



1 **Urban sewershed overflow analysis using super-resolution weather radar**
2 **rainfall**

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6

7 **Abstract**

8 In urban areas, a prevalence of combined sewer systems (CSS) exist that carry both
9 storm water runoff and sanitary sewer flows in a single pipe, these system are considered
10 combined sewers. In the absence of rainfall-runoff most of these systems function
11 adequately, however CSS capacity is typically inadequate to carry peak stormwater runoff
12 volume. In order to minimize sewage flooding into streets and backups into homes and
13 businesses, most CSS (as well as separate sanitary sewer system) are designed to overflow
14 into surface waters such as streams and rivers, lakes and seas.

15 The primary factor causing overflows to occur is excessive precipitation with rainfall
16 at high intensity or high volume. A framework for the application of radar-rainfall data to
17 identify rainfall characteristics (spatial and temporal) associated with CSO events is presented
18 in this work. An innovative component of the work is the identification of a relationship
19 between weather radar reflectivity and ground-level rainfall. Additionally, the sewershed specific
20 radar-rainfall region is extracted for use in defining CSO triggering rain event characteristics at
21 sewershed spatial scale. Results show underestimation of rainfall is more problematic than
22 overestimation. An optimal radar-rainfall relationship is developed to address reflectivity (Z) to
23 rainfall (R) transformation and improves rainfall estimates in the higher reflectivity range (greater



24 or equal to 46 dBZ). A large portion of quarter-hourly rainfall accumulations occurring at lower
25 radar reflectivity, less than 46 dBZ, indicate optimal reflectivity-rainfall (Z-R) relation
26 parameters range from [300, 1.4] to [250, 1.4] for convective storm types, and [250, 1.2] to
27 {[80, 1.4], [120, 1.4]} for tropical rainfall types. Both rainfall and overflow events are
28 identified using criteria proposed by United States Environmental Protection Agency
29 (USEPA) to define the physical continuity of natural rainfall processes and the corresponding
30 hydrologic response. The methodology framework is illustrated using an urban sewershed,
31 denoted as CSO 130, located in Louisville, Kentucky (USA). The role of specific rainfall
32 event characteristics: total volume, intensity, duration, continuity, and storm types are shown
33 to govern the overflow in the approximately 13-ha (30-ac) sewershed. Through discriminant
34 analysis, the coupled rainfall and overflow events are categorized by overflow severity.
35 Results indicate that use of fine-resolution radar-rainfall in this urban hydrologic system can
36 reveal insights for planning CSO control and prevention measures for specific rainfall event
37 regimes.

38

39 **1. Introduction**

40 In many urban areas, combined sewer systems (CSS) carry both storm water runoff
41 and sanitary sewer flows in a single pipe. In the absence of rainfall-runoff most CSS
42 adequately convey waste water flow, however system capacity may be overwhelmed when it
43 must also transport significant stormwater runoff. In order to prevent sewage from flooding
44 streets and backups into homes and businesses, most CSS (as well as separated sanitary sewer
45 systems) are designed to overflow into surface waters such as streams and rivers, lakes and
46 seas. This overflow occurrence is considered a combined sewer overflow (CSO) event and
47 has a detrimental impact on aquatic environments and degrades downstream water quality.



48 In the United States (USA), regulations were established to eliminate CSO events in
49 urban areas (EPA 1994). Although CSS are now considered an outdated approach to waste
50 water collection, these legacy water collection systems form a considerable portion of the
51 sanitary sewer network in the United States. It is estimated that 860 communities across the
52 USA are served by combined sewer systems with over 10,000 CSO outfalls directed into
53 natural surface waters. These communities include approximately 40 million people in more
54 than 30 states (EPA 2004). The direct solution to eliminate overflow occurrence through
55 modification or replacement of CSS with separate sewer and storm drains is cost prohibitive,
56 disruptive to the community, and difficult or infeasible to accomplish in existing urban
57 environments (Lyandres and Welch, 2012). When a CSO event occurs, the effect on receiving
58 waters can be significant. The overflow transports microbial pathogens, oxygen depleting
59 substances, suspended solids, toxics, nutrients, and debris including floatables and trash
60 directly into the natural aquatic environment (EPA 2004). Furthermore, in most urban areas
61 CSO occurrence is often a sudden phenomenon, due to both characteristics of the triggering
62 rain storm and hydrologic conditions in the sewershed, resulting in a surge of runoff (Romnée
63 et al. 2015).

64 Understanding the role of CSO triggering precipitation events is considered in
65 previous studies on the relationship between rainfall and CSO occurrence. Recent work by
66 Mailhot et al. (2015) developed a relation between annual duration of overflow occurrence
67 and rainfall threshold category derived from rain gauge data. Mailhot et al. (2016) describe
68 the value of rainfall data in terms of spatial co-location and temporal coincidence, and
69 mention the limitations of rain gauge data in evaluation of CSO occurrence. The work of
70 Mounce et al. (2014) includes radar-rainfall information and focuses on forecasting CSO
71 occurrence and less on identification of catchment-scale rainfall characteristics. Both
72 Montalto et al. (2007) and Lucan and Sample (2015) incorporate scenarios of runoff modeling



73 using modified forms of traditional design rainfall derived from regional climatology to
74 illustrate the performance impact of a variety of Green and LID (low impact development)
75 strategies on CSO occurrence.

76 This work moves toward understanding rainfall through downscaling in urban areas as
77 a means to identify specific rain event spatio-temporal characteristics. A occurrence may be
78 improved by defining fine spatiotemporal resolutions. The challenge in CSO mitigation
79 however, is that for most sewersheds, common operationally measured rainfall characteristics
80 (rain event duration, total rain volume, intensity, continuity (inter-event time, IET),
81 seasonality and storm type (e.g., stratiform, convective, frontal, orographic, tropical storm
82 remnants), are determined based on spatially distant point source rain gauges and lack
83 catchment specific detail. Data records with relevant spatial and temporal details describing
84 precipitation variability is necessary to define the characteristics of storm events triggering
85 CSO events.

86 Historically, rainfall monitoring by ground-level rain gauge networks is considered a
87 reliable measurement system for many hydrologic applications because it physically captures
88 pluvial water. In hydrologic engineering and research, rain gauge measurements frequently
89 serve as a reference for evaluation of indirect or remote sensing rainfall estimation systems
90 such as weather radars and satellites (Habib et al., 2012; Price et al., 2014; Chen et al., 2015;
91 Fencil et al., 2015). Several recent studies have utilized existing rain gauge data from single
92 points or networks. However, the detection of spatial rainfall variation by gauge networks is
93 limited, in particular at finer temporal resolution. Qi et al. (2016) studied the quality control of
94 a rain gauge network of hourly data to alleviate error sources. Girons Lopez et al. (2015)
95 focused on spatial variation of the rainfall for a sizeable watershed (30000 km²). Gianotti et
96 al. (2013) mentions the limitation of rain gauges use in seasonal weather prediction. Based on



97 these studies, indications are that both rain gauge location and data quality control are
98 important. The focus of this study is application of radar and rain gauge data in the small-
99 scale sewershed and consideration of spatial variation. Additionally, a fine temporal
100 resolution is maintained to preserve coincidence of rainfall and peak overflow variation and
101 reduce information loss. Thus, this study includes characteristics of localized rainfall events,
102 which may vary significantly from spatial averages, through use of radar-rainfall products and
103 therefore explicitly incorporates rainfall spatial variation.

104 Hydrometeorologic rainfall monitoring and measurement technology of the weather
105 radar has advanced in recent decades (Karamouz and Nazif, 2013; Morita, 2011; Yang et al.,
106 2013). While existing research has been directed to developing Z-R relationships for one-
107 hour rainfall accumulations (Baeck and Smith, 1998), this study focused on linking radar
108 reflectivity to rain gauge networks for short duration applications (less than one-hour). By
109 synchronizing radar rainfall with rain gauge measurements the dependency (and associated
110 uncertainty) of the Z-R conversion on storm type classification (convective, tropical, east cool
111 stratiform and stratiform) is diminished. Unfortunately, the Z-R relationship is not typically
112 calibrated for a particular hydrologic climate or rainfall type and no real-time automated
113 optimization is implemented (Chumchean et al., 2003; Ice, 2014). Synchronizing radar
114 reflectivity data with the rain gauge network, a more precise estimate of rainfall (depth,
115 spatial and temporal variations) indicate improved rainfall estimates at scales of 0.5 km² and
116 0.5 hours. In this study, support vector classification (SVC) is used to partition storm events by
117 underlying characteristics and includes an optimization process for Z-R parameter estimation;
118 the radar-rainfall data are areal rainfall observations at the sub-hectare (radar polar coordinate
119 pixel size) resolution at sub-hour temporal intervals.



120 Identification of rainfall events, for example, using the EPA criteria for urban areas
121 and a defined inter-event time (IET), provides a context for identifying rainfall spatial and
122 temporal characteristics associated with CSO overflow events. Accordingly, preparation of
123 accurate rainfall data, quality controlled weather radar data, identification of independent
124 rainfall events and corresponding CSO event hydrographs are essential to developing a
125 quantitative understanding of the phenomenon.

126 To this end, an objective for this study includes application of locally optimized radar-
127 rainfall to an urban sewershed (watershed) using fine-scale spatiotemporal resolution data,
128 and evaluation of rain event characteristics resulting in CSO events. This work generates a
129 coincident data set of coupled radar-rainfall-CSO events. Categorization of the severe rainfall
130 events inducing CSO occurrence can provide insights for hydrologic and hydraulic design
131 guidelines to reduce sewer overflows from combined sewer systems in an urban area.

132

133 **2. Local weather radar optimization**

134 **2.1. Radar rainfall source and preprocessing**

135 The study region for this work is the city of Louisville, Kentucky (USA) during the
136 period January 2010 to December 2014. Rainfall data from an operational rain gauge
137 network, managed by the local utility agency Metropolitan Sewer District (MSD), are the
138 ground reference values (Hyun et al., 2016). The region's Next-Generation Radar
139 (NEXRAD) (denoted by call letters KLVX) is located at Fort Knox, Kentucky about 40-km
140 southwest of the city of Louisville.

141 In case studies of rainfall spatiotemporal structure, a correlation near 0.6 at 5-km
142 distance for quarter-hour temporal resolution using ground based rain gauges is shown (Ciach
143 and Krajewski, 2006; Jung et al., 2014; Mandapaka and Qin, 2013). The average inter-gauge



144 distance in this application is slightly greater and the gauge network can therefore benefit
145 from the complementary spatial detail provided by weather radar. Although the radar data are
146 not explicitly filtered for error adjustment, the large quantity of data compiled for use, from
147 gauge network and radar archives, is expected to minimize bias. Additionally, the proximity
148 of the study area relative to the radar site, at about 40 km range, is expected to diminish the
149 influence of common radar error influences such as range effects of signal attenuation,
150 anomalous propagation, beam blockage, and beam spreading (Ciach et al., 2003; Gorgucci
151 and Baldini, 2015; Hunter, 1996; Kalogiros et al., 2013; Krajewski and Vignal, 2001; Morin
152 et al., 2003; Seo et al., 2000; Vignal and Krajewski, 2001).

153 The fifteen rain gauges of the MSD network are mechanical tipping-bucket type with
154 resolution of 0.01 inch and temporal interval of five minutes. The data records for radar base-
155 scan reflectivity (Level II - NEXRAD dual polarization, 0.5 dBZ increment) were retrieved
156 from the National Climatic Data Center (NCDC) at National Oceanic and Atmospheric
157 Administration (NOAA). The data cover the entire five-year study period, 2010-2014, in the
158 format of coded reflectivity volume scans. The raw reflectivity was converted to a Cartesian
159 coordinate (ESRI ASCII grid files) system using NCDC's Weather and Climate Tool Kit
160 (WCT), version 3.7. The WCT provides visualization and export tools to manipulate radar
161 data. The Constant Altitude Plan Position Indicator (CAPPI) data, 1-km above the radar
162 elevation, forms the base-scan reflectivity array over the study area. The spatial pixels are
163 approximately 220-m square in a Cartesian coordinate grid over the study area, thus pixel area
164 is less than 5-hectare (15-acre).

165 The raw radar reflectivity data are instantaneous values and require conversion to
166 rainfall intensity and accumulation to define volumetric rainfall. In order to geo-synchronize
167 reflectivity pixel locations with reference network gauge locations, radar reflectivity pixels



168 with spatial locations corresponding to MSD gauge locations were identified. In the same
169 vein, a temporal synchronization was performed to identify radar scan time stamps
170 corresponding to the local time zone (accounting for daylight savings time as appropriate).
171 For each rain gauge site, the collocated radar pixel and adjacent eight pixels were identified
172 for use in data evaluation. Among these nine radar pixels, the single collocated radar pixel
173 value was selected when reflectivity was within 50% of the average of surrounding pixel
174 values. Where the difference between the center pixel value and surrounding values was
175 more than 50%, the averaged reflectivity value was assigned. In the case where a majority of
176 the 9 radar reflectivity data showed a status or condition as “not available” the pixel status
177 was defined “not available”.

178 The KLVX radar data management system applies a Z-R relationship according to
179 four storm types: convective, tropical convective, stratiform, and east cool stratiform.
180 Reflectivity transforms into rainfall intensity as an instantaneous value, whereas the gauge
181 values are demonstrate accumulated rainfall over five minutes (Ulbrich and Lee, 1999).
182 Therefore, instantaneous intensity is further transformed into accumulated rainfall following
183 application of the Z-R relationship. The first step considers all four reflectivity to rainfall
184 intensity (mm/hr) conversions. Additionally, temporal synchronization was required since
185 radar observations are not recorded at equal or uniform temporal intervals. Instead,
186 reflectivity scan intervals cover a 4- to 10-minute range due to the operational mode of the
187 weather radar. Generally, three or four instantaneous base scans cover the quarter-hourly
188 period, and each volumetric scan is weighted according to the inter-scan time interval within
189 the quarter-hour interval. The process is defined in Equation (1) (Appendix) based on a
190 weighted time of occupation for each scan within the quarter-hourly interval. For each
191 reflectivity volume scan, the time interval is defined as the duration from the observation until



192 the next observation recorded (inter-scan interval) or the end of the fifteen-minute
193 accumulation window.

194 Figure 1 illustrates the volumetric radar rainfall products at monthly to quarter-hour
195 temporal resolutions. The quality of quarter-hourly radar rainfall estimation is relatively low
196 while hourly and longer accumulated rainfall products reveal better agreement with gauge
197 rainfall. However, this study focuses on the shorter duration, quarter-hourly interval, in order
198 to illustrate radar rainfall products for use in smaller urban catchment applications (Cunha et
199 al., 2015; Krajewski et al., 2010; Smith et al., 2007; Wright et al., 2014). In Figure 1, most
200 data are found at the depth range of 5 mm or less for quarter-hourly rainfall because rain
201 gauge data reliability and detection is sensitive during light rainfall (Ciach, 2002; Humphrey
202 et al., 1997). For these reasons, a quarter-hour rainfall accumulation threshold of 5 mm was
203 implemented for evaluating the Z-R relationship in the remaining portion of this study.

204 **2.2. Radar rainfall optimization by support vector classification**

205 Application of the optimal Z-R relationship, selected as the one yielding lowest Root-
206 Mean-Square-Error (RMSE), for each 15-min rainfall accumulation and each rainfall type
207 category, is summarized in Figure 2 (origin at 5mm rainfall threshold). The rain type
208 categories corresponding to tropical and east cool stratiform show a dispersed result.
209 Conversely, the convective and stratiform types tend toward agreement with gauge values as
210 indicated by the lower variance and narrower clustering along the one-to-one line. Further
211 optimization processes are considered for the stratiform type rainfall values since the result
212 shown is considered adequate for this work. In the case of east cool stratiform type, most
213 rainfall depths are less than 10 mm, and this depth is less significant from a hydrologic runoff
214 generation perspective. For this reason, the east cool stratiform rainfall type is not considered
215 in the remaining part of this study. This leaves convective and tropical type rain categories



216 for consideration, and the focus is on development of an optimization process to improve
217 agreement of radar-based and gauge-measured rainfall accumulation.

218 Figure 3 presents a comparison of the convective storm type radar depths and the
219 gauge rainfall depths. The lighter shaded markers indicate use of the standard Z-R
220 transformation with parameters (a:300, b:1.4) and the darker marker dots indicate the
221 optimized Z-R result. A simplex optimization procedure was applied to optimize the Z-R
222 parameters over value ranges of 10 to 500 and 0.5 to 3 for a and b respectively. Optimization
223 decreased RMSE and Z-R parameters values of 300 and 1.4 were modified to 250 and 1.4 for
224 a and b respectively. The optimized Z-R parameters eliminated the systematic
225 underestimation but the dispersion is unchanged; the simplex optimization centered all values
226 about the one-to-one line.

227 The tropical convective rainfall type contains a large number of high intensity values
228 and has the widest spread of the comparison groups. An interesting and challenging issue is
229 that bias cannot be eliminated by calibration of the Z-R parameters alone. As shown in
230 Figure 4 (upper-left), underestimation of rainfall remains following optimization of Z-R
231 parameters a and b. In Figure 2 (upper-right, red), the result is shown for the best fit Z-R, yet
232 the tropical type rainfall appears to form two distinct groups. The first group is slightly above
233 the one-to-one line with limited dispersion, whereas a second group is under the one-to-one
234 line with wider variability. This indicates that a single Z-R relationship for tropical type may
235 not suffice to encompass the observed characteristics of tropical type rainfall for this region.

236 In order to investigate a solution for this issue, a SVC optimization procedure was
237 developed. The SVC optimization incorporates an unsupervised learning algorithm applied in
238 the context of a two dimensional surface (x-axis: gauge rainfall and y-axis: radar rainfall).
239 The concept is a data-based learning process; the SVC creates a linear hyperplane separating



240 two binary groups according to a separation margin criteria. The hyperplane forms a linear
241 separation at the maximum margin and is highly efficient in differentiating the non-linear
242 rainfall characteristics. The determinant in the SVC is a kernel method transformation into a
243 feature vector (Cristianini and Shawe-Taylor, 2003). In Figure 4 (upper-right), the maximum
244 instantaneous reflectivity among the group of influential reflectivity values for quarter-hourly
245 rainfall accumulation defines the kernel. The averaged radar rainfall error (difference from
246 gauge value) is at the range of 44 dBZ to 47 dBZ and reflectivity of 46 dBZ is selected in
247 order to balance the number of data values in each group. The kernel method is described in
248 Equation (2) in the Appendix and defines the two groups through the linear hyperplane. The
249 similarity function of the kernel method follows training data instead of a fixed set of
250 parameters, and this feature involves the similarity function k , denoted as kernel in Equation
251 (2). More simply, the kernel is a weighted sum of similarities between the trained example
252 input and the new unknown input. The kernel is used as a binary classifier in terms of \hat{y} , the
253 binary classifier for clustering the two tropical groups. In Figure 4 (lower-left) the linear
254 hyperplane shows two data groups, one group fit with the tropical type Z-R relationship and
255 the second group in the underestimated region. Following the SVC process, calibration of the
256 Z-R parameters (RMSE minimum) was completed and the result is shown in Figure 4 (lower-
257 right). This result demonstrates gains in information for the tropical type rainfall when two
258 Z-R parameter sets (a, b) are used. The original fan-shaped dispersion is greatly reduced, as
259 well as the original underestimation issue. The SVC-based solution process provides a multi-
260 category classification and overcomes limitations of binary classification (Xie et al., 2013).

261 Use of an uncalibrated Z-R relationship for conversion of reflectivity to rainfall
262 intensity for short-duration accumulations may result in differences from ground-level rain
263 gauge observations. An example of these differences is presented in Figure 5 (upper-left)
264 where results show a fan-shaped spreading with correlation of 0.68 between gauge and radar



265 rainfall. Coincidentally, underestimation of rainfall may be more problematic than
266 overestimation in applications of hydrological management and design, and this result is
267 relevant for the tropical type rainfall category. In Figure 5 (upper-left), the comparison shows
268 the best fit standard Z-R relationship (minimum RMSE), and the tropical Z-R relationship
269 corresponding to the solid red line in Figure 5 (upper-right). This indicates the tropical Z-R
270 may not capture a complete description of rainfall variability at higher intensity rainfall rates.
271 This study introduced an alternate Z-R relationship formed using an SVC optimization
272 process. Use of the alternate Z-R relationship produced the results in Figure 5 (lower-left)
273 and Figure 5 (lower-right). A comparison of the alternate Z-R (red dotted line) and NWS
274 tropical Z-R (red solid line) relationships are included. This alternate Z-R relationship,
275 designated as “tropical-2”, is more influential in the higher reflectivity range (greater or equal
276 to 46 dBZ). The Z-R relations shown in Figure 5 (lower-right) illustrate the placement of the
277 existing NWS tropical (tropical-1) Z-R relationship between the convective (black solid line)
278 and tropical-2 (red dotted line). Graphically, the tropical-1 relationship fills the gap between
279 the other two convective Z-R relationships. A notable point is that a large portion of the
280 quarter-hourly rainfall accumulations occurring at lower radar reflectivity, less than 46 dBZ,
281 are well represented by the tropical-1 Z-R relationship. The focus of this study on a relatively
282 shorter, quarter-hourly, rainfall accumulation interval, and the focus on more intense rainfall
283 values are factors influencing the need to partition this extreme- type rainfall (NWS tropical)
284 into two sub-groups.

285 In general, the two tropical sub-groups are similar in the low reflectivity range and
286 deviate more from one another for reflectivity above 45 dBZ to 50 dBZ. Based on the use of
287 categorized Z-R relationships in the region of more extreme rainfall intensity, quarter-hourly
288 rainfall estimation is improved with a correlation of 0.72 in Figure 5 (lower-left). For



289 applications in urban hydrologic designs and simulation of historical events, the shorter
290 temporal resolution of rainfall is useful.

291

292 **3. CSO130 overflow analysis**

293 **3.1. Urban sewershed setting and CSO location**

294 The sewershed CSO130 is part of the urban CSS and located in an older
295 neighbourhood, called Buchertown, in Louisville, Kentucky. The specific location of
296 CSO130 is along Webster Street and its overflow control structure type is a diversion dam.
297 The sewershed is approximately 13-ha (30-ac) and land-use is a mixture of commercial and
298 dense residential. The land-use is about 75% impervious with the portions distributed as
299 residential (24%), commercial (25%), industrial (32%), vacant land (6%), and roads and other
300 uses (13%). The CSO130 outfall discharges into the nearby stream, Beargrass Creek, which
301 is a tributary of the Ohio River.

302 MSD operates a rain gauge network across the city region and one rain gauge is
303 located near the study area. However, data from this gauge serves only as a reference to
304 evaluate radar rainfall quality rather than as rainfall for the sewershed. The benefit and
305 challenge of using weather radar data for operational applications is illustrated and the spatial
306 variation of rainfall derived from weather radar products described. The radar records are
307 extracted and optimized, with spatiotemporal resolution of quarter-hour and less than five-
308 hectare (15-acre), in order to be applicable for the urban hydrologic scale.

309 **3.2. Coupled radar rainfall and overflow event record**

310 Only rain events resulting in a CSO event are considered and a quality control
311 threshold is applied to select rain-overflow events exceeding a ratio of 0.60 for overflow



312 depth to rainfall depth. Discriminant analysis is used to categorize the coupled rainfall-
313 overflow events according to overflow severity; a threshold of the overflow depth of 1.5-mm
314 partitions the event categories. Results indicate that overflow depth has a strong linear
315 relationship with rainfall depth and other environmental factors are influential.

316 Identification of rainfall events, using the EPA criteria for urban areas and a defined
317 inter-event time (IET), provides the context for identifying overflow events in the CSO flow
318 record. Accordingly, preparation of accurate rainfall data, quality controlled weather radar
319 data, and a record of independent rainfall events, are essential. In radar rainfall estimation,
320 super resolution data are suitable to define rainfall variation over urban areas.

321 Figure 6 shows radar rainfall comparisons with gauge rainfall data sources near the
322 study area. An MSD rain gauge, gauge number TR05, is located about 600-m away from the
323 study area, and this data record is used as a reference to evaluate spatial variation of rainfall.
324 The improved radar data shown in Figure 6 (upper-right) has improved the correlation to 0.79
325 compared with a 0.70 correlation in the original estimate (Figure 6 upper-left). Two other
326 rain gauges, TR12 and TR03 show correlation of 0.55 and 0.05 with the TR05 data
327 respectively. Within a distance of 15-km, rainfall is spatially uncorrelated ($\rho=0.05$), and
328 correlation decreased to 0.55 within 5km distance at TR12. This reveals the high spatial
329 variation of the rainfall at quarter-hourly temporal resolution and the benefit of radar-rainfall
330 over the limitation of reliance solely on ground-based rainfall measurement.

331 The CSO mechanism in the sewershed is not only related to the rainfall characteristics;
332 depth, duration and intensity, but also the continuity of the rainfall event. Figure 7 illustrates
333 the extreme overflow cases at CSO130 in time-flow manner and the hydrologic response is
334 related to rainfall variations within the rain event. The nine overflow events shown indicate
335 that most were triggered immediately following the heaviest rainfall interval. Naturally, the



336 rainfall volume is the primary influence on overflow amount, but it is not the only factor. The
337 more sizeable rainfall peaks affect the overflow amount and time distribution. For example,
338 the sixth greatest overflow in Figure 7, with overflow amount of 10.68-mm, has precipitation
339 duration less than an hour but the overflow was significant because of high intensity rainfall.
340 On the contrary, the overflow event which ranked in fourth has no clear intense rainfall
341 observed; instead rainfall is steady and uninterrupted. These results indicate rainfall event
342 continuity as another factor triggering overflow event occurrence.

343 One definition of a rainfall event is provided by the EPA for rainfall event in the context
344 for urban regulatory settings (Driscoll et al. 1989). The EPA document defines a rainfall
345 event as “A minimum storm volume of 0.1-inch (2.54-mm) was specified for the analysis that
346 were performed, so that the analysis would produce statistics of ‘runoff producing’ events
347 within 6 hours.” In short, a single rainfall event is completely independent if no sizeable
348 rainfall, greater than 2.54-mm (0.1-inch), occurs within six hours. The rainfall event defined
349 by EPA regulation and corresponding time for the overflow event were determined from the
350 time rainfall began until six hours from the end of the rainfall event. By EPA definition, a
351 rainfall event is followed by at least a six-hour dry period and so the implied time available
352 for overflow to occur is limited to six hours following the rain event. Based on this, there are
353 95 rain events with coupled CSO occurrence in the sewershed for CSO130 over the three-year
354 study period, January 2011 to December 2013.

355

356 **3.3. CSO130 overflow analysis**

357 The CSS CSO130 control structure is a 0.61-m (24-inch) circular brick sewer pipe
358 flowing with an average of 12 overflow incidents (events) per year (averaged 2.33 hours of
359 duration and 90,000 gallons of combined sewer per incident) (MSD, 2014).



360 **3.3.1. Quality control of coupled rainfall/overflow event**

361 The number of CSO events identified directly from data records of rainfall and
362 overflow analysis indicates the number of incidents is 95, and this is a greater number than
363 the 35 to 40 otherwise expected according to the average number of reported incidents over
364 the same three-year study period (MSD 2104). Potentially, the method of identification and
365 event partitioning (IET) may influence the number, but proper quality confirmation is
366 required for data reliability. To this end, a means of screening outliers and poor quality data
367 records is utilized. Application of a common rainfall-runoff index threshold screening, based
368 on watershed characteristics, is not possible since the total runoff for each CSO event
369 partitions flow into two directions, one part is the overflow and the remaining portion
370 continues to the water treatment plant. During an overflow event it is not possible to separate
371 the portion attributed only to stormwater runoff. To address this issue, CSO event data are
372 partitioned into acceptable and non-acceptable clusters. Figure 8 (left) shows the normalized
373 runoff-rainfall index ratios of overflow depth to radar-rainfall depth and overflow depth to
374 gauge rain depth for each event. The plot spreads in a two-dimensional field; with x-axis:
375 ratio for rain gauge MSD TR05 (600m from CSO130), and y-axis: ratio for radar rainfall. A
376 ratio greater than 1 indicates runoff greater than rainfall, and this unlikely occurrence may
377 indicate data error or other issues; for this reason, these data are excluded from the study. The
378 use of two rainfall sources lessens the uncertainty concerning rainfall occurrence and
379 incorporates both these practical hydrologic observations into this study. Figure 8 shows a
380 notable absence of overflow occurrence between ratio values of 0.60 and 0.80. Therefore, a
381 threshold ratio of 0.60 was defined as the acceptable coupled rainfall and overflow event
382 criteria; this is the boundary where data are densely populated and shown as the inner region
383 defined by a bold solid line forming a quarter-circle in Figure 8 (left). The right portion of
384 Figure 8 shows all CSO events and the bold solid line indicates a value of 0.6 for the radar



385 overflow ratio. The result identifies two groups of CSO events: acceptable (blue) and non-
386 acceptable (red). This process indicates 52 coupled rain-overflow events and this corresponds
387 well with the expected number as suggested by the MSD report for the three-year study
388 period (MSD, 2014).

389 **3.3.2. Analysis of coupled rainfall and overflow events**

390 **3.3.2.1. Overflow relation to rainfall depth, intensity and duration**

391 The coupled rain and overflow record for CSO130 shows the sewershed runoff
392 response is prompt with a hydrograph form similar to a smoothed and time-lagged reflection
393 of the hyetograph. That being so, understanding the rain event characteristics provides
394 insights into the timing, intensity and amount of overflow. Fundamentally, the quantitative
395 relation between rainfall and overflow has a visible linearity as in Figure 9 (left). Rain
396 volume is an important factor and shows a linear relationship with overflow. As shown in
397 Figure 9, when rainfall is less than about 8-mm a low overflow volume occurs and overflow
398 amount increases linearly above this rainfall depth. For overflow values above a 0.40 ratio of
399 rainfall volume the sewer overflow volume is more significant and likely to impact
400 environmental quality in the Beargrass Creek. It is expected that total rainfall depth is a
401 significant factor triggering an overflow, but this simplified conclusion cannot completely
402 explain the behaviour and a search to understand the contributing factors causing overflow
403 events is warranted.

404 The rain event duration and peak intensity (15-minute temporal resolution) are
405 important in determining overflow volume in Figure 9 (right). In the duration versus rainfall
406 depth field (Figure 9 right), the events clearly divide into two groups when clustered by peak
407 rainfall intensity. The two groups have somewhat different tendencies in the two-dimensional



408 space with the strong peak intensity group showing a relatively short duration but larger
409 volume of rainfall. On the other hand, rainfall volume tends to be relatively stable and less
410 relevant as an overflow trigger no matter the event duration. In the small-scale urban
411 watershed setting, existence of high-intensity peak rainfall may produce significant
412 volumetric rainfall, thus, rainfall intensity significantly impacts drainage system performance
413 in urban areas (Arnbjerg-Nielsen et al., 2013; Mamo, 2015). Considering this result in a
414 practical application, rainfall depth, intensity and duration are all factors indirectly
415 incorporated into historic intensity-duration-frequency (IDF) curve used to define volumetric
416 rainfall for urban hydrologic design. However, variations between rainfall observations and
417 IDF design values illustrates the uncertainty for applications requiring fine spatiotemporal
418 resolution such as urban sewersheds where runoff response occurs well under the sub-hour
419 temporal scale.

420 **3.3.2.2 Overflow relation to rainfall depth, storm type and continuity of rain**

421 There is a thread of inter-connection between instantaneous heavy rainfall, storm type
422 and resulting overflow in this small watershed. A concurrence of rainfall characteristics and
423 watershed condition, for instance, existing antecedent moisture, wet or dry surfaces and soils,
424 which effect rainfall retention and percolation, may influence overflow occurrence.
425 Therefore, rainfall continuity in terms of single events is considered as an additional factor.
426 The extreme overflow events in Figure 7 reveal the importance of the rainfall continuity since
427 there are four high ranked overflows (rank number: 3, 4, 8, and 9) associated with rainfall
428 events with relatively insignificant peak intensity (below 5-mm/15minute), but continuous
429 and uninterrupted rainfall. In other words, the length of the duration of rainfall within a single
430 event is an influencing factor related to the CSS capacity and resulting CSO for this
431 sewershed.



432 The ratio of the time rain falls during a rain “event” to total event duration represents
433 the continuity of the rainfall or rainfall occupancy ratio. Figure 10 (left) illustrates the
434 relationship between rainfall depth and rainfall occupancy by rain type and season; warm
435 season (April to September) and cold season (October to March). The radar rainfall product
436 indicates rainfall type for each 15-minute rainfall accumulation. The characteristics of a
437 single storm, in motion over CSO130 sewershed, are dynamic and a series of storm cells may
438 move over the area. The convective storm type may have a single or multiple cells within the
439 developed storm structure associated with severe rainfall (Caine et al, 2013; Cetrone and
440 Houze, 2006; Feng et al., 2014; Peter et al., 2015; Zawilski and Brzezińska, 2014).

441 Identification of rainfall type is based on the ratio of number of convective type radar
442 pixels to total rain pixels in the storm. Applying a threshold ratio of 0.45 results in the two
443 event groups; a convective prevalence group and a stratiform prevalence group. The
444 stratiform group has no discernible spatial pattern features other than the continuity of rainfall
445 coverage, while the convective group has a tendency toward increasing intensity beginning
446 around a ratio of 0.60. The highest three rain depth events are in the convective group. The
447 reappearance of the rainfall overflow plot (Figure 10, right), with seasonal rainfall group
448 details added, demonstrates the characteristics of the overflow inducing rainfall events. Prior
449 to presentation of this figure, the nine ranked overflow inducing rainfall events show a 0.81
450 ratio of rainfall occupancy and no event with lower than a 0.60 ratio. This indicates the
451 rainfall event group most likely to generate a CSO are the convective rain group in summer
452 season. The mitigation of combined sewer overflow events can use this information in
453 hydrologic design to improve future approaches to stormwater runoff reduction. The overflow
454 of CSO130 is a response to the interaction of natural rainfall variability, the urban landscape,
455 land-use and hydrologic environment. In addition to rainfall variability, other qualitative
456 factors influence the likelihood of overflow occurrence. Therefore, understanding the



457 temporal and spatial structure of overflow inducing rain events is useful to estimate overflows
458 in CSOs.

459 **3.3.2.3 Discriminant analysis in overflow inducing rainfall events**

460 This study shows that an overflow event in a sewershed is induced through the
461 integration of factors from two fields; natural rainfall variability and the constructed
462 sewershed conditions. The fundamental assumption is that rainfall induces the overflow event
463 in a small-scale sewershed because the runoff response is rapid and the hydrograph structure
464 resembles the hyetograph. Thus, preventing overflow events inevitably requires
465 understanding of rainfall characteristics. The volumetric rainfall depth was shown to relate
466 linearly with overflow and other factors, such as rainfall intensity, duration, and continuity of
467 rainfall (as a ratio of rainfall occupancy) as influential factors. Discriminant analysis is
468 introduced to classify these precipitation factors. The discriminant analysis uses the
469 combination of features from the continuous independent variable (rainfall characteristics) to
470 define a separation of the discrete dependent variable (Martinez and Kak, 2001; Tahmasebi et
471 al., 2010) and is applied broadly in water resource (Sangam et al., 2008, Boyacioglu, 2010).
472 In order to apply discriminant analysis, the dependent variable (overflow) must be categorical
473 unlike the continuous independent variables. In Figure 11, a threshold overflow depth set at
474 1.5-mm, for the CSO130 sewershed, and categorizes the coupled rainfall-overflow events into
475 two groups; a significant overflow group (23 events referred to as group-1) and non-
476 significant overflow group (29 events referred to as group- 0).

477 In Table 1, the mean values of the rainfall related variables influencing the overflow
478 events are presented in discriminant groups. As expected, this highlights differences between
479 groups and provides a quantitative distinction of the decisive overflow factors. The mean
480 rainfall depth is 8.85-mm in the non-significant group (group-0) and 23.70-mm in the



481 significant group (group-1). Overall, volumetric rainfall governs the overflow in this small
482 scale sewershed. The peak rain intensity has a similar tendency showing 3.76-mm per 15-
483 minute and 6.20-mm per 15-minute for group-0 and group-1, respectively. Commonly, the
484 rainfall depth and the rainfall intensity (peak) have positive correlation with overflow amount.
485 However, the duration of rainfall indicates a contrast to this expected result. In Figure 5
486 (right), the majority high rainfall depth events have shorter durations. These shorter rainfall
487 duration events are expected to fall into group-1 considering the relationship between rainfall
488 depth, intensity and overflow occurrence. In this case, the continuous, uninterrupted and
489 longer duration rainfall induces the overflow. This is due to the inverse correlation between
490 rainfall duration and rainfall continuity, where a correlation of -0.64 is indicated between
491 these independent variables. A longer rainfall duration is more likely to also contain a non-
492 rain period resulting in proportionally lower continuity.

493 Another matter that merits mention is the definition of rainfall event duration. The
494 study incorporates the USEPA (EPA, 2004) definition for continuous rainfall and independent
495 event identification. The emphasis is on whether event independence, using the temporal
496 separation of a six-hour dry period for a small-scale sewershed, is appropriate since both the
497 sequence of rain depth and continuity of rainfall within the rain event are influencing factors.
498 The differences are investigated here using discriminant grouping by rain type and rainfall
499 continuity, nevertheless overflow occurrence is associated more with rain events in group-1.
500 The definition of a rainfall event may be improved with incorporation of factors such as
501 watersheds size, land-use characteristics, and hydrologic goals.

502 Table 2 shows 78.8% (41 of 52) rainfall events are correctly classified using the linear
503 combinations identified by discriminant analysis. Under the predefined threshold overflow
504 depth of 1.5-mm, the 29 and 23 coupled events fall into non-significant and significant groups



505 respectively. This threshold considered a balance for the number of events in each group. The
506 objective discriminant group clustering indicates 12 events in the significant group and 40
507 events in the non-significant group. The linear combination of rainfall factors, $\bar{w} \cdot \bar{\mu}$, include
508 the mean and variance for the clustered factors. The cluster grouping decision includes the
509 ratio of variances within and between the groups as defined by equation (3) (appendix).
510 Based on this formulation, each group was established by the lowest variance of rainfall
511 factors. The corresponding overflow depth is found to be about 4.6-mm for a rain event with
512 24-mm depth (single rain event category).

513 This type of information, specifically identifying overflow volume associated with
514 rainfall event characteristics, may serve as an indicator of overflow potential in a CSO
515 sewershed. Information defining a gradation of overflow potential may be useful for
516 operational optimization such as, real-time likelihood of an overflow occurrence, design of
517 overflow dam height or pipe size, or design of retro-fit infrastructure to mitigate significant
518 overflow events. In this study, CSO occurrence in a small-scale sewershed is investigated
519 with a focus primarily on rainfall characteristics.

520 **4. Conclusions and Future works**

521 Improving and preserving water quality and the aquatic environment in urban areas is a
522 focus of the EPA and a component of regulatory guidelines limits the allowable occurrence of
523 CSO (combined sewer overflow) events (EPA 1994, EPA 2004). The approaches for
524 mitigating overflow events require information to define existing CSO conditions and event
525 occurrence in terms of flow volume, seasonal variation, and pollutant type and concentration.

526 Use of an uncalibrated Z-R relationship for conversion of reflectivity to rainfall intensity
527 for short-duration accumulations may result in differences from ground-level rain gauge
528 observations. Coincidentally, underestimation of rainfall may be more problematic than



529 overestimation in applications of hydrological management and design, and this result is
530 relevant for the tropical type rainfall category. This indicates the tropical Z-R may not capture
531 a complete description of rainfall variability at higher intensity rainfall rates. This study
532 introduced an alternate Z-R relationship formed using an SVC optimization process. This
533 alternate Z-R relationship, designated as “tropical-2”, is more influential in the higher
534 reflectivity range (greater or equal to 46 dBZ). A notable point is that a large portion of the
535 quarter-hourly rainfall accumulations occurring at lower radar reflectivity, less than 46 dBZ,
536 are well represented by the tropical-1 Z-R relationship. For applications in urban hydrologic
537 designs and simulation of historical events, the shorter temporal resolution of rainfall is
538 useful.

539 The volumetric approach of CSS overflow event study in a small-scale sewershed is
540 presented using the radar-rainfall characteristics. The study incorporates details of radar-
541 rainfall data evaluation, rain event definition, and reveals the dependency of CSS overflow
542 events on rainfall depth, duration, intensity, type and continuity. The radar derived rainfall is
543 necessary to determine rain depth over the region of interest where the coverage of rain
544 gauges is limited.

545 Fundamentally, a linear relation exists between rainfall and overflow depths governing
546 the occurrence of CSO events in this small-scale sewershed. The identification of
547 corresponding rainfall and overflow events requires evaluation of coupled rain-overflow
548 events and the study determined an overflow depth to rainfall depth ratio of 0.60 indicative of
549 valid events. The discriminant analysis clustered overflow events into overflow severity
550 classes. The objective classification categorized most events correctly and the discriminant
551 analysis provided an indication of the volumetric relationship between the rainfall and
552 overflow in this sewershed system.



553 The more significant sewer overflow events occur rapidly, typically within a few hours
554 following rainfall and from rainfall event durations less than a half day. This means daily or
555 longer rainfall records may not be suitable for overflow analysis for small-scale sewersheds.
556 This is in part due to the lack of independence in the identification of overflow inducing rain
557 events where rain intensity, rain continuity and variability definition within a single rain event
558 are necessary. An in-depth investigation of rainfall and overflow relationships across a range
559 of hydrologic settings and sewershed characteristics may reveal an index for the practical
560 design of a sewer overflow prevention structures. This type of study is essential for optimal
561 development of objective and quantitative methods to mitigate CSS overflows in urban
562 environmental systems.

563

564 **Appendix: Mathematical background**

565 Equation (1)

$$566 \mathbf{R}_Q(\mathbf{t}, \mathbf{x}) = \sum_{i=1}^n \left(\frac{\mathbf{R}_i}{4} \right) \left(\frac{\mathbf{t}_{i+1} - \mathbf{t}_i}{2} \right)$$

567 where,

568 $\mathbf{R}_Q(\mathbf{t}, \mathbf{x})$ is weighted accumulation of quarter hourly rainfall capsule at the fixed location where
569 reference data are corresponded in arbitrary time, \mathbf{t}

570 \mathbf{n} is influential number of reflectivity values for $\mathbf{R}_Q(\mathbf{t}, \mathbf{x})$ which fall into the quarter hourly
571 capsule and front and the rear reflectivity value when it is influential to the capsule.

572 \mathbf{R}_i is converted rainfall rate in millimeter per hour among four different NWS Z-R relationships

573 \mathbf{t}_i is time of observation of instantaneous radar base scan

574 Equation (2)



575 $\hat{y} = \text{sgn} \sum_{i=1}^n \mathbf{w}_i \mathbf{y}_i \mathbf{k}(\mathbf{R}_i, \hat{\mathbf{R}})$

576 where,

577 \mathbf{R}_i and \mathbf{y}_i are instance-based learners for the i -th training example

578 \mathbf{w}_i is a corresponding weight

579 $\hat{\mathbf{R}}$ is an unlabeled input

580 \mathbf{k} is a function of the weighted sum of similarities which is called kernel

581 \hat{y} is a prediction label of kernelized binary classifier

582 Equation (3)

583
$$\mathbf{T} = \frac{(\bar{\mathbf{w}} \cdot \bar{\boldsymbol{\mu}}_{\text{Significant}} - \bar{\mathbf{w}} \cdot \bar{\boldsymbol{\mu}}_{\text{Non-Significant}})^2}{\bar{\mathbf{w}}^T \mathbf{COV}(\mathbf{R}_{i,j})_{\text{Significant}} \bar{\mathbf{w}} + \bar{\mathbf{w}}^T \mathbf{COV}(\mathbf{R}_{i,j})_{\text{Non-Significant}} \bar{\mathbf{w}}}$$

584 where,

585 \mathbf{T} is a decision factor for the clustering of Significant and Non-Significant groups of the overflow

586 event

587 $\bar{\boldsymbol{\mu}}_i$ is mean value for the clustered group.

588 $\mathbf{R}_{i,j}$ is rainfall variables among rainfall depth, duration, intensity, type, continuity.

589

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595

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- 754



755 **Tables**

756 Table 1. Group Mean Values of Rainfall Characteristics by Discriminant Analysis.

Groups	Variables	Mean
Non-Significant Overflow (group 0)	Duration (hour)	4.57
	Rain Total (mm)	8.85
	Rain Peak (mm/15min)	3.76
	Rain Type (convective ratio)	0.47
	Rain Continuity ratio	0.56
Significant Overflow (group 1)	Duration (hour)	6.14
	Rain Total (mm)	23.7
	Rain Peak (mm/15min)	6.20
	Rain Type (convective ratio)	0.50
	Rain Continuity ratio	0.60
Total Events	Duration (hour)	5.37
	Rain Total (mm)	15.4
	Rain Peak (mm/15min)	4.84
	Rain Type (convective ratio)	0.48
	Rain Continuity	0.58

757

758



759 Table 2. Classification Result and Predicted Group Membership by Discriminant Analysis.

Overflow Severity			Predicted Group Membership		Total
			Non-Significant	Significant	
Original	Count	Non-Significant	29	0	29
		Significant	11	12	23
	Percentage	Non-Significant	100	0	100
		Significant	47.8	52.2	100

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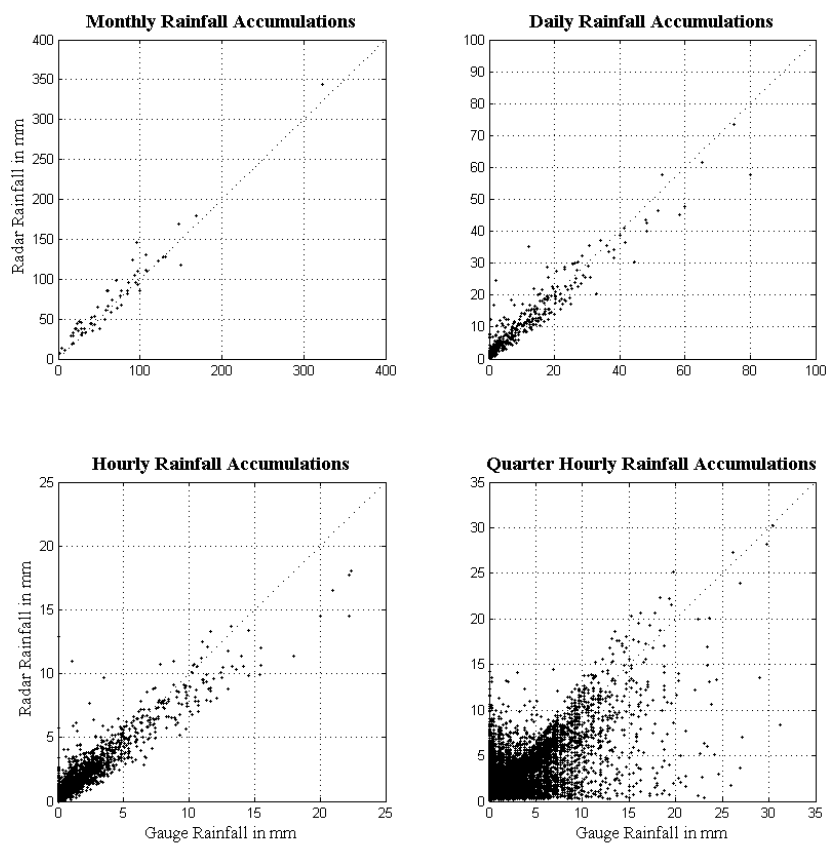
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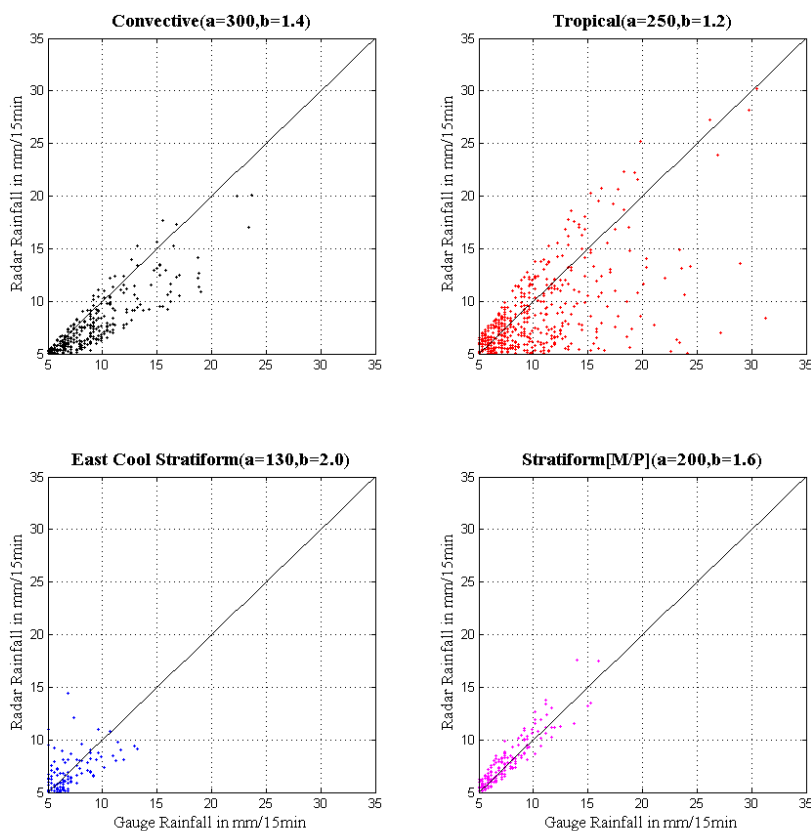


773 **Figures**



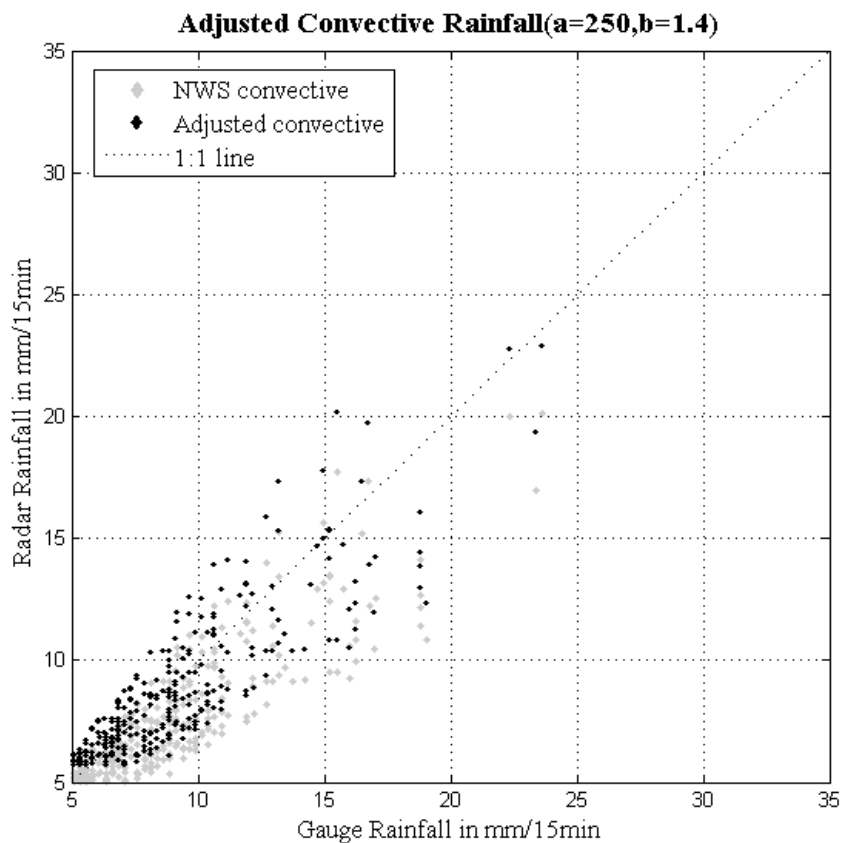
774

775 Figure 1. Gauge and Radar rainfall depth in 2-dimensional space (gauge-radar volume) across
776 temporal resolutions: monthly (upper- left), daily (upper-right), hourly (lower-left), quarter-
777 hourly (lower-right)



778

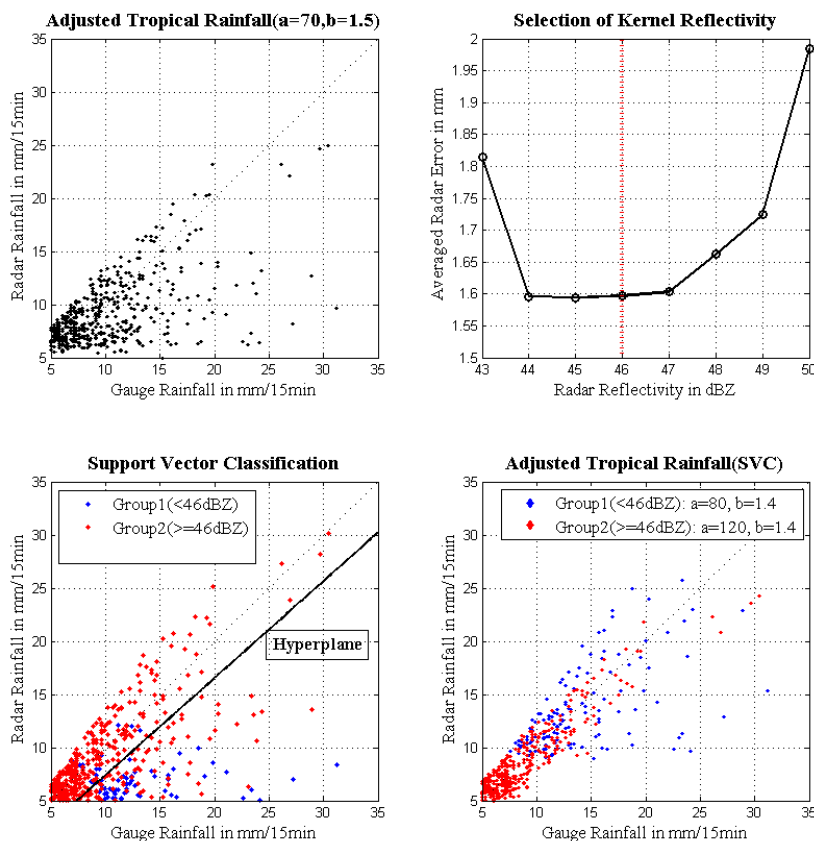
779 Figure 2. Scatter plots of rainfall volumes for each storm type after optimization (minimum
780 RMSE error): convective type (upper-left), tropical type (upper-right), east-cool-stratiform
781 type (lower-left), stratiform – Marshall/Palmer - type (lower-right)



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783 Figure 3. Convective rainfall type: radar and gauge comparison with (a) standard NWS Z-R

784 relation (light shade marker), and (b) optimized Z-R relation (minimum RMSE error)



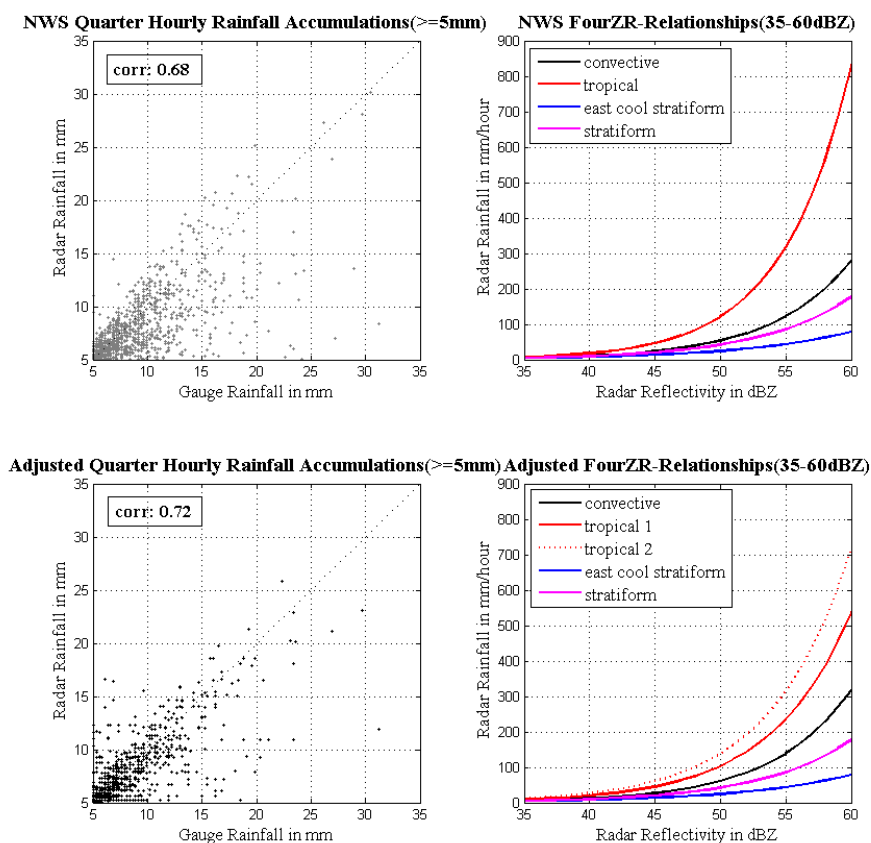
785

786 Figure 4. Tropical type rainfall results: Optimized minimum RMSE error (upper-left);

787 Decision schematic for SVC kernel within least RMSE error range (upper-right); SVC binary

788 clustering hyperplane (lower-left), SVC-based optimization with two rainfall groups (lower-

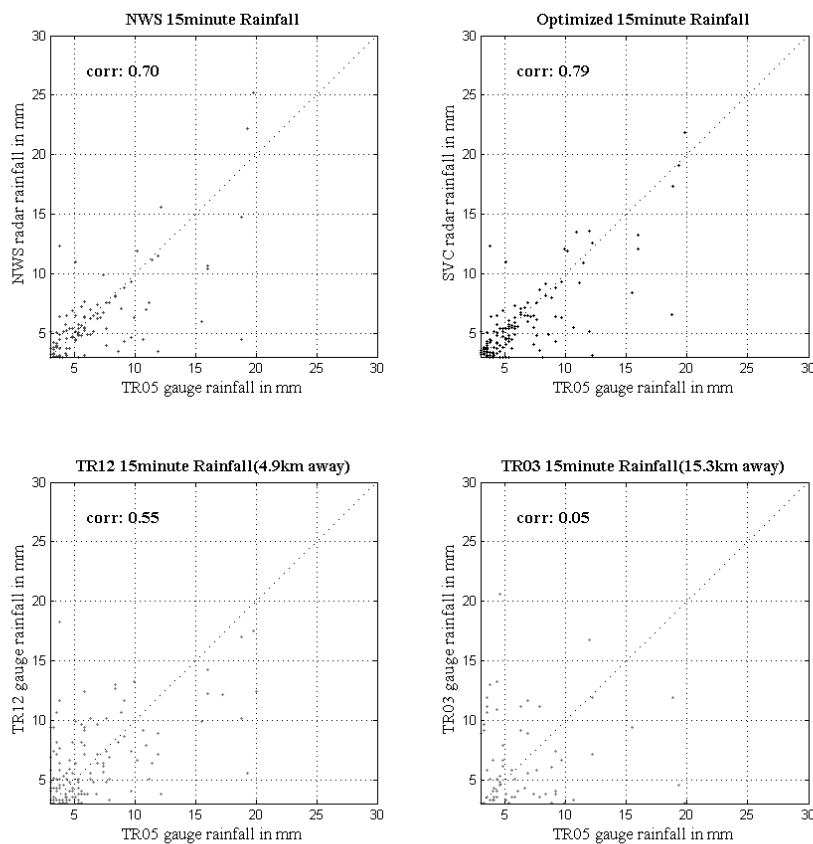
789 right)



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791 Figure 5. Comparison of local radar rainfall estimations and corresponding Z-R relationships:
792 (NWS Standardized Z-R-based quarter-hourly rainfall accumulation (upper-left); four
793 empirical NWS Z-R relationships (upper-right); Optimal SVC-based quarter-hourly rainfall
794 accumulation (lower-left); SVC-based optimal Z-R relationships (lower-right) (adapted from
795 Hyun et al., 2016c).

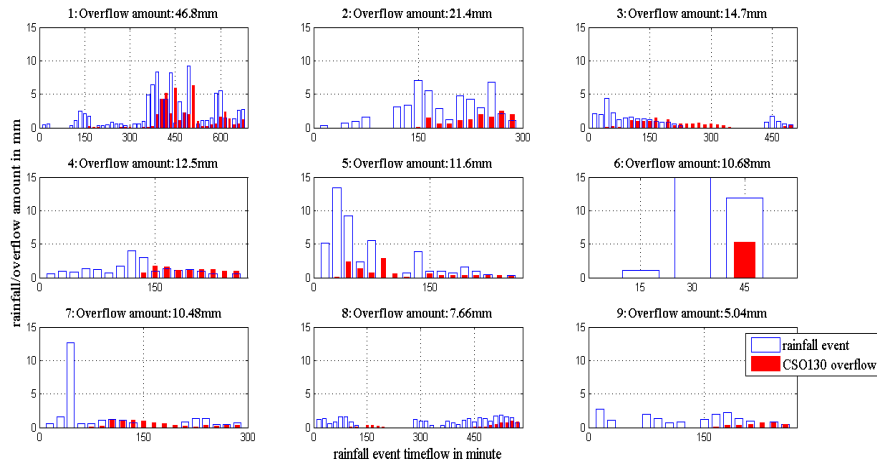
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798 Figure 6. Rainfall data quality comparisons with the reference rainfall data (TR05): NWS
799 radar data (upper-left), Quality-improved radar data by SVC (upper-right), MSD rain gauge-
800 TR12; 4.9km away from the study area (lower-left), and MSD rain gauge-TR03; 15.3km
801 away from the study area (lower-right).

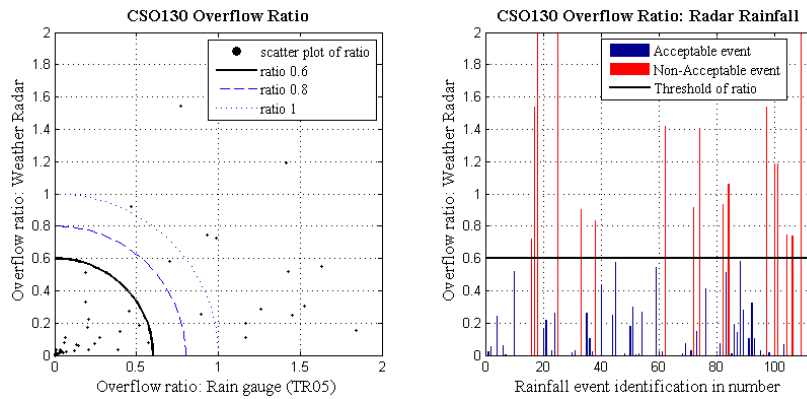
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804 Figure 7. Selected CSO events and corresponding rainfall events; Event number denotes the
 805 rank of the overflow amount through the outfall structure to Beargrass Creek, Louisville, KY.

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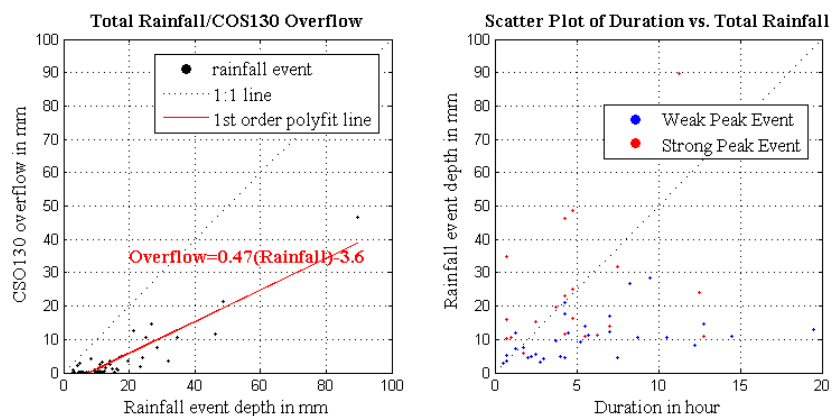
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808 Figure 8. Overflow ratio plots. Left side: Two-dimensional radar & gauge rainfall field; x-axis
 809 shows rain gauge ratio-MSD TR05 (nearest study area), y-axis shows radar ratio-NWS
 810 weather radar KLVX. Right side: Criteria threshold for valid event selection: 52 acceptable
 811 events (blue) below the 0.60 overflow/rainfall threshold, and 43 non-acceptable events (red)
 812 exceed the threshold.



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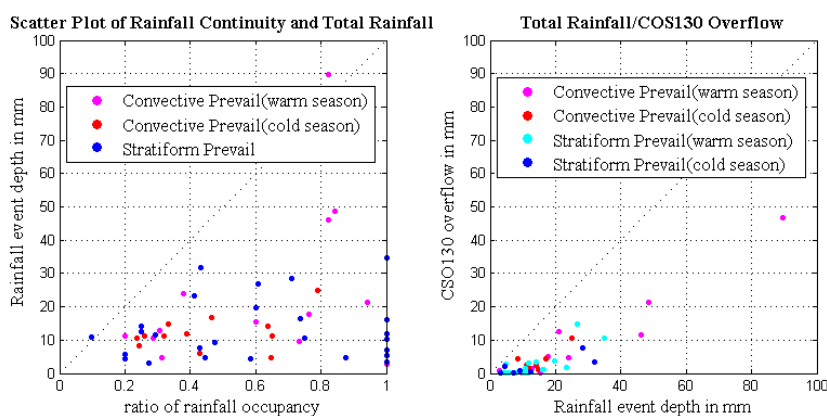
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816 Figure 9. Event-based rain depth versus overflow depth (left), and rain event duration versus
 817 rainfall depth grouped by peak rain intensity (right). Intensity threshold peak is
 818 4.87mm/15minute to identify weak (blue) and strong (red) peak event groups.

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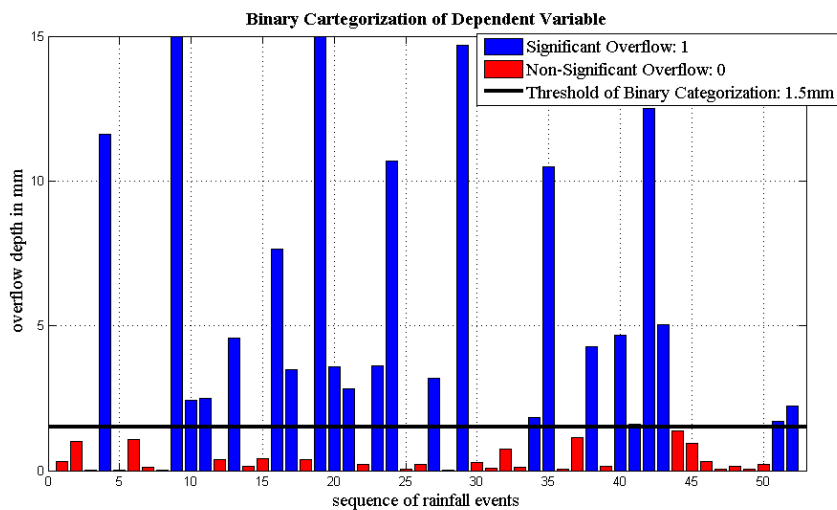


820

821 Figure 10. Rainfall occupancy ratio (ratio of continuous rain duration to total event duration)
 822 and total rainfall event depth: convective event type in warm season (magenta), convective
 823 type in cold season (red) and stratiform (blue) (left). Event-based rainfall depth versus



824 overflow depth: convective-warm season (magenta), convective-cold season (red), stratiform-
825 warm season (cyan), and stratiform-cold season (blue) (right).



826

827 Figure 11. Overflow event and 1.5-mm depth threshold separating overflow events into two

828 binary categories – significant (denoted as 1) and non-Significant (denoted as 0).