

Low Impact Development Measures Spatial Arrangement for Urban Flood Mitigation: An Exploratory Optimal Framework based on Source Tracking

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Abstract

Urban areas are vulnerable to fooding as a result of climate change and rapid urbanization and thus food losses are becoming increasingly severe. Low impact development (LID) measures are a storm management technique designed for controlling runoff in urban areas, which is critical for solving urban food hazard. Therefore, this study developed an exploratory simulation–optimization framework for the spatial arrangement of LID measures. The proposed framework begins by applying a numerical model to simulate hydrological and hydrodynamic processes during a storm event, and the urban food model coupled with the source tracking method was then used to identify the food source areas. Next, based on source tracking data, the LID investment in each catchment was determined using the inundation volume contribution ratio of the food source area (where most of the investment is required) to the food hazard area (where most of the fooding occurs). Finally, the resiliency and sustainability of diferent LID scenarios were evaluated using several diferent storm events in order to provide suggestions for fooding prediction and the decision-making process. The results of this study emphasized the importance of food source control. Furthermore, to quantitatively evaluate the impact of inundation volume transport between catchments on the efectiveness of LID measures, a regional relevance index (*RI*) was proposed to analyze the spatial connectivity between diferent regions. The simulation–optimization framework was applied to Haikou City, China, wherein the results indicated that LID measures in a spatial arrangement based on the source tracking method are a robust and resilient solution to food mitigation. This study demonstrates the novelty of combining the source tracking method and highlights the spatial connectivity between flood source areas and flood hazard areas.

Keywords Low impact development · Regional relevance · Source tracking · Spatial arrangement · Urban flood model

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1 Introduction

Hydrological responses are signifcantly afected by interactions between the temporal and spatial variability of rainfall, and watershed characteristics. These interactions are extremely pronounced in urban areas, where runoff generation is quick because of the high degree of impervious cover (Cristiano et al. [2019](#page-14-0)). Over the past few decades, due to climate change and rapid urbanization, urban fooding has become a global challenge (Li et al. [2017;](#page-15-0) Duan et al. [2016](#page-14-1); Kim et al. [2017](#page-15-1)). Several trends indicate that urban food hazard will only increase with time. An increase in extreme rainfall events, particularly high intensity and short duration rainfalls has been observed recently (Willems et al. [2012\)](#page-15-2). In addition, as urbanization is expanding to accommodate increasing populations, the transition of natural catchments into urbanized catchments causes urban food through reduced infltration (Becker [2018\)](#page-14-2). Furthermore, corresponding to the transformation of rural landscape into urban area, an obvious relationship between local micro-climates and urban areas has developed. In some cases, "urban heat island" increases rainfall volume in regions downwind of urban areas. Without interference, the damage caused by food globally may increase by up to a factor of 20 by the end of the century (Winsemius et al. [2016\)](#page-15-3).

Low impact development (LID) measures, which is a storm management and non-point source pollution treatment technique, was frst adopted in North America and New Zealand in the 1980s (Fletcher et al. [2014](#page-15-4)). It aims to control the runoff and pollution generated from storm events via a decentralized and small-scale source control to ensure that the development area is as similar as possible to the natural hydrological cycle. LID planning and implementation for urban food mitigation have been proposed as an indispensable component of urban stormwater management. Selecting a proper spatial arrangement of LID measures and placing them in the suitable location is crucial when designing LID measures spatial layout schemes under given investment constraint. As policymakers are concerned about how to achieve a positive multi-functional return, especially regarding the food hazard aspects. Thus, there is an urgent need to reach a balance between economic issues and LID spatial arrangement.

Some studies have indicated that scenario analysis methods for LID spatial arrangement design can address these concerns. Scenario analysis methods are driven by a set of infuencing factors, wherein each planning scenario is designed based on certain prerequisites. For example, Gilroy and McCuen [\(2009](#page-15-5)) indicated that flood reduction capacity of single LID measure is determined by the potential mechanism, and the spatial arrangement of the measure greatly afects the food control efectiveness of multiple LID measures. However, the quality of scenario assumptions greatly infuences the reliability of scenario analysis (Urich and Rauch [2014\)](#page-15-6). In addition, the inability to identify all potential scenarios, scenario analysis does not seek the most cost-efective solutions, which often result in schemes far from pareto optimality (Xu et al. [2017\)](#page-15-7). The shortcomings of scenario analysis methods have led to many researchers to design LID measures spatial arrangement based on urban food models coupled with optimizing algorithm. For example, Cano and Barkdoll ([2017](#page-14-3)) adopted a multi-objective optimization algorithm to analyze spatial arrangement of LID measures for stormwater management. The results indicated that in terms of cost–beneft ratio, implementing LID measures in upstream areas is the most efective approach. Optimization allows researchers to identify the optimal solution set from a large number of results. However, optimization often leads to non-unique solution sets. In addition, previous studies

mostly focused on coupled simulation–optimization methods, which normally require large computational burdens (particularly for two-dimensional food modeling). Thus, it is desirable to develop more efficient ways of conducting evaluation and future design.

A city is a complex space formed by the interaction of multiple interoperable catchments, in which water is central to many of these interactions as it can be transported to diferent catchments via food pathways. An obvious disconnect between the most efective locations for food management investment and the locations where foods are most likely to occur. While researches exist regarding the selection of LID measures depending on a specifc location, they usually obtain information regarding only one aspect of urban fooding such as traffic channel or infrastructure that may be at risk. Moreover, few approaches are available that explicitly link the source of a food problem, its potential impact, and the specifc food management interventions within existing urban systems. Therefore, identifying food source areas (i.e., target locations that have the greatest impact on reducing food hazards) can help guide the spatial priority of food management measures. For this purpose, an exploratory analysis framework was proposed that aims to guide strategic decision-making for LID measures spatial arrangement designs. This framework involves a methodological process that combines food mitigation strategies with spatial connectivity and uses the regional relevance index (*RI*) to quantitatively measure the connection between food source areas and food hazard areas based on source tracking. Furthermore, the output of the framework is especially important as it highlights the spatial connectivity between the food source area (requiring most of the LID measures) and the benefciary area (the areas where fooding is mostly reduced), thereby creating a basis for strengthening cooperation between these areas. By applying this framework to the urban watershed of Haikou (China), we identifed the potential prioritization of LID spatial arrangement using source tracking data as a driving force.

2 Materials and Methods

2.1 Overall Framework

The overall framework of the proposed method is illustrated in Fig. [1](#page-3-0). First, an urban food coupled model was established using a hydraulic model, hydrologic model, and source tracking module. Second, using the coupled model, the inundation volume was simulated under typical scenarios combining rainfall and tide level. Third, according to the inundation volume, the regional flood transfer coefficient (A) and RI were calculated. Finally, the spatial arrangement ratio and LID investment ratio (*KI*) for LID measures in diferent catchments are determined, and efficacy evaluation of adaptive LID measures are proposed for diferent scenarios.

2.2 Source Tracking Method Based on PCSWMM Model

2.2.1 Source Tracking Method

Source tracking methods have been signifcant in providing rich insights into runof sources, flow paths, and water age that cannot be established by simple rainfall–runoff dynamics alone (Birkel and Soulsby [2015\)](#page-14-4). In recent years, tracer-aided hydrological models in rainfall-runoff process simulation have been rapidly developed (Soulsby et al.

[2015](#page-15-8)). Within models, stable tracer can be used to "track" water fuxes, infer mixing relationships in internal stores and explore how the evolution of water ages occurs in relation to fow path dynamics (Van Huijgevoort et al. [2016\)](#page-15-9). Numerical simulations using source tracking method can provide process-based information for the dynamic analysis of complex urban systems. Furthermore, urban food models coupled with source tracking methods have rarely received attention. The source tracking method depends on the relationship of a certain tracer with a specifc host, wherein the origin of the host can be defned. In this study, tracers were employed to trace the entire process of stormwater runof between diferent catchments in order to obtain the composition and source contribution of the inundation volume. According to the composition of the inundation volume in the hazard areas, a spatial arrangement of LID measures can be developed to achieve the optimal urban flood mitigation strategy.

For example, during a storm event, the urban watershed (as shown in Fig. [2](#page-4-0)), which consists of three catchments (*S1*, *S2*, and *S3*), can food in response to rapid runof. The arrows represent the preferred direction of water fow. The runof generated by catchment *S1* fows into *S2* and is mixed with the inundation volume generated by *S2*. Subsequently, the inundation volume of *S2* divides into two parts. Some of the water fows into *S3*, while the rest remains in *S2*. We adopted tracers with the same concentration of A, B and C to track the runof of catchment *S1*, *S2*, and *S3*. According to the conservation of mass equation, the cumulative inundation volume from catchment *S1* expresses the ratio of the mass of tracer A to the corresponding concentration, as described in Eq. (1). Although the urban watershed is much more complex than the area in Fig. [2](#page-4-0), the calculation method of the conservation relationship between inundation volume and tracer transfer is still efective.

Fig. 2 Schematic diagram of the runoff source tracking process in urban watershed

$$
\begin{cases}\n\frac{C_1 V_1}{V_1 + V_2 + \dots + V_n} = C_1 \\
\frac{C_2 V_2}{V_1 + V_2 + \dots + V_n} = C_2 \\
\dots \\
\frac{C_n V_n}{V_1 + V_2 + \dots + V_n} = C_n\n\end{cases} (1)
$$

where $C_1, C_2,...C_n$ are the initial tracer concentrations for catchment *S1*, *S2,*…*Sn*, which are constant values. Meanwhile, C_1 ['], C_2 ['],... C_n ['] are the concentrations of tracers in flood hazard areas, and V_1 , V_2 ,..., V_n represent the amount of inundation volume contributed by the 1–*n* catchment (i.e., flood source areas) to the flood hazard areas, respectively.

2.2.2 PCSWMM

The PCSWMM combines SWMM 5 and GIS to provide a complete package for onedimensional and two-dimensional analyses of stormwater modeling in urban watersheds (Xu et al. [2018\)](#page-15-10). In the PCSWMM, water quality routing within the conduit links and nodes assumes that the behavior of a continuously stirred tank reactor, and the concentration of a constituent exiting the conduit at the end of a time step are determined by integrating the conservation of mass equation, using average values for quantities that might change over time, such as the flow rate and conduit volume (CHI. [2014\)](#page-14-5). In this study, water quality routing (including the buildup and washoff module) in the PCSWMM was adopted to generate a tracer source with a constant concentration. The Event Mean Concentration (EMC) model is described by Eq. (2). Due to the tracer only distinguishes the inundation volume, the tracer concentration settings in diferent catchments are the same. The EMC model can ensure that the runoff generation and convergence processes of different catchments form a constant concentration of tracer sources.

$$
EMC = \frac{\int_0^T C_t Q_t dt}{\int_0^T Q_t dt}
$$
 (2)

where EMC is the event mean concentration (mg/L), T is the total runoff time, C_t is the pollutant concentration (mg/L), which varies with runoff time, and Q_t is the runoff flow (L/s) , which varies with runoff time.

2.3 Adaptive LID Spatial Arrangement Scheme

2.3.1 Quantifying the Regional Relevance

The inundation volume contribution from the source area can be quantifed using the source tracking data. If the inundation volume in the hazard area comes from multiple catchments, then the regional relevance is strong, and the source food mitigation strategies will engender a better food mitigation efect. To quantify regional relevance, the regional relevance index (*RI*) was developed to determine the importance of inundation volume transfer between food source and hazard areas during urban food mitigation. The following method can be adopted to quantify the *RI* for coastal cities. First, the regional food transfer coefficient (A) is calculated as follows:

$$
A_{i,j} = \frac{\sum_{t=0}^{t=n} (V_{i,j})_t}{\sum_{t=0}^{t=n} (W_{i,j})_t}
$$
(3)

where $V_{i,j}$ and $W_{i,j}$ are the transferred and generated inundation volumes, respectively, in an urban watershed under diferent combinations of rainfall and tide level. *i* and *j* represent the design return period of the rainfall and tide level, respectively, and *t* represents the time step of the flood simulation.

However, the calculation of $A_{i,j}$ must be adjusted as the design periods of rainfall and tide level do not coincide, and the revision can be resolved in two cases.

(1) Regarding rainfall, the following revision should be included:

$$
C_1 = (A_{1,1} + A_{1,2} + \cdots \cdots A_{1,n})/n
$$
\n(4)

$$
C_1 = (A_{n,1} + A_{n,2} + \cdots \cdots A_{n,n})/n
$$
\n(5)

$$
\beta = \frac{C_1 - C_1}{h_1 - h_1} \tag{6}
$$

$$
\begin{cases}\np_{ij} = A_{ij} + \beta(h_j - h_i) & i < j \\
p_{ij} = A_{ij} & i = j \\
p_{ij} = A_{ij} - \beta(h_i - h_j) & i > j\n\end{cases} \tag{7}
$$

$$
P_1 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} P_{ij}}{n^2}
$$
 (8)

where $A_{1,l}$, $A_{1,2}...A_{1,n}$ are calculated by using Eq. (3) when the rainfall is h_1 (the minimum design rainfall) and tide level changes from z_1 (the minimum design tide level) to z_n (the maximum design tide level). $A_{n,l}$, $A_{n,2}$... $A_{n,n}$ are calculated by using Eq. (3) when the rainfall is h_n (the maximum design rainfall) and the tide level changes from z_1 (the minimum design tide level) to z_n (the maximum design tide level). Further, β represents the unit change in rainfall, $p_{i,j}$ represents the revision value of $A_{i,j}$ in the rainfall change, and p_j is the average revision value under diferent combinations of rainfall and tide level.

(2) Regarding tide level, the revision is defned as follows:

$$
C_3 = (A_{1,1} + A_{2,1} + \cdots + A_{n,1})/n
$$
\n(9)

$$
C_4 = (A_{1,n} + A_{2,n} + \cdots + A_{n,n})/n
$$
\n(10)

$$
\gamma = \frac{C_4 - C_3}{z_n - z_1} \tag{11}
$$

$$
\begin{cases}\nq_{ij} = A_{ij} - \gamma (z_j - z_i) & i < j \\
q_{ij} = A_{ij} & i = j \\
q_{ij} = A_{ij} + \gamma (z_i - z_j) & i > j\n\end{cases}\n\tag{12}
$$

$$
q_1 = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} q_{ij}}{n^2}
$$
 (13)

where $A_{1,1}$, $A_{2,1}$... $A_{n,l}$ are calculated by using Eq. (3) when the tide level value is z_1 (the minimum design tide level) and the rainfall changes from h_1 (the minimum design rainfall) to h_n (the maximum design rainfall). $A_{1,n}$, $A_{2,n}$. $A_{n,n}$ are calculated by using Eq. (3) when the tide level is z_n (the maximum design tide level), and the rainfall changes from h_1 (the minimum design rainfall) to h_n (the maximum design rainfall). In addition, γ represents the unit change in design tide level, $q_{i,j}$ represents the revision of $A_{i,j}$ in the design tide level changes, and q_i is the average revision value under different combinations of rainfall and tide level. Thus, the *RI* is determined as follows:

$$
RI = \frac{q_1 + p_1}{2} \tag{14}
$$

2.3.2 Spatial Arrangement Ratio for LID Measures

Using the urban food model, the inundation volume of each catchment can be calculated under diferent combinations of rainfall and tide level. Further, the inundation volume contribution from the source area can be quantifed based on the source tracking data. Then, the scale of the LID measures in diferent catchments is determined according to the ratio of each catchment's inundation volume contribution to the food hazard area. The inundation volume contribution ratios of diferent catchments to the food hazard area are determined as the investment ratio of the LID measures. Equation (3) can be used to calculate the *A* under diferent combinations of rainfall and tide level. The value of rainfall and tide level with the maximum *A* were used as inputs for the food model to calculate the LID investment ratios (KI) of different catchments (as described in Eq. (15) (15) (15)). To reduce the food risk of the entire study area, the food hazard was defned as the entire study area.

$$
KI_k = \left(\frac{\sum_{t=0}^{t=n} (T_{i,j})_t}{\sum_{t=0}^{t=n} (W_{i,j})_t}\right)_k
$$
 (15)

where (T_i) _k is the inundation volume contribution produced by the catchment *k* to the entire area, and $W_{i,j}$ is the inundation volume of the entire study area. The design rainfall return period with the maximum value of *A* is adopted as the inputs of Eq. [\(15\)](#page-7-0).

A comprehensive cost and beneft analysis is required to determine the LID allocation. In this work, the benefts can be defned as inundation volume reduction due to implementation of food mitigation strategies. Based on the source tracking method, LID investment in each catchment was determined by the inundation volume contribution ratio of the source area to the hazard area, especially within strict budget constraints. Equations (16) – (17) (17) (17) were adopted to identify the urban flood mitigation strategy at a budget constraint.

$$
C_k = C_{total} \times K I_k \tag{16}
$$

$$
C_k = \sum_{i=1}^{N} P_k \times C_P \tag{17}
$$

where P_k is the area of the LID measures in catchment *k*, which was retrofitted with the LID measures, C_p is the cost of unit area of the LID measures, and C_{total} represents the total implementation investment of the food management strategy.

3 Case Study

3.1 Coupled Urban Flood Model with Source Tracking Method in Haikou City

3.1.1 Study Area

The main districts of Haikou City (Fig. [3\)](#page-8-0) were selected as the study area. The urban watershed is located in the north of the Hainan Province, which is adjacent to the Qiongzhou Strait. The annual average temperature and rainfall are 24.3 °C and 2067 mm, respectively, which is a typical of tropical oceanic monsoon climate (Chen et al. [2018](#page-14-6)). The study area is vulnerable to urban fooding because of its high population density and fat terrain. For example, the occurrence of typhoon "Rammasun" during July 17–19, 2014, resulted in heavy rainfall on July 18, causing eight deaths and losses worth nearly 9 billion yuan.

3.1.2 Establishing Coupled Model in Haikou City

The dataset adopted for the urban food model included rainfall, tide level, digital elevation model data, river data, and pipe network data, which were provided by the Haikou

Fig. 3 Study area and urban food model was established based on the PCSWMM

Municipal Water Authority. The urban food model (Fig. [3b](#page-8-0)) comprised 4401 links, 4563 nodes, 4 catchments, and 48 subcatchments. Based on the measured rainfall data from 1974 to 2012 derived by the Haikou Station, the design rainfall and tide level distributions were ftted with a Pearson type-III (P-III) distribution and the same-frequency amplifcation method. The return periods of 2 years, 10 years, and 20 years suggested by Akhter and Hewa [\(2016](#page-14-7)) were adopted as model inputs to analyze the flood response.

The source tracking method in the PCSWMM adopted the EMC washoff model, which can generate a stable tracer source for overland fow. The source tracing only marks the volume of runoff in different catchments. Note that the washoff coefficient value in PCSWMM was set to be the same for all catchments.

3.1.3 Model Calibration and Validation

The Nash–Sutcliffe efficiency (NSE) index and coefficient of determination (R^2) were used to measure the goodness of ft between the observation and simulation inundation depth to evaluate the accuracy of the coupled model. In this study, the calibration inundation data were acquired during the typhoon "Rammasun" event. The observation locations are shown in Fig. [4.](#page-9-0) The values of NSE and R^2 were 0.844 and 0.874, respectively. Model calibration is deemed satisfactory if NSE and R^2 values are greater or equal 0.50 (Ahiablame and Shakya [2016\)](#page-14-8). Hence, the coupled model is feasible and can be used to simulate a given food scenario.

3.2 Flood Simulation in Compounding Rainfall and Storm Tide Events

The total inundation volume, which can refect holistic severity, were obtained during the simulation period. Based on source tracking method, the inundation volume of the entire study area is divided into 4 catchments (namely, L, JN, D, and DS), wherein the

Fig. 4 Simulation food during the "Rammasun" typhoon storm event

related inundation volume process is shown in Fig. [5](#page-10-0). It shows that the contribution ratio of the source inundation volume in the catchment varied. For example, when the return period of rainfall and tide level were both set to 20 years, the peak inundation volume contribution ratios of the catchments L, JN, D, and DS were 28.90%, 40.44%, 11.32%, and 19.34%, respectively. Hence, regarding the food disaster reduction strategies, it is necessary to focus on the source food control of catchments JN and L.

In addition, the design return periods of rainfall and tide level also afected the contribution ratio. For example, during the compound storms of 2-year rainfall with 2-year, 10-year, and 20-year tide, the inundation volume contribution ratios of catchment JN were 53.91%, 53.33%, and 51.35%, respectively. Furthermore, the inundation volume contribution ratios of catchment JN were 53.91%, 44.40%, and 42.29% for the compound storms of 2-year tide level with rainfall periods of 2 years, 10 years, and 20 years, respectively. These results indicate that, compared with the tide level, change in rainfall has a greater impact on inundation volume generation in the food source area of catchment JN.

Fig. 5 Diagram of food source area inundation volume contribution to hazard area under design return periods

3.3 Quantification Analysis of Regional Relevance

An urban food model was used to simulate food process under the combined impact of rainfall and tide level, wherein source tracking data were used to determine the source of fooding in a disaster area. The value of *A* calculated by using Eq. (3) are listed in Table [1](#page-10-1). The results indicated that the *A* increases with increasing rainfall return period and tide level. Specifcally, for a return period of rainfall was 2 years, with tide level of 2 years, 10 years and 20 years, the values of *A* were 0.347, 0.349, and 0.352, respectively. Further, at return period of tide level was 2 years, with return periods of designed rainfall are 2 years, 10 years and 20 years, the values of *A* were 0.347, 0.368, and 0.392, respectively. These results show that, compared with tide level, rainfall change has a greater impact on inundation volume generation in values of *A*.

Using Eqs. ([4\)](#page-5-0)–([5](#page-5-1)) to revise the inconsistency between rainfall and tide level, the *RI* of the study area was calculated to be 0.375, indicating that 37.5% of the inundation volume in the study area realized cross-regional transfer under stormwater events. This emphasizes the importance of source food control in urban food mitigation strategies.

3.4 Simulation Scenarios

Herein, we simulated the placement of permeable pavement that increases on-site storage as the water slowly penetrates into the underlying soil, the water is stored in a highly permeable matrix. The cost of implementing food mitigation technologies varies considerably based on certain system specifcations, soil type, and the location of implementation. Therefore, this study selected a representative cost of 194 yuan/ $m²$ for installing permeable pavement (Men et al. [2020](#page-15-11)). The total LID cost was selected to be 1 billion yuan, which is equivalent to a two-year government investment in a single pilot area of the "Sponge city" program construction in China.

A series of scenarios were explored to determine the placement of LID solutions for various storm events and budget constraints in main districts of Haikou City. Considering the essential diference between the food source and food hazard areas, scenarios considering three conditions of the LID measure allocation strategies were simulated:

A1–Without interventions, refecting the actual state of fooding in the urban watershed.

A2–Local control interventions based on the inundation volume ratio of the food hazard area.

A3–Source control interventions based on the inundation volume ratio of the food source area to the flood hazard area.

Owing to investment constraints, policymakers should allocate LID measures efectively to alleviate fooding. Hence, a spatial arrangement framework with the ability to mitigating the inundation volume was proposed to determine the optimal layouts of LID measures. In the spatial arrangement framework, the objective is to mitigating the inundation volume in the watershed within the budget constraints under the worst designed storm.

According to the three scenarios, diferent spatial arrangement schemes were developed. The A2 scenario is based on food hazard area control, wherein the ratios of the LID measure investment in four catchments are equivalent to the ratio of inundation volume of each catchment to the inundation volume of the entire study area. Meanwhile, the A3 scenario is determined by food source area control, which is based on source tracking data, wherein the inundation volume of the entire study area is distinguished by the source of inundation, and the source inundation volume contribution ratios of the four catchments to the study area are determined to be the investment ratio of the LID measures in each catchment. Each scenario was simulated during the compound storm of 20-year rainfall with 20-year tide (designing scenario under maximum *A* value). The spatial arrangement ratio in scenario A2 and A3 are summarized in Table [2.](#page-11-0)

3.5 Efficacy Evaluation of Adaptive LID Measures

To alleviate the urban fooding under diferent return period, LID measures were determined for two scenarios (Fig. [6](#page-13-0)). The results show that LID efects vary with the return period of storm events. Specifcally, the peak inundation volume reduction rate increases when the storm events are less intense. Compared with the A1 scenario, LID measures can reduce the peak inundation volume by 11.42%–25.04% (scenario A2), $24.59\% - 32.48\%$ (scenario A3), respectively. In general, the efficiency of the hazard inundation volume reduction was as follows: scenario $A1 \lt$ scenario $A2 \lt$ scenario $A3$.

Furthermore, with increasing return period, the efective reduction rate of scenario A3 was higher than that of scenario A2. At the return periods of 2 years, 10 years, and 20 years, scenario A3 reduced the peak inundation volumes by 7.44%, 9.03%, and 13.17%, respectively, as compared with those of scenario A2. This is because with increasing design return period, the *RI* increases, thereby increasing the regional inundation volume transfer ratio, which makes the food source area control strategy more efective. This validates the efectiveness of the proposed framework.

4 Conclusions

In this study, a simulation–optimization framework for designing LID strategies that adopts the source tracking technique was proposed. These fndings are especially important for highlighting food source control to mitigate urban food hazard. The framework was successfully applied to Haikou City, and the results revealed the importance of the spatial connectivity of LID measures. The main conclusions are as follows:

- The framework frst introduced the source tracking method in LID measure spatial arrangement, based on source tracking data in order to distinguish the source of the hazard area inundation volume and determine an LID allocation strategy according to the food contribution ratio of the food source area. These fndings are especially important for highlighting food source control to mitigate urban food hazards. The source tracking method was frstly introduced in the urban food mitigation strategies. Through this framework, the contribution of the food source area to the inundation volume of the hazard area can be determined, so as to realize the concept of source flood control.
- To quantify regional relevance, a regional relevance index (*RI*) was developed to determine the importance of inundation volume transfer between food source and hazard areas during urban food mitigation. These results show that the regional inundation volume transfer greatly impacts the efficacy of LID measures. The higher RI value indicates the higher water activity within the urban watershed, which means that the largest hazard area may not be the food control area. Furthermore, diferent disaster-causing factors have diferent degrees of impact on the *RI*. Moreover, compared with the tide level, the *RI* is more sensitive to rainfall, wherein the greater the rainfall, the higher *RI* in diferent regions.
- For diferent design return period storm events, the efectiveness of the LID measures is better for low return periods than moderate and heavy stormwater events. In

Fig. 6 Comparative diagram of inundation volume in three scenarios under diferent return periods

addition, the LID solutions for peak inundation volume reduction in the food control source area is more effective than that in the hazard area.

The focus of this research is to optimize the spatial arrangement of LID measures. *RI* was proposed to evaluate the transfer of inundation volume from the source area to the hazard area, and verify the efectiveness of the LID measures spatial arrangement by considering the disconnect between the food source area and hazard area. Other sources of uncertainty were not considered such as rainfall characteristics and the division of study area in modelling tasks. *RI* is obviously discrepant in diferent urban watersheds, and such change has a signifcant impact on the spatial arrangement of LID measures, and this is also an important research direction in the future.

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Availability of Data and Materials The data and code that support the study are available from the corresponding author upon reasonable request.

Declarations

Consent to Publish The authors are indeed informed and agree to publish.

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