urban hydrology that contains greater spatial variability (Downer and Ogden, 2006; Sharif et al., 2017).

The Land-use Evolution and Impact Assessment Model (LEAM). LEAM is a dynamic spatial model that projects LUC based on dynamic relationships between various socioeconomic and biophysical factors, such as population, landforms, and transportation networks. In the model, development probabilities are computed by travel time-based accessibility to attractors (e.g., population centers) that determine the location-choice of the development in a gravity-type function in which the attraction power decays by distances. LEAM generates sequential land-use maps at a fine scale (30m × 30m), answering scenario-based 'what-if' and 'so-what' questions. Detailed modeling descriptions are noted in our previous LEAM work (see (Chen et al., 2021; Deal, 2001; Pan et al., 2019a)) and also introduced in the Methods section.

LEAM has been utilized to test various policy scenarios for different cities and regions to improve its practicality and has been coupled with various models to improve its scalability and functionality as an integrative Planning Support Systems (PSS) tool. REIM (Regional Input-output Model) is one of the representatives synthesized with LEAM for investigating sophisticated interactions between LUC and socioeconomic projections and assessing their impacts (Chen et al., 2021; Pan et al., 2019b). There also have been several attempts to integrate hydrological models with LEAM to predict hydrological consequences in response to growth scenarios. For example, Choi and Deal (2008) use a semi-distributed model (HSPF; Hydrological Simulation Program—Fortran) for the Kishwaukee River basin in Illinois.

Cell-based model coupling. Mainly because of high computational time and demand and model complexity, a few fully distributed hydrological models have been utilized (Marsik and Waylen, 2006; Ocio et al., 2019) and integrated with spatial land-use projection models. We claim that integrating cell-based spatial models that are free from the physical scale issues can play an important role in making complex simulations, which are often considered "rocket-science," useful and accessible to practitioners. Both GSSHA and LEAM are spatially explicit models that allow for spatiotemporal assessment of dynamic interrelations in sociohydrological systems and are able to generate graphically understandable visual maps with high flexibility of their uses (Furl et al., 2018; Kwak et al., 2021; Pan et al., 2018; Sharif et al., 2010).

3. Methods

3.1. Study area

Situated in Chicago Metropolitan Area and located 30 km west of Lake Michigan, McHenry County is home to around 300 thousand people with a total area of 1,582km2. It has experienced the pressure of (sub)urbanization, especially on the southern and eastern portions of the county (Fig. 1). The 2016 NLCD (National Land-Cover Dataset) indicates that row crops –agricultural use, is the predominant land-use covering 48.3% of the total area, followed by residentials (18.7%) and forestry (10.9%). Along the Kishwaukee River and the North Fox River that flows through the county and around Crystal Lake, flooding has been the most severe weather event affecting the region. Projections of an increase in precipitation signify that the risk of flooding is expected to increase, causing significant disruption with residents and damages to infrastructures. The increasing risk can negatively affect the quality of life

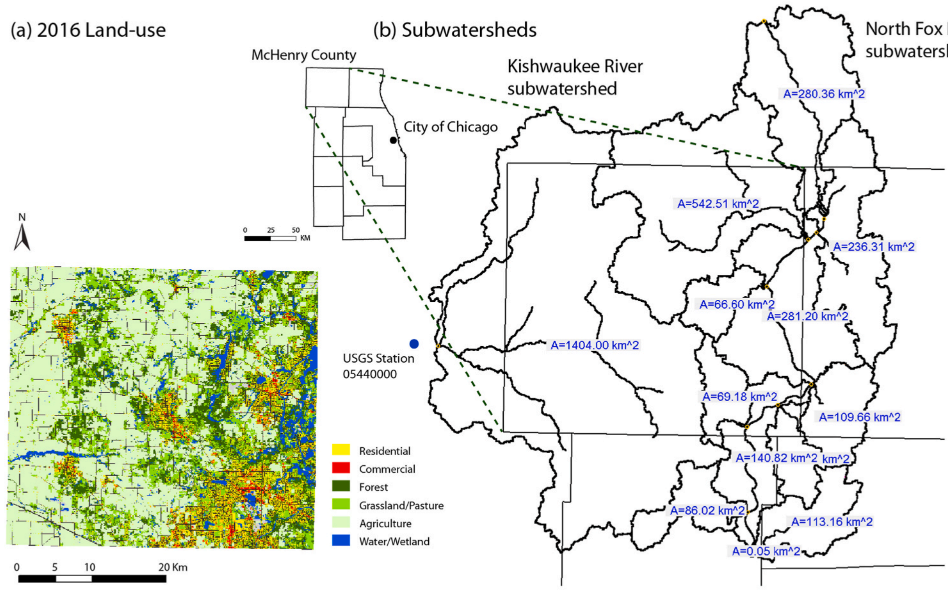

Fig. 1. 2016 land-use in McHenry County and subwatersheds crossing the region.

and the spatial patterns of growth.

3.2. Overview of the model integration process

The coupled modeling system is illustrated in Fig. 2. The system has been developed under an assumption that the patterns of runoff affect the location-choices of land development and has been processed in the following interactive steps. First, hydrological simulations for the two subwatersheds are conducted by GSSHA with the initial-run year land-use dataset. Second, two simulation raster outputs are merged and converted into a LEAM input variable. LEAM uses attraction values on a finely scaled (30m × 30m) lattice as input variables that measure the accessibility to amenities of interest. The LEAM attraction is described in a later section in details. Third, LUC are forecasted within the political boundary of McHenry County for the second-run year by LEAM based on the Chicago region's population and employment projections (Chicago Metropolitan Agency for Planning, 2018). The LUC projection in which hydrological conditions are taken into consideration depicts the impact of runoff on the location-choices of land development. Fourth, in turn, the projection result is fed back to GSSHA as a land-use dataset of the second-run year in order to simulate the impact of LUC on the regional hydrology. Fifth, this feedback process is iterated until the GSSHA-LEAM model running reaches the target (final-run) year.

As a dynamic process, the proposed framework enables an analysis of a wide range of scenario-based futures by changing model settings or changing the interval of model runs. For example, changing the precipitation inputs in GSSHA allows testing climate change scenarios, and changing socioeconomic projection inputs or setting different "no-growth" zones in LEAM allows comparing LUC outcomes under different growth scenarios. Also, testing multiple intervals of model runs can help policymakers capture an optimal interval to update a growth policy to adaptively respond to runoff issues.

Three counterfactual simulation scenarios are established in this study. The first one is a business-as-usual (BAU) that simulates one-directional impacts in a typical way. This scenario assumes that policymakers generate a 30-year long-term growth plan based on the current developmental patterns and trends and keep the plan with no modification from 2016 to 2045. The effects of runoff on future development are not considered, but proximity to water (**Supplementary Materials)** is instead included as an environmental factor in projecting future growth. The second scenario is runoff management without monitoring (RXM). This scenario is basically under the same assumption as the BAU scenario (no modification to 2045). Yet, the interrelations between runoff and LUC are taken into consideration, which means that

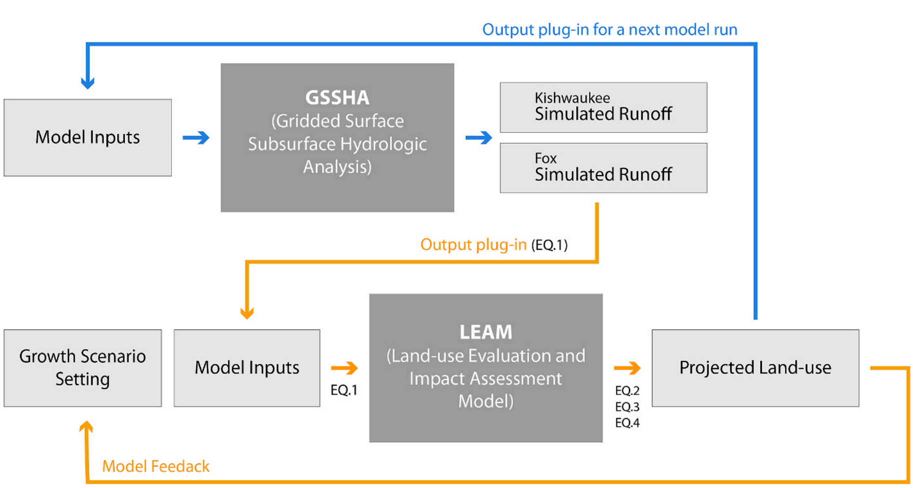

Fig. 2. A Framework of Model Integration. Blue lines represent the process of GSSHA, and orange lines represent the process of LEAM. An output from each model is fed back to the other. The final land-use projection output from LEAM can be used to establish alternative growth scenarios. In the LEAM modeling linkage, corresponding equation numbers are given and represented in section 3.4. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

a spatial runoff result from GSSHA is included in projecting future development. The last scenario is runoff management with monitoring (RWM), where policymakers keep monitoring runoff distributions over the region and update the development plan accordingly every 10 years. This scenario assumes that flooding is continuously one of the most concerning issues in McHenry County affecting the spatial patterning of land development, and policymakers, therefore, try to deal with the issues by adaptively deploying new developments. An overview of the modeling process for the three scenarios is displayed in Fig. 3 and Table 1.

BAU scenario consists of a general set of land-use variables (socio-economic and environmental variables) while RXM and RWM scenarios include an alternative runoff variable, resulted from GSSHA. $f()_t$ refers to the logistic-based function of projecting land-use P at time step t. Note that the base year is 2016 ($t = 1$). $g()$ is the function for the GSSHA-LEAM model iteration, described in Fig. 3.

3.3. GSSHA model set-up

The GGSHA model set up follows the flowchart displayed in Fig. 4. Two subwatersheds flowing through McHenry County (the Kishwaukee River subwatershed and the North Fox River subwatershed, shown in Fig. 1) are first delineated based on the 1/3 arc second (approximately, 10m) DEM dataset retrieved from the U.S. Geology Survey. In the model, we use cleaned NLCD land-use data for 2016 and the soil type data, obtained from the U.S. Department of Agriculture, to generate index maps (grid datasets with parameters). The model is set up for each watershed on a 30m grid cell to match with the spatial unit of LEAM, and each watershed simulation is conducted separately. The stream channels in each watershed are smoothed manually to control some of the adverse (negative) channel slope resulting from errors in the DEM. A uniform trapezoidal channel profile is adopted for defining stream cross sections. The Alternative Direction Explicit (ADE) method, which is known for the most robust one (Downer and Ogden, 2006), is selected for overland flow routing, and the Green and Ampt with Redistribution (GAR) is selected to simulate the infiltration. The descriptions of ADE and GAR are not repeated here (see (Chintalapudi et al., 2017; Sharif et al., 2017)).

It should be noted that we use two different precipitation settings for the main simulations and the model calibration/validation, respectively. We apply a uniform precipitation (a historical record in Northern Illinois, obtained from the National Weather Service: https://www.weather.go) for the main runs. It is because predicting precipitation patterns spatiotemporally over 30 years is a subject outside of this study and this study does not seek to calculate runoff depths in high accuracy for particular storm events. We simulate maximum surface runoff depths to illustrate the relative intensity of runoff occurrence over the region. However, it does not mean that the model parameters do not need to be calibrated and validated. The model should perform reasonable accuracy in terms of its outcomes –spatial distributions of runoff depth. For the calibration and validation, the initial parameters were taken from the GSSHA manual (Downer and Ogden, 2006), and calibrated by comparing the resulting hydrographs with observed data at USGA gauging station 05440000 (Fig. 1) for a storm event on April 28th to May 7th in 2020. The observed rainfall data, measured at the five rain stations, were obtained from the Midwestern Regional Climate Center, and interpolated by using the Inverse Distance Weighted method. Then two additional storm events, including August 10th to 13th, 2020 and November 10th to 14th, 2020 were used to validate the model. Detailed descriptions of the calibration and validation processes (e.g., Nash-Sutcliff efficiency and RMSE) are documented in **Supplementary Materials**. The parameters applied in the GSSHA simulations are presented in Table 2.

Table 1
Scenario equations.

Scenarios	Descriptions
BAU (business-as-usual)	$P = f(a_1, a_2, a_3, a_{water})_t$
RXM (runoff management without monitoring)	$P = f(a_1, a_2, a_3, a_{GSSHA})_t$
RWM (runoff management with monitoring)	$P = \sum_{t=1}^{n} g(f(a_1, a_2, a_3, a_{GSSHA})_t)$

3.4. LEAM model set-up

LEAM computes the probability of land development considering a set of socioeconomic and biophysical drivers and allocates new residential or commercial land-uses on 30m cells that exhibit higher probabilities. The locations of future development are influenced by the spatial relations between the drivers, and the extent of development is determined by the official growth projections. The model drivers influencing the location choices of future development are defined as “attractors.” Attractors are comprised of cell-based attraction values that account for the accessibility from each cell to locations-of-influences, such as population centers, road networks, and runoff-prone areas, based on the shortest travel time (e.g., to population centers) or the shortest Euclidean distance (e.g., to runoff-prone areas). Putting it simply, the attraction values spatially and quantitatively illustrate people’s preferences in their location choices (e.g., people may prefer to live near urban centers with shorter travel time while they may not want to locate new development adjacent to runoff-prone areas) are measured by a gravity-like model as follows:

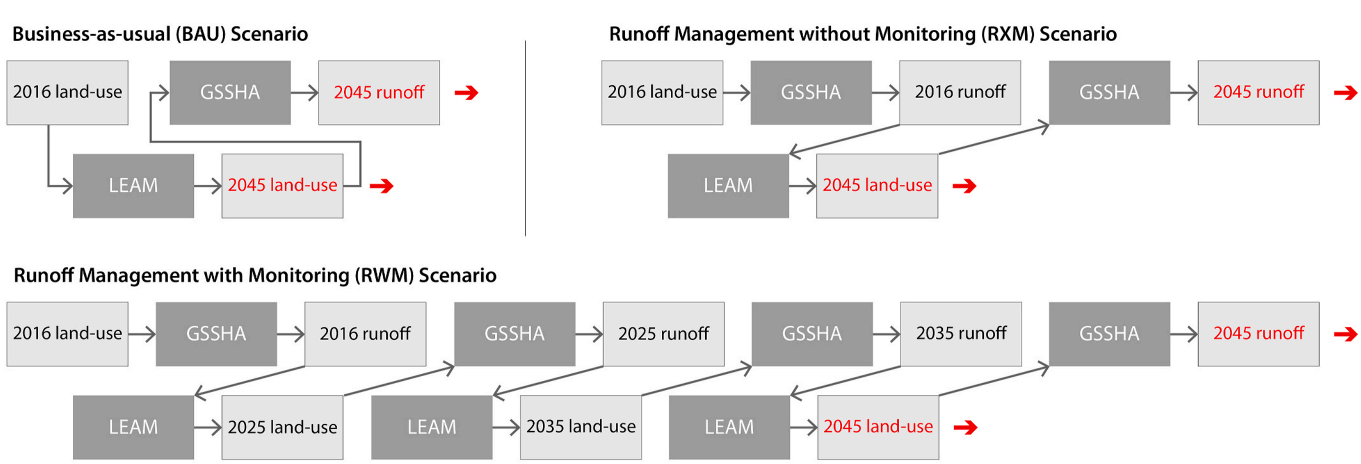

Fig. 3. Modeling processes for each scenario. The final simulation outputs for the year 2045 are highlighted in red. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

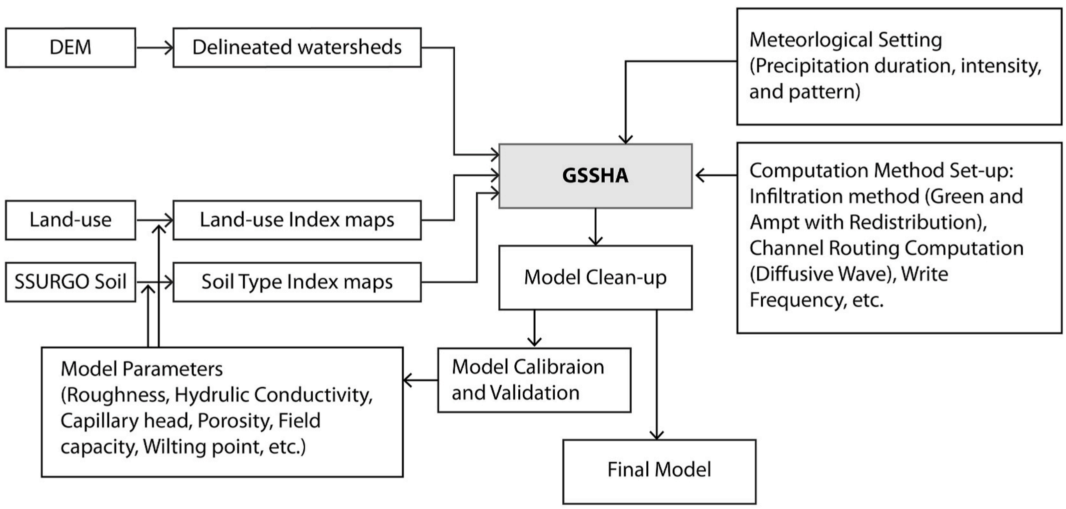

Fig. 4. A simplified modeling flowchart of GSSHA. Adapted from (Sharif et al., 2017).

Table 2
Calibrated GSSHA Parameters for Soil Types and Land-uses (corresponding land-use codes are noted).

Soil Texture/Major Land-use (code)	Manning's Roughness	Hydraulic Conductivity (cm/h)	Capillary Head (cm)	Porosity	Pore Distribution Index
Loam	–	1.32	8.89	0.463	0.252
Silty Clay Loam	–	0.2	27.3	0.471	0.177
Muck	–	0.06	31.63	0.475	0.165
Silt Loam	–	0.68	16.68	0.501	0.234
Residential (21)	0.011	–	–	–	–
Commercial (23)	0.012	–	–	–	–
Forest (42)	0.150	–	–	–	–
Agriculture (82)	0.035	–	–	–	–

$$a_{ik} = \sum_{j \in S_i} \frac{p_j}{d_{jk}} \quad \text{Eq. (1)}$$

where a_{ik} refers to the attraction value for the attractors type i on land-use cell k, S_i refers to set of attractors type i, p_j is the level of attractions (e.g., number of employment) on cell k, and d_{ik} is the travel time between jth attractor in S_i and cell k.

The socioeconomic attractors used as the LEAM drivers for this study are shown in Fig. 5.

The socioeconomic attractors illustrate how certain locations-of-influence attract new developments with the shortest travel time on the road networks. However, whether new developments are repelled from (or attracted to) runoff-prone spots should be measured by a different way since runoff events occur along streams not roads, and the way people perceive flooding events is likely pertaining to proximity (how physically close) rather than accessibility (how accessible). In this regard, we define "runoff inverse-attractor" that illustrates how storm-water runoff repels future developments by distances. From Equation (1), p_j refers to the depth of runoff on cell k, and d_{jk} refers to the Euclidean distance from jth depth cell to stream cell k. It should be noted that this process allows for conversion of 0 runoff depth values on streams or rivers, surrounded by high runoff depths, to high repellent

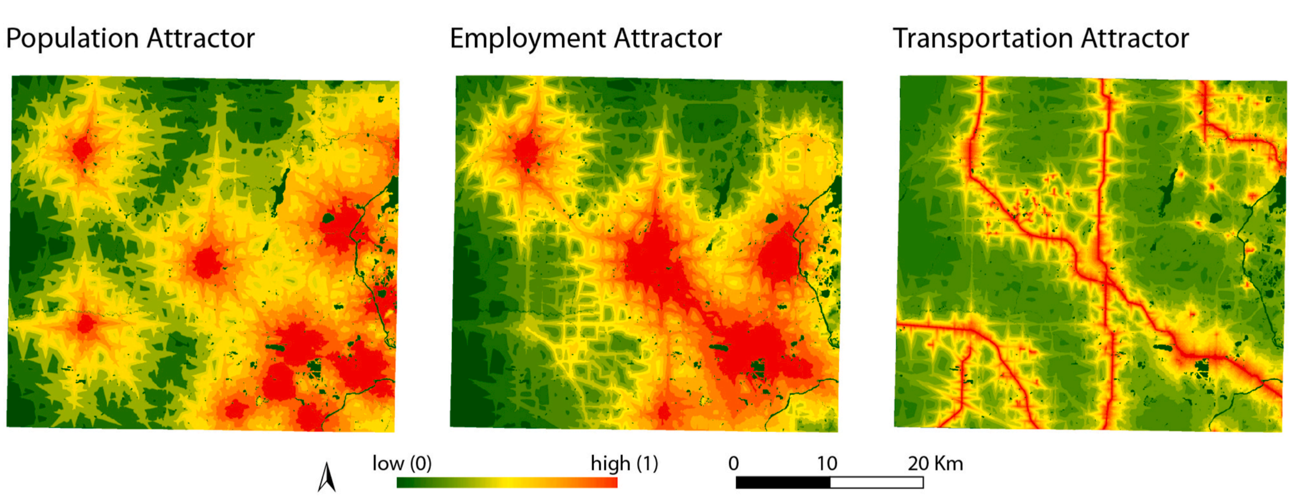

Fig. 5. Attractor maps for McHenry County based on the 2016 dataset. Warmer colors refer to higher attraction values, and greener ones indicate lower values. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

values because of the shortest distance. The maximum depths of surface runoff for 2016 are simulated by GSSAH for the two subwatersheds and converted to a "runoff inverse-attractor" within the political boundary of McHenry County by applying Equation (1), as shown in Fig. 6.

The model calculates the development probabilities at time step t applying modified logistic regression presented in Equations (2) and (3), and the model allocates new land-uses following Equation (4).

$$Z = \beta_0 + \beta_1 a_{(1,k)} + \beta_2 a_{(2,k)} + \beta_3 a_{(3,k)} + \beta_4 a_{(4,k,t)} \quad \text{Eq. (2)}$$

$$P_{(k,t)} = \frac{\exp(Z)}{1+\exp(Z)} \times \theta_{(k,\ t)} \times N_k \quad \text{Eq. (3)}$$

where $P_{(k,t)}$ refers to the development probability on land use cell k at time step t; $a_{(n,k)}$ is attraction value of population attractor a_1, employment attractor a_2, and transportation attractor a_3 on cell k, respectively; $a_{(4,j,t)}$ is a repellant value of runoff inverse-attractor at time step t, calculated by GSSHA and Eq (1), or is a Euclidean distance to water bodies for the BAU scenario; $\theta_{(k,\ t)}$ refers to stochastic perturbation representing unconsidered factors (White and Engelen, 1993) on cell k; N_k is a binary value of whether cell k is located inside (0), or outside (1) of "no-growth" zones such as Illinois protected areas.

$$D_{(k,\ t)} = \begin{cases} 1 & P_t' \leq P_{(k,t)} \\ 0 & P_t' > P_{(k,t)} \end{cases} \quad \text{Eq. (4)}$$

where $D_{(k,t)}$ represents whether cell k at time step t change to projected residential or commercial land-uses (1 for develop and 0 for not develop), P_t' is the minimum development probability value when selecting the number of cells in order which indicates the total growth demand specified by the official document at time step t, $P_{(k,t)}$ is a probability value on cell k.

4. Results

The relationship between potential development and accessibility to amenities is many times in a non-linear, dynamic form (Zhang et al., 2021). We run regressions to examine the dynamic relationships between the probabilities of future development and socioeconomic and hydrological attractors. We then simulate spatial patterns of LUC and runoff by the coupled GSSAH-LEAM model under three scenarios from 2016 to 2045. Different results between the scenarios are shown to prove the growth mechanisms associated with both socioeconomic and hydrological systems. Lastly, we spatially compare the results for a small city in the study region across the scenario to explore the impacts at a fine scale. We evaluate detailed spatial characteristics needed for physical applications that are hardly captured by regional-scale analyses.

4.1. Different effects of sociohydrological drivers on land development

Akaike Information Criterion (AIC) values are calculated to determine the relationship best describing how attractors (accessibility to locations of influence) drive land development in the study region. Fig. 7 displays the relationships between socioeconomic (population attractor, employment attractor, and transportation attractor) and hydrological (runoff inverse-attractor, and proximity to water) drivers and the probabilities of residential or commercial developments. In this graph, the horizontal axis is the accessibility to the locations of influence, measured by travel time and normalized to 0 and 1. The vertical axis represents the probability of a cell being developed to residential or commercial land uses (from its existing use). The line represents the growth trend associated with each attractor. The lowest AIC value models can be found in Table 3.

In general, both the probabilities of residential and commercial developments increase as the locations are closer to existing residential areas (higher population attraction values) and commercial areas (higher employment attraction values). This describes agglomeration effects that have been well documented in the land-use literature (Johansson and Quigley, 2003; Rosenthal and Strange, 2004). More specifically, the probability of residential development becomes exponential when the population attraction values are over 0.4 and the same trend appears for the commercial development when the employment attraction values are over 0.6. One notable difference between residential and commercial development is found in the relationships to

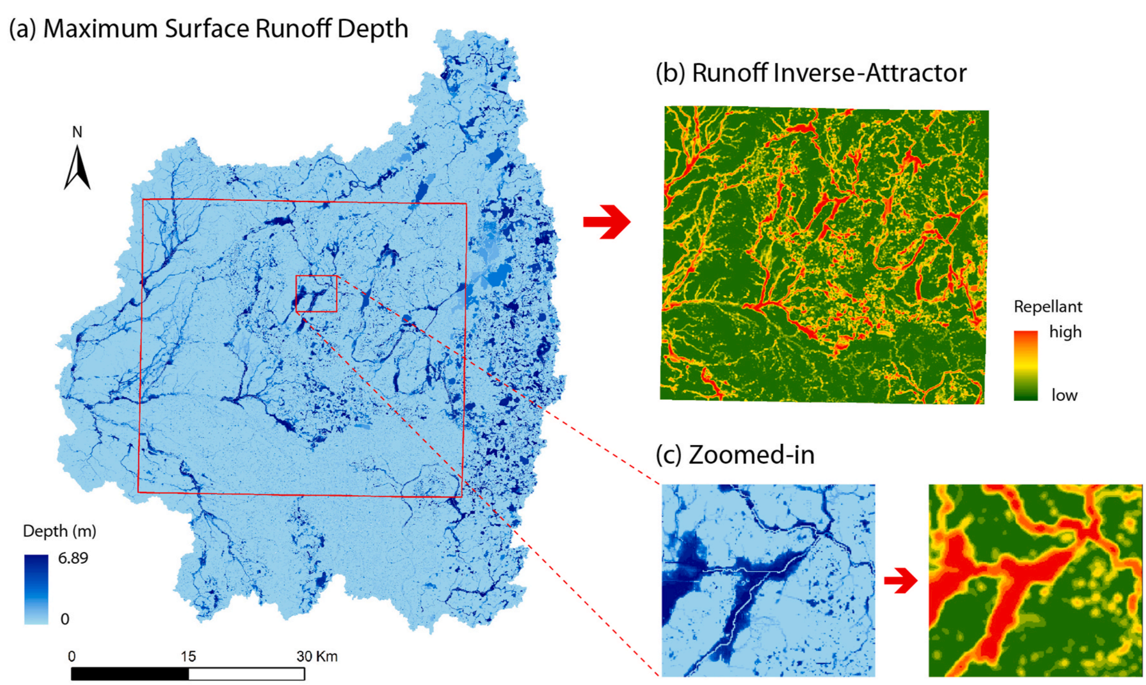

Fig. 6. (a) Maximum runoff depth simulated by GSSHA for the year 2016, (b) Runoff Inverse-Attractor, and (c) Zoomed-in maps to show the difference between (a) and (b).

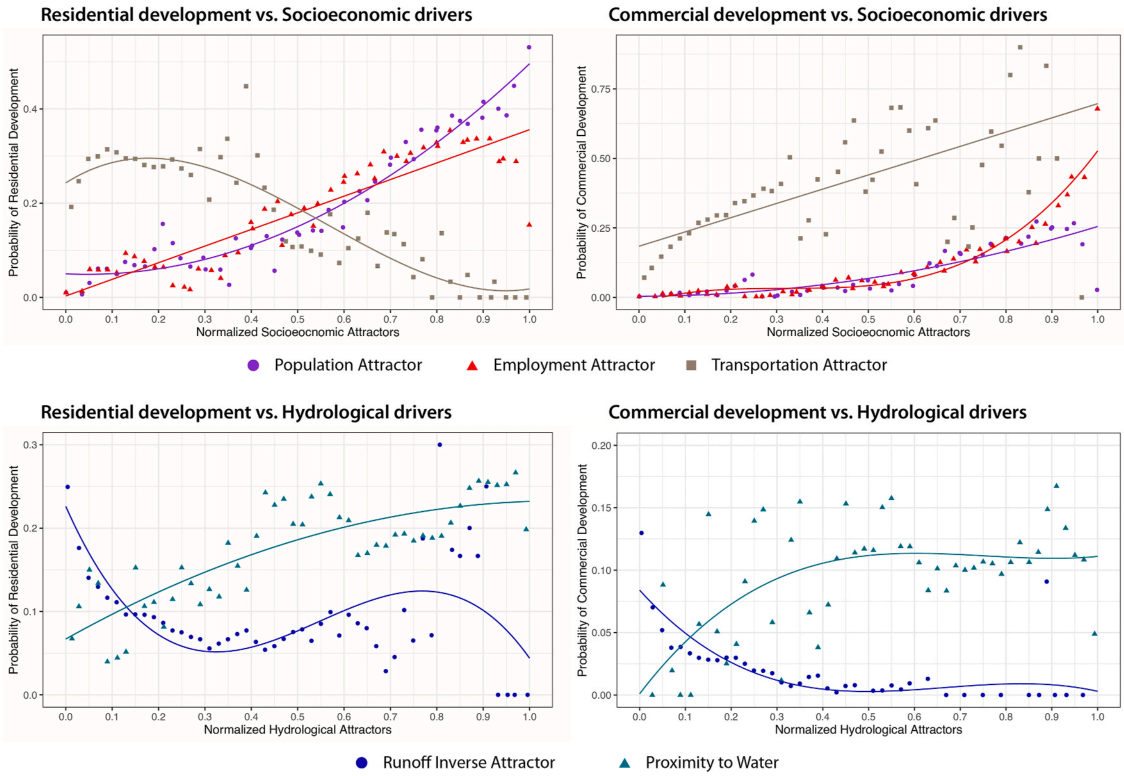

Fig. 7. Mapping relationships between probabilities of land-use occurrence in available lands (y-axis) and accessibility to attractors (x-axis) in McHenry County.

Table 3
Lowest AIC values for sociohydrological attractor variables.

Development type (DV)	Attractor variable (IV)	Best Model
Residential	Population	$y = 0.05 + 0.05x - 0.49x^2$
	Employment	$y = 0.35x$
	Road Network	$y = 0.24 + 0.63x - 2.07x^2 + 1.23x^3$
	Runoff	$y = 0.23 - 1.25x + 2.74x^2 - 1.68x^3$
	Water Proximity	$y = 0.07 + 0.31x - 0.15x^2$
Commercial	Population	$y = 0.01x + 0.25x^2$
	Employment	$y = -0.02 + 0.48x - 1.50x^2 + 1.56x^3$
	Road Network	$y = 0.18 + 0.51x$
	Runoff	$y = 0.08 - 0.41x + 0.65x^2 - 0.33x^3$
	Water Proximity	$y = 0.48x - 0.66x^2 + 0.29x^3$

All p-values are less than 0.001.

road networks (transportation attractor). A quadratic model describes how the accessibility to road networks steers residential location choice –residential development is only attracted by reasonable access to highways (attraction<0.2) while it does not favor being located in too close proximity due to noise, safety issues, or other possible concerns. This corresponds to our previous findings for other regions in Illinois (Chen et al., 2021; Pan et al., 2019a). On the other side, commercial development shows a monotonic increasing trend with the accessibility to road networks, which is explainable given that the development is highly related to the ease of distribution and supply of products.

The relationships between land developments and hydrological drivers show notable results. These relationships determine the difference in LUC projections between BAU, RXM, and RWM scenarios. The proximity to water appears highly attractive to both residential and commercial developments because water provides various sociocultural and environmental ecosystem services promoting human well-being (Keeler et al., 2012). For some big cities, negative relationships are often found, illustrating that water forcefully repels new developments due to higher property values in close proximity or zoning regulations (Pan et al., 2019a). However, people's preference for living or working closer to water (Doss and Taff, 1996; Orford, 2002) is evident in our results. It is possibly because McHenry County is a suburban region where housing prices less affect the location choices than highly urbanized areas, such as Chicago.

Residential development shows a complex relationship to the runoff inverse attractor (proximity to runoff-prone areas). As shown in the residential developmental trend associated with the accessibility to road networks, this quadratic curve demonstrates that residential location choices generally involve more complexity than commercial location choices. Considering the positive relationship with the proximity to water, this result suggests that attraction to water outweighs repellant from runoff when it reaches a certain level. In other words, people prefer to live near water even with runoff risk if they can have scenic water landscape. However, the probability of commercial development decreases exponentially as runoff vulnerability increases. Logically, this suggests that businesses are reluctant to take any risk of flood when deciding their locations, even with the preference for locating close to water.

Our results show that runoff vulnerability has a notable effect on location choices of land development. Given the previous findings that prove the effects of LUC on hydrological systems (Akhter et al., 2016; Li et al., 2018), this work validates our assumption that there are bi-directional impacts between changes in land-use and surface runoff. It also shows that hydrological responses drive residential and commercial developments differently.

4.2. Land-use projections under three scenarios

The probabilities of residential and commercial developments for McHenry County, estimated by applying Equation (2), are displayed in Fig. 8. Illustrating agglomeration effects, the development probabilities show that most new developments would occur near existing urban centers and sprawl toward fringe areas. No notable difference in developmental patterns is reported between projections considering runoff (Fig. 8a and **b**) and those not considering runoff (Fig. 8c and **d**). However, we find marked patterns of runoff with 0 values of the development probability on Fig. 8a and c, which exhibits that higher runoff risks repel land development. Fig. 8a displays slightly more sprawling patterns than Fig. 8b. This may suggest that there is more demand for residential development in fringe areas, causing sprawling, when an assessment of runoff vulnerability is incorporated in a development policy. This is counter intuitive. However, this is understandable given that a runoff-considered policy protects inner-city infill development on runoff-prone areas and diverts the growth demand further into outskirts. This is also explainable in that some fringe areas with a certain range of runoff risks along the Kishwaukee river or the Fox river attract residential development, likely because of reasonable proximity to water bodies, as shown in Fig. 7.

Based on our probability estimations, land-use changes from 2016 to 2045 for the three scenarios are forecasted and shown in Fig. 9. As described above, these projection results demonstrate that scenarios that mitigate urban exposure to potential runoff would result in more sprawling patterns of residential development. For instance, we find that more future residential land-uses are projected on the fringe areas of the city of Woodstock (the black circle in Fig. 9) under RXM scenario than the LUC allocations under BAU scenario. The spatiotemporal patterns of sprawl development over time can be seen in Fig. 9c.

4.3. Spatial comparison at a city level for physical applications

The city of McHenry, which is the county seat, is selected for the spatial comparisons of potential runoff exposure to provide information of detailed spatial characteristics that are hardly captured by larger-scale observations. Fig. 10 exhibits an overlay of projected new developments and maximum runoff depth ($\geq$0.5 m) in 2045 under each scenario, respectively. Not unexpectedly, the results present that BAU scenario, where the hydrological effects on LUC are not considered, result in the highest percentage of cells exposed to runoff (10.38%), followed by RXM scenario (6.29%) and RWM scenario (6.24%). The results demonstrate a benefit of hydrological assessment applied to urban growth management in terms of runoff exposure. In other words, it is anticipated that when new developments proceed without consciously avoiding potential runoff-prone areas, more new developments are likely to be exposed to runoff risk in the future because water bodies (the Fox River and the Boone Creek, situated in the city) are attractive to high-value residential development possibly because of with their scenic landscapes.

We also find that RWM scenario results in a better effect in growth management against surface runoff than RXM scenario. The difference in the exposure of new development to runoff risk (depth $\geq$0.5 m) between the two scenarios appears negligible, showing only 0.05% of the difference. However, we also find that property damage from runoff can be considerably reduced under RWM scenario. While the average runoff depth on the new development lands exposed to runoff risk is 1.44 m under RXM scenario, the depth under RWM scenario appears 1.08m. The most probable explanation is that RWM scenario successfully

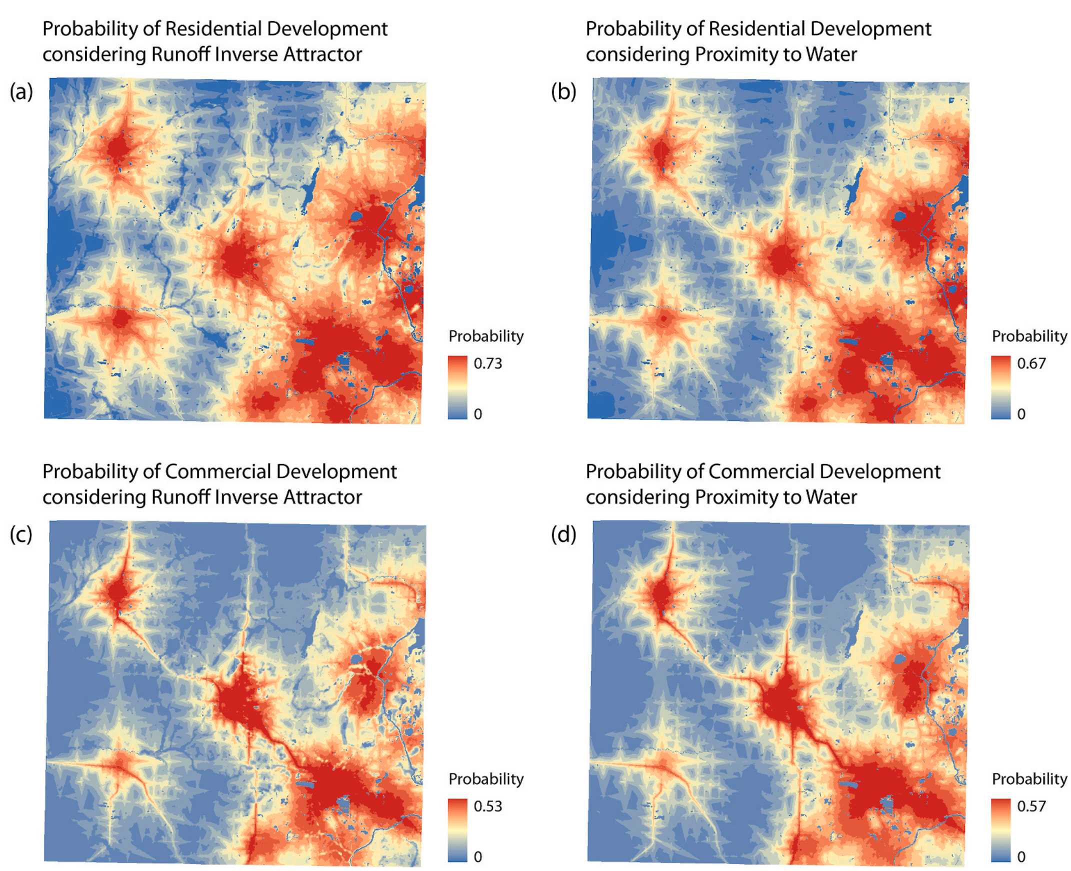

Fig. 8. Probability maps of residential and commercials development. (a) and (c) are the projection results where runoff configurations (GSSAH outputs) are considered, and (b) and (d) are the results where water proximity are considered. Warmer colors refer to higher probability of development while cooler colors refer to lower probability. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

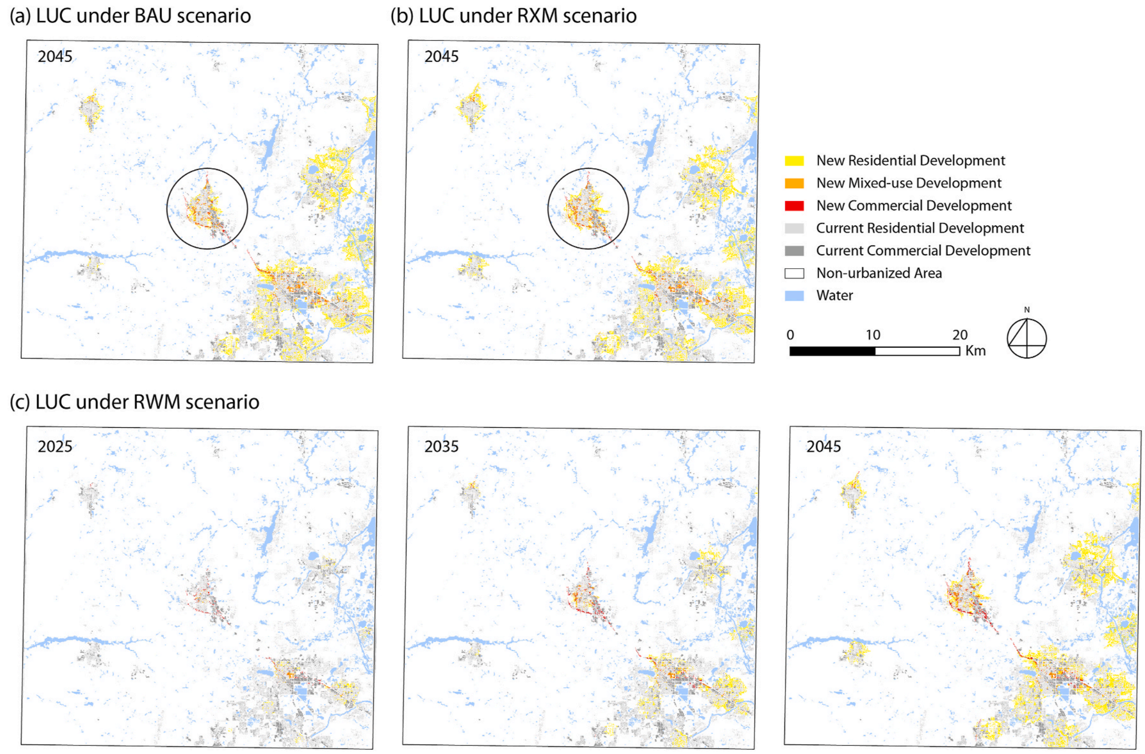

Fig. 9. Projected land use changes in McHenry County for the year 2045 under three scenarios. Yellow cells are new residential land-uses and red cells are new commercial cells. Orange cells represent mixed-use land-uses where new residential and commercial developments are projected to occur on the same cell locations. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

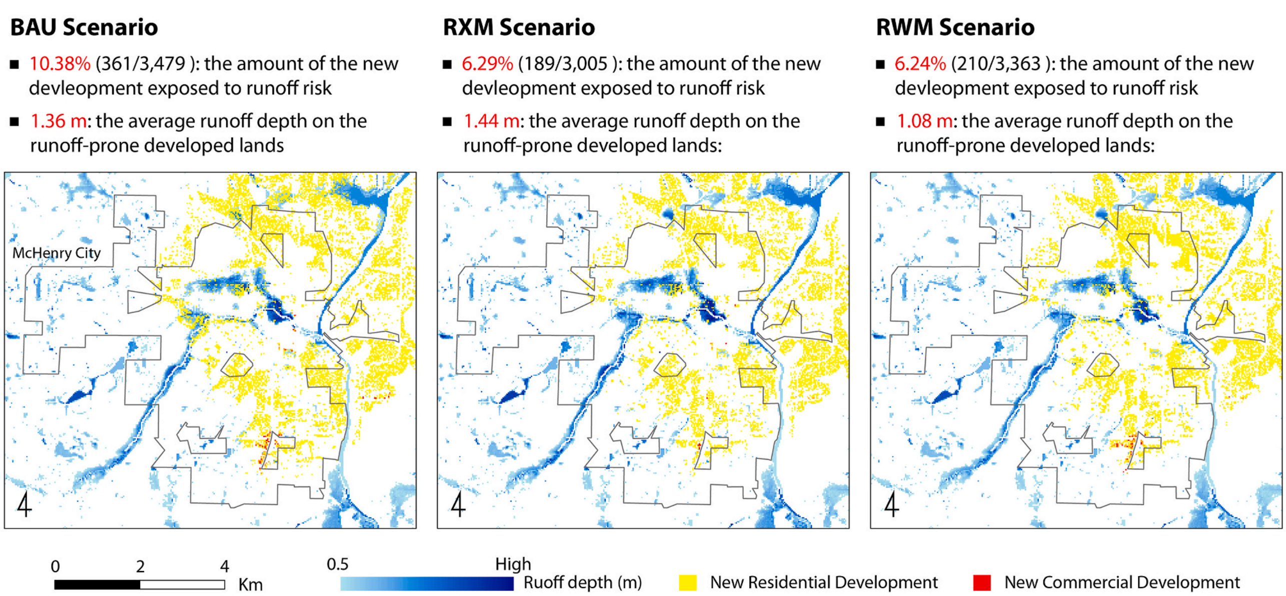

Fig. 10. Projected land-uses and runoff for the city of McHenry in 2045. Only runoff depth values over 0.5m are displayed. Note that highest values vary across the scenarios. The results indicate that RWM scenario show a better mitigation in terms of the number of exposed cells and the severity of runoff.

captures the bi-directional impacts over time so that helps location choices of land development avoid the areas that are highly prone to runoff.

In order to turn these findings into information for physical applications, more steps to examine how the bidirectional impacts work at the city (or smaller) level are required. From the results, we find seemingly contradictory preference in determining development locations –people prefer to live or work closer to water but farer away from runoff-prone areas, but those prone areas are generally around linear water bodies (creeks or rivers). Fig. 11 informs how this preference has physical and contextual implications. More specifically, this informs where the attraction to water and the repellent from water (runoff) occur and where developmental trends dramatically change by distance in the McHenry city. This contextual, city-level results appear quite different from the regional results, shown in Fig. 7. The probability of residential development largely increases as the cell locations move away from water, which is opposite to the regional results but is explainable given that most residential lands in the city are clustered in

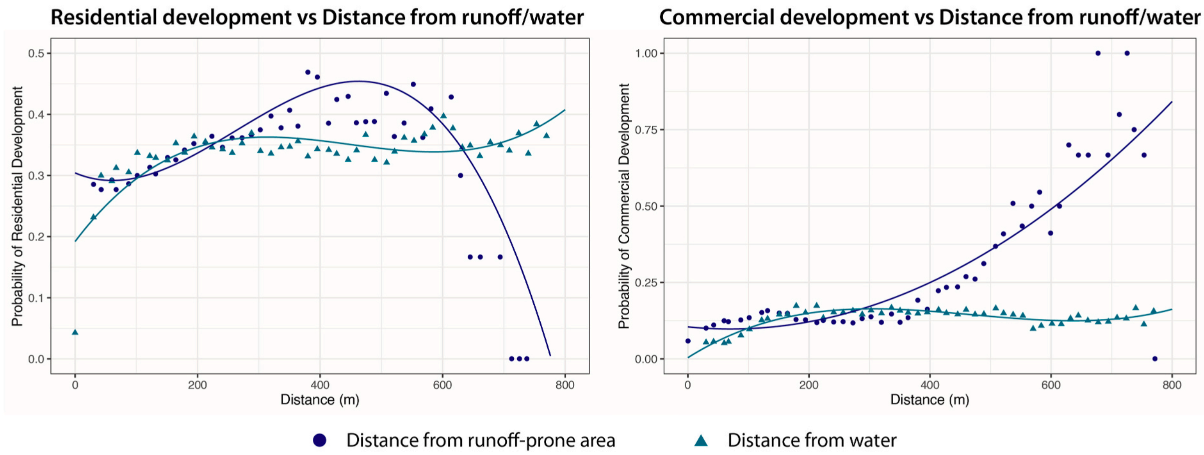

Fig. 11. Relationships between development probabilities to residential or commercial lands and distance from runoff-prone areas or water.

the city center. This suggests that scenic water landscape situated in outskirt of the city is not a determinant factor in location choices, compared with urban amenities situated in the city center. One notable finding is that water attracts residential development when lands are located between about 300m and 600m from water, which may suggest a preferable location range of the residents for living with water in the city. The relationship with distance from runoff shows complexity similar to the trend at the regional level but the graph delivers more explicit information that runoff vulnerability does not repel the development anymore when distance reaches a certain level (approximately 480m from runoff-prone areas). Commercial development in the city exhibits more drastic trends. Runoff strongly repels development, and the influence of water attraction appears marginal compared with that of runoff repellent. Most possibly due to agglomeration effect, commercial development is likely to take place closer to the city center, away from water.

We expect this local-scale result to significantly vary across cities and towns in the region. In a small town where residential lands are not clustered in its center, for example, scenic water landscapes may attract residential development like the regional results. In conjunction with the spatially explicit simulation outcomes (Fig. 10), our analyses help policymakers and practitioners specifically identify how and where physical interventions should be deployed at a community level. For example, in the city of McHenry, green infrastructure (GI) for stormwater management, such as a rain garden, can be suggested in the areas located between about 290m and 630m from the Fox River, providing GI services to the locals. Also, a "no-growth" area can be re-delineated considering '480m' – the distance that runoff vulnerability may start losing its influence to developmental location choice.

5. Discussion

Our results of potential changes in both land-use and surface runoff, projected by a coupled GSSHA-LEAM, demonstrate a substantial bi-directional relationship between socioeconomic and hydrological functions that most studies examining one-directional impacts (i.e., the effect of LUC on runoff) might have missed. We emphasize that the bi-directional impacts that this study explores can provide critical insight into growth management for urban resilience. Implications of this study are discussed with the following three points.

First, timely capturing potential surface runoff allows future developments to adaptively respond to increasing risks of runoff affected by LUC. The extent of development exposure to runoff can be reduced in part as land developments show a tendency to be repelled by high runoff vulnerability. This is especially important given the ecological resilience that is measured by the ability to adapt to potential dynamic states. Since we cannot accurately predict or forcibly prevent climate change or urban growth, building resilience in urban systems should essentially be a process of adaptation for "living with" changes rather than controlling or fighting (Folke, 2006; Liao, 2012). In this sense, this study does not suggest how to control the extent of urban growth or how to reduce the amount of surface runoff. Instead, this study allows future developments and runoff to occur in the way that they are supposed to do in response to changing demands, then seeks ways to adapt to the probable changes, and assesses the expected impacts. More specifically, we find that McHenry County is expected to face more sprawl patterns of land development if policymakers take into consideration the spatiotemporal patterns and severity of surface runoff in growth policymaking. In our results, the sprawling in McHenry County is neither a negative impact of population influx to be regulated nor a cause of stormwater runoff to be managed but a developmental trend that is naturally affected by the bi-directional responses. It is an adaptive response to "live with" runoff, mitigating the damage from it and meeting the developmental demand. Capturing the spatiotemporal configurations of potential runoff enables to plan new land developments timely without eroding the capacity of the sociohydrological system of the region.

Second, compared with conventional techniques (floodplain development regulations for example), our simulations of bi-directional impacts propose an alternative, spatially specific approach. Development regulations on floodplains (i.e., conservation areas), especially along rivers, are one of the effective ways to manage growth and prevent flood disasters. Such regulations aim to keep urban systems remain at an optimal state (no or minimized damage). It is much true that establishing larger no-growth zones can better protect communities from stormwater runoff or other natural disasters. However, this arguably conflicts with increasing developmental demands and preferences in their location choices. With socioeconomic growth, more urban land-uses are likely to occupy areas near water in the future because proximity to water attracts both residential and commercial developments. Yet, we find another significant implication that the location choices are repelled by the risk of runoff (although residential location choices show complexity). In short, people in McHenry County might prefer to live or work closer to water while keeping away from runoff-prone areas. Our sociohydrological simulations that account for this seemingly contradictory (but natural) preference can help understand how to balance developmental demands and preferences with hydrological responses. In other words, our spatially explicit projections can help optimize existing conservation areas in a way that supports human services while adapting to environmental processes instead of configuring zones for no-growth in a mass along floodplains.

Finally, the issue of scale is important in applying hydrological findings into planning and design projects (Boongaling et al., 2018;

Margerum and Whitall, 2004). It is also especially important when we operationalize such scientific information for resilience (Kwak et al., 2021). The lens that hydrological systems are typically viewed is macroscopic and cannot be readily applied to physical applications at the community level (Boongaling et al., 2018). Watershed-based models (i.e., lumped parameter models) are not compatible with land-use plans for a municipal boundary nor physical designs at a smaller scale. The ability to zoom-in with spatial explicitness across multiple scales is useful in identifying particular locations for intervention.

Still, several limitations should be addressed for possible improvement of this research. Although we emphasize the importance of accessibility of complex modeling systems in collaborative plan-making among stakeholders, scientists, and practitioners, GSSHA (or most existing fully distributed hydrological models) is too complex for easy use and has a high computational demand. This means that in order for the proposed coupled modeling system to be used practically in the real-world settings, expert interventions for model set-up and running are still required (LEAM has been developed as a user-driven Planning Support System (PSS) tool (http://leam.illinois.edu/)). Also, this study does not account for the hydrological effects of climate change. We instead simulate a maximum runoff depth by applying the historical precipitation record to the model to deal with potential effects. Additional scenarios with varying precipitation inputs will make this research more valuable and useful. Lastly, for physical applications, much finer visual outputs and contextual factors would be needed. For example, suitable sizes and types of green infrastructure to deal with social issues, such as ecosystem service inequality, or any possible negative impact on vulnerable groups cannot be determined with the information generated from this study, perhaps requiring additional contextual information.

6. Conclusions

This paper substantiates the argument that it is necessary to develop an integrated, cell-based dynamic model that is capable of assessing both anthropogenic and hydrological impacts in a spatially explicit way. Our results show that location choices of land development are affected by not only typical socioeconomic variables (e.g., population and employment) but also hydrological variables, and that those relationships appear to be nonlinear. The coupled GSSHA-LEAM system enables the exploration of bi-directional effects between LUC and runoff by iteratively coupling modeling inputs and outputs at a similar spatial scale (30m × 30m). Our projection results under the three scenarios represent that damages from runoff can be mitigated by taking into account and adjusting growth management policies in a timely manner (Q1). We also find that different land developments respond to hydrological changes differently, and that there is a conflict in developmental demand between being located near water and being located away from water. This provides an important insight that cannot be effectively captured by conventional 'one-directional' modeling processes (Q2). In terms of the utilization of this complex modeling system in policy-making, planning, and design, (Q3), we show that spatially explicit outcomes contain locational information needed for physical design and planning applications.

To date, fully distributed hydrological models such as GSSHA, have rarely been used due to high computational time and cost. However, this research attempts to underscore the advantages of using such models, especially given the optimization of physical applications at the policy level. And as computational efficiencies continue to increase these costs are likely to come down.

The GSSHA-LEAM system simulates fine-scaled cell-to-cell interactions produces spatial and quantifiable outputs with very specific, locational information. This can support questions of where to develop, where to avoid, and how those areas might change over time. Our finding can be used to spatially optimize existing development zoning regulations (e.g., no-growth zones on floodplains) in a way that corresponds to increasing developmental demands and adapts to changing hydrological systems.

This research will contribute to efforts to move toward more robust and resilient regional planning and design applications that take into account changing environmental and social conditions. In terms of methodologies, this paper examines bi-directional mechanisms in sociohydrological systems by constructing a cell-based and temporal dynamic model. In terms of applications, this paper converts complex modeling results into spatially explicit information that is useful to non-expert policymakers and practitioners. This research supports the need for cell-based forward-looking dynamic modeling to better understand potential sociohydrological interactions and strategically establish a resilient built environment.

Credit author statement

Yoonshin Kwak: Conceptualization, Methodology, Validation, Formal analysis. Investigation. Data Curation, Writing - Original Draft, Visualization. Funding acquisition. **Brian Deal:** Conceptualization, Writing - Review & Editing, Supervision. Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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