

1 **Title: Effects of Urban Imperviousness Scenarios on Simulated Storm Flow**

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15

16 **Abstract**

17 The amount and distribution of impervious surfaces are important input parameters of
18 hydrological models, especially in highly urbanized basins. This study tests three different
19 methods to input impervious surface area information to a semi-distributed hydrological model in
20 order to examine their effects on storm flow. The three methods being evaluated include: (1) a
21 constant value for impervious surfaces in the entire urban area, (2) constant values of
22 imperviousness for commercial and residential land uses, respectively, and (3) different
23 imperviousness for the residential land use in each subbasin. Storm flow of the Milwaukee River
24 Basin in southeastern Wisconsin (USA) was modeled using the Hydrological Simulation
25 Program–Fortran. The results show that the three methods resulted in substantially different
26 amounts of storm flow. The storm flow simulated with the third method was the largest and had
27 the largest variability among the subbasins. The differences among the scenarios are generally
28 larger in subbasins with high percentage of urban land use types. The results suggest that the
29 effect of different input methods is amplified in urbanized subbasins and the spatial variability of
30 imperviousness should be commensurate with the spatial variability of the model configuration.

31 Keywords: hydrological model, impervious surface, urban land use, runoff, storm flow

32 **Introduction**

33

34 Impervious surfaces prevent infiltration of water into the soil, and are used as a measurable
35 indicator of the impacts of urban development on stream ecosystem (Allan 2004). Urban growth
36 inevitably accompanies an increase in impervious surfaces such as rooftops and pavements
37 (Randhir 2003). The increasing extent of impervious surface changes the landscape from an
38 infiltrative sink to a source of runoff (Booth and Jackson 1997). The increasing imperviousness
39 also alters the hydrological cycle by blocking infiltration, increasing runoff production, and
40 reducing lag time between precipitation and runoff peaks, as summarized by Shuster et al. (2005).
41 Such impacts on hydrological processes can be studied using hydrological models where
42 imperviousness is one of input parameters (e.g. Choi and Deal 2008; Caldwell et al. 2012; Dams
43 et al. 2013; Zhou et al. 2014; Sunde et al. 2016; Chen et al. 2017). The amount and distribution of
44 impervious surfaces are important input parameters of hydrological models, especially in highly
45 urbanized basins. Therefore, the way imperviousness data is treated in hydrological models can
46 change the model simulation results.

47 Imperviousness of land surface is defined by its total extent and the degree to which it is directly
48 connected to the stream channel. The total impervious surface area is the most general
49 measurement of imperviousness, and it is usually expressed as a proportion or percentage of total
50 area (Shuster et al. 2005). Therefore, impervious surface area is a continuous measurement,
51 ranging from 0 to 1 across any land parcel or pixel (Xian et al. 2011). The total impervious
52 surface area in the conterminous United States was found to have increased on average by 4.11%

53 between 2001 and 2006 (Xian et al. 2011). Moreover, grid cells in the data with high
54 imperviousness increased more than those with low imperviousness (Xian et al. 2011).

55 Continuous impervious surface percentage can be most accurately derived by utilizing remote
56 sensing data. It can be accomplished by several different methods such as spectral mixture
57 analysis (Wu and Murray 2003; Wu 2004; Lu and Weng 2006), regression tree modeling (Yang
58 et al. 2003a, b; Xian and Crane 2005), decision tree classification (Dougherty et al. 2004),
59 subpixel classification (Civco et al., 2002), neural network classification (Civco and Hurd, 1997),
60 and regression (Bauer et al. 2004, 2005). However, such procedure is not always feasible, e.g.
61 due to data unavailability, or some hydrological models simply cannot use the continuous
62 impervious cover information as input parameters. Instead, such hydrological models require
63 impervious surface information in a discrete manner on a land use/cover class basis, for example,
64 a specific land use/cover class is assigned a specific impervious surface area. Therefore, some
65 input methods are needed to enter continuous imperviousness data in a discrete manner into the
66 hydrological model. Such methods and their effects on hydrological modeling have been
67 compared by Chormanski et al. (2008), Batelaan et al. (2007), and Voorde et al. (2006).
68 Chormanski et al. (2008) found substantial difference in hydrological modeling results from
69 different impervious surface area input methods. Batelaan et al. (2007) argue that the most
70 accurate imperviousness input should be used for fully-distributed grid-based hydrological
71 models for urban runoff simulation. Voorde et al. (2006) obtained similar results among different
72 input methods for runoff.

73 The studies by Chormanski et al. (2008), Batelaan et al. (2007), and Voorde et al. (2006) were
74 conducted using grid-based distributed hydrological models. Although distributed hydrologic
75 models can use spatially continuous impervious surface cover as input, they have some
76 disadvantages. Such distributed and physically based models actually are lumped conceptual
77 models with excessive number of parameters, and it can cause very iterative works for both the
78 computer and the researcher during the calibration phase (Beven 1989, 1996). Compared to
79 distributed hydrologic models, semi-distributed hydrological models where the domain is divided
80 into subbasins have less parameters and require less computing capability, thus are more
81 convenient to use. Instead, such models cannot take full advantage of the most accurate
82 impervious surface cover measurements, thus take the imperviousness information in a simplified
83 form.

84 Our goal in this study was to investigate the extent to which the model results differ between the
85 methods assigning imperviousness. Specifically, we compared the effects of three different
86 imperviousness input methods on storm flow simulated by a semi-distributed hydrological model
87 by modifying the approach adopted by Chormanski et al. (2008). The simulation was conducted
88 for a river basin that has subbasins with varying degrees of urbanization and simple topography.
89 In addition, we examined the results among subbasins with respect to the extent of urban areas in
90 the subbasin.

91

92

93 **Study Area**

94 We selected the Milwaukee River basin (US Geological Survey Hydrologic Unit 04040003)
95 located in southeastern Wisconsin as the study area (Figure 1a). It is located between 42° 50' N
96 and 43° 50' N latitude, and between 87° 50' W and 88° 30' W longitude. The total population of
97 the basin is about 1.3 million, and the basin area is approximately 2267 km². The southeast part,
98 where the city of Milwaukee is located, is the most densely populated and urbanized area in the
99 state and contains 90 percent of the population in the basin. The total length of the reaches is
100 about 800 km including the Milwaukee River, Cedar Creek, Menomonee River, and Kinnickinnic
101 River (WDNR 2001). Because the southern portion of the basin is highly urbanized (Figure 1b),
102 storm flow is of great concern in the context of flooding and water quality. When the city of
103 Milwaukee and its suburbs suffered flash flooding in July 2010, even an Individual Assistance
104 Declaration was issued by the President of the United States (FEMA 2010).

105

106 **Hydrological Model**

107 We selected the Hydrologic Simulation Program-Fortran (HSPF) model (Duda et al. 2012) to
108 simulate storm flow in this study. HSPF is a comprehensive, physically based, semi-distributed
109 hydrological model (Bicknell et al. 1997). Specifically, we used WinHSPF, which is the
110 Windows® interface of HSPF and available as part of the U.S. Environmental Protection
111 Agency's Better Assessment Science Integrating point & Non-point Sources Version 4.1 (U.S.
112 EPA 2013). HSPF has been employed for studying hydrological variables such as streamflow,

113 sediment yield, and non-point source pollution in many projects conducted around the world (e.g.
114 Choi et al. 2017; Alarcon et al. 2009; Hsu et al. 2010; Hayashi et al. 2008; Tzoraki and
115 Nikolaidis 2007).

116 In HSPF, the study area is divided into subbasins according to topography, and each subbasin
117 contains pervious and impervious land segments and a stream channel (and/or a reservoir).
118 Accordingly, there are three compartments in HSPF to simulate different physical conditions,
119 namely PERLND, IMPLND, and RCHRES. PERLND simulates hydrological processes on
120 pervious land segments, whereas IMPLND is for those on impervious land segments. Both
121 PERLND and IMPLND simulation results will merge into RCHRES and then RCHRES
122 simulates hydraulic processes in a channel or a reservoir. In this study, 33 subbasins were
123 delineated (Figure 1c).

124

125 **Data**

126 **Land use**

127 The land use/land cover data for the Milwaukee River basin (Figure 1b) was obtained from the
128 US Geological Survey (USGS) National Land Cover Database 2001 version, which were derived
129 from satellite imageries from the Multi Resolution Land Characteristics Consortium (Vogelmann
130 et al. 2001). Predominant land use types include planted/cultivated, residential, forest, and
131 wetlands (Table 1).

132 **Table 1.** Land use statistics of the Milwaukee River basin

| Land use type | Area (km²) | Percentage (%) |
|----------------------|------------------------------|-----------------------|
| Water | 21.2 | 1.0 |
| Residential | 314.0 | 14.1 |
| Commercial | 18.2 | 1.0 |
| Other urban | 382.1 | 17.2 |
| Forest | 240.5 | 10.8 |
| Shrubland | 15.0 | 0.7 |
| Herbaceous | 15.9 | 0.7 |
| Planted/Cultivated | 949.6 | 42.8 |
| Wetlands | 261.7 | 11.8 |
| Total | 2220.0 | 100 |

133

134 **Imperviousness input for HSPF**

135 We adopted an impervious surface cover percentage dataset (Figure 1c) produced by Li et al.
 136 (2018). It was produced by building a linear regression model to predict impervious surface
 137 distributions in residential and commercial land uses. The map is a continuous raster data and
 138 each grid pixel (30m × 30m) contains a value of impervious surface cover percentage. In order to
 139 use it for HSPF, the imperviousness raster data were firstly disaggregated into 33 subbasins and
 140 then the average impervious percentages of residential land use types were calculated for each
 141 subbasin. Also, the entire raster impervious data and land use map were used together to calculate
 142 the average impervious percentage of the commercial land use type. These impervious
 143 percentages were then inputted into HSPF during the model setup.

144

145 **Climate data**

146 The temperature and precipitation input data for HSPF were obtained from the high-resolution
147 gridded daily data sets for Wisconsin (Serbin and Kucharik 2009). The data were produced by
148 interpolating weather stations data across the state to a grid mesh of 8 km by 8 km (Figure 1a) for
149 the period 1950-2006. The gridded data were aggregated to four locations corresponding to the
150 four USGS streamflow gauge stations for the convenience of data input. The four gauge stations
151 are 04086600 Milwaukee River near Cedarburg, 04087000 Milwaukee River at Milwaukee,
152 04087120 Menomonee River at Wauwatosa, and 04087159 Kinnickinnic River @ S. 11th Street
153 @ Milwaukee (for detailed information regarding the stations, search on
154 <http://waterdata.usgs.gov>). The Thiessen polygon method (Thiessen 1911) was used to determine
155 the control area for each gauge station. Other weather data were downloaded from the BASINS
156 4.1 Web site as part of the model package.

157

158 **Methods**

159 Chormanski et al. (2008) compared three different methods for estimating impervious surface cover
160 on the prediction of peak discharges. The three methods are (1) average percentage of
161 imperviousness for the entire urban area; (2) average percentage of imperviousness for different
162 types of urban land use; and (3) local percentage of imperviousness for every individual cell
163 within the urban area. By using the impervious surface cover percentage map (Figure 1c) and

164 modifying the approach by Chormanski et al. (2008), we developed three scenarios of
165 imperviousness input methods as follows:

166 Scenario 1 (S1): A constant value for impervious surfaces in the entire urban area

167 This scenario assumes that the entire urban area has the same impervious surface cover
168 percentage. A spatial mean (29.3%) of the impervious percentage was calculated from the
169 impervious surface cover map (Figure 1c) and was assigned to the entire urban land use for
170 HSPF. Other land use types were assigned zero for impervious percentage value.

171 Scenario 2 (S2): Constant values of imperviousness for commercial and residential land uses,
172 respectively

173 In this scenario, commercial and residential land uses were assigned different values of
174 imperviousness. Similar to S1, spatial means of the impervious percentage were calculated but
175 separately for commercial and residential land uses. The commercial land use was assigned a
176 value of 62.2% and the residential land use was assigned a value of 27.3%.

177 Scenario 3 (S3): Different imperviousness for residential land use of each subbasin

178 In this scenario, spatial variations of imperviousness of residential land use type were taken into
179 account by assigning a different value of residential imperviousness to each subbasin. As shown
180 in Table 2, the residential land use types of all subbasins were assigned different imperviousness
181 percentage values. The impervious percentage values range from 3.9 % to 94.5 %.

182 Imperviousness with the highest values is located in highly urbanized subbasins and lowest
 183 values located in the rural area. The imperviousness for commercial land uses was fixed at 62.2%
 184 in this analysis because their areal extent was very small and their imperviousness did not vary
 185 widely by location.

186 **Table 2.** Imperviousness percentage of each urban land use type in S3. The numbers in front of
 187 ‘residential’ indicate the subbasin, e.g. ‘1 residential’ means that the residential land in subbasin 1
 188 has an average imperviousness of 7.5%.

| Legend | Imperviousness (%) | Legend | Imperviousness (%) |
|----------------|--------------------|----------------|--------------------|
| commercial | 62.2 | 17 residential | 12.0 |
| 1 residential | 7.5 | 18 residential | 9.1 |
| 2 residential | 4.0 | 19 residential | 6.8 |
| 3 residential | 11.3 | 20 residential | 19.7 |
| 4 residential | 4.8 | 21 residential | 46.7 |
| 5 residential | 4.7 | 22 residential | 23.6 |
| 6 residential | 4.3 | 23 residential | 28.2 |
| 7 residential | 8.5 | 24 residential | 47.1 |
| 8 residential | 13.2 | 25 residential | 39.2 |
| 9 residential | 4.7 | 26 residential | 42.5 |
| 10 residential | 13.2 | 27 residential | 52.6 |
| 11 residential | 4.0 | 28 residential | 90.2 |
| 12 residential | 3.9 | 29 residential | 93.6 |
| 13 residential | 4.1 | 30 residential | 94.5 |
| 14 residential | 19.6 | 31 residential | 52.1 |
| 15 residential | 8.3 | 32 residential | 51.1 |
| 16 residential | 16.3 | 33 residential | 47.0 |

189
 190 The HSPF model was set up using three different scenarios of imperviousness input for the
 191 period from January 1986 to December 1995. It was assumed that imperviousness did not change

192 during the time. The time period coincides with that in the study by Choi et al. (2017) where
193 HSPF was applied for the same basin and calibrated. In this study, the three scenarios resulted in
194 total flow values which were different from the observed total flow at Subbasin 21 by less than
195 4%. The simulated storm flows from the three scenarios were compared graphically and a *t*-test
196 was used to determine if there were significant differences between them. After comparing the
197 simulated storm flow from the three scenarios, the relationships between these differences and
198 the percentage of urban land use across subbasins were examined.

199

200 **Results and Discussion**

201 **Impervious areas from the different imperviousness input methods**

202 Percent imperviousness among the 33 subbasin showed the largest variability with S3 and the
203 smallest variability with S1 (Figure 2). At the same time, the median was largest with S1 and
204 smallest with S3. In S1, 29.3% imperviousness was assigned to all residential and commercial
205 land uses, and a highly urbanized subbasin had imperviousness exceeding 50% whereas as a very
206 rural subbasin had imperviousness of almost 0%. In S3, some subbasins had imperviousness
207 exceeding 60%. Even though residential lands in some subbasins were assigned imperviousness
208 of more than 90%, the subbasins-wide imperviousness remained below 70%. The increasing
209 variability from S1 to S3 is expected since S2 and S3 have more spatial variability of
210 imperviousness values for residential and commercial than S1 and S2, respectively.

211

212

213

214 **Simulated storm flows from the three imperviousness input methods**

215 When averaged across subbasins, S3 resulted in the largest mean annual storm flow with 73.09
216 mm, followed by S1 (72.63 mm) and S2 (72.47 mm). Because higher imperviousness tends to
217 result in higher storm flow, it is not surprising that S3 resulted in larger mean annual storm flow
218 than S1 and S2. However, the percent differences were small. Storm flow from S3 was larger
219 than S1 by 0.6% and larger than S2 by 0.9%. When it comes to variability among subbasins, S3
220 resulted in the largest variability and S1 resulted in the smallest (Figure 3). S1 and S2 had very
221 similar variability whereas S3 had a smaller median than S1 and S2, like in Figure 2. Because
222 storm flow is highly influenced by imperviousness in HSPF, the variability of imperviousness
223 among subbasins is reflected on the variability of storm flow among subbasins.

224 A paired samples *t*-test ($n = 33$) was conducted between each pair of the three scenarios results.
225 The result illustrates that all three pairs of scenarios are significantly different (Table 3). S1 and
226 S2 produced very similar annual storm flows (Figure 3), but their difference is found to be
227 nonetheless significant. As mentioned above, the differences were no larger than 1%. Even larger
228 percent differences could result from model configuration and other factors. Therefore, the effect
229 of the imperviousness input methods is deemed negligible when the results are averaged across
230 subbasins.

231

232

233 **Table 3.** Paired samples *t*-test for annual storm flows (mm) of three scenarios

| Pair | Paired errors | | Standard Error | 95% confidence interval | | Sig. (2-tails) |
|-------|---------------|----------|----------------|-------------------------|-----------|----------------|
| | Mean | St. dev. | | Lower | Upper | |
| S1-S2 | 4.32E-04 | 2.17E-03 | 3.59E-05 | 3.61E-04 | 5.02E-04 | 0.00 |
| S1-S3 | -1.69E-03 | 2.10E-02 | 3.48E-04 | -2.38E-03 | -1.01E-03 | 0.00 |
| S2-S3 | -1.26E-03 | 2.15E-02 | 3.56E-04 | -1.96E-03 | -5.64E-04 | 0.00 |

234

235 **The relationship between simulated storm flow differences and percentage of urban land**
236 **use**

237 Figure 4 portrays the spatial distribution of the differences of simulated storm flow between any
238 two scenarios. Like in Figure 3, the difference between S1 and S2 (Figure 4a) is not as large as
239 the difference involving S3 (Figures 4b and 4c) across the subbasins. Between S1 and S2, largest
240 differences were found in subbasins 25, 26, and 27 and the magnitude is up to 24 mm. Figures 4b
241 and 4c show clusters of large differences in the downstream subbasins and the difference is larger
242 than 60 mm in some subbasins. As seen in Figures 1b and 1c, they are heavily urbanized and
243 impervious subbasins. On the other hand, upstream subbasins show very small differences in
244 storm flow regardless of the scenario pairs. Therefore, the effect of different input methods
245 appears to be amplified in urbanized subbasins.

246 The simulated storm flow differences and the urbanized land use percentage were positively
247 correlated ($p < 0.05$) for all pairs (Figure 5). For the S1-S2 pair (Figure 5a), the urban percentage
248 explains only 16% of the variability of storm flow differences and the correlation is weak. For the
249 other two pairs, r^2 values are much higher and the slopes are steeper (> 0.4). Overall, in more
250 urbanized subbasins, the effects of imperviousness input methods tend to be larger. In other
251 words, the way imperviousness information is handled in a hydrological model matters much
252 more in urbanized areas than rural ones.

253 In Figure 5a, there are two cases (subbasins 21 and 28) that may be considered as outliers. Both
254 subbasins are very small and located in an area of stream intersection (Figure 6). We speculate
255 that subbasins with such small sizes can be very sensitive to the change of imperviousness input.
256 Figures 5b and 5c also show some outliers, well below or above the regression lines. These
257 figures involve S3, where the residential land use type was assigned different imperviousness
258 values whereas the commercial land use was assigned a constant one. Thus, if some subbasins are
259 mostly covered by commercial land use, the differences from different imperviousness input
260 methods would be very small. Subbasins 28 to 30 are such cases. Subbasins 21 and 25 have
261 similar imperviousness across the scenarios, at about 40%. As a result, the differences in storm
262 flow are quite small. For subbasins with high urban percentage values and well above the
263 regression line, such as 24, 26, 27, 31, and 32, imperviousness input increased substantially from
264 S1 or S2 to S3.

265 This study found significant differences among the results from different imperviousness input
266 methods similar to Chormanski et al. (2008). However, unlike Chormanski et al. (2008), this

267 study used a semi-distributed hydrological model instead of a fully distributed model. The raster-
268 based imperviousness data have been aggregated to different levels of spatial variability to be
269 input to the hydrological model. For a study using a semi-distributed model, this aggregation
270 process was necessary and lead to statistically significantly different results. Aggregation for each
271 subbasin (S3) resulted in particularly different results for urbanized subbasins from aggregations
272 for the entire basin (S1 and S2).

273

274 **Conclusions**

275

276 This study tested three different methods to input imperviousness information to a semi-
277 distributed hydrological model to examine their effects on model-simulated storm flow. The three
278 methods evaluated include: (1) a constant value for impervious surfaces in the entire urban area,
279 (2) constant values of imperviousness for commercial and residential land uses, respectively, and
280 (3) different imperviousness for the residential land use in each subbasin. The methods represent
281 increasing spatial variability of imperviousness values in residential land use. Storm flow of the
282 Milwaukee River basin was simulated by HSPF using the three imperviousness input methods.

283 The study found very small but statistically significant differences in spatially-averaged annual
284 storm flows between the methods. In a qualitative sense, we think the differences are negligible.
285 However, the differences were generally larger in more urbanized subbasins. The results were
286 particularly different when imperviousness values were differently assigned for each subbasin.

287 Therefore, we conclude that the spatial variability of imperviousness should be commensurate
288 with the spatial variability of the model configuration. Even though impervious surface area data
289 are available as a continuous, high-resolution raster data set, the way it is used for a semi-
290 distributed hydrological model can produce different results. Aggregating the impervious surface
291 are data for the entire basin negates the spatial variability of storm flow simulated by the semi-
292 distributed hydrological model.

293

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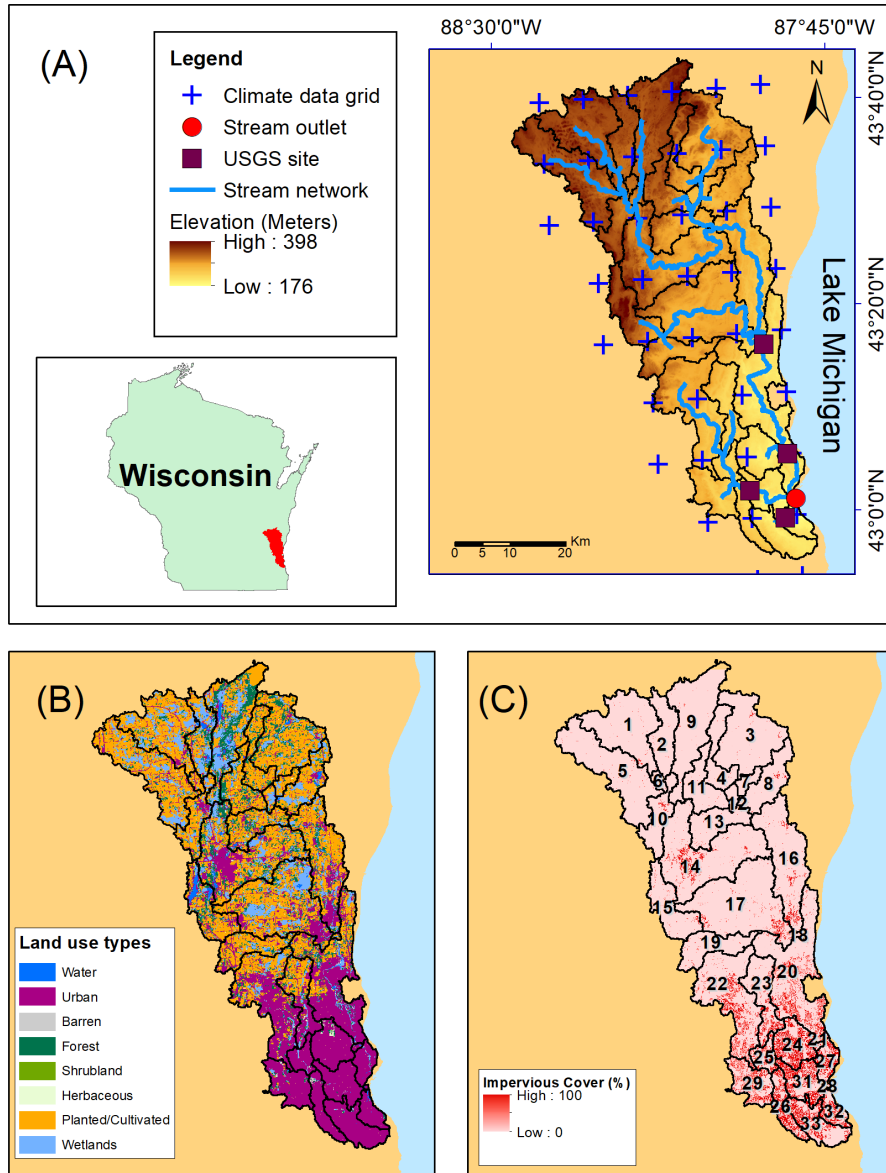
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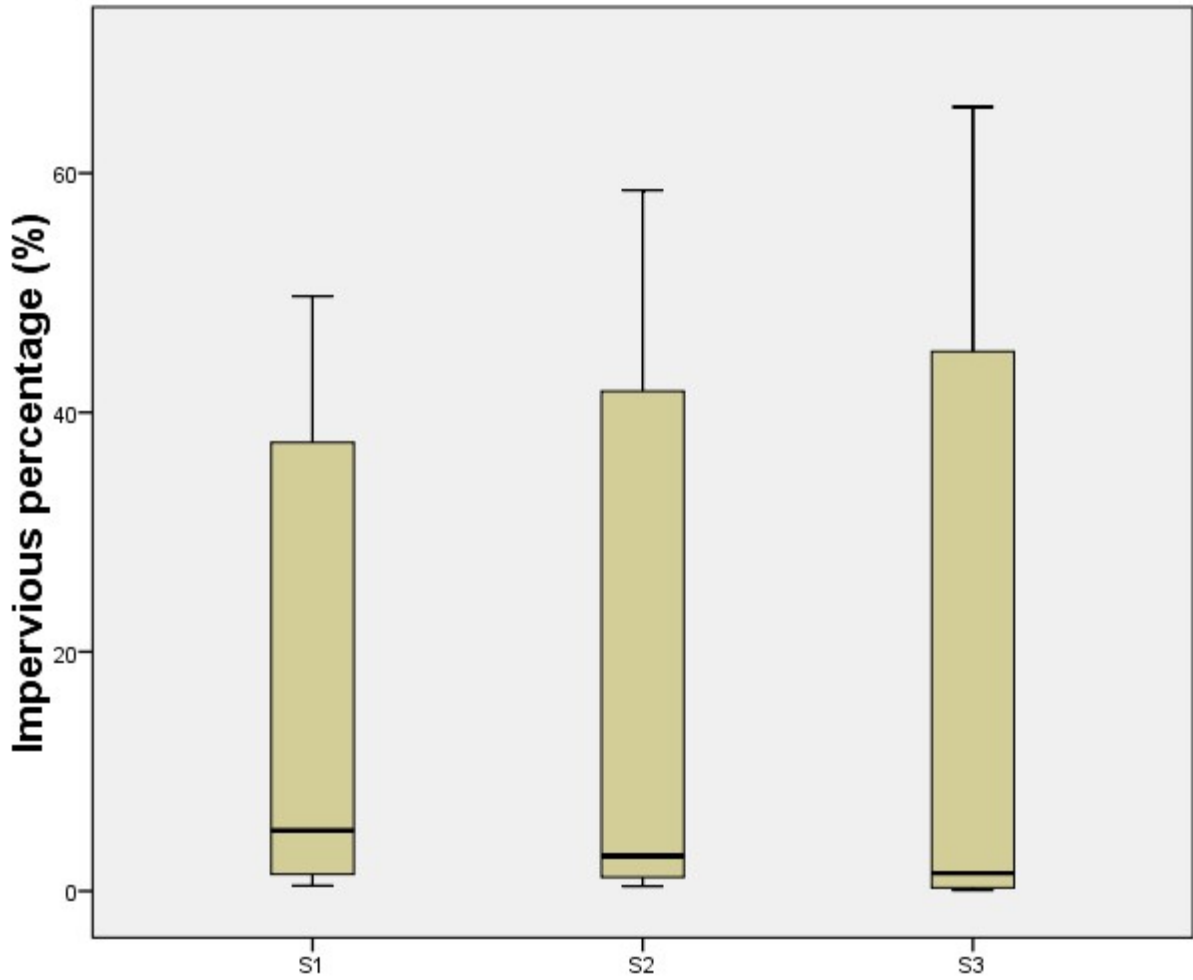
414 **Figure Captions**

415 **Fig. 1.** Boundaries of the Milwaukee River basin and 33 delineated subbasins. (A) elevation,
416 stream network, and climate data grid; (B) land use distribution; (C) percent imperviousness by
417 pixel



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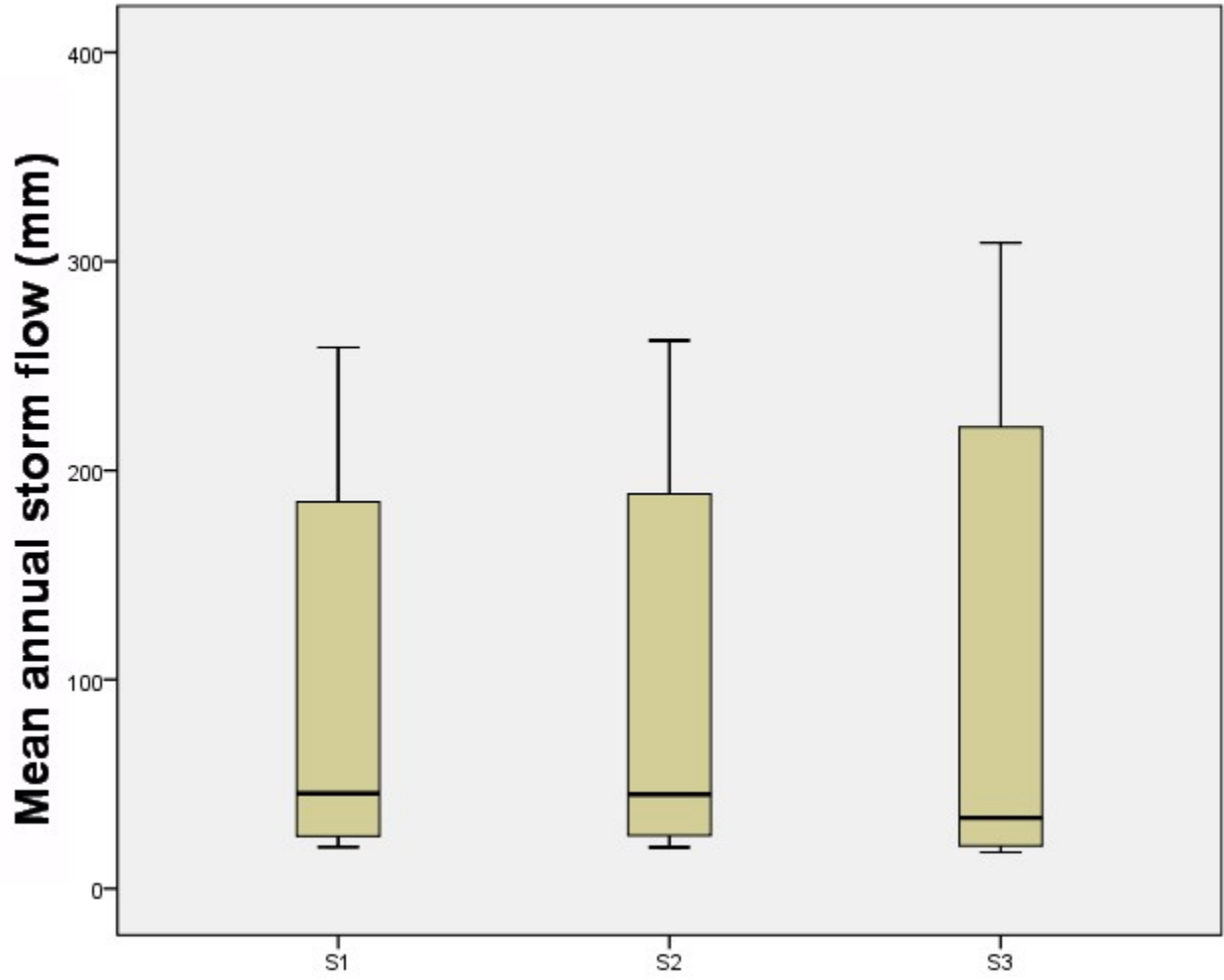
419 **Fig. 2.** Boxplots of impervious percentage from the three imperviousness input methods. The
420 variability is among the 33 subbasins



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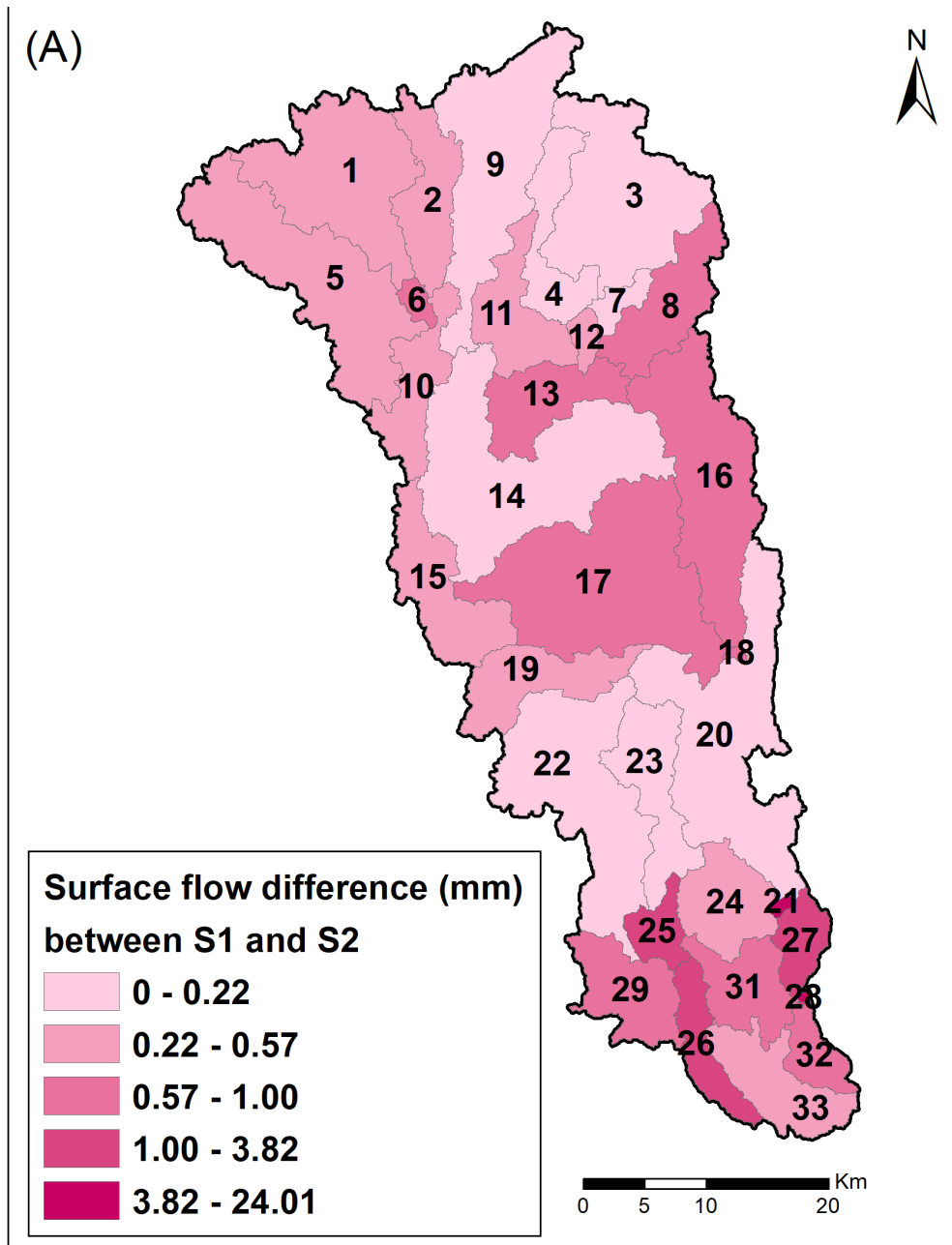
423 **Fig. 3.** Boxplots of the simulated storm flow using the three imperviousness input methods for
424 the 33 subbasins



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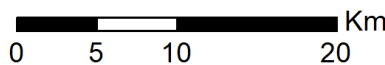
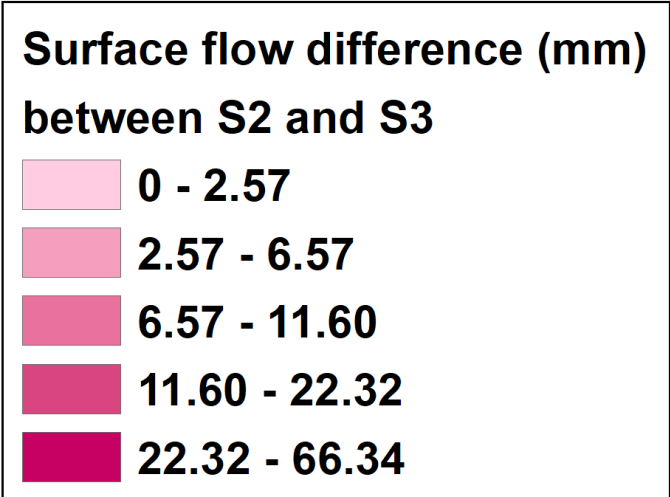
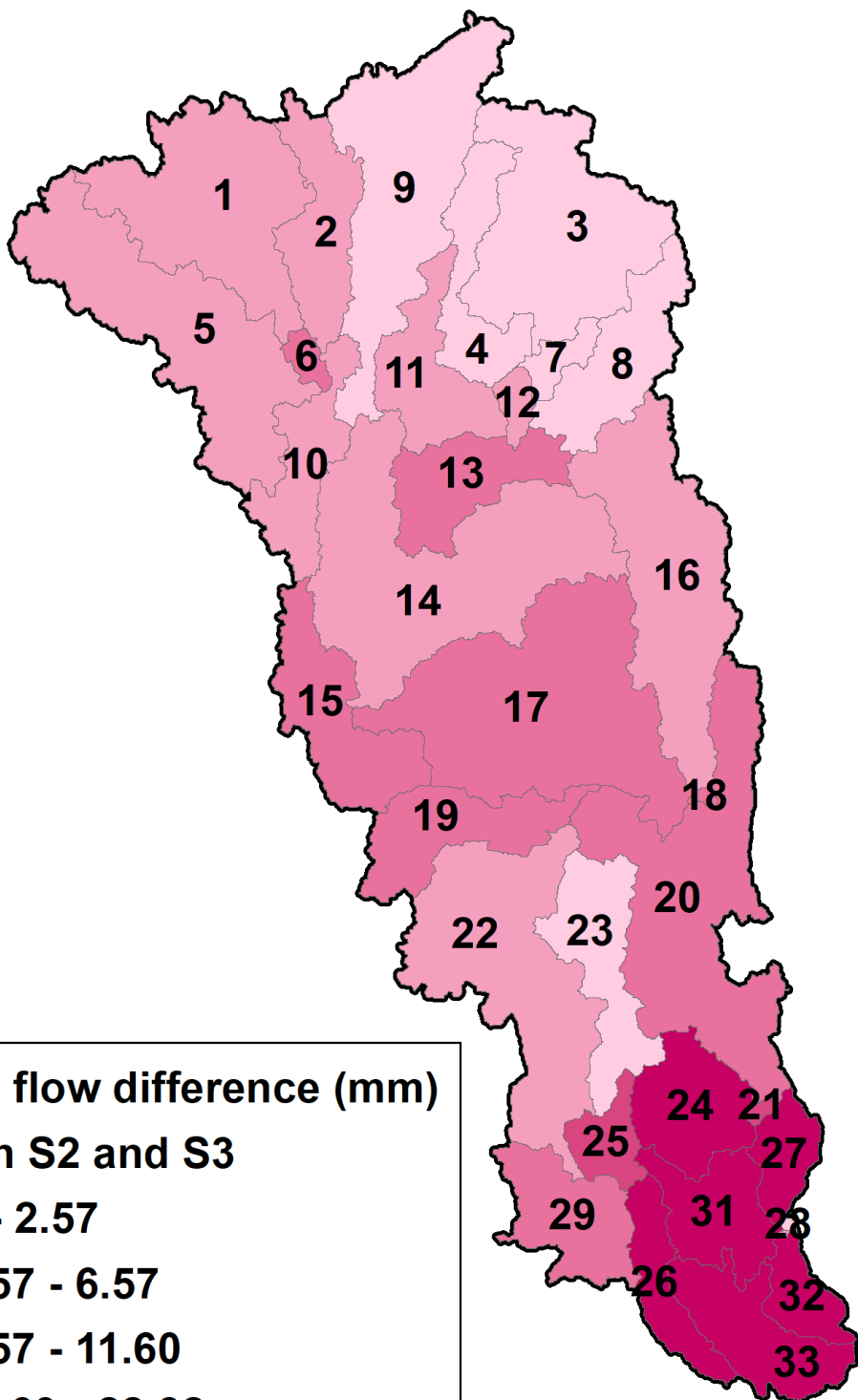
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427 **Fig. 4.** Storm flow differences by subbasin between S1 and S2 (A), S2 and S3 (B), and S1 and S3
428 (C) (the differences were calculated as the latter minus the former)

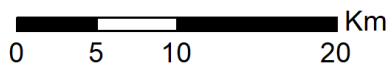
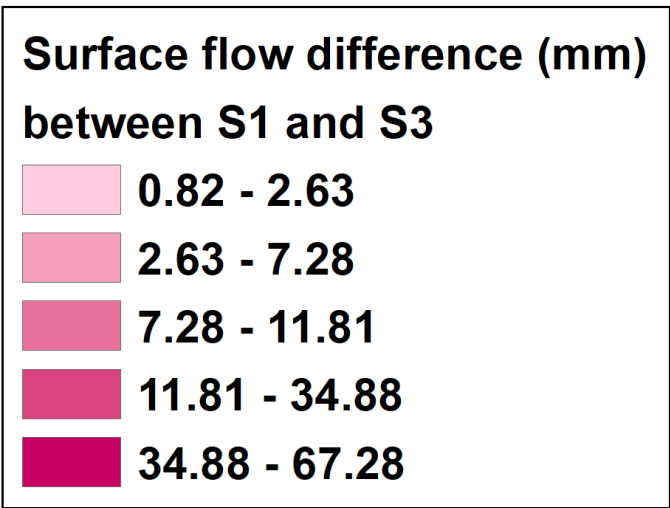
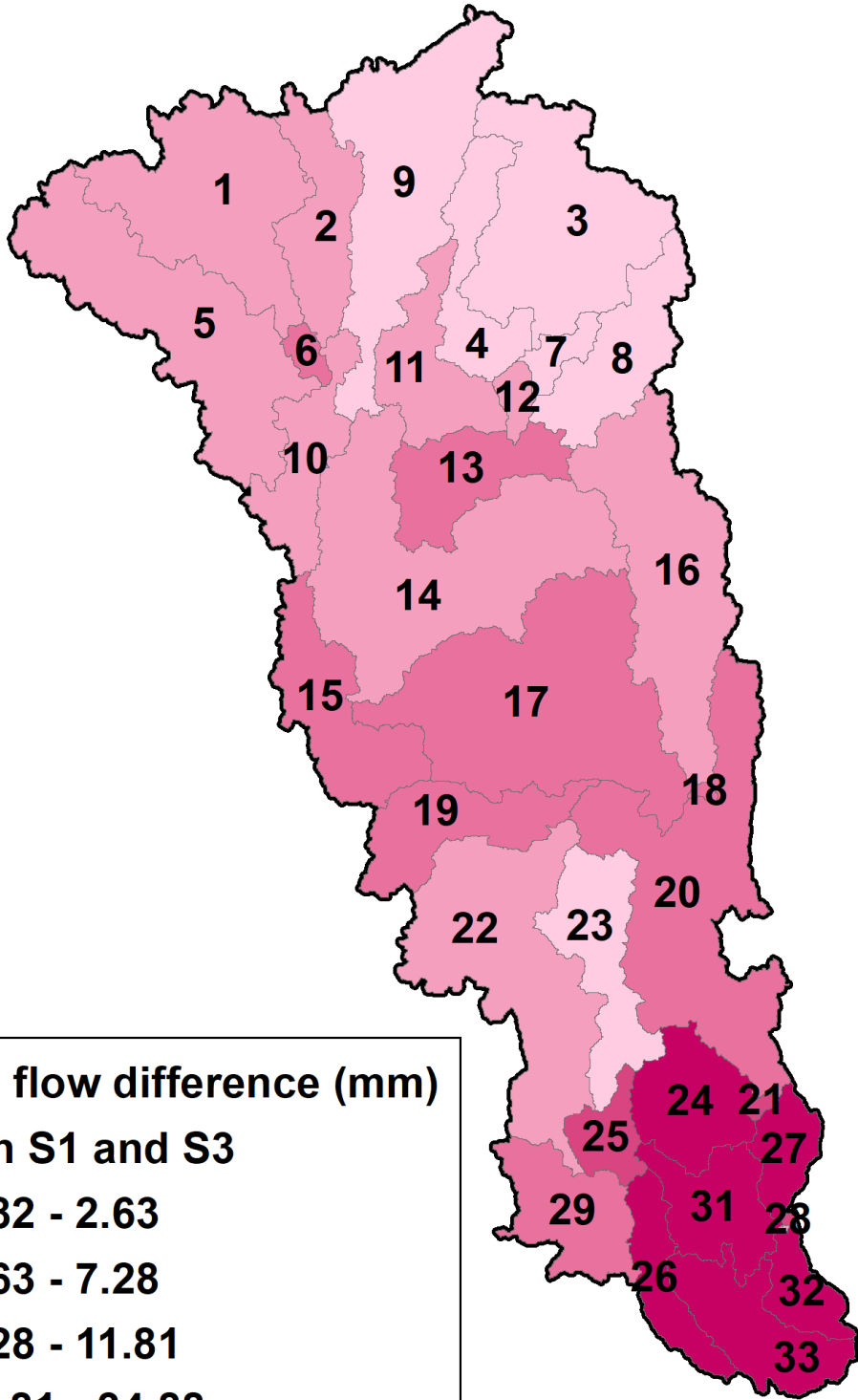


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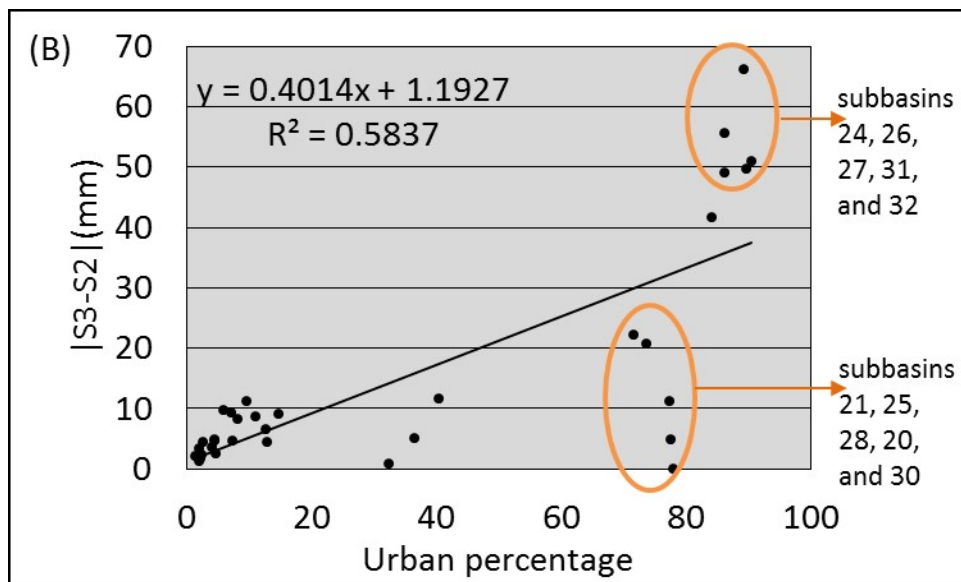
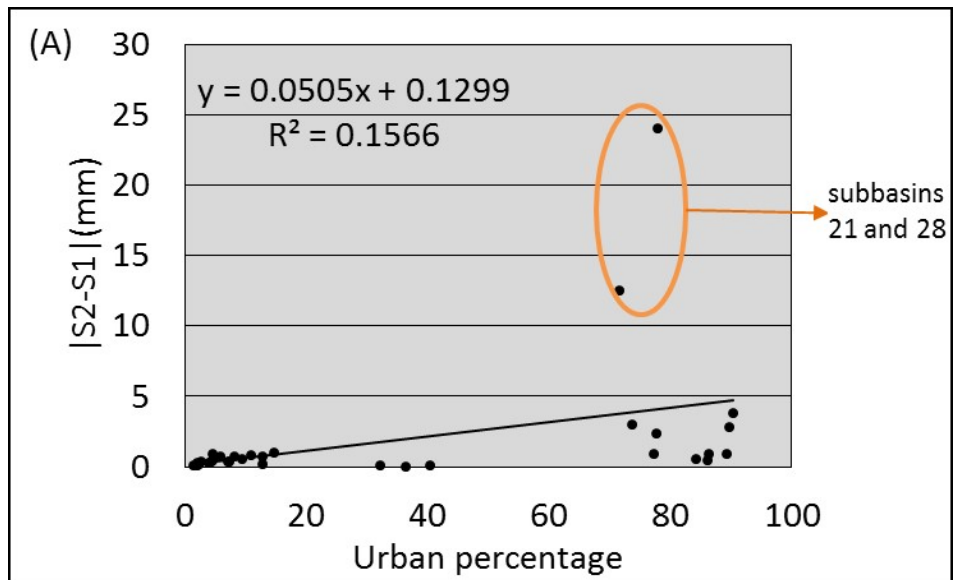
(B)

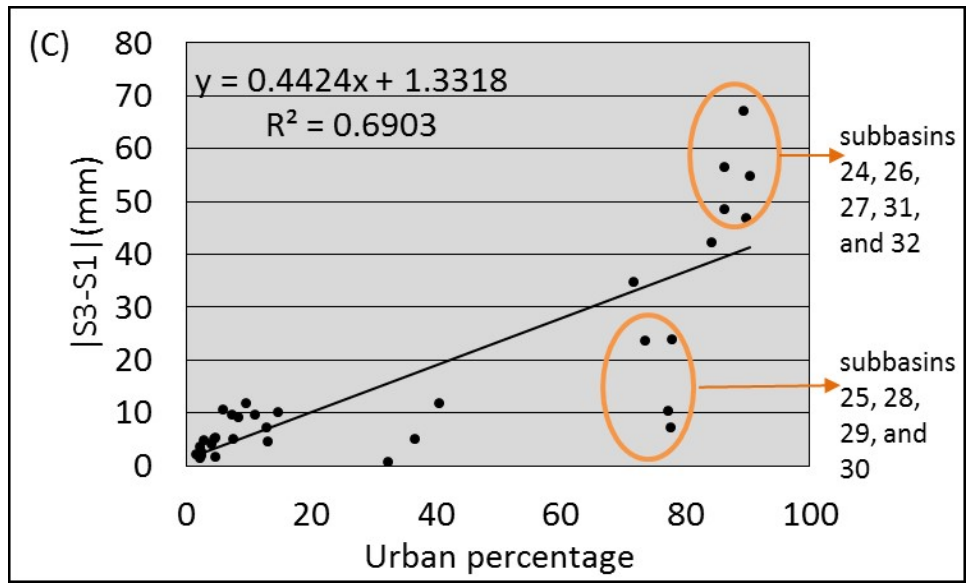


(C)



432 **Fig. 5.** Linear regression between the urban percentage and storm flow differences across
433 subbasins





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437

Fig. 6. Residential and commercial grid pixels of downstream subbasins

