Assessing Permeability Controls and Flood Risks Related to Urban Impervious Surface Expansion: A Case Study of the Southern Part of Kunming City, China

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Research Article

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DOI: https://doi.org/10.21203/rs.3.rs-606230/v1
Assessing permeability controls and flood risks related to urban impervious surface expansion: A case study of the southern part of Kunming City, China

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Abstract: Because of climate change and rapid urbanization, urban impervious underlying surfaces have expanded, causing Chinese cities to become strongly affected by flood disasters. Therefore, research on urban flood risks has greatly increased in the past decade, with studies focusing on reducing the risk of flood disaster. From 2012 to 2020, the impervious underlying surface has increased, and the permeable underlying surface has decreased annually in Kunming City. This study was conducted to investigate the impact of continuous changes in the urban underlying surface on flood disasters in the Runcheng area south of Kunming City from 2012 to 2020. We constructed a two-dimensional flood model to conduct flood simulations and flood risk analysis for this area. The relationship between the permeability of the underlying surface and urban flood risk was simulated and analyzed by varying the urban underlying surface permeability (30%, 35%, 40%, 45%, 50%, 55%, and 60%). The simulation results indicate that the urban flood risk increased with increases in the impervious underlying surface, with a threshold permeability of 35%. Once the permeability of the urban underlying surface decreased to below 35%, the flood risk increased rapidly. We demonstrated the impact of the urban underlying surface permeability on the risk of urban flood disasters, which is useful for urban planning decisions and urban flooding risk controls.

Keywords: urbanization, urban flood disaster, flood risk analysis, impervious underlying surface, hydro-hydrodynamic model

1. Introduction

In recent years, global warming has increased, extreme weather has occurred more frequently, and urban flooding has become more likely to occur. With continuous urbanization, the water surfaces of cities have decreased, and their impervious surfaces have increased. Increases in the impermeable surfaces reduce the absorption capacity of urban surfaces for rainwater, shorten the duration of surface runoff formation, and intensify the "Rain Island Effect". The permeability of underlying surfaces of cities has decreased continuously, such that
the urban areas of some cities have permeabilities below 30%. When a rainstorm occurs, the drainage and infiltration capacities of a city with a low underlying surface permeability are insufficient to cope with the scale of rainfall, increasing the risk of urban flood disasters. From 1989 to 2018, 3945 major flood disasters occurred worldwide. China, India, the United States, and Indonesia experienced the most frequent disasters, with a total of ~1200 events. According to Emergency Events Database statistics, 109 flood disasters occurred in 2018, with a relatively small number of flood deaths (1995) and victims (12.62 million).

Urban flood disasters result in serious population and economic losses. From 2008 to 2010, approximately 137 cities experienced more than three floods, and nearly 58 cities experienced more than 12 h of disastrous flooding during a single precipitation event from 2008 to 2010 (Liang 2016). On July 21, 2012, a torrential rainstorm occurred in Beijing, resulting in 79 deaths, the collapse of 10,660 houses, and damage to 163 immovable cultural relics, with 1.602 million victims, traffic losses of 11.64 billion yuan, congestion, and road interruptions. In the past five years, more than 300 cities in China have experienced various degrees of flood disasters characterized by wide ranges, long-term ponding, serious subsequent impacts on urban development and management, and huge losses of life and property. In August 2018, Typhoon "Winbia" caused torrential rain on August 18–19 in Shouguang City, Shandong Province, China. Many villages along the Mihe River in Shouguang City were flooded, and many buildings, farmland, greenhouses, and breeding farms were affected by the flood, resulting in heavy losses and causing serious impacts on urban roads and populations that resulted in economic losses as high as 9.2 billion yuan. Because of rapid urbanization and the effects of climate change, the frequency of flooding has increased, and the impact of flooding has become increasingly extensive (Shi 2012; Quan 2014). Rapid urbanization, increases in the impervious underlying surface, and population growth are the main reasons for urban flooding in China (Yin et al. 2015), and flood disasters have become a common concern of the Chinese government and the public.

Currently, urban storm water models can be divided into three categories: hydrological models, hydrodynamic models, and simplified models (Jun et al. 2018; Qi et al. 2021). Each model has advantages and disadvantages. The Environmental Protection Agency’s Storm Water Management Model (SWMM) is a representative hydrological model but has high data requirements and limitations. Hydrodynamic models use differential equations to calculate the flow movement with high accuracy but have a low calculation speed. Other simplified models, such as the cellular automata (CA) model, have become popular in hydrological modeling because of their low data requirements and fast computing speeds. For urban flood simulation, the Infoworks ICM software of HR Wallingford company in the United Kingdom has significant advantages, as it couples an urban drainage network system model and river channel model to accurately simulate interactions between the underground drainage network system and surface water. Moreover, the Infoworks ICM model adopts the of complete solution method, in which the Wiener equation is used to simulate flow in an open channel, whereas the Preissmann slot method is used to simulate overload of the open channel. This model can simulate a variety of complex hydraulic conditions and uses the storage capacity to reflect the pipe network reserves, so as to avoid incorrect predictions of pipeline overload and flood disasters.
Extensive research on urban flooding has been conducted, and researchers have made good progress regarding its simulation and control. The concepts of low-impact development and the "sponge city" have been presented to divert and control urban runoff as to alleviate urban flooding. Currently, researchers mainly use the SWMM, MIKE software, Infoworks ICM, and other software to simulate urban flood disasters (Xu et al. 2019; Seenu et al. 2019; Bisht et al. 2016). Digital city models have been generated based on three-dimensional hydrodynamic models of digital aerial photogrammetry (Rong et al. 2020). In addition, others have proposed using the ponding diffusion algorithm (Hou 2020) and two-dimensional (2-D) inundation analysis algorithm (Huang and Jin 2019) with geographic information system (GIS) and remote sensing (RS) technology, the SWMM, and effective urban storm inundation simulations using the distributed hydrological model (Meng et al. 2019). One of the main challenges in urban flood simulation is the lack of data regarding flood parameters and location and nature of land cover. Some researchers have used the 2-D hydrodynamic model (Mike urban) to simulate flooding events and measured parameters including infiltration rate, soil moisture, and soil texture in the field to fit the model (Hossain anni et al. 2020). Others have proposed a dynamic impact assessment method for rainstorm and waterlogging based on land use data (Zhu et al. 2019). In addition, the urban hydrological hydrodynamic coupling model was established to analyze the uncertainty of the urban flood model based on the generalized likelihood uncertainty estimation method and shuffled complex evolution Metropolis sampling algorithm (Liu et al. 2020).

Research has also been conducted using urban flood simulations and analyses. For example, some researchers have used the SWMM to construct urban flood simulation models based on pipe networks and 2-D surface ponding to study the causes and countermeasures of coastal urban flooding (Xu et al. 2019). The SWMM has also been used to build multi-level regulation systems for rainwater runoff in sponge reconstruction communities, and to analyze the impact of sponge reconstruction on the rainwater regulation ability before and after reconstruction (Chen et al. 2020). Scenario simulation methods were used to simulate urban flooding and ponding under designed rainfall conditions (Wang et al. 2020). Furthermore, comprehensive urban drainage models were built based on the Infoworks ICM, different measured rainstorms were selected for simulation analysis, and the model was used to simulate the drainage capacity and ponding depth of a regional drainage network system under rainstorm scenarios with different return periods (Huang et al. 2017; Wang 2018; Wang and Zhou 2018), as well as perform analyses based on multi-model coupling (Li et al. 2019; Tao 2017; Geng et al. 2019). In addition, CA has been used to build urban storm flood models (Li et al. 2020; Wang et al. 2020). For flood risk assessment, a risk assessment index system was established based on GIS, and analytic hierarchy processes were used to determine the index weight to assess flood risks (Hu et al. 2017; Chakraborty and Mukhopadhyay 2019).

Urban flooding poses a great threat to societal and personal safety annually. Therefore, the governance of urban flooding is an urgent problem faced by urban development, and its governance and transformation have become hot topics of current urban research (Kong et al. 2021). In previous studies, six different years (1966, 1971, 1976, 1981, 1986, and 2000) and six simulated land use scenarios (0%, 20%, 40%, 60%, 80%, and 100% impervious surface areas) were considered to evaluate the impact of urbanization on changes in urban flood risks in coupled hydrological and hydraulic models (Feng et al. 2021). The impervious underlying
surface was used to explore the process of urbanization (Peng 2016; Yu et al. 2018). In this study, we mainly investigated the influence of different underlying surface permeabilities on urban flood disasters using the Infoworks ICM drainage flood model and by controlling the urban underlying surface permeability, combined with different rainfall conditions. We also evaluated the influence of urban underlying surface changes on urban flooding risks. This study provides reference urban underlying surface permeability data for controlling urban flooding risks.

2. Study area and data

2.1 Study area

Kunming is located in Southwest China, in the center of the Yunnan Guizhou Plateau (24°23’–26°22’ N, 102°10’–103°40’ E). Dianchi Lake is located to the south and is surrounded by mountains on three sides and the Dianchi Lake Plain. The maximum E–W distance is 140 km, and the maximum N–S distance is 220 km. Kunming is located in a subtropical zone in northern latitudes. However, most of the region does not experience severe heat in the summer or severe cold in the winter, and the region has a typical temperate climate. The overall terrain is high in the north and low in the south, gradually decreasing in a stepwise pattern. The central part of the region is uplifted, whereas the eastern and western sides are low-lying. The altitude ranges from 1500 to 2800 m. The altitude of the city center is ~1891 m. The lake basin is dominated by karst plateau landforms. By 2019, Kunming had a total area of 21,473 km², built-up area of 483.52 km², permanent resident population of 6.95 million, urban population of 5.1152 million, and urbanization rate of 73.6%. The average precipitation in Kunming during 2019 was 48.6 mm, which was 7.5 mm more than that of the previous year. During the rainy season, Kunming City experiences serious urban flood disasters that cause major social and economic losses, as well as environmental disasters, seriously damaging the image of the city. The study area is in the Runcheng area in the south of the Panlong District, adjacent to Dianchi Lake. Frequent urban floods have exposed some issues in the urbanization process, including rapid city development, increasing areas of houses and roads, old and weak drainage pipeline systems and associated infrastructure, and problems regarding the normal operation and maintenance capacities of urban underground drainage pipelines. In this study, the current network system in the main urban section of the southern Runcheng area was selected for analysis, which has an area of 7.64 km² (Fig. 1). The Runcheng area is a typical urban flooding area. In recent years, serious flood disasters have often occurred in this area.

2.2 Data

2.2.1 GIS data

The experimental data were mainly provided by the underground pipeline detection and Management Office of Kunming City and included geophysical data, rainfall measurements, RS imagery, digital elevation model data, historical waterlogging location information, and other data, as shown in Table 1. The original geophysical data included inspection well coordinates, elevations, pipe diameters, pipe bottom elevations, and pipe top elevations, which
were the most recent data (collected in 2018).

### 2.2.2 Image data

The remote sensing (RS) images included satellite imagery of Kunming from 2012, and 2020, which had a resolution of 0.5×0.5 m and was obtained from the Google Earth platform. RS images can be used for underlying surface analysis, which can be divided into the following six categories: roads, buildings, green spaces, bare soil, hardened surfaces, and water bodies. Buildings and hardened surfaces hinder the infiltration of rainwater, whereas the permeability of green space is generally higher than that of bare soil. Therefore, it is necessary to set different infiltration rates and other parameters for the different underlying surfaces to produce more accurate simulation results.

The underlying surfaces in the study area are shown in Fig. 2 (a) and (b), which are the results of RS image analyses of data from 2012 and 2020, respectively. Figure 2 shows that, with the gradual development and utilization of urban land resources, the yellow bare soil sections later became buildings and roads. According to the underlying surface results, the proportion of permeable underlying surfaces gradually decreased from 47% to 31%, from 2012 to 2020, while the proportion of impervious underlying surfaces increased from 53% to 69% (a 16% increase in area), which is an important factor in flood disasters in most cities.

### 2.2.3 Rainfall data

The rainfall data included measured rainfall amounts and rainfall types, which were generated using the rainstorm intensity formula. Different types of rainfall have different influences on the underlying surface, making it necessary to select representative rainfall events. The rainfall data used in this study were collected at Wuda village station in Kunming on August 16, 2020 (Wuda village station is in the northern part of the study area), at an interval of 5 min, yielding a total rainfall of 99 mm. In addition, short-term rainfall data were generated by using the rainstorm intensity formula in Kunming City, with recurrence periods of 1, 2, 3, 5, and 10 years, respectively. These values were used as the boundary conditions for simulation.

The rainstorm model selected for this study was the Chicago rainstorm model (Keifer et al. 1957). A heterogeneous synthetic rainstorm process line model was proposed according to the relationships between rainfall intensity, duration, and frequency (Chicago rainfall process line model), which has been widely used. The rainstorm intensity formula is as follows:

\[
q = \frac{167A_t(1+C\log P)}{(T+b)^d}
\]

where \( q \) is rainstorm intensity (L/(s·hm²)), \( A_t \) is the rainfall in different return periods (mm), \( C \) is the rainfall variation parameter, \( P \) is the rainfall return period (a), \( T \) is the rainfall duration (min), and \( B \) and \( n \) are constants reflecting changes in the designed rainfall intensity over time. For a specific return period, the molecular \( A_t(1+C\log P) \) of the rainstorm intensity formula is a constant, set as \( a \).

The Kunming rainstorm intensity formula (2015 version) was derived from the Notification of Kunming Dianchi Administration on the Issue of the Kunming rainstorm intensity formula (2015 version) issued by the Kunming Flood Control and Drought-Relief...
Headquarters Office of the Kunming Meteorological Bureau (No. 3 of Kunming Qi Lianfa [2015]). The rainstorm intensity formula for Kunming City is:

\[
q = \frac{1226.623 \times (1+0.958 \lg P)}{(t+6.74)^{0.648}}
\]  
(Eq. 2)

The data used to generate this formula were the minute-scale rainfall data from the Kunming National Benchmark Climate Observation Station (1981–2014), and are mainly applicable to the downtown area of Kunming.

### 3. Methods

In this study, simulation was performed using the hydro-hydrodynamic model, which is a dynamic wave model used to solve the one-dimensional (1-D) Saint-Venant equations. The 2-D inundation model was based on Triangulated Irregular Network to solve the shallow water equation using the finite volume method. The Infoworks ICM integrated watershed drainage system model, which is capable of 1-D and 2-D simulations, has been used widely for drainage system status assessments, urban flood disaster prediction assessments, controlling urban rainfall and runoff, and storage design evaluations. Using the 1-D urban drainage pipe network hydraulic model for the drainage system, 1-D river systems hydraulic model, 2-D city/flooded river basin flood model for the city water cycle, complete system simulation to achieve the urban drainage pipe network system model, and river model integration, a more realistic simulation of the underground drainage pipe network and interactions between the receiving water body and network can be constructed. The main modules of the model included: a drainage pipe network hydraulic model (a hydrological module, pipeline hydraulic module, and sewage volume calculation module), river channel hydraulic model, 2-D urban flood and inundation model, real-time control module, water quality module, and sustainable structures module.

The hydrological calculation module adopts a distributed model to simulate rainfall runoff and carries out runoff calculations based on detailed spatial divisions of sub-sets of water areas and surface compositions with different runoff characteristics. In this study, this module was used to build and simulate the production and confluence of a subset of the water area. For the runoff generation model, the Horton model was selected, which involves fewer parameters and is suitable for small watersheds. For the confluence model, the SWMM nonlinear equation was selected, which has clear physical concepts and high calculation accuracy:

\[
\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = 0,
\]  
(Eq. 3)

\[
\frac{1}{g} \frac{\partial v}{\partial t} + v \frac{\partial v}{\partial x} + \frac{\partial z}{\partial x} = -\frac{\tau}{gR},
\]  
(Eq. 4)

\[
\frac{\partial h}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial x} = q_{ID},
\]  
(Eq. 5)

\[
\frac{\partial hv}{\partial t} + \frac{\partial}{\partial x} \left( hv^2 + \frac{gh^2}{2} \right) + \frac{\partial (hv)}{\partial y} = S_{0,x} - S_{f,x} + q_{ID}v_{ID},
\]  
(Eq. 6)
where $A$ is the area of the water crossing section, $Q$ is the discharge, $t$ is the time, $x$ is the length in the runoff direction, and $v$ is the velocity in the $x$ direction. $Z$ is the water level, $g$ is the gravitational acceleration, $\tau$ is the average shear stress around the wet section, $\gamma$ is the density of water, and $R$ is the hydraulic radius of the wet section. $h$ is the water depth, $u$ is the velocity in the $y$ direction, $q_{1d}$ is the areal discharge, $S_{0,x}$ and $S_{0,y}$ are the slopes in the $x$ and $y$ directions, respectively, $S_{f,x}$ and $S_{f,y}$ are the resistance slopes in the $x$ and $y$ directions, respectively, and $U_{1d}$ and $V_{1d}$ are the velocity components of $Q_{1d}$ in the $x$ and $y$ directions, respectively.

There are many runoff models, among which the Wallingford fixed runoff model is based on the calculation of runoff volumes in the United Kingdom. According to the parameters of development density, soil distribution type, and pre-stage humidity of the sub-catchment area, the runoff coefficient is predicted by a regression equation. We adopted Horton's empirical model of surface permeability, which can generally be expressed as a time-related function. Horton's formula is as follows (Abulkadir et al. 2011):

$$ f = f_0 + (f_c - f_0) \times e^{-kt} \tag{Eq. 8} $$

where $f$ is the infiltration rate (mm/h), $f_c$ is the initial infiltration rate (mm/h), $f_0$ is the stable infiltration rate or limit infiltration rate, $K$ is the exponential parameter (1/h), and $T$ is the infiltration time (h).

The hydrological calculation module and 1-D drainage system hydraulic calculation module were used to build the rainwater system model. The 2-D urban/watershed ground flood evolution module was used to simulate and evaluate the surface water.

To select experimental parameters, we also measured the infiltration rate of grassland and bare land in the study area by performing a double-ring instrument experiment, and calculated the attenuation coefficient. The experimental principle of double-loop instrument is to inject water into the surface loose rock within a certain hydrogeological boundary to make the infiltration water reach a stable level, that is, when the infiltration water per unit time is approximately equal, the permeability coefficient ($S$) value can be calculated by using the principle of Darcy's law (Hou 2019). Darcy's Law is as follows:

$$ S = \frac{Q}{AI} \tag{Eq.9} $$

where $Q$ is steady seepage flow (m$^3$/min), $S$ is the permeability coefficient (M/min), $A$ is the inner diameter area of the double-loop (M$^2$), and $I$ is the hydraulic gradient.

### 3.1 Model construction

The 1-D drainage system hydraulic model calculation engine uses the fully solved Saint-Venant equation to simulate the flow in pipelines and open channels. The 2-D urban flood evolution module combines 1-D and 2-D models in Infoworks ICM software. A 1-D model was used to determine where the flood occurred, and then a combined 1-D and 2-D model was used to study the flood direction and depth in these areas, which can achieve economic efficiency in terms of modeling time and accuracy. In this study, this module was applied used to simulate the surface water and analyze the flood risk.
The network model, hydraulic model, and hydrological model were constructed based on the data for the drainage network, underlying surface analysis, and other pre-processing, respectively, and the sub-models were coupled to form a comprehensive urban flood model. The rationality of the model was verified by the measured rainfall, and multi-scenario simulation analysis was carried out in combination with the designed rainstorm under different working conditions to conduct risk assessment of waterlogging in the pipeline network area. Construction of the pipe network model included the inspection and correction of basic pipe network attributes and verification of basic data including manhole coordinates, topological relationships, pipe diameters, pipe bottom elevations, and pipe top elevations. The data were derived from the latest pipeline survey data, and the ArcGIS software package (ESRI) was used to integrate the information and establish the database. The Infoworks ICM model software is highly coupled to ArcGIS and can directly import ArcGIS data into the model to form the rainwater pipe network model in the study area. Hydrological models generally include a runoff generation model and runoff concentration model. The runoff generation model represents the amount of rainwater runoff on the ground, whereas the runoff concentration model represents the speed of rainwater runoff. Establishing the hydrological model first requires the study area to be divided into the sub-catchment areas according to the plot distribution, terrain, roads, distribution of rainwater pipelines in the community, and relevant data for catchment area divisions. These data are then combined with the GIS hydrological analysis method, and the rainwater sub-catchment areas are preliminarily divided, and then further divided into several sub-catchment areas by using Tyson polygons. The pipe network catchment area was divided into sewage catchment and rainwater catchment areas. The underlying surface of the built-up area includes traffic, roads, private houses, residences, green spaces, and impervious pavement, which can be approximately classified into three categories (roads, buildings, and green spaces). Therefore, the pipe network catchment area should be classified according to the different underlying surface conditions. Because sewage is generated from buildings, whereas roads and green spaces do not produce sewage, the sewage catchment area was the residential sewage catchment area.

All underlying surfaces produce rainwater runoff; however, different underlying surfaces produce different confluence conditions. According to the distribution of underlying surfaces in Kunming, the runoff generation and concentration coefficients of six types of runoff surfaces were set (Table 2). Compared to using the same fixed runoff coefficient for the whole area, this method can more accurately reflect the runoff characteristics of different catchment areas and ensure that the simulation results are more accurate and reliable. The runoff generation process of impervious surfaces is relatively stable, and thus the runoff coefficient method was used to predict rainwater runoff. According to the technical guide for sponge city construction and codes for outdoor drainage (2016 Edition) (GB 50014-2006), the road runoff coefficient is 0.9, roof runoff coefficient is 0.9, and unused land runoff coefficient is 0.45. The runoff generation process for permeable surfaces is relatively complex. In the rainfall process, the soil infiltration capacity decreases over time and runoff generation coefficient increases. Therefore, the fixed runoff coefficient method cannot reasonably simulate the runoff generation process for permeable surfaces. The Horton runoff generation model was therefore used to simulate the runoff generation process for permeable surfaces.
Model coupling means that the sub-models were coupled to achieve water exchange among the sub-models. The 1-D hydraulic model was used to simulate the flow movement in the channels of the pipe network, whereas the 2-D surface model was used to simulate the overflow evolution of surface water and interaction process between the inspection wells and surface flooding. This included coupling the surface production and confluence model with the pipe network confluence model, coupling the pipe network confluence model with the 2-D surface overflow model, coupling the pipe network confluence model with the channel confluence model, and coupling the channel confluence model with the 2-D surface overflow model.

3.2 Model calibration and validation

3.2.1 Model calibration

The model was calibrated by inputting the measured data into the model for simulation, and then comparing the results and actual measurements. After the drainage model was established, it was necessary to check and revise the model by comparing the simulated data with the measured data. According to the collected rainfall data and ponding data, the accuracy of the model was verified by using the measured rainfall data from Wuda village station in the Runcheng area of Kunming City on August 16, 2020. The beginning time of rainfall was 22:00 h on August 16, and the ending time was 0:00 h on August 18. The measured rainfall curve is shown in Figure 3. The rainfall gradually increased from around 2:00 h on August 17, reaching a peak at around 4:00 h, after which it gradually decreased.

As shown in Fig. 4, the maximum submerged depth was ~0.52 m, whereas the average submerged depth was ~0.4 m. At 4 h after the rainfall began, the underground drainage pipe gradually filled, and the road surfaces began to accumulate water. The water level peaked at 6 h, after which the rainfall gradually decreased and water level gradually decreased. However, the time during which water accumulated occurred later than the peak rainfall time, with a certain hysteresis.

The collected water data were limited and could only be obtained from the Internet, media, and citizens taking photos to determine the water situation and depth. By investigating network information and Kunming City news reports, we found that the main flooding point was at the intersection of Guangfu Road and Qianwei West Road, and that the water depth was ~40 cm. By importing the measured rainfall data from Wuda Village on August 16, 2020, into the model, the intersection of Guangfu and Qianwei West Roads was selected as the monitoring point in the operation results. A curve of the flooded depth in this location over time (Fig. 4) and the flooding scenario in a 2-D plane (Fig. 5a) were obtained. According to comparative analyses, the results of the model were consistent with the statistical flooding data. The water scenario at the intersection of Guangfu and Qianwei West Roads (Fig. 5b) was consistent with that of the collected water data, and the average water depth was ~0.4 m, verifying the accuracy of the model.
3.3.2 Parameter calibration

The infiltration rate is defined as the amount of water that infiltrates the soil per unit area and unit time, also known as the infiltration intensity (mm/min or mm/h). The infiltration rate under sufficient water supply conditions is known as the infiltration capacity. Soil infiltration laws are typically described quantitatively by the changes in the infiltration rate or capacity over time. The infiltration rate of dry soil decreases over time under sufficient water supply conditions, known as the infiltration capacity curve or infiltration curve. In the initial infiltration stage, infiltrating water is absorbed by soil particles and fills soil pores. This initial infiltration rate is very high. Over time and with increased seepage, the soil moisture content increases gradually, and the infiltration rate decreases. When the soil pores are full of water and infiltration is generally stable, the infiltration rate is referred to as the steady infiltration capacity or steady infiltration rate. The attenuation process from the initial permeability velocity to the stable permeability is determined by the attenuation coefficient $K$ in Horton’s formula (Eq. 8).

To ensure that the model infiltration rate and other parameters are suitable for local use, six different points were selected in the study area, and soil infiltration rate experiments were carried out by using a double-loop experiment. Table 3 and Table 4 show the records of the measured infiltration rate of two points in the study area and records based on the simulated value of the Horton attenuation coefficient $K$, respectively. According to the measured values and Houghton simulation results, the Nash-Sutcliffe efficiency coefficient (NSE) was used to calculate the soil infiltration rate and verify the rationality of the model. In general, NSE values $>0.7$ indicate a high degree of fit for the model. An NSE coefficient close to 1 indicates a better simulation effect. Nash’s formula is as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q'_0 - Q'_i)^2}{\sum_{i=1}^{n} (Q'_0 - Q')^2}$$

(Eq. 10)

where $Q'_0$ and $Q'_i$ are the measured and simulated values at time step $i$, and $n$ is the total number of time steps.

Table 5 shows the calculated values of the attenuation coefficients of green land and bare land and their NSE values. When $k=2$, the NSE value of green space reached a maximum value of 0.85. When $k=2.5$, the maximum NSE value for bare land was 0.77. At this time, the simulated results of the model were most similar to the measured data.

The model was constructed based on real pipe network data, localized parameters, and measured rainfall data, and the actual scenario was restored as much as possible. For pipe network data, only the main municipal road was retained, whereas redundant and insignificant rainwater grates and other small branches on both sides of the road were removed. Localized checking parameters were also adopted in setting the model parameters, and the rainfall data were derived from the measured data. To ensure the authenticity of the model, the running speed of the model was greatly increased.
4. Results

4.1 Flood risk analysis

According to the Code for Outdoor Drainage Design (GB20014-2006), 2014 edition, the depth of road water in the "Design Standard for Surface Water" refers to the depth of water at the lowest elevation of the road surface. When the depth of the water on the road exceeds 15 cm, the lane may be completely interrupted by the shutdown of motor vehicles. Considering the safety of pedestrians after increases in water levels, a water depth of 0.5 m was used as another water level classification. The degree of water accumulation in the central urban area of Kunming City was divided into three grades: low, medium, and high risks (Table 6).

Using the model simulation, rainstorms in the study area with recurrence periods of 1, 2, 3, 5, and 10 years were simulated, and a rainstorm pattern was generated using the rainstorm intensity formula (Fig. 6). The flood risk areas within the study area were identified for the different return periods to evaluate the flood risk in the area. As shown in Fig. 7, a higher rainfall return period is associated with greater rainfall and a greater flood risk.

As shown in Fig. 7, the flood risk was expressed visually on the map to determine the flood risk scenarios for certain locations. Because of factors such as delayed data updates, underground drainage pipe network data from 2015 are lacking; therefore, the current 2020 pipe network data were adopted for the simulation. As shown in Table 7, 15% of the study area showed a low risk, 53% of the study area showed a medium risk, and 32% of the study area showed a high risk. When the risk area proportion is large, flood disasters occur more easily. In addition, with continuous urbanization, flood risks in other areas increase annually.

4.2 Variations in flood risk with different underlying surface conditions

Because of the lack of imagery of the urban underlying surface from other years, the proportion of the underlying surface was artificially set in a simulated manner to study the changes in urban flood risk under different underlying surface conditions. The study area was generalized into three underlying surfaces: green spaces, buildings, and roads. Different permeabilities of the underlying surfaces were set using the equal proportion method, and seven different permeability area percentages were simulated (30%, 35%, 40%, 45%, 50%, 55%, and 60%) for flood disaster inversion. The runoff model was based on the surface drainages set, with buildings and roads using the fixed runoff coefficient method and a 0.015 confluence parameter. The early damage type was used for the absolute value type. The runoff coefficient of green spaces used the Horton coefficient, initial permeability was set to 227 mm/h, stable permeability was 110 mm/h, and the Horton attenuation coefficient $K$ was 2.

Figure 8 shows the flood risks for 30–60% surface permeabilities. Areas with risk values of 0.01–0.30 are low-risk areas, whereas 0.30–0.50 indicates medium-risk areas and risk values higher than 0.50 indicate high-risk areas. It can be seen from the figure that in the process of increasing the permeability of underlying surface from 30% to 60%, the area of ponding is decreasing, and the high-level flood risk is less and less.

More specific numerical results can be obtained by statistical analyses of the flood risk area. The total risk area is equal to the sum of the areas of each risk level. The weight of the flood risk grade is divided, and the contribution areas of different risk grades (low, medium,
and high risk) are obtained by multiplying different flood risk areas by their weight. The contribution areas of the three different risk grades are then added to obtain the total risk score. Therefore, after consulting the weight data, 0.02 was selected as the weight of the low-risk area, 0.04 as the weight of the medium risk area, and 0.07 as the weight of the high-risk area. The risk areas obtained from statistics were multiplied by these values, and then the calculation results of the three risk levels were added to determine the total risk score, as shown in Table 8.

As shown in Fig. 9, the proportion of the flood risk area at different surface permeabilities indicates that medium-risk areas are significantly larger than high-risk areas, followed by low-risk areas. Figure 10 shows that for a 30% permeable underlying surface, the total flood risk area is 261,205 and total risk score evaluation is 29,176. However, for a 60% permeable underlying surface, the total flood risk area is only 96,931 and total risk score is 10,364. When the permeability of the underlying surface was varied from 30–60%, the flood risk scores decreased by 182%, 127%, 92%, 65%, 42%, and 20%, respectively. The change in the curvature of the underlying surface permeability from 30% to 40% was larger than that of the other intervals, and the flood risk increased rapidly. Figure 10 shows that every 5% increase in underlying surface permeability increased the flood risk area score by 2122, 2200, 2440, 2818, 3617, and 5613, respectively, and a breaking point in the rate of increase occurred at the change from 35% to 30% permeability, at which point the risk increased most rapidly. Thus, once the underlying surface permeability is lower than 35%, the increasing rate of flood risk increases sharply. Therefore, the optimal urban underlying surface permeability should be greater than 35%.

5. Discussion

In this study, the underlying surface permeability was set using the arithmetic difference method to simulate changes in the underlying surface during urbanization and invert its influence on urban flood risk. The infiltration rates of green spaces and bare soil in the southern area of Kunming City were measured using a double-loop experiment, which localized the simulation parameters and made the results more accurate to the local scenario. Few researchers have localized the infiltration rate parameters of Kunming City. In the infiltration rate experiment, we found that the outer ring of the double-loop instrument did not damage the surface of the bare soil, and the inner and outer rings should be kept well-sealed, otherwise the water in the inner ring leaks to the outer ring, artificially causing the measured infiltration rate of the inner ring to be higher.

During modeling and simulations, although the data processing method of the basic pipe network was simple, time and energy are required. Whether the data processing of the basic pipe network was appropriate is related to water accumulation after operation of the entire model. The watershed method also had major influences on model operation, including the manual partitioning of a subset of the watershed and use of a Voronoi diagram, which led to large differences. The manual subset of watersheds has many limitations that may lead to no water and watershed model convergence problems, whereas such issues rarely occurred when using the Voronoi-derived divisions. The accuracy of the simulation was also largely related to the parameters used in the model. A major contribution of this experimental study was obtaining localized parameters using field measurements, and then applying them to the model to produce more accurate results.
6. Conclusions

In this study, an underground pipe network model constructed using the shallow water equation was used to simulate changes in the urban flood risk from 2012 to 2020 in the southern part of the Runcheng District of Kunming City under constantly changing underlying surfaces. We also analyzed the relationship between urban flooding and the underlying surface permeability during urbanization. We found that the underlying surface permeability was an important factor affecting urban flooding, and that the optimal urban underlying surface permeability is >35%. The underlying surface permeability should be maintained above 30% as the flood risk rate will increase rapidly once urban permeability is lower than 35%, resulting in the intensification of urban flooding.

The influences of different rain types on flooding with the same underlying surface permeability, as well as the influence of different underlying surfaces with the same rainfall type on flooding, can be analyzed. In addition, the influence of the underlying surface on flooding with the evolution of urban construction can be assessed. Although it is accepted that urban underlying surfaces can aggravate flooding, the specific impacts are not completely clear. Based on the simulation of historical rainfall conditions, urban flood disasters over many years can be compared, the formation of water accumulation locations can be determined, and relationship between the changes in green land rate and floor area ratio and changes in water accumulation can be analyzed. Such analyses can reflect the influence of the underlying surface on flooding caused by the evolution of urban construction. By simulating underlying surface ratio conditions, the water accumulation degree of different underlying surfaces in daily rainfall conditions can be compared. Combined with the localization parameters from Kunming City and combined analytical results of various conditions, simulations can provide suggestions and help control plot ratios and green land rates in urban development.

Declarations

Funding This study was supported by the National Natural Science and technology foundation of the people's Republic of China (NSFC) project: Research on thematic map information model and multiple expression based on full information theory (Grant No.41961064), and the Ministry of housing and urban rural development of the people's Republic of China (MOHURD) 2017 Science and technology project: Research on Evaluation of safe operation capacity of important urban underground pipelines (Grant No.2017-k4-009).

Conflicts of interest No conflict of interest.

Acknowledgements Thanks for the research support provided by Kunming urban underground space planning and Management Office and Kunming Drainage Facilities Management Co., Ltd.

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Figure legends

Fig. 1 Geographical location of Runcheng in the south of Kunming

Fig. 2 Underlying surfaces in the study area in 2012 and 2020

Fig. 3 Rainfall curve measured at the Wuda Village 816 site in the southern part of Kunming

Fig. 4 Diagram of simulated flooding depths at the Wuda Village 816 site in the southern part of Kunming

Fig. 5 Simulated diagram of accumulated water at the intersection of Guangfu and Qianwei West Roads

Fig. 6 Simulated rainfall patterns for the 1-, 2-, 3-, 5-, and 10-year return periods

Fig. 7 Simulated flood risks for the 1-, 2-, 5-, and 10-year return period rainfall

Fig. 8 Flood risks for 30–60% permeable surfaces

Fig. 9 Flood risks at different surface permeabilities

Fig. 10 Variations in total flood risk for different surface permeabilities

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Table 1. Data list

| Data type                                      | Data content                                                                 |
|-----------------------------------------------|-----------------------------------------------------------------------------|
| Geophysical data of rainwater and sewage drainage pipeline | Inspection well coordinate, elevation, pipe position, pipe diameter, pipe bottom elevation |
| Rainfall data                                  | Measured rainfall data collected from a rain gauge near Runcheng area in the south of Kunming |
| Historical waterlogging prone point information | Including the depth, time, and scope of ponding                              |
| Remote sensing image data                     | Image data of Kunming City in 2012 and 2020, from Google Map, 0.5 × 0.5 m resolution ratio |
| Digital elevation model data                  | Ground elevation point data                                                  |

Table 2. Runoff and concentration coefficients

| Underlying surface type | Runoff generation model | Fixed runoff coefficient | Initial infiltration rate | Steady seepage rate | Decay rate | Confluen ce model | Manning coefficient |
|-------------------------|-------------------------|--------------------------|---------------------------|--------------------|------------|-------------------|-------------------|
| Road                    | Fixed                   | 0.9                      | -                         | -                  | -          | SWMM              | 0.015             |
| Building                | Fixed                   | 0.9                      | -                         | -                  | -          | SWMM              | 0.015             |
| Vegetation              | Horton                  | -                        | 227                       | 110                | 2.0        | SWMM              | 0.200             |
| Bare surface            | Horton                  | -                        | 77                        | 46                 | 2.5        | SWMM              | 0.200             |
| Hardened surface        | fixed                   | 0.8                      | -                         | -                  | -          | SWMM              | 0.040             |
| River                   | fixed                   | 1.0                      | -                         | -                  | -          | SWMM              | 0.002             |

Table 3. Measured and simulated underground seepage rates

| Time (h) | Measured infiltration rate (mm/h) | \(f_0\) (initial infiltration rate(mm/h)) | \(f_c\) (steady infiltration rate(mm/h)) | \(f_1\) (k=1) | \(f_2\) (k=1.5) | \(f_3\) (k=2) | \(f_4\) (k=2.5) | \(f_5\) (k=3) |
|----------|-----------------------------------|------------------------------------------|-----------------------------------------|---------------|----------------|---------------|----------------|---------------|
| 0:05:22  | 227.75                            | 227                                      | 110                                     | 216.98        | 212.31         | 207.83        | 203.55         | 199.46        |
| 0:11:50  | 189.01                            | 227                                      | 110                                     | 206.05        | 197.03         | 188.86        | 181.45         | 174.74        |
| 0:18:56  | 172.15                            | 227                                      | 110                                     | 195.33        | 182.88         | 172.24        | 163.15         | 155.39        |
| 0:27:47  | 138.11                            | 227                                      | 110                                     | 183.63        | 168.41         | 156.34        | 146.76         | 139.16        |
| 0:35:33  | 157.37                            | 227                                      | 110                                     | 174.69        | 158.10         | 145.77        | 136.60         | 129.78        |
| 0:43:15  | 158.74                            | 227                                      | 110                                     | 166.90        | 149.68         | 137.67        | 129.29         | 123.45        |
| 0:52:27  | 132.85                            | 227                                      | 110                                     | 158.81        | 141.52         | 130.36        | 123.15         | 118.49        |
| 1:01:37  | 133.34                            | 227                                      | 110                                     | 151.89        | 135.07         | 125.00        | 118.97         | 115.37        |
| 1:08:55  | 133.95                            | 227                                      | 110                                     | 147.09        | 130.88         | 121.76        | 116.62         | 113.72        |
| 1:18:35  | 126.44                            | 227                                      | 110                                     | 141.57        | 126.40         | 118.52        | 114.42         | 112.30        |
| 1:24:08  | 110.11                            | 227                                      | 110                                     | 138.78        | 124.27         | 117.08        | 113.51         | 111.74        |

Table 4. Measured and simulated bare groundwater permeability values

| Time (h) | Measured infiltration rate (mm/h) | \(f_0\) (initial infiltration rate(mm/h)) | \(f_c\) (steady infiltration rate(mm/h)) | \(f_1\) (k1=1) | \(f_2\) (k=1.5) | \(f_3\) (k=2) | \(f_4\) (k=2.5) | \(f_5\) (k=3) |
|----------|-----------------------------------|------------------------------------------|-----------------------------------------|---------------|----------------|---------------|----------------|---------------|
| 0:07:00  | 77.36                             | 77                                       | 46                                      | 73.17         | 71.44          | 69.82         | 68.30          | 66.88         |
| 0:19:39  | 52.01                             | 77                                       | 46                                      | 68.34         | 64.96          | 62.102        | 59.67          | 57.60         |
| 0:30:13  | 57.83                             | 77                                       | 46                                      | 64.73         | 60.56          | 57.32         | 54.80          | 52.84         |
| 0:41:55  | 52.23                             | 77                                       | 46                                      | 61.41         | 56.87          | 53.66         | 51.40          | 49.81         |
Table 5. Attenuation coefficients ($k$) of green land and bare land and their corresponding NSE values

| NSE | $e_1$ ($k=1$) | $e_2$ ($k=1.5$) | $e_3$ ($k=2$) | $e_4$ ($k=2.5$) | $e_5$ ($k=3$) |
|-----|--------------|----------------|--------------|----------------|--------------|
| Green land | 0.49 | 0.84 | 0.85 | 0.74 | 0.60 |
| Bare land | 0.06 | 0.57 | 0.74 | 0.77 | 0.74 |

Table 6. Flood risk classifications

| Ponding depth (m) | 0–30 min | More than 30 min |
|-------------------|----------|-----------------|
| 0.15–0.30 m | Low risk | Medium risk |
| 0.30–0.50 m | Medium risk | High risk |
| More than 0.5 m | High risk | High risk |

Table 7. Risk areas and their proportions in the 2020 years flood simulation

| Risk level     | Area (m$^2$) | Percentage of risk area in total area |
|----------------|--------------|-------------------------------------|
| Low risk       | 38,314.325   | 15%                                 |
| Medium risk    | 140,484.422  | 53%                                 |
| High risk      | 84,382.154   | 32%                                 |

Table 8. Permeabilities and risk areas of the different underlying surfaces

| Number | Proportion of permeable area of underlying surface | Low risk area (m$^2$) | Medium risk area (m$^2$) | High risk area (m$^2$) | Total risk area (m$^2$) | Total risk score |
|--------|---------------------------------------------------|----------------------|--------------------------|------------------------|-------------------------|------------------|
| 1      | 30%                                               | 41,751               | 136,495                  | 82,959                 | 261,205                 | 29,176           |
| 2      | 35%                                               | 33,592               | 118,283                  | 74,602                 | 226,477                 | 23,563           |
| 3      | 40%                                               | 31,363               | 103,728                  | 61,224                 | 196,315                 | 19,945           |
| 4      | 45%                                               | 32,236               | 85,551                   | 53,546                 | 171,333                 | 17,127           |
| 5      | 50%                                               | 27,030               | 69,119                   | 47,871                 | 144,020                 | 14,687           |
| 6      | 55%                                               | 21,279               | 56,998                   | 41,672                 | 119,949                 | 12,486           |
| 7      | 60%                                               | 14,052               | 48,351                   | 34,528                 | 96,931                  | 10,364           |
Figure 1

Geographical location of Runcheng in the south of Kunming Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
Figure 2

Underlying surfaces in the study area in 2012 and 2020 Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
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Figure 6

Simulated rainfall patterns for the 1-, 2-, 3-, 5-, and 10-year return periods
Figure 7

Simulated flood risks for the 1-, 2-, 5-, and 10-year return period rainfall Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
Figure 8

Flood risks for 30–60% permeable surfaces Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.
Figure 9

Flood risks at different surface permeabilities
Figure 10

Variations in total flood risk for different surface permeabilities