Drivers of Model Uncertainty for Urban Runoff in a Tropical Climate: The Effect of Rainfall Variability and Subcatchment Parameterization

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Abstract

Urbanization continues to increase in countries with tropical climates and this trend, combined with the likely increasing frequency of extreme rainfall events due to a changing climate, places such development at risk and in need of resiliency assessment. Conceptual models to assess runoff dynamics can be an important component of resiliency assessment, but there are comparatively less data to calibrate these models than are available in the global north. As such, there also is less information with respect to the drivers of model uncertainty and sensitivity. To address this gap in knowledge, we summarize the calibration results of PCSWMM for subcatchment areas in a tropical climate study catchment for which there are substantial rainfall and runoff data. Subsequently, we used the calibrated model to evaluate the impact that rain gauge density may have on runoff estimates. We also investigated the sensitivity of PCSWMM peak flow and total volume estimates to physical subcatchment parameters other than rainfall. With between 38 and 87 events captured for each monitoring station, the NSE, r^2, and ISE ratings varied, but generally were in the respective ranges 0.7–0.8, 0.79–0.85, and good–excellent. It can be concluded that PCSWMM performed well in representing the tropical storm events. The rainfall pattern in the study catchment exhibited considerable spatial variability, both annually and seasonally, with annual rainfall increasing from 2063 mm near the coast to 3100 mm less than 17 km further inland. While the model was sensitive to %imperviousness, subcatchment width, impervious Manning's *n*, and, to a lesser extent, various surface storage and infiltration parameters, the spatial variability of rainfall had the greatest impact on model uncertainty.

1 Introduction

The spatial variability of rainfall is a well-known driver contributing to watershed modeling uncertainty (Schilling and Fuchs 1986; Perrelli et al. 2005; Arnaud et al. 2002; Schellart et al. 2012; Dotto et al. 2014; Nazari et al. 2016; Cristiano et al. 2017; Courty et al. 2018) and methods to reduce this uncertainty have included increasing the density of rain gauges, weather radar applications, and modeling of storm movement (James et al. 2002; Joksimovic et al. 2003; Vieux and Vieux 2005; Goormans and Willems 2013; Thorndahl et al. 2017; Yoon and Lee 2017). Historically, examination of the linkages between rainfall and runoff variability have focused on temperate climates, but with higher rainfall intensity and greater depths experienced in tropical climates, together with increasing urbanization (e.g., Rivard et al. 2006; Costa and Monte-Mór 2015; Schneider et al. 2015; Sadashivam and Tabassu 2016), there is a need to undertake more detailed evaluations in this environment. Certainly, the spatial variation of rainfall has been explored for major cities in southeast Asia (Desa and Niemczynowicz 1996; Siswanto et al. 2016; Cooper 2019; Lestari et al. 2019; Phuong et al. 2019; Bagtasa 2020; Rahardjo et al. 2020; Quan et al. 2021), but while urban runoff modeling is starting to be applied more frequently, there generally is a paucity of flow data for detailed model calibration and sensitivity analysis (Sothea et al. 2010; Chaosakul et al. 2013; Loc et al. 2015; Sovann et al. 2015; Ahmed et al. 2017; Sidek 2021; Chitwatkulsiri et al. 2022). The concept of resiliency (the ability of a system to respond and recover from disasters and including attributes that allow the system to absorb impacts) increasingly has been applied in planning for the management of urban flooding, particularly under a changing climate (Irvine 2013; Bertilsson et al. 2019; Chuang et al. 2020) and conceptual modeling has a clear role to play in resiliency assessment (Sörensen et al. 2016; McClymont et al. 2020; Yang et al. 2022). However, in this arena as well, gaps in knowledge with respect to model calibration, validation, and collaboration between the research community and practitioners remain (Rosenzweig et al. 2021).

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The objectives of this paper are fourfold: (1) summarize the calibration results of PCSWMM for subcatchment areas having substantial rainfall and runoff data in a study catchment of central Singapore; (2) characterize the spatial and temporal variability of rainfall in the study catchment; (3) given the spatial variability of rainfall within the study catchment, evaluate the impact that rain gauge density may have on runoff estimates using the calibrated PCSWMM; and (4) investigate the sensitivity of PCSWMM peak flow and total volume estimates to physical subcatchment parameters other than rainfall.

2 Methods

2.1 Study area

Located at the southern end of the Malaya Peninsula and 1.2° north of the equator, the island city–state of Singapore experiences a tropical rainforest (Af) climate with four seasons, the Northeast Monsoon, and the Southwest Monsoon, which are separated by two inter-monsoon periods. Annual precipitation averages approximately 2343 mm and while the wettest months generally are November, December, and January (Northeast Monsoon season), there is no true dry season, with even the driest month typically experiencing 8 d of rainfall (http://www.weather.gov.sg/climate-climate-of-singapore/, accessed 4 May 2021).

With a population of 5.69 million people in 2020 (https://www.singstat.gov.sg/modules/infographics/population, accessed 4 May 2021) and a total area of 715.8 km^2 (east–west length of 49 km and a north–south length of 25 km), Singapore's population density is 7949 people/km^2. Despite its high population density, Singapore has been identified as one of the greenest cities in the world (based on canopy cover from a study done by MIT (http://senseable.mit.edu/treepedia, accessed 4 May 2021; Li et al. 2015; Seiferling et al. 2017), which reflects its biophilic, urban livability approach to planning (Newman 2014; Liao 2019; Irvine et al. 2020; Loc et al. 2020). Singapore balances the need to efficiently capture stormwater runoff for its drinking water reservoirs and minimize the occurrence of localized flooding using an innovative closed-loop approach that has been described in detail elsewhere (Luan 2010; Irvine et al. 2014; Lim and Lu 2016).

The catchment examined in this study is located in central Singapore and has a contributing area of 100 km^2 that discharges to a waterfront reservoir. The catchment includes the downtown CBD, as well as high density and lower density residential areas, industrial estates, and the award-winning green areas of Bishan-Ang Mo Kio Park and the Singapore Botanical Garden.

2.2 Data collection

Rainfall data (5 min time steps, 2010–2017) for the spatial analysis and model uncertainty components of this study were obtained from the National Environment Agency (NEA) for 24 tipping bucket gauges located within and immediately adjacent to the study catchment. The locations of the gauges are shown in Figure 1. Flow was monitored at a total of 7 sites (Figure 2), primarily in 2014–2015, but also in 2019, at 5 min time steps. The flow data in 2014–2015 were collected with ISCO 2150 area–velocity meters, while in 2019 a Unidata 6526H Starflow Doppler area–velocity meter was used at site 7. In all cases, the flow data were stored on a commercial consultant's server and visualized in realtime through a dedicated project dashboard. The locations of the monitoring stations were selected based on locations used in previous projects, as well as a desire to reflect different land uses and different tributaries. An additional constraint was the need to be upstream of the considerable backwater effect produced by the reservoir. Examples of flow meter installations are shown in Figure 3. Rainfall data were measured (5 min time steps) at each flow station using tipping bucket gauges that were maintained by the study team (separate from the NEA network) for calibration of PCSWMM.

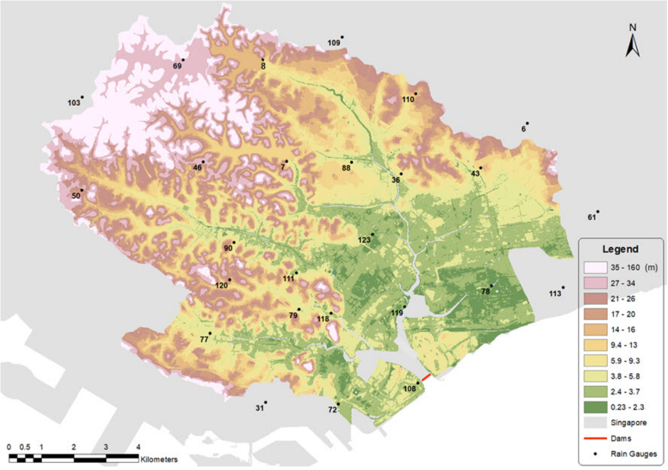

Figure 1 Study catchment with rain gauge locations and topography (elevation in meters).

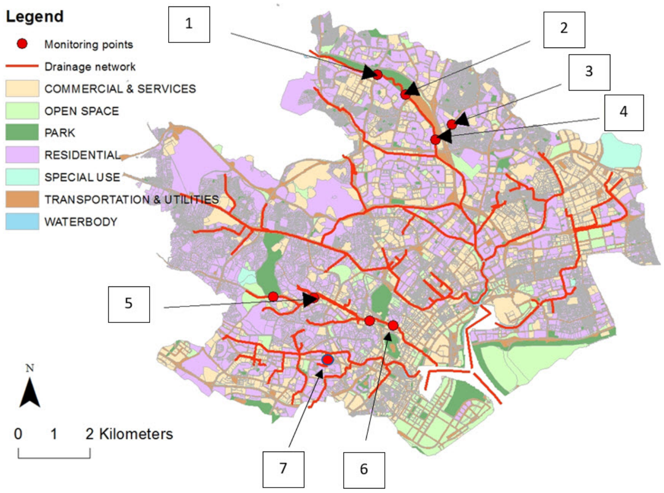

Figure 2 Flow monitoring locations.

Figure 3 Monitoring stations at Site 4 (top), Site 5 (lower left), and Site 6 (lower right).

2.3 PCSWMM configuration

The configuration of PCSWMM for the study catchment is shown in Figure 4. The model features 132 subcatchments, 126 nodes, 126 conduits, and 6 outfalls. The entire system is a separate drainage system that routes only stormwater flow and RDII. For the subcatchments, the Horton infiltration equation was employed, with values generally set at 143.3 mm/h for the initial maximum infiltration rate (f_o), 2.5 mm/h for the minimum infiltration rate (f_c), and 1.4 1/h for the decay constant (α). These values were based on field measurement conducted through other projects, including those reported by Irvine and Chua (2016). RDII was represented in the model for catchments having large green space areas, as Irvine and Chua (2016) showed that explicit consideration of RDII improved prediction of runoff for such land use in Singapore. PCSWMM can estimate RDII using either the R-T-K approach or with a modified Darcy's equation (Pang 2014). The Darcy's equation approach requires an extensive database to operationalize parameters for the aquifer, including hydraulic conductivity, hydraulic potential (sum of gravity and pressure heads, where pressure head is represented by the soil water tension), moisture content, field capacity, wilting point, and aquifer bottom elevation. Although conceptually more rigorous, these data frequently are not available for urban areas. Lai (2008) concluded that the R-T-K unit hydrograph approach is common-ly used in urban hydrology, and is relatively straightforward to parameterize (see also, Cheng et al. 2011; Siegrist et al. 2016). Under this approach, R represents the fraction of rainfall volume that enters the drainage network, T represents the time from the onset of rainfall to the peak of the unit hydrograph in hours, and K represents the ratio of time to recession of the unit hydrograph to time to peak. Because the R-T-K approach has been widely employed, including in Singapore (Irvine and Chua 2016) and requires relatively lesser parameterization that can be determined empirically, this approach was chosen for our study. Initial values for T and K were estimated based on empirical assessment for a subset of observed hydrographs, while R was adjusted through the model calibration. Values for the short-term R–T–K parameters were respectively 0.0167, 1.3, and 6.8; medium-term R–T–K parameters were respectively 0.0167, 1.2, and 1; and long-term R–T–K parameters were respectively 0.05, 1, and 1. The model was run in 1D using a dynamic wave routing approach.

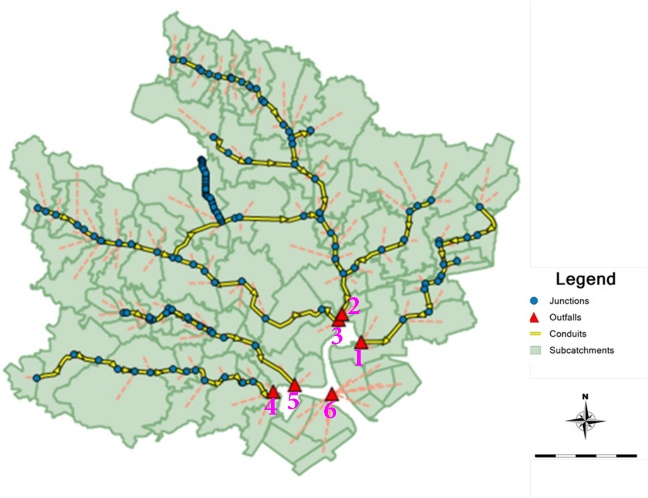

Figure 4 Study catchment as represented in PCSWMM; the numbered red triangles are the outfalls to the reservoir.

3 Results

3.1 PCSWMM calibration

A review of the measured data showed that monitoring was most reliable for Sites 1, 2, 3, 4, and 5, in 2014 and 2015, and these were used for model calibration. The 1:1 lines for the peak and volume of the modeled events are shown in Figure 5, where the number of modeled events ranged between 38 and 87. NSE, r^2, and integral square error (ISE) ratings varied from event to event and site to site, but generally were in the respective ranges 0.7–0.8, 0.79–0.85, and good–excellent. It can be concluded that PCSWMM performed well in representing the tropical storm events.

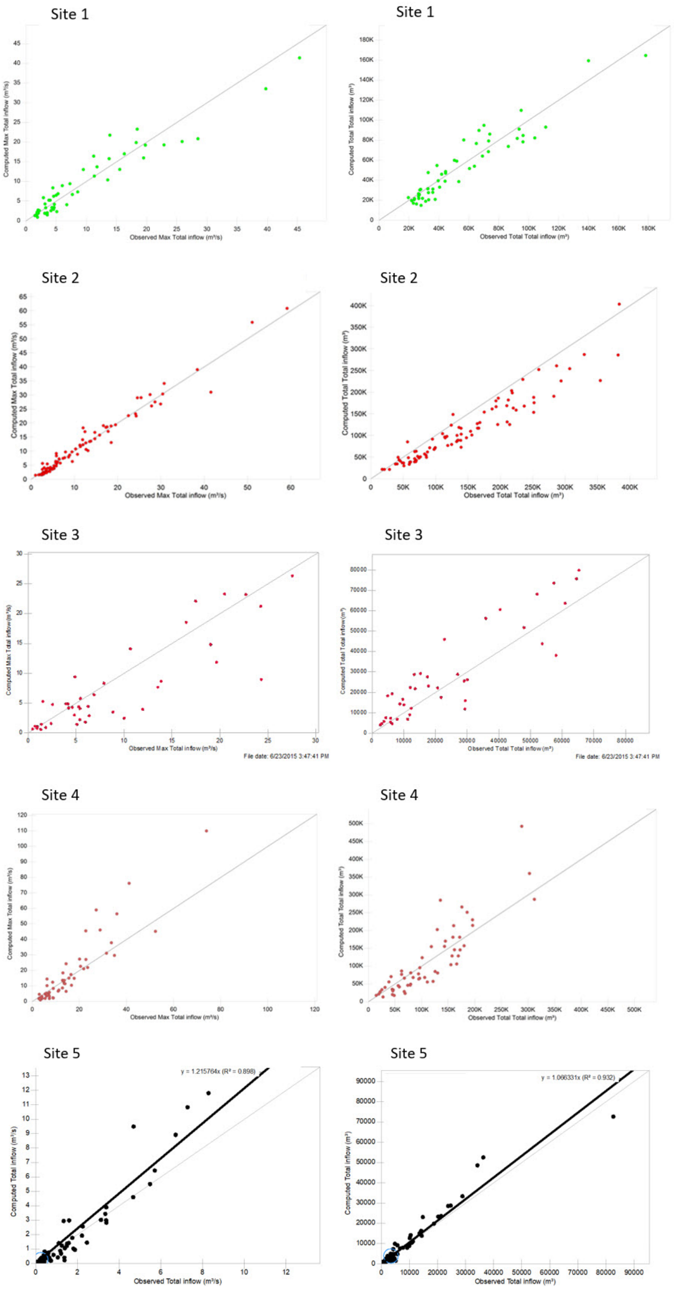

Figure 5 1:1 calibration lines, peak flow (left column), and event volume (right column).

3.2 Spatial variability of rainfall in the study catchment

A review of the NEA rainfall data revealed that of all years 2010–2017, the data for 2012 had the least missing or duplicate data. As such, in this section, we focus the spatial analysis on 20 rain gauges for 2012. Isohyetal maps were produced for the entire year (Figure 6) and by month (Figure 7). As illustrated (Figure 6), the annual rainfall varied from 2063 mm in the southeastern part of the catchment to 3100 mm in the northwest area of the catchment. This spatial variability potentially has a large impact on catchment model results. To some extent, the spatial variability of rainfall may reflect a slight orographic effect, with elevations increasing progressively inland, from 0 m up to 160 m above mean sea level (Figures 1 and 6). Figure 7 also shows there was considerable spatial variability in rainfall between months. The inter-monsoon months of October and November, and to a lesser extent April and May, appear to exhibit the greatest spatial variability, possibly because the rainfall is dominated by more localized, convectional rain events, whereas the monsoon seasons tend to reflect spatially larger events with greater rainfall depths.

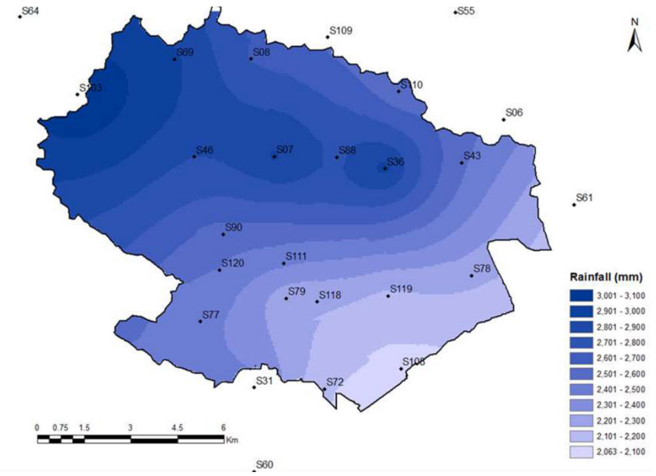

Figure 6 The annual (2012) isohyets for the study catchment.

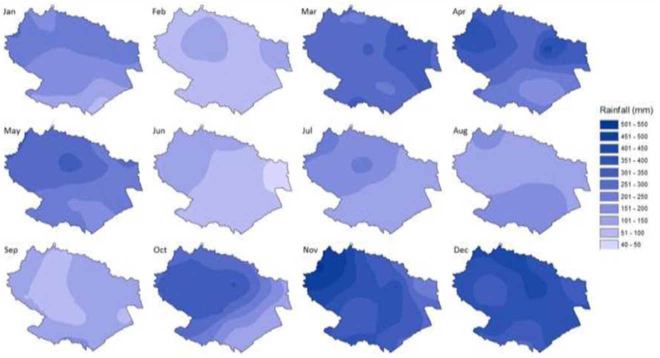

Figure 7 Monthly isohyets for the study catchment (2012).

3.3 Temporal variability of rainfall in the study catchment

The temporal variability of 5 min rainfall for each month was evaluated by averaging across all rain gauges using all data (2010–2017) and results are shown in Figure 8. The highest 5 min rainfall (4 mm–5 mm) is expected around 16:00 h–17:00 h from mid-November through mid-December, although the expected time spread of maximum intensity increases to15:00 h–17:00 h towards the end of December (Figure 8). For the later part of the Northeast Monsoon season (approximately late February and early March), there will be higher rainfall during 13:00 h–20:00 h, with highest rainfall values between 15:00 h and 17:00 h. During the inter-monsoon season of April and May, the highest rainfall occurs around 15:00 h–16:00 h. In the Southwest Monsoon season, June-September, and early October, the temporal variability of 5 min intensities exhibits a greater spread, 04:00 h–16:00 h. The early morning events would be associated with Sumatra Squall lines, which are more likely to occur during the Southwest Monsoon season (Beck et al. 2015).

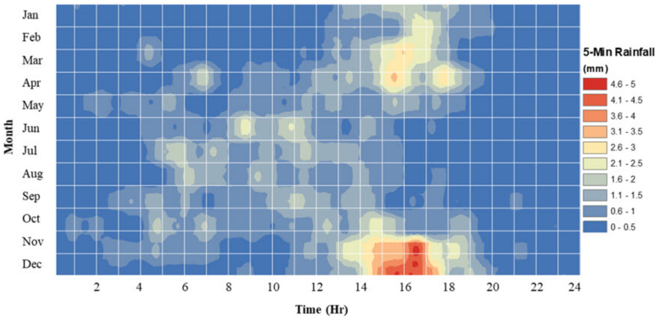

Figure 8 Temporal variability of 5 min rainfall for each month averaged for all study catchment rain gauges, 2010–2017.

Subsequently, the probability of exceedance for different rainfall durations (5 min, 10 min, 15 min, 30 min, 1 h, 2 h, 3 h, 6 h, 12 h, 24 h) were determined, as illustrated in Figure 9 (all stations have been depicted with the same color for a specific duration). To conduct the probability analysis, the MATLAB Pearson System was used, which fits a family of distributions including the normal, 4 parameter beta, symmetric 4 parameter beta, 3 parameter gamma, and inverse gamma distributions. The analysis showed the Pearson Type I (PT-I) and Pearson Type VI (PT-VI) distributions generally fit the data the best. All the stations follow a PT-I distribution for durations up to 30 min. However, for higher durations, PT-VI also was appropriate for some stations. Mandapaka and Qin (2013) assessed the three-parameter lognormal, generalized Pareto, Weibull, and Pearson Type III distributions for 49 rain gauges throughout Singapore, representing the period 1983–2010, and found the Pearson Type III to provide the best fit. It appears that some form of the Pearson probability distribution is most appropriate to represent rainfall in Singapore.

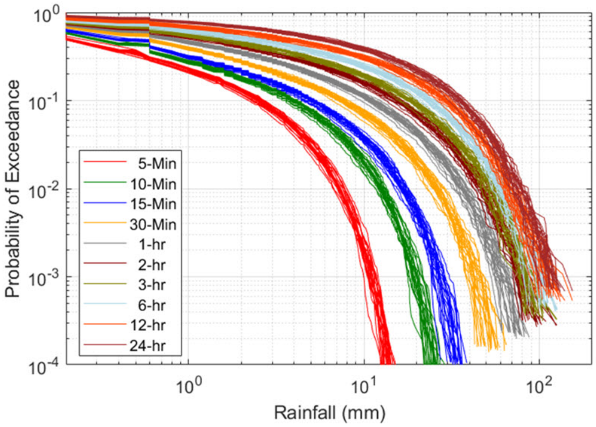

Figure 9 Probability of rainfall exceedance (based on fitted distributions).

High-resolution probability analysis was conducted for each station, using the weekly data of all years (2010–2017) collectively. This analysis generated a matrix of 52 (weeks in a year) by 288 (number of 5 min intervals during the day) for each rain gauge (i.e., 14 976 data cells). Each cell in this matrix contains 49 records where a Pearson Type I (PT-I) distribution is fitted; however, in some cells there were no proper records for fitting a distribution. For example, if the data have only 0–2 points or all the rainfall data are equal, a probability distribution could not be fitted to the data. Figure 10 shows an example of the distributions fitted to week 52, hours 17 and 18 at rain gauge S123. As illustrated in Figure 10, the observed and theoretical PT-I distributions match well, with a high probability of exceeding ~0.2 mm in 5 min for hours 17 and 18 in week 52. A number of years had 0 mm of rainfall in the 5 min periods for hours 17 and 18. The probability of rainfall amounts exceeding ~0.2 mm in 5 min decreased rapidly, although we do note that for one of the years in 2010–2017, around 5 mm of rainfall was observed during hour 18, resulting in the extended tail of the probability distributions.

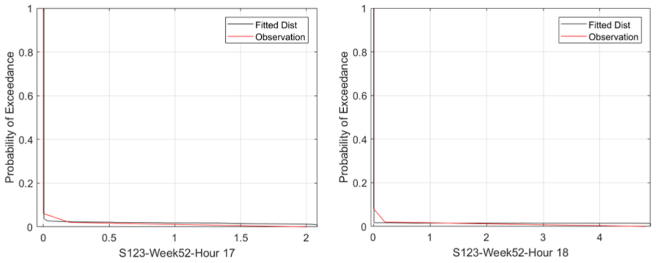

Figure 10 Pearson Type I distributions fitted to (a) hour 17, and (b) hour 18 of week 52 (2010–2017) rainfall depths, at rain gauge S123.

3.4 Impact of spatial and temporal variability on runoff model results

To evaluate the impact of spatial and temporal variability in rainfall on runoff estimates for the study catchment, the 5 min rainfall data representing the 97th percentile range, based on the probability analysis described in the previous section, for the entire year 2014 were used as input to PCSWMM. The density of the rain gauge network was sequentially reduced through four scenarios: (1) 19 rain gauges within the entire study catchment; (2) 9 rain gauges within the entire study catchment; (3) 4 rain gauges within the entire study catchment; and (4) 1 rain gauge within the entire study catchment. The distribution of the rain gauges for the different scenarios was based on an examination of the annual and monthly isohyetal maps, with an effort to provide a representative network for the entire catchment in each scenario.

PCSWMM results for the different scenarios are summarized in Figures 11–13. Figure 11 represents the 5 min 97th percentile data for each of the 52 weeks in 2014; for ease of interpretation, two example periods are shown in more detail (Figures 12 and 13). Results in Figures 12 and 13 indicate that for some larger magnitude events (e.g., April 2014) spatial variability of rainfall (based on the number of gauges used for modeling purposes) can have considerable impact on predicted runoff, while for other events (e.g., July 2014) the impact is not as large.

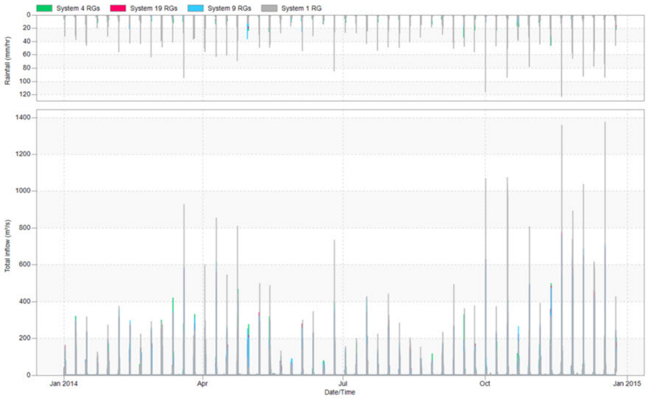

Figure 11 Rainfall and modeled runoff for 5 min 97th percentile rainfall data for each week of 2014.

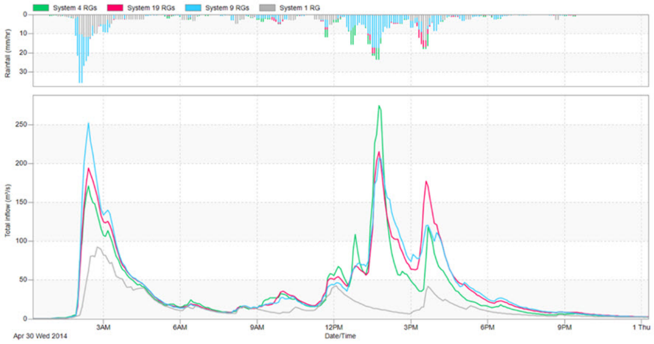

Figure 12 Example rainfall and modeled runoff for 5 min 97th percentile rainfall data for events in April 2014.

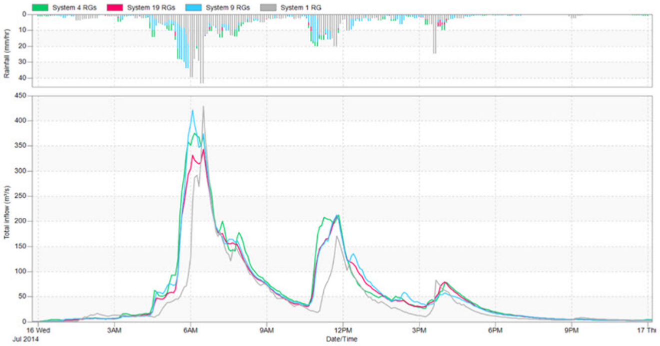

Figure 13 Example rainfall and modeled runoff for 5 min 97th percentile rainfall data for events in July 2014.

3.5 Model sensitivity and uncertainty related to catchment parameter values

Based on the study team's experience and the literature (Irvine et al. 1993; Wan and James 2002; Barco et al. 2008; James et al. 2010; Ogden et al. 2011; Li et al. 2014; Sun et al. 2014; Irvine and Chua 2016; Behrouz et al. 2020), we selected 10 parameters for sensitivity analysis, all related to surface catchment characteristics (i.e., drainage canal and pipe network characteristics were not considered):

1. %imperviousness;
2. Width of overland flow (subcatchment width);
3. Depth of pervious surface storage;
4. Depth of impervious surface storage;
5. Subcatchment slope;
6. Manning's *n*, pervious surfaces;
7. Manning's *n*, impervious surfaces;
8. Maximum infiltration rate, Horton infiltration equation;
9. Minimum infiltration rate, Horton infiltration equation; and
10. Decay coefficient, Horton infiltration equation.

Sensitivity runs for the study catchment runoff using November 2014 rainfall data were conducted with the PCSWMM sensitivity scenario tool and the ranges for the 10 parameters were varied between ±50%. Not all outfall points were sensitive to the same parameters and the top 5 sensitive parameters were selected using an aggregate low score based on their relative ranking for each outfall, with the results for the individual outfalls and entire system shown for peak flow in Table 1 and total volume in Table 2.

Table 1 Summary of top 5 sensitive parameters for peak flow.

Rank	Outfall 1	Outfall 2	Outfall 3	Outfall 4	Outfall 5	System
1	Imperv.	Imperv.	Imperv.	Imperv.	Imperv.	Imperv.
2	Width	Width	Width	Width	Width	Width
3	N Imperv	N Imperv	N Imperv	N Imperv	N Imperv	N Imperv
4	Slope	Slope	Slope	Slope	Slope	Slope
5	Dstore Imperv	Max. Infil. Rate	Max. Infil. Rate	Max. Infil. Rate	Decay Constant	N Perv

Table 2 Summary of top 5 sensitive parameters for total event volume.

Rank	Outfall 1	Outfall 2	Outfall 3	Outfall 4	Outfall 5	System
1	Imperv.	Imperv.	Imperv.	Imperv.	Imperv.	Imperv.
2	Decay Constant	Max. Infil. Rate	Max. Infil. Rate	Decay Constant	Max. Infil. Rate	Decay Constant
3	Max. Infil. Rate	Decay Constant	Decay Constant	Max. Infil. Rate	Decay Constant	Max. Infil. Rate
4	Min. Infil. Rate	Min. Infil. Rate	Min. Infil. Rate	Min. Infil. Rate	Min. Infil. Rate	Min. Infil. Rate
5	Dstore Perv	Width	Width	Dstore Perv	Width	Width

4 Discussion

There has been considerable discussion in the literature with respect to appropriate and effective model performance indicators and the benchmarking and interpretation of such indicators (Legates and McCabe 1999; Schaefli and Gupta 2007; Knoben et al. 2019; Lane et al. 2019) and it has been suggested that performance assessment be based on multiple indicators rather than a single indicator (McCuen et al. 2006; Jain and Sudheer 2008). The Nash–Sutcliffe efficiency index is a commonly used performance indicator, although the upper benchmark for acceptable performance seems to vary from as low as 0.5 up to 0.75 (Lin et al. 2017; Seibert et al. 2018; Lane et al. 2019). Shamsi and Koran (2017) recommended that a Nash–Sutcliffe value in the range 0.5–1.0 could be considered an excellent calibration result and as such, the model could be used for planning, preliminary designs, and final designs. Shamsi and Koran (2017) further suggested that ISE classifications of model calibration in the Very Good and Excellent categories could be used for planning, preliminary designs, and final designs, while model calibration achieving an ISE Good rating could be used for planning and preliminary designs. Based on model results presented in Figure 5 for the 1:1 lines, as well as the NSE (range 0.7–0.8), r^2 (range 0.79–0.85), and the ISE rating (Good–Excellent), we can conclude that the calibration of PCSWMM successfully captures runoff dynamics for tropical conditions.

Rainfall within the catchment exhibited clear spatial variability (Figures 6 and 7), although as noted in Figure 7, the inter-monsoon months of October and November, and to a lesser extent, April and May, appear to exhibit the greatest spatial variability. These seasonal differences likely occur because the rainfall in the inter-monsoon is dominated by more localized, convectional rain events, whereas the monsoon season tends to reflect spatially larger events with greater rainfall depths. The annual rainfall pattern (2012) varied from 2063 mm near the mouth of the reservoir, to 3100 mm near the upper catchment boundary, a distance of just under 17 km. Given this more than 1000 mm difference over a relatively short spatial distance (in this case, in part related to an orographic influence), it would suggest that spatial variability of rainfall may have an important impact on runoff modeling uncertainty. Rahardjo et al. (2020) also noted considerable spatial variability in annual and 5 d maximum rainfall for the entire island of Singapore but showed that at the annual scale, maximum rainfall was greatest in the northwest, while the 5 d maximum was greatest in the north and northeast. Doan et al. (2021) concluded that the urban effect contributes ~20%–30% of the total rainfall during late afternoons and evenings in Singapore. This effect represented an interactive set of drivers, including enhanced convection associated with the urban heat island (see Chow and Roth 2006; Ng 2015), increased frictional convergence due to building drag (see Ashrafi et al. 2022), the seaward shift of the sea-breeze front, and the increased inflow of boundary layer moisture by the stronger sea breeze (Doan et al. 2021).

With confidence in our PCSWMM model calibration, we used the model to explore the impact of rain gauge density on runoff estimates. As can be seen in Figures 11–13, model results indicate that for some larger magnitude events spatial variability of rainfall (as represented using differing numbers of rain gauges) can have considerable impact on predicted runoff, while for other events, the impact is not as large. These differences in rainfall impact may be related to dominant seasonal processes, as well as the drivers noted in the previous paragraph. Maintenance of a dense network of rain gauges can be a costly endeavour, and certainly Singapore has established a network density that exceeds the World Meteorological Organization recommendation for urban areas (Chang and Irvine 2014). Given the results in Figures 11–13, it seems that the 9-rain gauge configuration may be sufficient for model accuracy and representativeness, should Singapore look to optimize maintenance costs. We also explored the option of using weather radar products to enhance model accuracy related to a less dense on-the-ground gauge system, but at this point, the spatial resolution of available products is not sufficient. The available Integrated Multi-Satellite Retrievals for GPM (IMERG) as shown in Figure 14, for example, has a spatial resolution of 0.1° and 30 min temporal resolution. Both the spatial and temporal resolution of the IMERG imaging would be too coarse and, in particular, the study catchment is mainly covered by one IMERG cell, with partial coverage from three other cells. Hur et al. (2016) reported that other weather radar products available for Singapore, when compared to rain gauge data, tended to overestimate light rainfalls but underestimate high rainfalls and the length of dry spells, which has important implications for model uncertainty. More recently, Mandapaka and Lo (2020) evaluated the IMERG images for Singapore compared to rain gauges, and, consistent with Hur et al. (2016), found light to medium rainfalls were overestimated. However, Mandapaka and Lo (2020) did note that the IMERG images registered improved performance for larger storms (≥32 mm). Nonetheless, the spatial and temporal resolution of the IMERG products remain as constraining factors for runoff model application in Singapore.

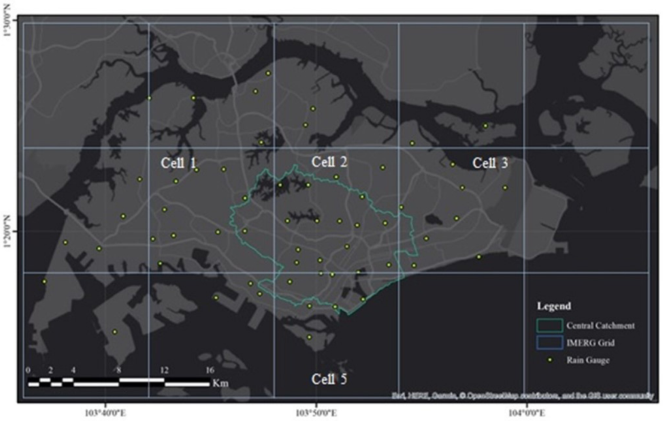

Figure 14 **IMERG coverage over the study (central) catchment.**

We employed a simple brute force method in assessing model sensitivity that might be refined in the future to consider some type of Bayesian, mutual information analysis–Latin hypercube, or genetic algorithm approach (e.g., Dotto et al. 2014; Li et al. 2014; Del Giudice and Padulano 2016). We found the sensitivity of PCSWMM to the set of model parameters investigated may differ for peak flow estimates compared to event volume (Tables 1 and 2), although %imperviousness had the greatest impact on both. Sensitivity of peak flow across the different major subcatchments was more consistent than event volume, with the model being secondarily sensitive to subcatchment width, followed by Manning's *n* for impervious surfaces. These results are in general agreement with those reported by Irvine et al. (1993) and Ogden et al. (2011). Event volume was variously impacted by the three different Horton infiltration parameters, the depth of pervious surface storage, and subcatchment width. It seems, then, that event volume estimates are more influenced by pervious surface infiltration and storage characteristics than peak flow. There is less uncertainty in determining apparent %imperviousness as compared to parameters such as subcatchment width, Manning's *n*, or surface storage depth since it can be measured initially using a combination of GIS/Autocad layers and remotely sensed images (see also Randall et al. 2017). We note that the initial estimate of apparent %imperviousness may be different from the actual directly effective hydrologic impervious area, which will be dynamic and contribute differently with different storm characteristics. This dynamism, in part, will be captured through the calibration process. Furthermore, all impervious runoff was routed directly to an outlet, and none was diverted to pervious surfaces. Given the abundance of water sensitive urban design (WSUD) features in Singapore, a more detailed and system-wide evaluation of the efficacy of such features, which necessarily would route impervious flow to pervious surfaces, should be considered in future modeling efforts.

Focusing specifically on peak flow, which arguably is a more important parameter than volume in managing urban runoff, the difference in peak estimates associated with the top four parameters from Table 1 was 28.8%, 13.8%, 13%, and 5.8% for %imperviousness, subcatchment width, Manning's *n* for impervious surfaces, and catchment slope, respectively. These differences consider all outfalls collectively for the month of November 2014, over a parameter value range of ±20%. The calibrated maximum peak flow (688 m^3/s) from the entire system in 2014 was associated with a storm event on 19 November. Rainfall for the event was 94 mm and maximum intensity was 49 mm/h. The estimated peak flow was between 650 m^3/s and 720 m^3/s, or a range of 70 m^3/s when the %imperviousness (the most sensitive but also one of the least uncertain parameters) was varied ±20% for all catchments. In comparison, the second event of April 2014, shown in Figure 12, exhibited a range of 250 m^3/s for modeled peak flow, depending on the rain gauges used for the modeling exercise. Even when there was less spatial variability in the rainfall, the larger first event of July 2014 shown in Figure 13 exhibited a range of 100 m^3/s for modeled peak flow. These results suggest that in general, there is greater model uncertainty introduced by spatial variability of rainfall than by parameter uncertainty and reinforces the importance of collecting good rainfall data for model input.

5 Conclusion

With an extensive rainfall and runoff dataset spanning between 38 and 87 events for 6 sites, PCSWMM performed well in representing the dynamics of tropical storms. Representation of RDII was important for good model results in this particular area and may be considered in other tropical areas as well. The study catchment rainfall pattern exhibited considerable spatial variability, both annually and seasonally, with annual rainfall increasing from 2063 mm near the coast to 3100 mm less than 17 km further inland. While the model was sensitive to %imperviousness, subcatchment width, impervious Manning's *n*, and to a lesser extent various surface storage and infiltration parameters, the spatial variability of rainfall had the greatest impact on model uncertainty.

Singapore has the benefit of an extensive rainfall and runoff monitoring program. However, given the increasing availability of cost-effective IoT-based meteorological and water level instrumentation, coupled with a new emphasis on Smart City development and big data for decision-making in the global south, it would be prudent for communities to plan and implement such water resource data collection systems. The combination of cost-effective monitoring and modeling will help urban communities in the global south to address resiliency issues, particularly in light of changing climate, land use patterns, and the desire for more liveable, sustainable cities.

This study has provided useful insights to important drivers of model uncertainty in tropical urban environments. While the focus of the study was Singapore, some of the findings, and in particular, the importance of spatial and seasonal variability of rainfall, and possibly considerations of RDII, may be extended to other tropical countries. However, Singapore also offers some unique infrastructure characteristics in relation to its well-established biophilic approach to development, separate as opposed to a combined sewer system, and a relatively dense network of well-maintained surface and subsurface drains. With the increased focus globally on Nature-based Solution designs for sustainable and resilient cities, we trust that some of the biophilic approaches to water management in Singapore may be adapted by other countries in the region. The study has also identified aspects of model uncertainty that need to be explored more fully and rigorously. In particular, a fuller, quantitative assessment of required rain gauge density relative to expected spatial variability of rainfall should be undertaken to provide guidance on the optimum number of gauges relative to cost. Although, at the moment, weather radar does not have sufficient spatial resolution to adequately capture rainfall characteristics at the subcatchment scale in Singapore, as these remote sensing technologies continue to evolve, they should be regularly assessed as an alternative approach to reduce uncertainty in runoff modeling.

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