Estimation of Rainfall Threshold for Flood Warning for Small Urban Watersheds Based on the 1D-2D Drainage Model Simulation

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1 Estimation of rainfall threshold for flood warning for small urban watersheds based on the 2 1D-2D drainage model simulation

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7 Abstract

9 This study proposed an equation for Rainfall Threshold for Flood Warning (RTFW) for small urban
10 watersheds based on computer simulations. First, a coupled 1D-2D dual-drainage model was developed
11 for nine watersheds in Seoul, Korea. Next, the model simulation was repeated for a total of 540
12 combinations of the synthetic rainfall events and watershed imperviousness (9 watersheds x 4 NRCS
13 Curve Number (CN) values x 15 rainfall events). Then, the results of the 101 simulations that caused
14 the critical flooded depth (0.25m-0.35m) were used to develop the equation that relates the value of
15 RTFW to the rainfall event temporal variability (represented as coefficient of variation or CV) and the
16 watershed Curve Number. The results suggest that (1) RTFW exponentially decreases as the rainfall
17 CV increases; (2) RTFW linearly decreases as the watershed CV increases; and that (3) RTFW is
18 dominated by CV when the rainfall has low temporal variability (e.g., $CV < 0.2$) while RTFW is
19 dominated by CN when the rainfall has high temporal variability (e.g., $CV > 0.4$). For validation, the
20 proposed equation was applied for the flood warning system with two storm events occurred in 2010
21 and 2011 over 239 watersheds in Seoul. The system showed the the hit, false and missed alarm rates at
22 69% (48%), 31% (52%) and 6.7% (4.5%), respectively for the 2010 (2011) event.

23
24 **Keywords:** Urban flood; Early flood warning; Rainfall threshold

1. Introduction

Floods have posed serious challenges to urban areas, with high concentration of population and properties. Urban floods in history often caused widespread devastation, economic damages, and loss of human lives across the globe (Braud et al., 2012; Hammonda et al., 2015; Miller et al., 2014;2017; Sarmah et al., 2017). Even worse, the magnitude of damages from the urban floods have been increasing at a rapid rate (O'Driscoll et al., 2010; Chen et al., 2015; Miller et al.,2017) due to following reasons. First, the number of people living in the urban areas is increasing. In 2008, a research from UN showed that half of the world's population lived in urban areas, and it was projected to rise to 60% in 2030 and 70% in 2050 (UN, 2008). This rapid urbanization rate is resulting in the increase of imperviousness and runoff in these areas, thereby leading to an increase in damage from the urban flood. Second, the climate change also led to the increase in magnitude and frequency of the rainfall events (Stott et al., 2004; Pall et al., 2011; Min et al., 2011). In some areas, 100-year flood event could become 2-5 year flood event in some areas leading to increase the flood risk and associated damages (Milly et al., 2002).

There have been various attempts to mitigate the urban flood damages, including structural and non-structural solutions. The structural solutions, such as levees, detention ponds, and underground conveyance tunnels, have been used to prevent the flooding itself. However, a typical structural solution is considered as expensive and ineffective for the urban areas because most of the ground surface and underground space are occupied by civil infrastructures. Conversely, early flood warning systems, which is the most popular and effective solution among non-structural solutions, do not require high costs that accompanies building the structural solutions. Thus, non-structural solutions are found to be more economic to reduce the flood damages in many urban places across the world compared with the structural measures (UNEP, 2002; WMO, 2011; Jha et al., 2012; Chen et al., 2015, Florian et al., 2015). The European Flood Awareness System, for instance, showed highly accurate performance in the early warnings for several recent heavy rainfall events, including the Balkan floods in 2014 (Pappenberger et al., 2015) and the Central European floods in 2013 (Haiden et al., 2014, Pappenberger et al., 2015). Paprotny et al. (2018) conducted study on the trend of losses due to flooding in the period of 150 years over Europe. The study found an increase in the flooded area and the number of affected people.

However, there has been a significant decrease in the flood-related fatalities, reduced by 4.3% per year during the period from 1950 to 2016, due to the efficient non-structural method of incorporating the early flood warning system to the existing structural solutions.

Performances of these early flood warning systems significantly depend on the rainfall threshold to initiate the flood warning (also known as Rainfall Threshold for Flood Warning or RTFW). It is typically defined as the cumulative rainfall depth or rainfall intensity for a given duration and an initial soil moisture condition that is likely to cause the floods (Golian et al, 2010; Priest et al, 2011; Jang, 2015; Thomas et al., 2018). The RTFW is derived based on either empirical or simulation-based approaches (Sene et al, 2008; Zêzere et al., 2015). The empirical approaches of deriving RTFW values are primarily based on the observed data. These approaches identify the relationship between the various characteristics of floods such as timing, flood area, and the corresponding rainfall. The empirical approaches have been widely applied for its methodological simplicity (Glade et al., 2000; Duncan et al., 2011; Caine, 1980; Hong et al. 2005; Dahal et al., 2009; Cannon et al., 2008; Guzzetti et al., 2007; Saito et al., 2010; Dao et al., 2020a, b). However, it is difficult to implement these methods for the urban flood analysis because of the challenges in detecting the urban flooding due to fast watershed response time (Emmanuel et al., 2012; Einfalt et al., 2004) and complex flooding mechanisms governed by drainage pipe network settings, terrain, and landcover (Chen et al., 2009, Zhang et al., 2014). Dao et al. (2020a) overcame this issue by using the flooded area data obtained from two massive field observation campaigns across the city of Seoul. A database containing every single flooded building during the two major flood events of 2010 and 2011 for 239 watersheds was used in the study. They discovered that the RTFW is strongly influenced by the temporal variability of the rainfall. A similar conclusion was found as Dao et al. (2020b) performed an analysis on Busan, Korea based on the flooded area data derived from Sentinel-1 synthetic aperture radar images.

Simulation-based approaches have been used to identify the rainfall threshold with hydrologic and hydraulic model simulations for various scenarios of rainfall and soil moisture conditions (Mogil et al., 1978). It is popular to define rainfall thresholds based on the numerical simulations for river and mountain basin (Reed et al., 2007; Miao et al., 2016; Golian et al., 2010; Kim et al., 2016; Zêzere et al.,

2015). However, the simulation-based approaches still have following challenges to be applied in the urbanized area. First, the approach requires extensive geospatial data, such as sewer network and high-resolution topography to develop a numerical urban flood model (Oh et al., 2016). Second, the urban flood simulations are computationally expensive, causing short warning lead time in operation (Chen et al., 2009, Zhang et al., 2014). Therefore, only few studies have been performed to determine the rainfall threshold for urban areas with the help of simulation-based method. Blanc (2012) proposed the method to derive RTFW based hydrodynamic model. The InfoWorks CS model, a kind of 1D/1D model, was used to simulate the flood for two urban areas in UK with various rainfall scenarios with rainfall duration and intensity ranging from 1 to 24h and 1 to 10 mm/h, respectively. Based on the analysis on the relationship between the flooded area and the rainfall duration and intensity, authors derived an equation to estimate RTFW as a function of rainfall duration and intensity. Jang (2015) has developed a method to determine the rainfall thresholds for urban areas over Taiwan based on the hydrodynamic modeling. In this research, the flood simulation model was set up for 252 watersheds with 22 rainfall events occurred from 2004-2012. The initial rainfall threshold of each watershed was identified when the simulated water depth at a specific point is 50 cm or higher. The rainfall threshold was then stochastically adjusted based upon the observed data of 22 flood events. The results showed that the performance of warning system based on the rainfall threshold shows high accuracy ranging from 0.6 to 0.9 and the hit ratios outperforms false alarm ratio.

In this study, the simulation-based method was applied to identify RTFW for urban areas. The first advantage of this study is the use of coupled 1D-2D model to simulate urban flood, which enables realistic reproduction of spatio-temporal progress of flooded area, which were subsequently used to derive the RTFW. Second, the RTFW suggested by this study considers not only watershed imperviousness but also the temporal variability of rainfall event. The influence of the latter was not clearly explained in the previous studies (Blanc et al, 2012; Jang et al., 2015). Third, the RTFW was provided as a mathematical equation for enhanced applicability.

2. Methodology

The XP-SWWM model was used in this study to simulate inundation in the selected basins. First, the model was calibrated by comparing simulated and observed water level in the pipe located at the watershed outlet. The calibrated model was then used to simulate the flooded area based on various synthetic rainfall scenarios generated by the Poisson cluster rainfall model. For each rainfall scenario, the rainfall intensity and respective flood depth were collected to establish their relationship, which served as fundamental basis to determine RTFW. Through this analysis, it was identified that rainfall event temporal variability significantly influences RTFW. Then, the model simulation was repeated by modifying the originally calibrated parameters (namely, NRCS curve number) to further investigate the influence of watershed imperviousness on flooding. From this investigation, the equation to find RTFW was derived as a function of rainfall coefficient of variation and watershed curve number.

2.1. Study area

This study was applied to the metropolitan city of Seoul, the capital of South Korea, for the analysis. It covers an area of 605 km² (Figure 1c) with highly dense population. The city is featured by mountainous topography with steep slopes (average slope of 8.57%) and high percentage of impermeable areas (48.64%), which makes it prone to flooding when a heavy rain occurs. In addition, the majority of residential and commercial areas are located on floodplain, exacerbating damages caused by the flood. From 1980 to 2015, Seoul experienced seven extreme rainfall events. In particular, the event of 2010 September 21st with a record accumulative rainfall of 480 mm caused flooding in 149 out of a total 239 watersheds across Seoul, causing financial loss of 42.9 million dollars and 17,905 flooded houses. The drainage system in Seoul is divided into 239 sub-watersheds (Figure 1c). Due to Han River flowing through the city, the city's main drainage system is designed to discharge the excess water into the river.

In this study, nine watersheds (blue polygons in Figure 1c) with high level of urbanization in Seoul were selected to perform flood simulation. These watersheds have area ranging from 0.82 to 4 km² and their average slope varies from 3% to 19.1%.

2.2. Data description

In this study, the data of rainfall, pipe network, and land cover were used as input for the XP-SWMM model to simulate inundation for the study areas. The data of the pipe network (Figure 2) are provided by the Metropolitan Government of Seoul (data source: <https://opengov.seoul.go.kr/sanction/2175286>). Characteristics of the pipe network including pipe length, slope, shape, and diameter are used as input for the 1D model to simulate the hydraulic behavior of the flow in the pipe, while the manhole elevation was used to develop the 2D model to simulate the movement of flow over land surface. In addition, the flow data at the outlet of the study watersheds were also collected to serve the model calibration process (Figure 2).

Input data for flood simulation models including pipes and manhole data were provided by Seoul metropolitan government. The drainage network data was then simplified to reduce the computation time as well as uncertainty in the simulation results (Yoon et al., 2017). Accordingly, pipes with diameters and lengths smaller than 0.5m and 100m, respectively, were removed. The characteristics parameters of drainage systems of watersheds used in the simulation model are listed in Table 1.

Observed rainfall data was used for model calibration. The in-situ rainfall data used in this study was collected from 31 ground-based stations located in and around Seoul with a measurement interval of 1 minute (Figure 1c). The rainfall event that occurred on July 23, 2013, which caused flooding in several areas in Seoul, were selected. To calibrate the simulation model, 1-minute pipe flow depth data was acquired for each of the catchments recorded between 04:20 AM and 10:10 AM. In addition, land cover data (Figure 1b) was used to calculate the curve number for each drainage area in the watersheds (data source: <http://www.neins.go.kr>).

2.3. Flood simulation model

Recent studies have shown that combining 1D and 2D models is the most appropriate approach for urban flood simulation (Leandro et al., 2009, Chang et al., 2015, Fan et al., 2017, Jahanbazi et al., 2014).

Therefore, the XP-SWMM model was chosen to conduct the analysis in this study. In the XP-SWMM, the study area is divided into sub-watersheds based on the location of the manholes and the topographic data. The rainfall-runoff process in each sub-watershed is simulated using RUNOFF package. Then, hydraulic behavior of the flow along the pipe network is modeled by 1D pipe network model, called EXTRAN package which uses a hydrodynamic equation and a continuous equation. Finally, 2D surface water model (TUFLOW package) simulates the movement of water routing onto the surface through manholes.

The model was simulated with rainfall input and the following parameters: curve number (CN), time of concentration of sub-watersheds, and roughness coefficient of pipe. Once the simulation was completed, each modeled water level was compared with the observed data at corresponding flow observation gauge. Based on the comparison results, a calibration process was conducted through adjusting the curve number and roughness coefficient of the pipe. This parameter adjustment follows the principle that the curve number affects amount of water and the roughness coefficient changes for the velocity of the flow in the pipe (USDA., 1986). Once these parameters were adjusted, the model was run again and the water level was compared and evaluated by the coefficients of determination method (R^2). This procedure was repeated until the R^2 between observed and simulated water depth reaches the highest possible value.

Figure 4 shows the flow depths (y-axis) of nine watersheds obtained from the simulation model (blue lines) and the observation data (dash-orange lines) corresponding to the analyzed rain event (x-axis). It indicates strong correlation between the simulated and the observed pipe water level height with R^2 value ranging from 0.71 to 0.96.

2.4. Inundation simulation with various scenarios of rainfall to derive the RTFW.

After the model was calibrated, the model was run with various rainfall scenarios, focusing on the changes in intensity and rain distribution over the time of events. The rainfall model of Kim and Onof (2020) was used for generation of rainfall. The model reproduces well the rainfall characteristics at the

time scales from 5 minutes to 10 years including extreme values as well as antecedent moisture conditions.

The 500 years of 10-minute rainfall time-series was generated. Then, 230 rainfall events were picked up from the 500 years of rainfall time-series. Here, 4 hours of inter-storm dry period was used to differentiate one rainfall event from another. The relationship between accumulated rainfall and duration of the selected events are shown in Figure 5. The color of the points represents coefficient of variation of rainfall event. Then, we further filtered out, for each of the watersheds, the events to obtain final 15 events of which average intensity ranges from 20mm/h to 90mm/h. Finally, the flood simulation model was run for 135 rainfall events (15 rainfall events x 9 watersheds) to derive flood map. For each simulation, we obtained the maximum flood depth and corresponding rainfall intensity to establish relationship. Note that the rainfall intensity may differ from a watershed for another even for the same rainfall event. This is because the intensity was calculated over the duration that is equal to the watershed time of concentration.

2.5. Consideration of watershed imperviousness simulation in deriving the RTFW.

The watershed imperviousness plays an important role in the flooding mechanism. Thus, it was assumed in this study that the watershed impermeability also has an impact on the relationship between rainfall intensity and inundation level in the study area. Therefore, instead of using the calibrated curve number (CN) values, various CN values (80, 85, 90, 95) were applied for all nine watersheds to simulate the inundation with the rainfall scenarios used in previous sections. With the CN values of 80, 85, 90, and 95 chosen for the analysis, 540 scenarios were simulated (9 Watersheds x 4 CN values x 15 rainfall events). Similarly, for each CN scenario, the relationship between flooding depth and rainfall intensity for the previously defined four ranges of CV was established to derive the fitted regression lines.

3. Results and discussions

3.1. Flooded depth versus flood inducing rainfall

Simulation results of 135 rainfall scenarios were used to establish the relationship between the rainfall intensity and the corresponding maximum flooding depth for the nine studied watersheds shown in Figure 6. The non-flooded cases were excluded from the plot. A positive relationship exists between the rainfall intensity and the maximum inundation depth across all watersheds, indicating that higher rainfall intensity leads to higher the inundation level. However, there are significant uncertainties residing in this relationship as suggested by the R^2 value ranging from 0.64 to 0.98.

3.2. Impact of rainfall temporal variability on depth-intensity relationship

We assumed that the uncertainty may stem from the temporal variability of the rainfall. To verify this assumption, coefficient of variation (CV) that represents the rainfall temporal variability was first calculated for 135 rainfall events. Then, the 135 events were classified into four categories based on four distinct intervals of the rainfall event CV. Here, boundaries of the four intervals were determined so that each category contains at least 20 events to secure the validity of further analysis including regression. Figure 7a-d shows the relationship between the rainfall intensity and the maximum flooded depth for the four intervals of the CV. The lines in these figures show best-fit exponential regression models ($y = ae^{bx}$) of the scatters.

Figure 7e shows the collection of the best-fit exponential regression lines shown in Figure 7a-d. The regression line corresponding to greater CV range is located at the higher position, which suggests that, although significant uncertainty resides in the relationship, a storm with higher temporal variability generally results in greater inundation. For example, Figure 8 compares the flood maps of the Hwagok watershed for the similar rainfall depths (63.56mm/h vs 62.49mm/h) but with different temporal variabilities (0.38 vs 0.13). Both the maximum flood depth and the flooded area were greater for the event with greater CV by 57 and 88 percent, respectively.

3.3. Impact of imperviousness on depth-intensity relationship

Figure 9 shows inundation depth versus rainfall intensity for four different CN values and four different CV intervals. The blue, red, yellow, and purple lines represent the CN value of 80, 85, 90, and 95, respectively. The results show that although there is great uncertainty residing on the relationship between flood depth and rainfall intensity, the regression lines follow a major trend that the line corresponding to higher CN value is located on upper side of the line of the lower CN. It suggests that watersheds with greater imperviousness (or higher CN value) causes greater flood depth for the same rainfall event. For example, Figure 10 shows the flooded area of Hwagok watershed with two different CN (80 vs 90) corresponding to the same rainfall event (intensity = 50.72 mm/h, CV=0.3). Both the maximum flooded depth and the flooded area are significantly greater for the case with greater CN.

3.4. Determination of RTFW

To determine RTFW, it is important to determine the threshold of flood depth over which the accumulated water is considered dangerous. This study adopted the flood depth threshold of 30 cm following Kramer et al. (2016). Therefore, this study chose only the rainfall events corresponding to inundation depth ranging between 0.25 and 0.35 for the analysis to determine RTFW. There were 101 out of 540 events meeting this criterion. The scatters in Figure 11 shows the relationship between rainfall intensity and coefficient of variation of these 101 events. Note that not all 101 events are clearly shown because many events share the same rainfall intensity and CV, so they overlap on the plot.

The next step is to determine the RTFW formula. Sections 3.2 and 3.3 show that both CN and CV have clear positive relationship with flood depth, so high values of CN and CV would lower the RTFW value. Following this finding and the pattern of the scatters in the plot, we first assumed that RTFW would exponentially decrease as CV increases as Equation 1. Then, we performed the least-square residual fitting on the pairs of CV (x) and intensity (y) corresponding to each of the CNs (80, 85, 90, 95). As a result, a set of parameters, namely b_1 , b_2 , and b_3 , was obtained for each of the CNs, which was shown in the subplots of Figure 11. The subplot suggests that the parameters have the clear relationship with CN, so each of them were expressed as the quadratic equations (Equation 1a, 1b, and 1c).

$$\text{RTFW}(\text{mm/hr}) = b_1 + (b_2 - b_1) \cdot \exp(-b_3 \cdot \text{CV}) \quad (1)$$

$$b_1 = -0.01438 \cdot \text{CN}^2 + 1.904 \cdot \text{CN} - 29.98 \quad (1a)$$

$$b_2 = 0.02137 \cdot \text{CN}^2 - 4.230 \cdot \text{CN} - 294.8 \quad (1b)$$

$$b_3 = 0.001449 \cdot \text{CN}^2 - 0.4268 \cdot \text{CN} + 34.01 \quad (1c)$$

, where RTFW, CN, and CV represent rainfall threshold for flood warning (mm/hr), watershed curve number, and rainfall temporal variability.

Solid color lines in Figure 11 graphically represent Equations 1. Each line represents different watershed imperviousness (CN). The relationship suggests that the RTFW is highly sensitive to the rainfall temporal variability at the range of CV less than 0.2. This is primarily because runoff amount corresponding to rainfall events with different temporal variability varies significantly at this low range of CV. Considering that the CV of frontal rainfall is generally low (Olivera et al., 2008; Kim et al., 2019), this result also suggests that the RTFW may be significantly different for the two similar frontal rainfall events even if they have slightly different temporal variability. Also note that, within this low range of the CV, the influence of the watershed imperviousness on the RTFW is not significant as suggested by little difference between the lines in the plot. This suggests that the influence of the rainfall temporal variability on rainfall-runoff process overwhelms the that of watershed imperviousness. For the range of large rainfall temporal variability (e.g. $\text{CV} > 0.4$), the difference between the curves is significant and each of the curves has low slope with regard to the value of CV. This means that the watershed imperviousness rather than rainfall temporal variability is a dominating factor of the RTFW within this range of the CV. This is because the rainfall event with large CV is likely to have a hyetograph with a temporally intensified pattern, and the abstraction of rainwater is likely to take place in the intensified portion of the hyetograph, which subsequently makes the runoff amount sensitive to the CV.

3.5. Validation of RTFW

This study validated the RTFW values that were estimated from against 149 rainfall events that occurred at 112 sub-watersheds in Seoul over the period of 2010 and 2011. During these two years, Seoul Metropolitan Government recorded every single flooded building (Open Data Platform, Seoul Metropolitan Government, 2020) in the city, which constitutes an accurate and precise spatial database for validation of the RTFW. The warning system first estimates the watershed parameters (i.e., Curve Number and time concentration) of the 239 watersheds of Seoul (Figure 1c). Urban Storm Drainage Criteria Manual (UDFCD, 2016) was used to calculate time of concentration, and Curve Numbers of the watersheds were estimated as area-weighted averages of the CN values based on the land cover of the watershed (Figure 1b). Second, rainfall that shed on each of the 239 watersheds was estimated based on the 10 minute-1 km radar-gauge composite rainfall field (see Han et al., 2021 and Dao et al., 2020 for radar-gauge rainfall data composition algorithm). This process is repeated every 10 minutes as the newly observed rainfall field is fed into the system. As a result of this process, each of the 239 watersheds is coupled with rainfall time series. Third, the most recent x-minute sub-time series is extracted from the time series for each of the watersheds. Here, the value x corresponds to the time of concentration of the watershed. Fourth, average rainfall intensity (I_{ave}) and the CV are computed based on the extracted sub-time series. Finally, the RTWF of each watershed was derived using Equation 1 based on the rainfall CV and the watershed CN, which is subsequently compared with the corresponding I_{ave} . If I_{ave} exceeds the RTWF, a flood warning is issued.

Figure 13 shows the validation result. In the figure, hits (Figure 13a) represent the number of watersheds that is flooded and warned; false alarms (Figure 13b) represent the number of watersheds that is not flooded but warned; and missed alarms (Figure 13c) represent the number of watersheds that is flooded but not warned. For the 2010 event, rate of hit, false alarm, and missed alarm were 69, 31 and 6.7 percent, respectively. For the event of 2011, the rate of hit, false alarm, and missed alarm were 48, 52, and 4.5 percent, respectively. The result of 2011 has lower rate of hit and higher rate of false alarm, which means that flood started to occur at lower rainfall intensity. This is primarily associated with the antecedent soil moisture condition of watershed, which plays a major role in flood generation.

The 2011 flood was a frontal event that lasted several days while 2010 flood was a convective event that lasted only 6 hours. One way to resolve this issue is to lower the RTFW by lowering the CN value based on the antecedent soil moisture condition, which may be inferred from the previous rainfall depths or remotely sensed data (Kim et al., 2016).

The size of the watersheds tested in the warning system ranges from 0.5 to 6.8 km², which means that the warnings can be given to a spatial scale of the smallest administrative unit in many countries. If the warning system runs on the merged watersheds with greater size, the rate of false alarm would significantly decrease and the rate of hit would also significantly increase (Dao et al., 2020b). Here, it is worth noting that the system failed to issue flood warning only for the 6.5 percent of all flood events in spite of the high spatial precision.

Also note that the RTFW and the warning system is designed to work with the 10-minute rainfall. Here, the RTFW is a function of the CV of the 10-minute rainfall. However, rainfall is not measured at this fine temporal resolution and measured mostly at hourly scale in many other regions of the world. This study further investigated the situation in which the rainfall data is provided to the system at only this coarse (e.g. hourly) temporal scale. If the measured hourly rainfall is uniformly distributed at 10-minute level, the CV would be zero. This subsequently decreases the RTFW and significantly increases the miss rate of the system from 6.7 percent to 79.2 percent. One way to overcome this issue is to apply the average CV (0.167) of the rainfall events instead of using the value of zero. The blue-green column in Figure 13a, 13b, and 13c shows the performance of the warning system based on the average CV, which is similar to that of the original case with the improved hit rate at the expense of increased miss rate.

4. Conclusions

This study introduced a method of estimating RTFW based on numerical simulations to be used as a core of flood warning system for urban areas. 1D-2D dual drainage hydrodynamic model (XPSWMM) was used to simulate and determine the extent and degree of the inundation. Then, the relationship

between flooding degree characterized by maximum inundation depth and rainfall intensity was established corresponding to the selected 135 rainfall scenarios. The results showed that the rainfall threshold ranged from 20 mm/h to 90 mm/h to induce inundation in the nine selected watersheds. Then, the relationship between the rainfall intensity and inundation depth was further analyzed in terms of the temporal variability of rainfall (coefficient of variation) and watershed imperviousness (Curve Number), both with great influences on the mechanism of flood formation in the urban areas. The rainfall event with greater CV (rainfall coefficient of variation) would cause higher inundation degree than one with smaller CV for a given same rainfall intensity. In addition, watersheds with higher CN (watershed Curve Number) will suffer more flooding than the ones with lower CN coefficients, given the same storm stimulus. Based on the analyzed results, an equation to determine the RTFW was found as a function of CV and CN. The RTFW exponentially decreased as the CV increased, and the RTFW decreased as the CN increased following a linear trend. We also identified two distinct regimes of the rainfall event temporal variability. When the CV is less than 0.2, the RTFW is more sensitive to the rainfall temporal variability than it is to the watershed imperviousness. The opposite was observed when the CV is greater than 0.4. This result suggests that the rainfall temporal variability should be carefully considered when giving the flood warning during the frontal rainfall event with low temporal variability. Conversely, watershed imperviousness should be carefully considered when giving the flood warning during the convective events that exhibit large high variability. The validation results showed high performance and accuracy of the RTFW-based flood warning system over the rainfall events occurred in 2010 and 2011.

The primary advantage of this study may be that it quantitatively addressed the rainfall temporal variability and the watershed imperviousness to derive the RTFW. As a result, the RTFW was provided as a simple mathematical function of which parameters are easy to obtain.

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Figures

Figure 1

(a) Map of South Korea, (b) the land use map of Seoul, (c) the map of 239 watersheds and rain gauge stations in Seoul 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

The watersheds and respective drainage networks chosen for the analysis 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 3

Detailed model of Sinwol-3 watershed in XPSWMM 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 4

The comparison between simulation and observation results for the nine selected watersheds

Figure 5

The Duration-depth relationship of 230 synthetic rainfall events that were used for urban flood simulation.

Figure 6

Maximum flooded depth versus rainfall intensity for the nine analyzed watersheds.

Figure 7

Relationship between rainfall intensity and flood depth for a) the range of CV 0.11-0.15; b) the range of CV 0.15-0.17; c) the range of CV 0.17-0.23; d) the range of CV 0.23-1.16. e) Regression line of each CV interval.

Figure 8

Flood map of two event with the similar value of rainfall intensity but with different temporal variabilities
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

Regression lines of the relationship between the maximum flooded depth and the rainfall intensity relative to the intervals of CV

Figure 10

Flood map corresponding to scenarios of CN values of 80 (a) and 90(b) 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 11

Intensity versus CV in the relationship with CN of the 101 events that caused the flood depth between 0.25-0.35 meters.

Figure 12

Operation procedure of the flood warning system

Figure 13

Performance of the flood warning system for the events of 2010 and 2011