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Article

Evaluation of the Structure of Urban Stormwater Pipe Network Using Drainage Density

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Abstract: In mega cities such as Seoul in South Korea, it is very important to protect the city from flooding, even for short periods of time due to the enormous amount of economic damage. In impervious areas of the city, a stormwater pipe network is commonly applied to discharge rainfall outside of the catchment. Therefore, the stormwater pipe network in an urban catchment should be carefully designed to discharge the runoff quickly and efficiently. In this study, different types of structures in the stormwater pipe network were evaluated using the relationship between the peak rainfall and runoff in urban catchments in South Korea. More than 400 historical rainfall events were applied in five urban catchments to estimate the peak runoff from different types of network structures. Linear regression analysis was implemented to estimate peak runoffs. The coefficient of determination of the regressions were higher than 0.9, which meant the regression model represented the relationship between the two peaks very well. However, the variation of the prediction became large as the peak rainfall increased and the variation became even larger when the network structure was branched. Therefore, it depends on the structure of the stormwater pipe network. When the water paths in the pipe network are unique (branched network), the increased amount of rainfall is congested around the rainwater inlets and the uncertainty of peak runoff prediction is increased. If there are many possible water paths depending on the amount of discharge (looped network), the increased rainfall is discharged more quickly through the many water paths. This can be a way to represent the reliability of the stormwater pipe network. The structures of the stormwater pipe network were evaluated using drainage density, which is the length of pipes over the unit catchment area and 95% confidence interval. As a result, the 95% confidence interval increased as the drainage density increased and as the accuracy of the peak runoff prediction decreased. As mentioned earlier, as the looped networks have many alternative water flowing paths, the elimination time of rainfall from the catchments becomes short, the 95% confidence interval becomes narrow, and the reliability of the peak runoff prediction becomes high. Therefore, it is beneficial to install a looped stormwater pipe network within an affordable budget. It is an important factor to determine the amount of complexity in the stormwater pipe network to decrease the risk of urban flooding.

Keywords: urban floods; stormwater pipe network; drainage density; flood risk

1. Introduction

Due to recent climate change, the frequency of torrential rains has increased in South Korea, particularly in urban areas. Torrential rains in urban areas can cause temporal and local surface flooding due to the lack of discharge capacity. According to the 2010 disaster report, torrential rains

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in Seoul caused 64,752 people to be injured and about 0.6 billion USD of property damage. As such, flooding in urban catchments could result in massive property damage and loss of human life. Therefore, it is important to analyze the accurate runoff and inundation calculation.

The Storm Water Management Model (SWMM) developed by US-EPA is popularly applied to calculate runoff in urban catchments. However, it is impossible to simulate the natural phenomenon resulting from rainfall. Therefore, the uncertainty of urban runoff is commonly applied to the interpretation of natural phenomenon for reliable flow analysis. Reference [3] calculated the uncertainty quantification index of the SWMM model parameters based on a case in Beijing, China. Parameters in the SWMM were optimized [16] using the Generalized Likelihood Uncertainty Estimation (GLUE) method. Reference [4] quantified the uncertainty of the model through repetitive simulations using a randomly selected set of parameters using Monte Carlo analysis. Reference [13] also analyzed the uncertainty by applying the Meta–Gaussian technique to the simulated runoff from the HEC–HMS model.

There is also an uncertainty in rainfall data. Reference [2] quantitatively assessed the impact on runoff using errors from rainfall observations. Reference [14] examined the structured and unstructured uncertainty of rainfall. Reference [5] noted that the spatial variability of rainfall was one of the major causes of the uncertainty. Reference [10] used radar rainfall to estimate the probability distribution for urban runoff.

The relationship between drainage density and runoff in the natural watershed was presented by [1] using 13 river basin data in the Eastern United States. For the natural watersheds, Reference [17] analyzed the impact of impervious areas and drainage density on the runoff where the effect of drainage density was the largest. In urban catchments, the stormwater pipe network is artificially constructed and the pipe network behaves like natural rivers. Therefore, the characteristics of a stormwater pipe network should be understood for the efficient design and mitigation of flooding. In this study, drainage density was applied in urban stormwater networks. The relationship between peak rainfall and peak runoff was analyzed to estimate the accurate runoff from the catchments.

2. Data Collection

2.1. Weather Data

Urban floods frequently caused by torrential rains would result in property damage and loss of life [13]. As of December 2003, in South Korea, there have been 719 frequently flooded areas, which means flooding occurs every year. According to [19], the main reasons behind the frequent flooding in the city were the poor drainage systems. More specifically, the drainage pipes do not have enough capacity to discharge the torrential rains, thus the lowlands are inundated and runoff cannot be discharged to the drainage systems.

To analyze the flood characteristics and stormwater pipe networks, historical flood damage data from Seoul and Busan, the two largest cities in South Korea, were collected as shown in Table 1.

Table 1. Flood damage in the study catchments during last 10 years (2004~2013) [22].

District	Total amount of flooding damage ($)	Number of flooding years
Yeongdeungpo-gu (Seoul)	900,000	4
Guro-gu (Seoul)	870,000	6
Geumcheon-gu (Seoul)	900,000	4
Yeonje-gu (Busan)	3,580,000	5

As mentioned, Seoul and Busan are the largest cities in South Korea and the urbanized rate is much higher than in other cities. There is a meteorological station in each city, as shown in Figure 1.

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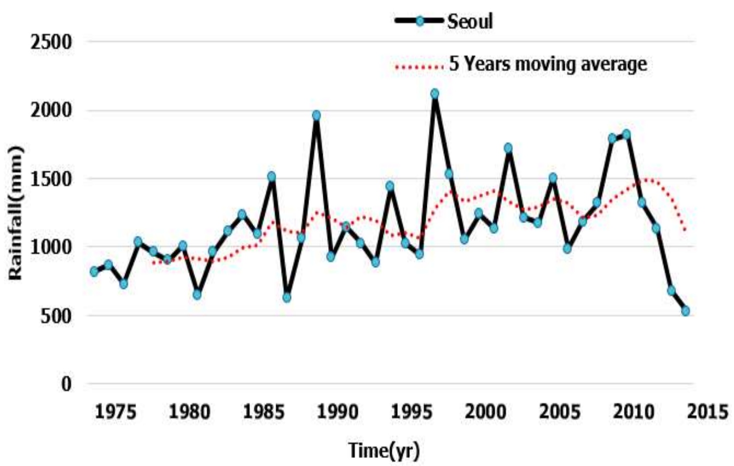
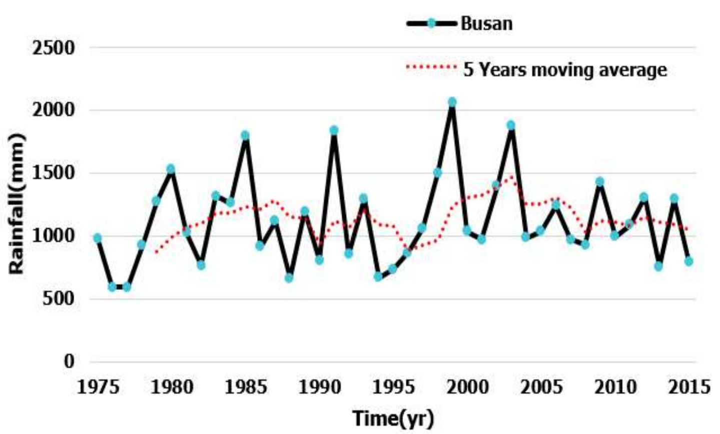
Average annual rainfall during the rainy season (June to October) from 1975 to 2015 slightly increased.



(**a**)



(**b**)

Figure 1. Annual rainfall during the rainy season (June-October) and moving average of meteorological stations in Seoul (**a**) and Busan (**b**).

2.2. Urban Catchments

The five urban catchments in Seoul and Busan were selected as shown in Figure 2. The number of subcatchments, number of nodes and links, catchment area, and total length of pipes are listed in Table 2. The structure of the stormwater pipe networks was originally constructed using GIS files provided by stormwater pipe information systems in Seoul and Busan. The original structures were simplified using the method of [18]. As shown in Figure 2, Network A is the simplest network with loops, and Network B is the most complicated network with many loops. Networks C and E are the common styles of stormwater pipe networks in South Korea, which is a combination of branched and looped networks. Network D is a typical type of branched network.

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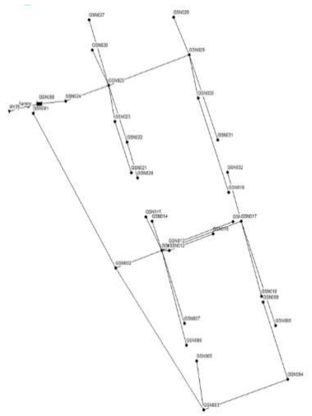
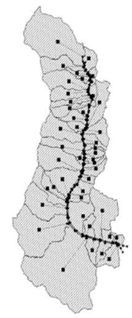


(a) **Catchment A**

(b) **Catchment B**

(c) **Catchment** C



(d) **Catchment D**

(e) **Catchment E**

Figure 2. Structure of the stormwater pipe networks in study catchments using the SWMM.

Table 2. Statistics of stormwater pipe networks in SWMM.

Catchment	No. of Subcatchments	No. of Nodes	No. of Links	Area (ha)	Total pipe length (m)
A	32	35	35	48	5219
B	1643	1881	2053	248	59976
C	620	620	632	892	37586
D	196	196	236	5724	29134
E	451	512	526	355.8	20120

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3. Methods

3.1. EPA-SWMM

EPA-SWMM was developed in 1971 to estimate the flow and water quality caused by rainfall in urban areas. Runoff in the SWMM is simulated from single or continuous rainfall and snowmelt [6]. The SWMM model is simulated by three types of analysis methods: steady state, kinematic wave, and dynamic wave methods. The kinematic wave method assumes that the friction gradient is the same as the slope gradient. Since the kinematic wave method has a large time interval, the long term is generally applied to the prediction. The dynamic wave method is applied in the unsteady flow to solve continuity and momentum equations. Additionally, the dynamic wave method is applied in the surface flow when the pipes are full of rainfall [15].

The dynamic wave method uses the momentum equation in Equation (1).

$$\frac{\partial V}{\partial t} + V\frac{\partial V}{\partial x} + g\frac{\partial y}{\partial x} + \frac{V}{\partial t}\,\overline{q} - g\left(S_0 - S_f\right) \tag{1}$$

In Equation (1), V is the average velocity of the flow; y is the depth of water; Sf is the slope or friction slope of the energy line; q is the lateral inflow; g is the gravitational acceleration; and So is the surface slope. The first term in the dynamic wave method is related to inertia force, the second term and the third term are the pressure, the fourth term is the momentum change, and the fifth term is related to gravity and frictional forces. To make the equation simple, the fourth term can be ignored. This is used to calculate flood wave movements in natural rivers, which are wide but not deep, such as flood propagation downstream due to dam breaks.

3.2. Simple Linear Regression Analysis

When observations are given in pairs, one variable is used to predict another variable. Linear regression analysis is a statistical analysis method that assumes that there is a linear relationship between two variables. The basic formula of the linear regression analysis is in Equation (2).

$$\mathrm{Y} = \alpha + \beta x \tag{2}$$

where Y is the dependent variable; x is the independent variable; α is the Y intercept; and β is the regression coefficient. The coefficient of determination (R-squared) is a measure of whether the proposed equation is appropriate to represent the dataset and is the percentage of the variable that can be explained by the proposed model. The coefficient of determination is defined by Equation (3).

$$R^2 = \frac{SSR}{SST} \tag{3}$$

where SST is the total sum of squares, and SSR is the sum of squares due to regression. SST represents how far the observed Y_i value is from the mean of the Y_i, and SSR is how far the estimate is from the mean. The range of the coefficient of determination is $0 \leq R^2 \leq 1$. The closer R^2 is to 1, the better the regression model explains the data.

3.3. Drainage Density

Drainage density is a numerical value indicating the degree of dense network in the watershed. High drainage density means that the length of stream per unit area is long, thus the drainage speed is relatively faster. Low drainage density means that the length of stream per unit area is short and the drainage speed is relatively slow.

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4. Analysis and Results

4.1. Peak Runoff and Peak Rainfall

In order to analyze the runoff from urbanized catchments, historical rainfall data are generally used and the rainfall data should be separated into rainfall events using concepts such as inter-event time definition (IETD). As recommended in [15], rainfall events were separated based on the 11 hours of IETD in each of the five catchments. Rainfall events were separated from the hourly-precipitation data observed at the Seoul and Busan Korea Metropolitan Administration (KMA) from 1975 to 2015. Only the total rainfall events where the total amount of rainfall was greater than 30 mm were selected for the runoff calculations. The number of rainfall events were 427 and 419 in Seoul and Busan, respectively.

The runoff was calculated using the SWMM model, as mentioned previously. The dynamic wave method was used to consider the flow characteristics during surface flooding and the pressure effects due to inverse slope in some parts of the catchments.

Regression analysis between the peak rainfall and runoff was implemented as listed in Table 3. The coefficient of determination (R^2) in all cases was 0.9 or higher. The regression graph is presented in Figure 3 and shows that the peak runoff increased almost linearly as the peak rainfall increased. However, when the peak rainfall was high, the variation of peak runoff was increased. Average widths of 95% confidence intervals in the A, B, C, D and E basins were 0.6 m^3/s, 0.3 m^3/s, 2.56 m^3/s, 20.8 m^3/s, and 1.6 m^3/s. Catchment B had the smallest width of 95% confidence interval and the highest R^2, which was close to 1. This means that the accuracy of peak runoff prediction in Catchment B was higher than the other catchments as it had many loops and a complicated network structure as shown in Figure 2. Therefore, there were many alternative water flow paths when the peak rainfall was high and the peak runoff was discharged without delay through the various water flow paths.

In contrast, Catchment D had the largest width of 95% confidence interval and the smallest R^2. As shown in Figure 2, the stormwater pipe networks in Catchment D had a branched pipe network structure which has a unique water flow path. When the rainfall intensity and peak rainfall increased, the capacity of the stormwater pipes was exceeded and surface flooding could occur locally. After a short time period of flooding, the exceeded runoff was also discharged through the stormwater pipes, however, the surface flooding might already have caused property damage.

Catchments C and E were also branched networks, however, the average width of 95% confidence intervals were smaller than Catchment D because the catchment area of C and E were much smaller than Catchment D. Therefore, it was expected that the catchment area and the length of water flow paths played an important role in estimating the accurate peak runoff. The short travel time of Catchments C and E decreased the uncertainty of the peak runoff prediction and increased the reliability.

Table 3. Results of regression analysis between peak rainfall and peak runoff in urban catchments.

Catchment	Regression equation	R^2	Average width of 95% confidence interval (m/s)
A	y = 0.1182x – 0.2834	0.9787	0.6
B	y = 0.6554x – 0.907	0.9969	0.3
C	y = 1.4049x – 3.0924	0.9522	2.6
D	y = 9.7278x – 34.355	0.9079	20.8
E	y = 1.0245x – 2.2035	0.9610	1.6

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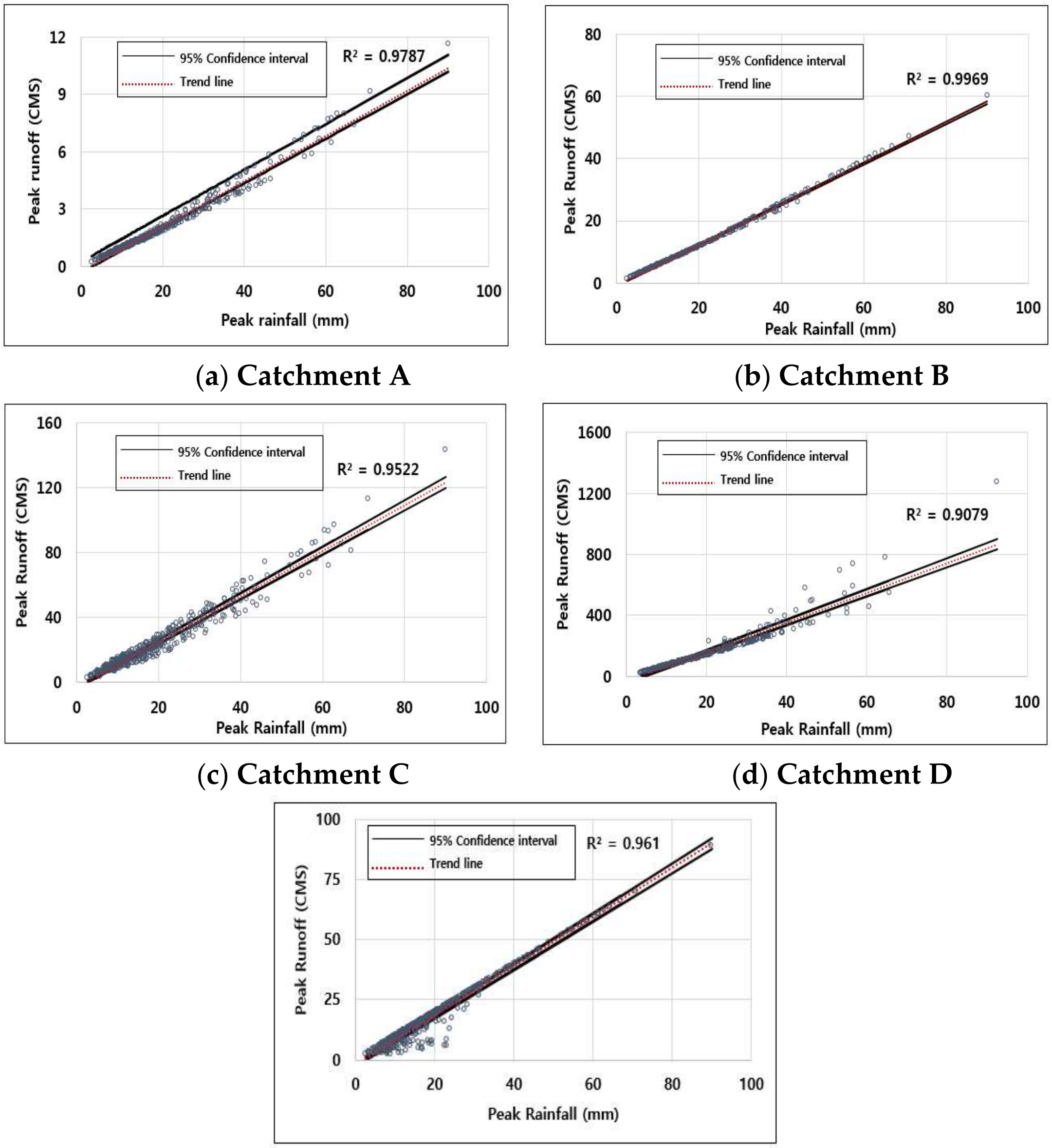

(**a**) **Catchment A** (**b**) **Catchment B**

(**c**) **Catchment C** (**d**) **Catchment D**

(**e**) **Catchment E**

Figure 3. Regression analysis between peak rainfall and runoff in urban catchments.

4.2. Drainage Density Analysis

As mentioned earlier, the catchment area and length of water flow path are important to predict the peak runoff. Therefore, the drainage density of the study catchments were calculated as listed in Table 4. The drainage density of Catchments A, B, C, D, and E were 107.7 ha/m, 241.3 ha/m, 42.1 ha/m, 5.1 ha/m, and 1.6 ha/m. Catchment B had the highest drainage density and R^2, and the lowest average width of 95% confidence interval and coefficient of variation. As mentioned previously, Catchment B had a complicated looped pipe network structure and it was easier to estimate the accurate peak runoff when the peak rainfall was increased due to the various water flow paths. This means that Catchment B discharged the rainfall the most efficiently among the study catchments.

On the other hand, Catchment D had the lowest drainage density and R^2, and the highest average width of 95% of confidence interval and coefficient of variation. Therefore, the pipe density over the catchment was low and the runoff was discharged inefficiently due to the lack of capacity of the pipes. This can cause surface flooding for a short time of period and make the travel time longer.

Table 4. Results of drainage density calculation.

Watersheds	Drainage density (m/ha)	R^2	Average width of 95% confidence interval (m/s)	Coefficient of variation
A	107.7	0.9787	0.6	77.8
B	241.3	0.9969	0.3	72.7
C	42.1	0.9522	2.6	80.0
D	5.1	0.9079	20.8	85.6
E	56.5	0.9610	1.6	77.4

Figure 4 shows a change of the average width of the 95% confidence interval and R^2 depending on drainage density. As shown in Figure 4, as the drainage density increased, the average width of the 95% confidence interval decreased and R^2 increased. This means that the uncertainty of the prediction of peak runoff is increased as the drainage density is decreased.

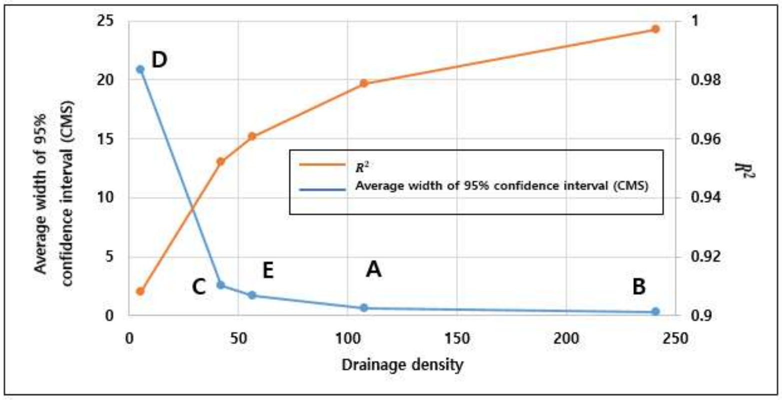

Figure 4. Changes of R^2 and 95% confidence interval depending on drainage density.

5. Conclusions

In mega cities such as Seoul in South Korea, urban floods cause an enormous amount of economic damage. In impervious areas of the city, a stormwater pipe network is commonly applied to discharge rainfall outside the catchment. However, inundation occurs around the rainwater inlets due to the lack of pipe capacity when the rainfall intensity is higher than the design capacity. The inundation is usually diminished after a short period of time; however, the property damage may not be small. In this study, the structures of stormwater pipe networks were evaluated using the relationship between the peak rainfall and runoff in urban catchments of Seoul and Busan in South Korea. Forty-one years of historical rainfall data from 1975 to 2015 and more than 400 rainfall events were applied in five urban catchments. Linear regression analysis was implemented to estimate peak runoff from different peak rainfalls. The coefficient of determination of the regressions were higher than 0.9, which meant that the regression model represented the relationship between the two peaks very well. However, the variation of the prediction became large as the peak rainfall increased as it depends on the structure of the stormwater pipe network. When the water paths in the pipe network were unique (branched network), the increased amount of rainfall congested around the rainwater inlets and the uncertainty of peak runoff prediction increased. If there were many possible water paths depending on the amount of discharge (looped network), the increased

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rainfall was discharged through the many water paths in the relatively shorter time. This can be a way to represent the reliability of the stormwater pipe network. The structures of the stormwater pipe network were evaluated using drainage density, which is the length of pipes over the unit catchment area and the 95% confidence interval. As a result, the 95% confidence interval was increased as the drainage density increased as the accuracy of the peak runoff prediction was decreased. As mentioned earlier, as the looped networks had many alternative water flowing paths, the elimination time of rainfall from the catchments became short, the 95% confidence interval became narrow, and the reliability of the peak runoff prediction became high. Therefore, it is beneficial to install a looped stormwater pipe network within an affordable budget. It is an important factor to determine the amount of complexity in a stormwater pipe network to decrease the risk of urban flooding.

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