Landscape-Scale Simulation Analysis of Waterlogging and Sponge City Planning for a Central Urban Area in Fuzhou City, China

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ABSTRACT

The urban underlying surface is key component in waterlogging control and low-impact development initiatives, including sponge cities. Using remote sensing and geographic information system data, we analyzed the relationship between natural green infrastructure (NGI) landscapes and urban submerged areas in the central urban region of Fuzhou, China. For simulations of centennial-returning storm with 2 or 4 hours of rainfall, submerged depths were 3.943 and 4.055 m, respectively. Submerged areas were characterized by high population densities and high levels of human activity. Between 2006 and 2014, NGI landscapes disappeared and were converted to impervious surfaces. Spatial association rule mining revealed a strong association between areas that were converted from NGI landscape and areas that were submerged in our simulations. Finally, we make some suggestions for sponge city planning based on our analyses of the change in urban NGI landscape patterns using ecology indices.

INTRODUCTION

The urban underlying surface heavily influences waterlogging (Arnold and Gibbons 1996). During the urbanization process, vegetation, water, and wetlands are replaced by impervious surfaces, including steel, cement, and other building materials. During the late-1990s, governments began to pay closer attention to the influence of urban underlying surfaces on storm water management. They started to develop low-impact development (LID) practices (Carlson et al 2014; Martin et al 2015; Palla and Genecco 2015), which seek to use the landscape to control the water source and reduce the shock loads of storm water. Typical LID practices include green roofs, permeable pavements, and other green infrastructures. With the introduction of the Sponge City concept, China has gradually been introducing LID technology to improve the urban underlying surface and the spatial distribution of landscape (Chou 2015).

Most previous research of LID analyzed simulation experiments and storm water management at the small-scale level (Allan et al 1997; Meerow and Newell 2017), whereas little analysis has been done at the urban level. Moreover, few studies have considered the influence of the natural green infrastructure (NGI), which refers to landscape that is good at receiving water. Here, we analyzed the urban central area of Fuzhou City, China, using remote sensing (RS) and geographic information system (GIS) data to divide the urban underlying surface into NGI and non-NGI landscapes. We extracted the impervious surface from the non-NGI landscape and used the precipitation-volumetric method to simulate waterlogging scenarios. We determined the area of rainwater submersion by simulation experiments, the change in the NGI landscape by overlaying images of the region, and the association between these features by data mining. Using the change in ecology indices, we ascertained the changing spatial patterns of the NGI landscape and used these findings to formulate suggestions for Sponge City planning in Fuzhou. Overall, our work combines three research themes, urban waterlogging, landscape ecology, and data mining, for a deep analysis of the relationship between the NGI landscape and storm runoff in an urban environment.

STUDY AREA AND DATA SOURCES

The study area was the central urban area in Fuzhou, China, which was planned in the "Fuzhou City Master Plan (2011–2020)". The study area includes the districts of Gulou, Taijiang, Cangshan (northern parts only), and Jinnan (built environment only) (Figure 1). Acceleration of urbanization in Fuzhou resulted in the disappearance of many inland rivers. "The Scientific Development Report of Water Supply and Drainage in Fujian Province" showed that Fuzhou has a low effective rate of utilization of water resources, an inability to receive water properly, and a large sewerage output. As a result of these deficiencies, waterlogging is a serious problem in Fuzhou City.

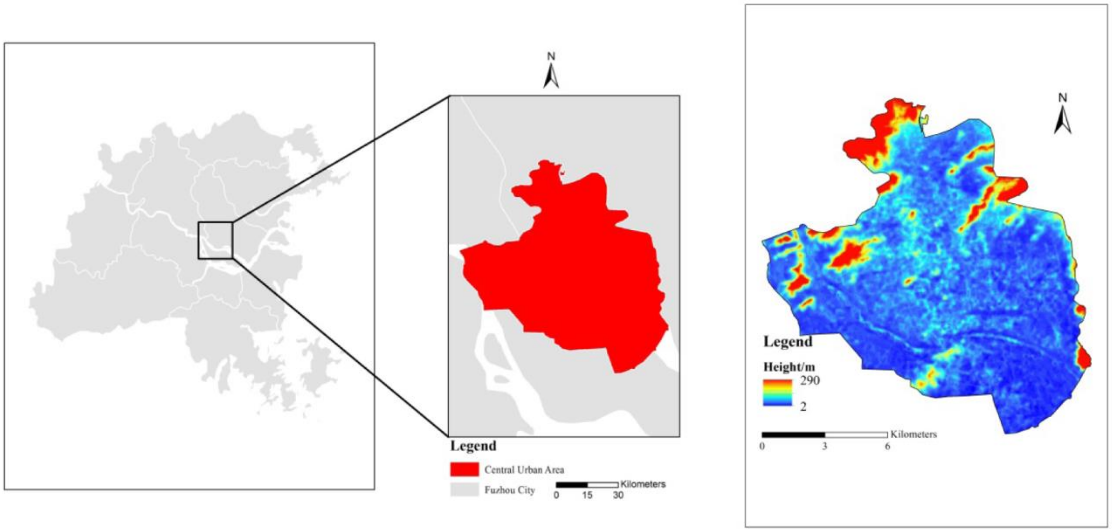

Figure 1. Location of study area (left) and digital elevation model data (right).

This study used data from multiple sources. Satellite data included three Landsat images, taken on 6 November 2006, 24 May 2010, and 13 December 2014. All images were subjected to atmospheric and geometric corrections before processing. Spatial vector data were from the

Digital Cadastral Database of the National Territorial Program Bureau, the Sixth Population Census Data of 2010 from the Fuzhou Bureau of Surveying and Mapping, the point of interest (POI) data of Sina Weibo from Data Tang (http://www.datatang.com/), and the global digital elevation model data for Fuzhou City (Figure 1b) from the Geospatial Data Cloud (http://www.giscloud.cn/).

METHODS

Study framework: As described in Figure 2, we used RS and GIS data to simulate waterlogging scenarios and employed landscape analysis to develop a Sponge City plan for Fuzhou City.

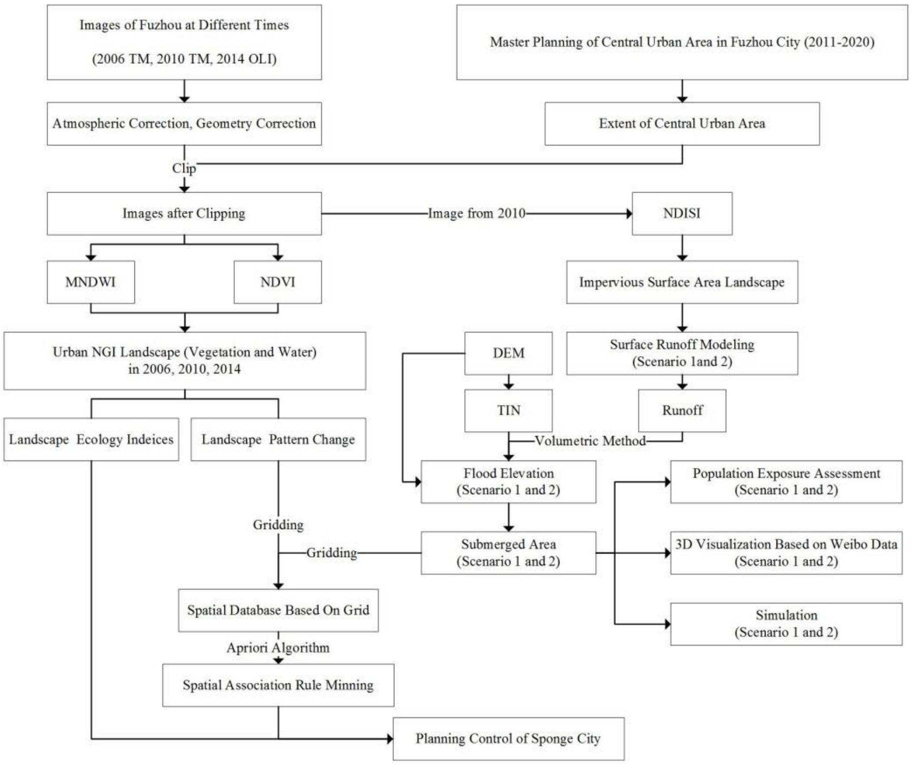

Figure 2. Flow chart of the study.

Landscape classification: Surface porosity influences whether rainwater can infiltrate the underlying surfaces in urban environments. Impervious surfaces are impermeable to rain. We used three RS indices to classify the landscape: the normalized difference impervious surface index (NDISI), the modified normalized difference water index (MNDWI), and the normalized difference vegetation index (NDVI). These indices are based on bands of the thermal (TIR), near-infrared (NIR), middle-infrared (MIR), green (Green), and red (R) regions.

NDISI has been widely applied in the extraction of impervious surfaces (Xu 2009) and is defined as follows:

$$\mathrm{NDISI} = \frac{TIR - \left(MNDWI + NIR + MR\right)/3}{TIR + \left(MNDWI + NIR + MR\right)/3} \qquad (1)$$

TIR and MNDWI are enhanced by maximum-minimum (0–255) linear stretching when computing the NDISI. Data used in the study are from the TM5 image taken in 2010. MNDWI is a more accurate modification of the normalized different water index. This modification considers the emission of green and middle-infrared bands (Xu 2005) and is defined as follows:

$$\mathrm{MNDWI} = \frac{Green - MR}{Green + MR} \tag{2}$$

Finally, NDVI is used to analyze vegetation cover (Loveland et al 2000) and is defined as:

$$\mathrm{NDVI} = \frac{NIR - R}{NIR + R} \tag{3}$$

Waterlogging simulations: We used the precipitation-volumetric method to simulate waterlogging scenarios in the central urban area of Fuzhou City. We calculated the storm intensity q ($\mathrm{L \cdot s^{-1} \cdot ha^{-1}}$) by using a formula published by the Fujian Provincial Department (Fuzhou Planning Design and Research Institute and Fuzhou Urban and Rural Planning Bureau 2009):

$$\mathrm{q} = \frac{2136.312\left(1 + 0.700 lgTe\right)}{\left(t + 7.576\right)^{0.711}} \tag{4}$$

where Te is the return period (years), and t is the duration of rainfall (min). Next, we calculated surface runoff Q ($\mathrm{L \cdot s^{-1}}$) as follows (Hao 2012):

$$\mathrm{Q} = \varphi \mathrm{qF} \tag{5}$$

where F is the area of the impervious surface (ha), and Ψ is the runoff coefficient (0.75 for Fuzhou City, according to Shao and Pan 2012).

Ecology index and association rule mining for changes in landscape patterns: We defined A as the change in the landscape pattern or waterlogging. The pattern was denoted as “Change” when the NGI landscape was transformed into a non-NGI landscape, or “Stay” otherwise. “Submerged” means that a place was submerged, whereas “No Submerged” indicates otherwise. A and B are subsets of the state of land T. An association is designated by “=>”. A is the precondition of the association rules, while B is the result of the association rules.

Rules A=>B are constrained by support and confidence (Kotu and Deshpande 2014):

$$\mathrm{support}\left(A \Rightarrow B\right) = \mathrm{P}\left(A \cup B\right) \tag{6}$$

$$\mathrm{confidence}\left(A \Rightarrow B\right) = P\left(B \mid A\right) \tag{7}$$

We used lift to test the independence of A and B, and its formula is as follows:

$$\mathrm{lift}\ (A \Rightarrow B) = \frac{support(A \cup B)}{support(A) \cdot support(B)} \tag{8}$$

We used the weighted mean fractal dimension of the patch area (AWMPFD) and the weight mean Euclidean nearest-neighbor distance of the patch area (ENN_AWM) to analyze changes in landscape patterns (Guo 2012). These variables were calculated with the following formulas (McGarigal 2012):

$$\mathrm{AWMPFD} = \sum_{i=1}^{n} \sum_{j=1}^{n} \left[\left(\frac{2ln0.25 p_{ij}}{ln a_{ij}} \right) \left(\frac{a_{ij}}{A} \right) \right] \tag{9}$$

$$\mathrm{ENN\_AWM} = h_{ij} \left(\frac{a_{ij}}{A} \right) \tag{10}$$

where p_{ij} is the perimeter of the patch, a_{ij} is the area of the patch, A is the area of the landscape, and h_{ij} is the distance (m) from patch_{ij} to the nearest neighboring patch of the same type (class), based on patch edge-to-edge distance, computed from cell center to cell center. Finally, we calculated the change of a given ecology index for a given period ($\mathrm{EIC}_{\mathrm{i,T}}$) as follows:

$$\mathrm{EIC}_{i,T} = \frac{EIC_{i,t2} - EIC_{i,t1}}{EIC_{i,t1}} \tag{11}$$

where *i* is AWMPFD or ENN, and t is the period.

RESULTS

Simulation and three-dimensional (3D) visualization of urban submersion: We extracted the impervious surface at the threshold of 0.175 from NDISI by comparison with the real image (Figure 3a) and obtained an impervious surface area of 60.623 km^2. We calculated the submerged depth and submerged area by the precipitation-volumetric method based on GIS data after computing the waterlogging runoff (Zhao 2010). We assumed centennial-returning storm, with rain for 2 and 4 hours for scenarios 1 and 2, respectively, and with uniform rainfall throughout the region (passive flooded state). We assessed how many people were exposed to waterlogged areas by using the Sixth Population Census Data from 2010. Simulation results are summarized in Table 1.

Table 1. Simulation results of storm water scenarios

Simulated parameter	Scenario 1	Scenario 2
Storm intensity ($\mathrm{L{\cdot}s^{-1}{\cdot}ha^{-1}}$)	163.183	101.847
Runoff ($\mathrm{L{\cdot}s^{-1}}$)	5.342×10^6	6.668×10^6
Submerged depth (m)	3.943	4.055
Maximum submerged depth (m)	1.943	2.055
Submerged area (km^2)	1.345	6.032

Submerged areas in different scenarios are shown in Figure 3b. The main submerged area in Fuzhou included the central business district. Numbers of people exposed to the submerged areas of scenarios 1 and 2 were 12,840 and 46,460 people, respectively.

Human activity and space in an urban area can be determined from the number of check-in sina weibo and photos. We overlaid the submerged area of scenario 2 with maps of human activity and space by using 3D visualization tools. We simulated scenario 2 using ArcScene and City Engine. The number of people who were exposed to the submerged area was very large. There were several submerged areas, with the frequency of Check in Sina Weibo reaching the peak value in the 3D heat map. Submersion occurred in places of high population density and high levels of human activity, implying greater harmfulness of waterlogging. In terms of the number of people exposed to submerged areas, the town of Gaishan was the most affected district of Fuzhou, followed by Shangdu Street and the town of Gushan.

Sponge City planning based on changes in landscape patterns and association rule mining: The Chinese government proposed the Sponge City concept to solve the problem of waterlogging in urban areas. This approach involves building up the NGI landscape to accommodate water in the urban underlying surface. We extracted the areas of vegetation and water from images taken in 2006, 2010, and 2014, using thresholds of NDVI and MDNWI(vegetation, water) (0, 0.11), (0, 0.85), and (0.85, 0.88). Next, we analyzed changes in the NGI landscape pattern in the central urban area of Fuzhou City from 2006 to 2014 (Figure 4).

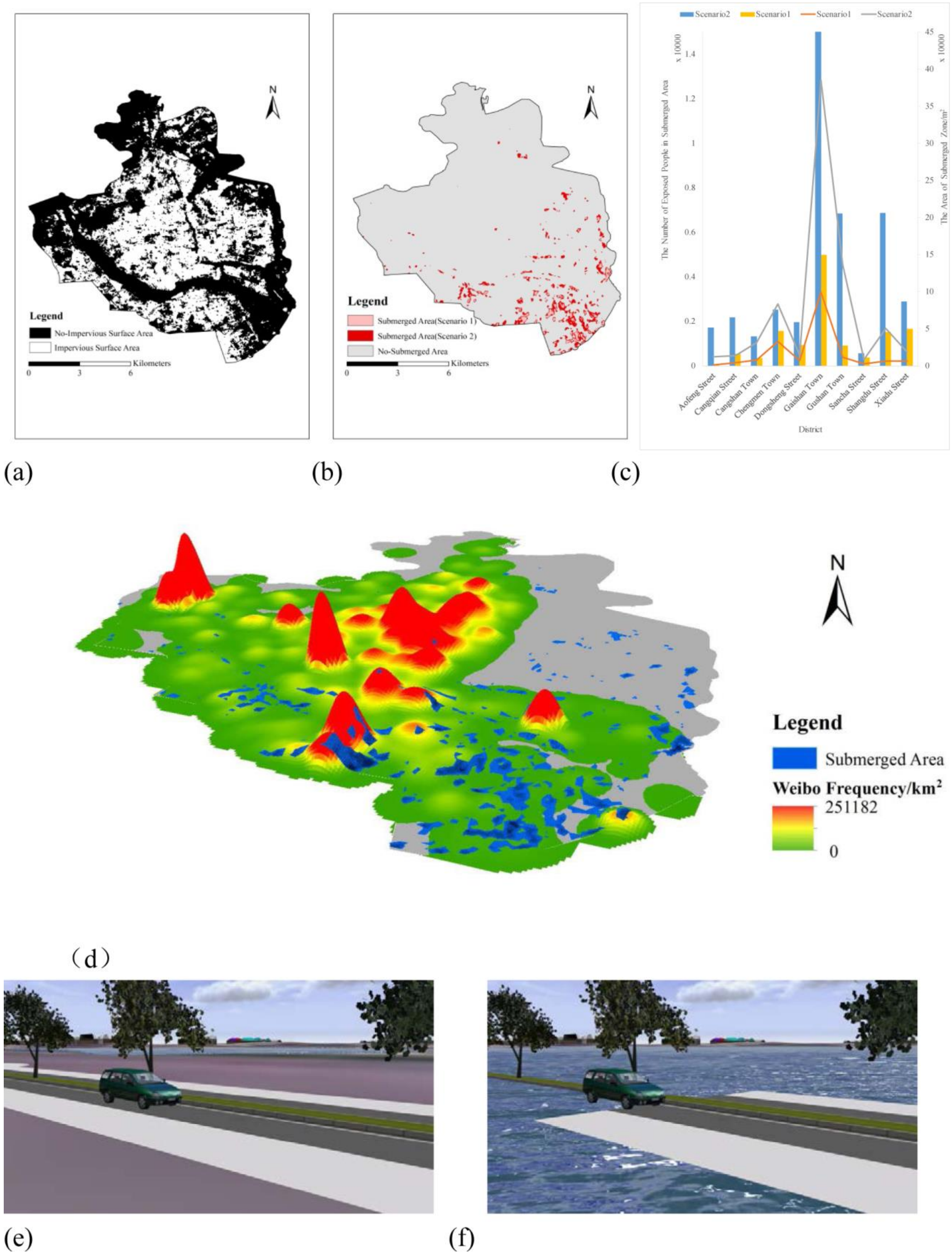

Figure 3. Maps showing (a) impervious and non-impervious surfaces and (b) submerged areas in scenarios 1 and 2. (c) Numbers of people exposed to submerged areas in different regions of Fuzhou. (d) 3D heat map of check-in and photos in Sina Weibo. (e) Visual representation of simulation results for (e) scenario 1 and (f) scenario 2.

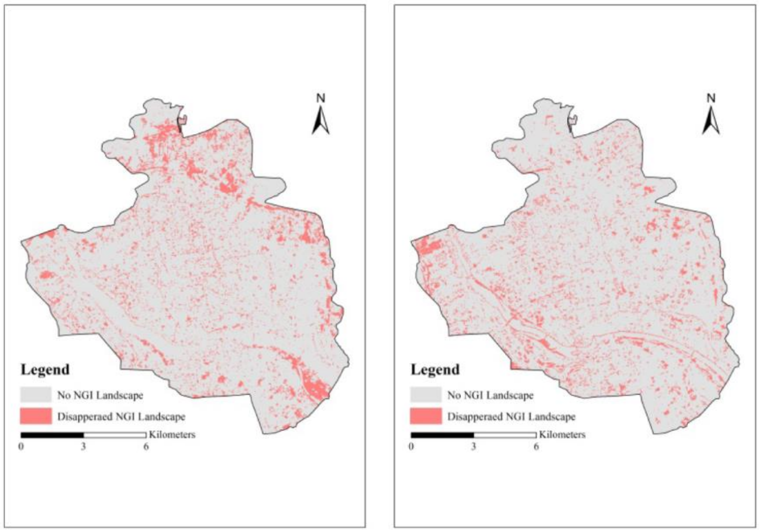

Figure 4. Landscape conversion in Fuzhou (left) during 2006–2010 and (right) 2010–2014.

The NGI landscape has become fragmented, as indicated by its spatial distribution in the central urban area of Fuzhou City. The area of vegetation decreased from 48.254 to 38.838 km^2 during the past 10 years (5.751 km^2 decrease over 2006–2010 and 3.665 km^2 decrease over 2010–2014), while the area of water decreased from 13.739 to 8.769 km^2. Loss of NGI landscape was most prominent at the edges of the central urban area from 2006 to 2010, whereas this landscape conversion was mostly found at the sides of rivers from 2010 to 2014. We analyzed the land use type of the converted landscape using the Digital Cadastral Database. During the period from 2006 to 2010, urban residential land accounted for about 40% of the converted landscape.

We used association rule mining to analyze changes in landscape patterns quantitatively. We created a 30-m grid system of 164,949 grids that intersected all features of the submerged areas in scenarios 1 and 2 and the converted landscapes in 2006–2010 and 2010–2014. We obtained sparse matrices to analyze the change in landscape patterns, and we mined the association rules using an apriori algorithm (Figure 5, Table 2). The association rule with the highest lift was Submerged => Change, which had support and confidence values of 0.002 and 0.212, respectively. Thus, the area that was submerged and converted landscape only covered 0.2% of the central urban area. The main reason of landscape conversion was the submerged area. If an area was submerged, then the probability that the area was converted landscape was 21.2%. Another rule indicated that the area that was not submerged and not subject to landscape conversion covered 86.5% of the central urban area. Thus, if an area was not subject to landscape conversion, then the probability that it would not be a submerged area was 99.2%.

These findings show that NGI landscape conversion had an important influence on urban waterlogging. Most of the built environment of the urban underlying surface was impervious, leading to a low capacity for water seepage, receiving water, or drainage. With the landscape conversion, torrential rains could not penetrate into the ground, leading to runoff, puddles, and waterlogging. To transform Fuzhou into a Sponge City, the NGI landscape must be redesigned to restore the drainage and water storage capacities of the urban underlying surface. From a global perspective, NGI landscape should cover land at the boundary of the central urban area. By connecting to a large area, the NGI landscape will have a stronger capacity for water seepage, receiving water, and drainage. Impervious surface divides and fragments the NGI landscape in the central urban area, and inland rivers have almost entirely disappeared. The northern part of Minjiang River crosses the central urban area of Fuzhou City, but this river is not able to receive large amounts of water. The NGI landscape in the central urban area could not consist of an entire ecological functional corridor dedicated to receiving water, which would cause serious damage.

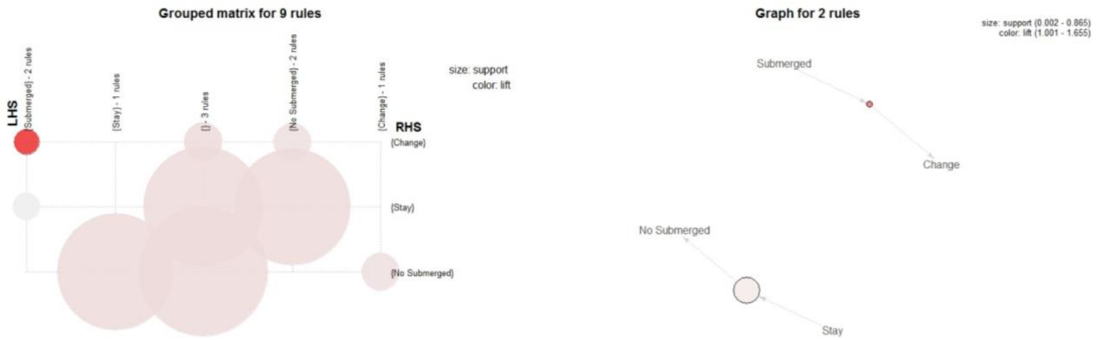

Figure 5. Visualization of rule mining. Grouped matrix for nine (left) and two rules (right).

Table 2. Results of association rule mining

Rules	Support	Confidence	Lift
Submerged=>Change	0.002	0.212	1.655
Stay=>No Submerged	0.865	0.992	1.001

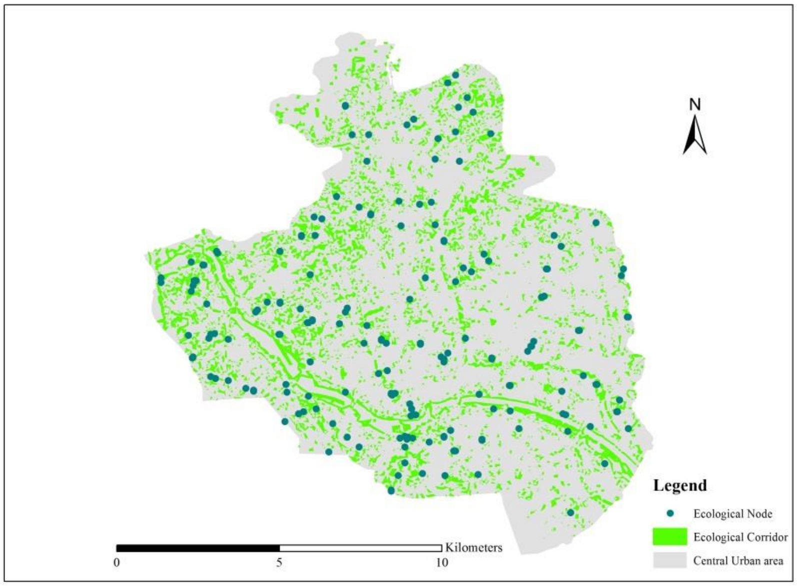

Figure 6. Ecological nodes and corridors based on EIC results.

We analyzed the spatial pattern of the NGI landscape by calculating the changes in two ecology indices, AWMPFD and ENN_AWM, to identify the ecological problems of the urban NGI landscape. This analysis proceeded from the ecology and sustainable development angles. Higher AWMPFD indicates stronger human activities and increased fragmentation. Higher ENN_AWM indicates a worse degree of connection and higher risk of waterlogging. EIC measured the change in the ecology indices and reflected the change in landscape patterns. An area with an EIC of 0 or less should not be considered for ecological protection. An area with an EIC above 0, designated as an ecological node or ecological corridor, should be the focus of ecological protection (Figure 6).

It is important to protect the NGI landscape of the ecological functional corridor outside the central urban area, manage the inland rivers, and build the NGI landscape functional corridor based on the ecological nodes/corridors. Rather than vegetation and water, urban NGI landscapes use artificial landscapes, such as green roofs and permeable roads. On the background of the ecological nodes/corridors, we used multisource open data (e.g., street view of Baidu map) and traditional data (e.g., reports) to understand the submerged areas better. We divided the submerged areas into four kinds of urban functional areas (Table 3) and made some suggestions for the Sponge City planning of Fuzhou (Zhu et al 2015; Tang 2010).

Table 3. Planning for different types of submerged areas

Type of Submerged Area	Typical Area	Planning
Central business district	Wuyi Square, government of Cangshan	Green corridor (10 m)
Countryside along the road	Gushan town, Xindian town	Green roof, permeable road
Urban residential	Metro, Chengmen town	Green roof
Other	Strait International Exhibition Center	River corridor (300 m)

CONCLUSIONS

Based on the results of this study, we derived the following conclusions:

- Simulation analysis for the central urban area of Fuzhou City, assuming a 100-year storm with rainfall durations of 2 and 4 hours, resulted in submerged depths (areas) of 3.943 m (1.345 km^2) and 4.055 m (6.032 km^2), to which 12,840 and 46,460 people, respectively, were exposed. Submerged areas were found at locations of stronger human activity, which caused a higher risk of waterlogging.
- The area covered by NGI landscape in the central urban area of Fuzhou City decreased considerably and became more fragmented from 2006 to 2014. Urban residential area covers 40% of the converted landscape.
- Results of association rule mining showed that the submerged area has an important relationship with the NGI landscape conversion that, in turn, makes waterlogging frequent in urban areas. We used EIC to measure the change in landscape patterns and spatial distribution of the NGI landscape. Based on the results, we identified some ecological nodes and corridors and made some suggestions related to the Sponge City planning of Fuzhou City.

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