



1 Storm-Type Influence on Spatial Rainfall–Surge

2 Dependence and Compound Flood Boundary Condition

3 Generation in a Coastal Watershed

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15 Abstract

16 In coastal catchments, co-occurring rainfall and storm surge can compound flood depth
17 and extent through combined hydrodynamic effects, while remote co-occurrence of the
18 two drivers can compound impacts, e.g., by straining emergency response resources. This
19 study characterizes the spatial structure of rainfall–surge dependence in the Mullica River
20 Basin, New Jersey, using a high-resolution gridded rainfall dataset and a high-resolution
21 coastal water level reanalysis. Dependence between rainfall and the non-tidal residual
22 (NTR) is quantified separately for tropical cyclone (TC) and non-TC events using Kendall's τ
23 and fitted copulas. TC events exhibit stronger and more spatially variable dependence than
24 non-TC events, and results are largely insensitive to coastal point choice except where
25 sheltered from open-coast by a barrier island. Representing coastal forcing with total water
26 level rather than NTR substantially weakened apparent TC dependence, underscoring the
27 need to isolate the NTR in compound flood analyses. Joint return periods for the 10-year
28 rainfall and the 10-year NTR design event are 30–60 years across most of the watershed,
29 shorter than the 100-year period expected under independence and are governed primarily
30 by copula tail dependence rather than correlation strength alone. Joint return-period
31 estimates based on a locally composited rainfall record, constructed from mean hourly
32 rainfall across AORC grid points within a ~30 km radius of the coastal point, more closely
33 reproduce the basin-wide estimates than those based on either the rain gauge nearest to
34 the coastal point or basin-averaged rainfall. A response-based framework for generating
35 synthetic compound flood events using basin-averaged rainfall showed some systematic



36 correlation bias, particularly for TC events, and underestimated short-return-period non-TC
37 water levels driven by spring tides.

38 1. Introduction

39 Compound flooding through the co-occurrence of multiple flood drivers such as heavy
40 rainfall and coastal storm surge poses disproportionate risks to coastal watersheds.
41 Understanding how these hazards interact has become critical for flood risk assessment,
42 as reflected by the rapid proliferation of compound flooding literature over the past decade
43 (Green et al., 2025). Although compound impacts are possible when the flood drivers are
44 geographically remote (Brunner, 2023), the potential and extent of physical compounding
45 depends on the spatial and temporal overlap of the drivers (Baer et al. 2026). Within a
46 catchment, however, the strength of this dependence between rainfall and coastal water
47 levels (WLs) can vary spatially depending on local hydrometeorological and
48 geomorphological characteristics (Glas et al. 2026).

49 The nature of spatial and temporal overlap of the drivers, and thus the potential for
50 compounding, differs between storm types. Tropical cyclones (TCs) generate both heavy
51 precipitation and storm surge within a compact but tightly organized system, with rainfall
52 and wind fields structured concentrically around the storm center (eyewall and rainbands),
53 producing strong spatial correlation between flood drivers (Kim et al., 2023; Nasr et al.,
54 2023). Storm characteristics such as size, translation speed, approach angle, and intensity
55 modulate this compound behavior (Gori et al., 2020). In contrast, extratropical storms are
56 typically much larger in spatial extent but present a more fragmented internal structure.
57 While nor'easters and frontal systems can generate both flood drivers, their large size and
58 frontal organization frequently displace the precipitation maximum from wind-driven surge
59 centers, weakening the spatial correlation between the two. Mesoscale convective
60 systems (MCS) further amplify this spatial decoupling, producing intense localized rainfall
61 with minimal coastal water level response (e.g., Amorim et al., 2025), although high coastal
62 water levels remain possible if intense MCS rainfall coincides with the high tide.

63 Screening level approaches to quantifying rainfall-surge dependence operate at limited
64 spatial resolutions. Most studies adopt one of three strategies: pairing a single rain gauge
65 with a tide gauge (e.g., Jane et al., 2020), constructing composite rainfall from multiple
66 gauges (e.g., Wahl et al., 2015), or averaging precipitation over small watersheds (e.g.,
67 Maduwantha et al., 2024; Amorim et al. 2025). Each involves trade-offs. Point
68 measurements cannot capture spatial heterogeneity in larger catchments; composite
69 methods require subjective aggregation rules; basin averaging, while appropriate for small
70 or homogeneous systems, risks masking localized zones of strong dependence. In small



71 catchments storm type may exert a stronger influence than aggregation method on
72 dependence strength (Chen et al., 2025), implying that physical mechanisms may be more
73 influential than spatial sampling effects. However, it is untested whether this finding
74 extends to medium-to-large watersheds, where greater spatial variability might amplify the
75 importance of measurement location.

76 Recent advancements of computationally efficient reduced-physics compound flood
77 inundation models such as the Super-Fast INundation of CoastS (SFINCS) model (Leijnse
78 et al., 2021) have enabled high-resolution scenario-based flood risk assessment. These
79 models require spatially varying rainfall inputs to adequately capture the heterogeneity of
80 flood drivers across the modeled domain. Existing approaches for generating boundary
81 conditions for these compound flood models implicitly account for rainfall-coastal water
82 level dependence by modeling spatially varying rainfall through re-scaling historical events
83 (Maduwantha et al., 2026) or stochastic rainfall generators (Villarini et al., 2022). However,
84 whether these approaches adequately capture the marginal characteristics and spatial
85 dependence structure of rainfall and coastal water levels within catchments has yet to be
86 established.

87 This study aims to characterize the spatial structure of the dependence between rainfall
88 and non-tidal residual (NTR) dependence within a medium-sized coastal watershed and
89 evaluate whether they are captured by an existing framework for generating boundary
90 conditions for compound flood assessments. Using high-resolution datasets, we pursue
91 three objectives. First, we quantify how the magnitude and spatial organization of
92 dependence varies across storm types and which storm types contribute most to
93 compound flood hazard potential. Second, we evaluate the ability of commonly used
94 point-based and spatial aggregation approaches to adequately capture the strength and
95 spatial structure of rainfall-coastal water-level dependence. Third, we assess whether an
96 established method to generate spatially varying rainfall fields and coastal water level
97 hydrographs, by re-scaling historical events, preserves the marginal characteristics and
98 dependence structure of the two drivers.

99 2. Case Study Site & Data

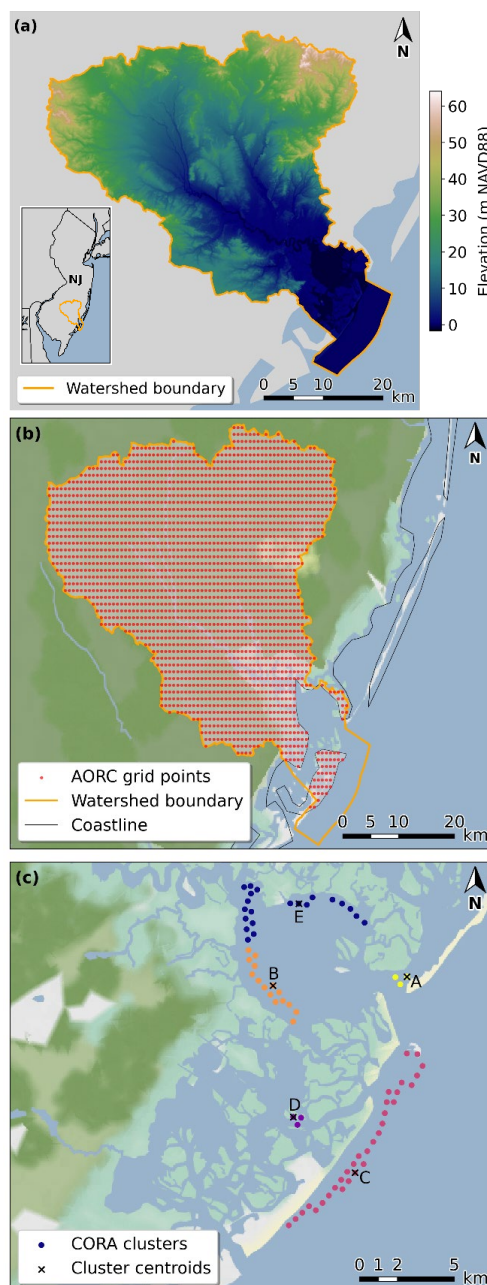
100 2.1 Case Study Site

101 The Mullica River Basin, located in southern New Jersey (Figure 1a), drains approximately
102 1,474 km² before discharging into the Great Bay estuary (Bunnell et al., 2003). It is one of
103 the least developed basins in the northeastern United States, with extensive upstream
104 protection from the Pinelands National Reserve and state-managed lands including



105 Wharton State Forest and Bass River State Forest (Lathrop et al., 2003), resulting in minimal
106 anthropogenic hydrologic alteration. The river originates near Berlin in central Camden
107 County and flows approximately 90 km east-southeast across the state, crossing Wharton
108 State Forest before entering a tidal estuary that discharges into Great Bay (Medeiros et al.,
109 2012); the tidal transition zone extends roughly 21 km inland, with the tidal limit near Lower
110 Bank (Medeiros et al., 2012). The basin's flat, low-lying topography, sandy soils, and
111 extensive wetlands (Rhodehamel, 1973) allow coastal water elevations to propagate inland
112 while high infiltration capacity moderates surface runoff, producing spatial variability in
113 how flood drivers manifest across the catchment. Basin topography is shown in Figure 1a
114 for context; elevation was not used in this analysis.

115 The Mullica River catchment experiences a humid subtropical climate with two primary
116 storm regimes with fundamentally different spatial characteristics. Tropical cyclones
117 (June-November) produce intense rainfall (often >100 mm/24hr) with coincident storm
118 surge; notable events include Hurricanes Floyd (1999), Irene (2011), and Superstorm Sandy
119 (2012), which despite undergoing extratropical transition before landfall generated
120 devastating compound impacts. Non-TC extremes are dominated by extratropical
121 cyclones, particularly nor'easters (October-April), which generate sustained rainfall and
122 coastal flooding through persistent onshore winds (Catalano and Broccoli, 2018).
123 Additional non-TC sources include atmospheric rivers and slow-moving frontal systems,
124 which can produce storm surge, while warm-season mesoscale convective systems rarely
125 generate surge and thus typically show weak coastal water level correlation (Schumacher
126 and Johnson, 2005).



127 *Figure 1: Mullica River Basin. (a) Topography of the basin (USGS, 2026; Chagini et al., 2021).*
 128 *Inset shows the catchment's location within New Jersey. (b) AORC precipitation grid points*
 129 *($n = 2356$) within the watershed boundary. (c) CORA coastal water-level station clusters,*
 130 *cluster centroids, and coastline used for coastal forcing.*



131 2.2 Data

132 Hourly rainfall data are obtained from the National Weather Service's 1-km resolution
133 Analysis of Record for Calibration (AORC) dataset version 1.1 (Fall et al., 2023). AORC
134 integrates large-scale reanalysis, ground observations, and gridded analysis products to
135 produce gridded near-surface meteorological variables over the contiguous United States
136 and Alaska. The dataset has been extensively validated against ground observations
137 demonstrating reliable performance for both TC and non-TC events (Kim and Villarini,
138 2022). AORC spans February 1, 1979, to near-present, with continuous updates
139 incorporating 10-day-lag corrections from Stage IV radar-gauge products and NLDAS
140 forcing data. Within the Mullica Basin, 2,356 grid cells provide spatially distributed rainfall
141 estimates at hourly resolution (Figure 1b).

142 Hourly water level data are obtained from the National Oceanic and Atmospheric
143 Administration's (NOAA) Coastal Ocean Reanalysis (CORA) dataset (Keeney et al., 2025).
144 CORA couples the ADvanced CIRCulation (ADCIRC) model with the Simulating Waves
145 Nearshore (SWAN) model. CORA is forced with ERA5 atmospheric fields (sea level pressure
146 and 10-m winds) and astronomical tides at open boundaries with data assimilation of
147 hourly tide gauge observations to improve skill. The reanalysis covers January 1, 1979, to
148 December 31, 2022. Coastal points are identified as CORA grid cells within 0.65 km of the
149 Natural Earth coastline (Met Office, 2026), yielding 74 locations distributed along the
150 Mullica estuary and adjacent Great Bay coastline (Figure 1c).

151 This study analyzes the overlapping period from February 1, 1979, to December 31, 2022,
152 providing 44 years of concurrent high-resolution rainfall and water level data for spatial
153 dependence analysis.



154 3. Method

155 The conditional sampling copula framework with storm-type stratification proposed by Kim
156 et al. (2023) is used to characterize the joint behavior of extreme rainfall and coastal water
157 levels (Section 3.1). This approach explicitly accounts for differences in dependence
158 structure between TC and non-TC storm types. Section 3.2 introduces the approaches for
159 representing watershed-scale rainfall, and Section 3.3 presents the response-based
160 approach, which builds on the framework by Kim et al. (2023) (see also Amorim et al.
161 (2025)).

162 3.1 Conditional Sampling Copula Framework

163 3.1.1 Selection of Representative CORA Centroids

164 To balance computational efficiency with spatial representativeness, we apply K-means
165 clustering to the 74 coastal CORA grid cells, identifying five representative locations (Figure
166 1c) that capture the spatial variability in water level dynamics across the Mullica estuary.
167 These five coastal points are paired with all 2,356 AORC rainfall grid cells within the basin,
168 creating 11,780 rainfall-water level pairs for dependence analysis.

169 The five water level time series were detrended by subtracting a 30-day running mean. Year-
170 by-year harmonic tidal analysis was then performed using the Unified Tidal Analysis and
171 Prediction (UTide) package in MATLAB (Codiga, 2011). The NTR was obtained by subtracting
172 the predicted astronomical tide from the total (detrended) water level.

173 3.1.2 Extreme Event Selection

174 The statistical models require independent and identically distributed (i.i.d.) data. To obtain
175 independent univariate extremes, rainfall and NTR time series were declustered using a
176 peaks-over-threshold (POT) approach with a storm separation window of three days.
177 Thresholds were selected to yield an average of five extreme events per year (e.g., Kim et al.
178 (2023); Maduwantha et al. (2024)). The conditional sampling component of the framework
179 (Section 3.1.3) was then implemented for rainfall accumulation times ranging from 1 to 48
180 hours. For each accumulation time, conditional samples were constructed and the
181 dependence between rainfall and NTR was evaluated based on the correlations within
182 these samples. The rainfall accumulation time yielding the strongest correlation was
183 subsequently selected for the conditional extreme-value analysis.

184 3.1.3 Construction of Conditional Samples

185 Two conditional samples are constructed for each location pair (per rainfall accumulation
186 time). First, a rainfall-conditioned sample pairs each n-hour rainfall exceedance with the



187 maximum hourly NTR occurring within the same n-hour window. Second, an NTR-
188 conditioned sample pairs each hourly NTR exceedance with the maximum cumulative
189 rainfall from any event occurring within ± 3 days, where rainfall events are defined as
190 precipitation sequences separated by at least 6 hours without measurable rainfall. This
191 two-sided conditioning approach accounts for potential asymmetries in dependence
192 structure depending on which variable drives the extreme event.

193 3.1.4 Storm Type Stratification

194 Both conditional samples are stratified by storm type: TC or non-TC yielding four samples
195 per location pair. Following Maduwantha et al. (2024), an event is classified as TC-driven if
196 a tropical cyclone track passes within 350 km of the location within ± 3 days of the event
197 midpoint. The event midpoint is defined as the temporal center of the rainfall accumulation
198 period (for rainfall-conditioned samples) or the time of maximum NTR (for NTR-conditioned
199 samples). Tropical cyclone tracks at 6-hour resolution are obtained from the National
200 Hurricane Center's HURDAT2 database (Landsea and Franklin, 2013). All events not
201 meeting the TC criteria are classified as non-TC, encompassing extratropical cyclones,
202 frontal systems, and MCS.

203 3.1.5 Dependence Modelling with Copulas

204 For each of the four stratified samples (TC rainfall-conditioned, TC NTR-conditioned, non-
205 TC rainfall-conditioned, non-TC NTR-conditioned), we model the dependence structure
206 using copulas. Marginal distributions for the conditioning variable are fit using Generalized
207 Pareto Distributions (GPD), appropriate for modeling POT extremes. The conditioned
208 variable is fit to parametric distributions selected from a suite of candidates: zero-
209 truncated distributions (gamma, lognormal, Weibull) for rainfall and unbounded
210 distributions (Gaussian, logistic) for water level. The copula family is selected from 40
211 options available in the VineCopula R package (Nagler et al., 2026), with the Akaike
212 Information Criterion (AIC) determining the best-fitting marginal and copula models for
213 each sample.

214 3.1.6 Estimation of Joint Exceedance Probabilities and Return Periods

215 Following Bender et al. (2016) and others, Annual Exceedance Probability (AEP) of an event
216 (r, ntr) for each storm type is given by:

$$217 \quad AEP^{TC}(r, ntr) = \max\{AEP_{con R}^{TC}(r, ntr), AEP_{con NTR}^{TC}(r, ntr)\} \quad (1)$$

$$218 \quad AEP^{non-TC}(r, ntr) = \max\{AEP_{con R}^{non-TC}(r, ntr), AEP_{con NTR}^{non-TC}(r, ntr)\}. \quad (2)$$

219 Under the assumption of independence between TC and non-TC event occurrence the total
220 annual non-exceedance probability (ANEP) is calculated as follows:



221
$$ANEP(r, ntr) = (1 - AEP^{TC}(r, ntr))(1 - AEP^{non-TC}(r, ntr)). \quad (3)$$

222 The joint return period is then calculated as

223
$$T_{joint}(r, ntr) = \frac{1}{1 - ANEP(r, ntr)}. \quad (4)$$

224 3.1.7 Design Event Selection

225 To examine the influence of dependence on joint return periods, we analyze the compound
226 event comprising the 10-year (univariate) return level for both rainfall and NTR. This design
227 event is sufficiently extreme to cause potential impacts while remaining within the
228 observational range, enabling robust statistical inference. For each rainfall-NTR pair,
229 univariate GPDs are fit to declustered extremes (3-day separation, ~5 events/year
230 threshold), and the 10-year return levels are extracted. Joint return periods for this event
231 are then computed across all location pairs using the framework described above,
232 revealing spatial patterns in how often these marginal extremes co-occur.

233 3.2 Approaches for Representing Watershed-Scale Rainfall

234 Three existing approaches for characterizing watershed-scale rainfall are evaluated to
235 determine whether they provide robust estimates of potential compound flood hazard, as
236 quantified by joint return period. The approaches include one point-based method and two
237 spatial aggregation methods for representing watershed-scale rainfall at each study
238 location:

239 **Method 1 - Point-to-point pairing:** A rain gauge is paired directly with a tide gauge. This is
240 the simplest and most widely adopted approach, involving no spatial aggregation.

241 **Method 2 - Local composite:** Rainfall is represented by the spatial mean of rainfall from
242 multiple gauges or gridded rainfall-product points located within a specified radius of the
243 tide gauge.

244 **Method 3 - Basin average:** Rainfall is spatially aggregated across the full watershed,
245 typically applied in small catchments and derived from gridded rainfall products rather
246 than in-situ gauge records.

247 For each approach, we recompute the 10-year, 10-year joint return period following the
248 procedure described in Section 3.1, substituting the corresponding rainfall series for the
249 distributed grid-cell representation.



250 3.3 Time varying boundary conditions

251 Maduwantha et al. (2026) adapted the storm-type-stratified conditional sampling–copula
252 approach of Kim et al. (2023) from a design-based to a response-based framework. Instead
253 of selecting single event pairs at a pre-determined joint return period, they sample directly
254 from fitted copula models in proportion to each conditional sample’s historical frequency
255 of co-occurrence, generating a large number of simulated years in which at least one driver
256 is extreme. These sampled events are rendered time-varying using re-scaling methods
257 introduced by Kim et al. (2023) and refined in Maduwantha et al. (2026) and described in
258 the following subsections.

259 3.3.1 Re-scale historic events

260 To generate a temporally varying rainfall field for a simulated event, an independent
261 historic rainfall event is sampled from events identified using a six-hour dry-spell criterion.
262 The historic event is selected with a probability inversely proportional to the difference
263 between the peak rainfall accumulations of the simulated and observed events, where the
264 accumulation period corresponds to the optimal rainfall accumulation time identified in
265 Section 3.1. The sampling probabilities favor historic events with peak totals closer to that
266 of the simulated event. The hourly rainfall totals of the selected historic event are then
267 rescaled by the ratio of the simulated and selected historic events' peak rainfall
268 accumulations over the selected accumulation period. This preserves the temporal
269 structure of the historic event while matching its peak rainfall accumulation to that of the
270 simulated event. To prevent unrealistic distortion of the historic rainfall pattern, the scaling
271 factor is capped at 4 through rejection sampling.

272 An analogous procedure is implemented to obtain hourly NTR time series. The scale factor
273 is the ratio of simulated to selected events peak. The scaling factor for NTR is also capped
274 at 4.

275 3.3.2 Water level hydrograph construction

276 To obtain a water level hydrograph, the NTR series has to be combined with mean sea level
277 and tide. All three components exhibit seasonal variation, which must be accounted for
278 during event simulation. A 3-day window of hourly tidal signal centered on each high tide is
279 extracted from the last 18.6 years of record to capture the lunar nodal cycle. The tidal
280 series are grouped by calendar month, and the mean sea level of each calendar month is
281 calculated. A month is then sampled from the historical monthly frequency distribution of
282 TC events if the simulated event is drawn from a copula fitted to TC events, or from the
283 corresponding non-TC distribution otherwise. A mean sea level and tide value are then
284 chosen at random from within the sampled month.



285 A time lag between NTR and subsequent high tide observed during NTR conditioned events
286 is sampled to account for the tide–NTR interaction. Once the peaks of the tide and NTR are
287 shifted to give the series this lag the water level components are added to give the water
288 level hydrograph.

289 3.3.3 Temporal alignment of rainfall fields and water level hydrographs

290 An observed time lag between rainfall and NTR peaks is sampled from the sample
291 corresponding to the model from which the simulated event is drawn i.e., depending on
292 whether the simulated event is drawn from the rainfall-conditioned or NTR-conditioned
293 model.

294 4. Results and Discussion

295 4.1 Spatial Correlation by Storm Type

296 4.1.1 Sensitivity of conditional sample correlations to rainfall accumulation 297 times

298 To select a rainfall accumulation time for the conditional sampling–copula component of
299 the analysis, existing frameworks, including Maduwantha et al. (2024), perform conditional
300 sampling over rainfall accumulation times from 0 to approximately 48 hours and select a
301 single accumulation time that maximizes the correlation for at least one of the TC
302 conditional samples (Kim et al. (2023); Maduwantha et al. (2024)). This approach provides
303 a common temporal basis for comparing conditional samples. In contrast, other studies
304 permit the accumulation time to vary between conditional samples at the same site (e.g.,
305 Amorim et al. (2025)), thereby reducing the risk of underestimating the rainfall–NTR
306 correlation when the optimal accumulation times differ between samples.

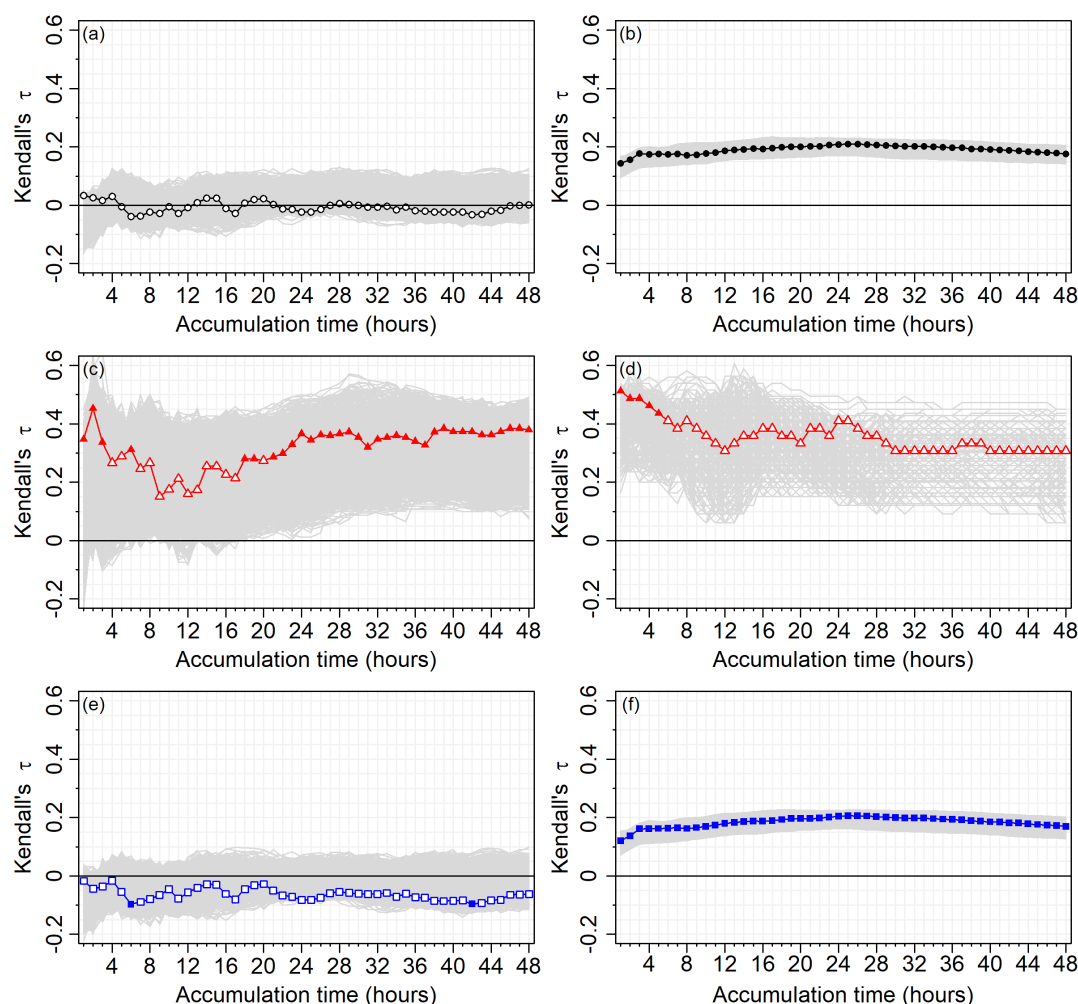
307 Figure 2 illustrates the sensitivity of the rainfall–NTR correlation to rainfall accumulation
308 time for the unstratified, TC, and non-TC samples, both for basin-average rainfall (colored
309 lines) and for point rainfall estimates (grey lines) using CORA centroid C. When
310 conditioning on rainfall, the basin-average unstratified sample exhibits weak, non-
311 statistically significant correlations across all accumulation times (a). In contrast, the
312 corresponding TC sample shows a moderate statistically significant positive correlation for
313 accumulation times greater than approximately 18 hours (c), whereas the non-TC sample
314 remains weakly negative and is statistically significant at only two accumulation times (e).

315 Conditioning on NTR yields moderate positive correlations for the unstratified sample
316 across the full range of accumulation times, which is similarly seen for the non-TC samples



317 (f). In contrast, the TC sample exhibits particularly strong correlations for accumulation
318 times shorter than approximately 4 hours, likely reflecting the influence of intense storm
319 events that produce coincident peaks in rainfall and NTR. For longer accumulation times
320 the correlations are moderately positive but not statistically significant. Across all
321 conditional samples, TC correlations show greater spatial variability than the
322 corresponding non-TC correlations. The basin-average estimates generally follow the
323 median behavior across sites and remain within the 95% confidence intervals of the
324 AORC–CORA point-pair estimates (Figure S1).

325 The AORC–CORA point-pair conditioned samples associated with TC events exhibit greater
326 variability across rainfall accumulation times than those associated with non-TC events,
327 owing to the lower frequency and limited spatial footprint of some TC events. For both TC
328 and non-TC samples, the NTR-conditioned sample exhibits less variability than the
329 corresponding rainfall-conditioned sample. This lower variability in the NTR-conditioned
330 sample arises because every location in the basin is conditioned on the same NTR event,
331 whereas in the rainfall-conditioned sample, different locations in the basin are associated
332 with different NTR events.



333

334 *Figure 2: Variation in Kendall's τ correlation coefficient between rainfall and NTR with*
 335 *accumulation time. Grey lines show correlations at individual location pairs for samples*
 336 *conditioned on rainfall volumes (left column) and NTR peaks (right column) for all events (a,*
 337 *TC events (c, d), and non-TC events (e, f). Colored lines show basin-average estimates,*
 338 *with filled symbols indicating statistically significant correlations at the 5% significance*
 339 *level.*

340 4.1.2 Sensitivity of conditional sample correlations to CORA point

341 The Kendall's τ correlations between rainfall and NTR within the conditional samples,
 342 evaluated using the five CORA points (centroids A–E), are shown in Figure 3. The TC
 343 samples conditioned on rainfall are small ($n = 29$), with a moderately strong correlation ($\tau \approx$
 344 0.2 – 0.4) across most of the watershed. Correlation weakens toward the eastern part of the



345 watershed, particularly near the coast, where it falls to approximately -0.2. The
346 corresponding non-TC conditional samples are larger ($n = 191$) and the correlation is also
347 mostly positive but weaker in magnitude than in the TC samples ($\tau \approx 0.0$ – 0.15). Correlation
348 turns negative in the northern part of the watershed and, in the southeast near the coast,
349 where it drops to approximately -0.05. Both the TC and non-TC rainfall-conditioned
350 samples show little sensitivity to the choice of CORA centroid.

351 For the TC samples conditioned on NTR, correlation ranges from $\tau \approx -0.1$ to 0.5 . Due to the
352 small sample sizes ($n = 11$ – 15), the correlation is sensitive to individual events within the
353 sample. The correlation is relatively homogeneous among CORA points, except for point D.
354 Point D is sheltered behind a barrier island and consequently is not affected by all storms.
355 Correlation at point D is negative near the coast and increases with distance inland. For all
356 other CORA centroids, the correlation is almost exclusively positive.

357 For the larger non-TC samples conditioned on NTR ($n = 205$ – 209), correlation lies within a
358 narrow range ($\tau \approx 0.12$ – 0.22) and is more sensitive to CORA point than the TC samples:
359 there is a negative gradient with distance from the coast for CORA point C, D, and to a
360 lesser extent A, while the opposite pattern emerges for points B and E. Although the
361 direction of this gradient varies by centroid, the differences are modest: correlation across
362 CORA points spans a range of only approximately 0.05 .

363 As CORA is a coastal ocean reanalysis product, its representation of hydrodynamic
364 conditions is expected to be less reliable within estuaries than on the adjacent open coast.
365 Consequently, the remainder of the analysis was undertaken using the CORA centroid C,
366 which better represents the open coast environment.

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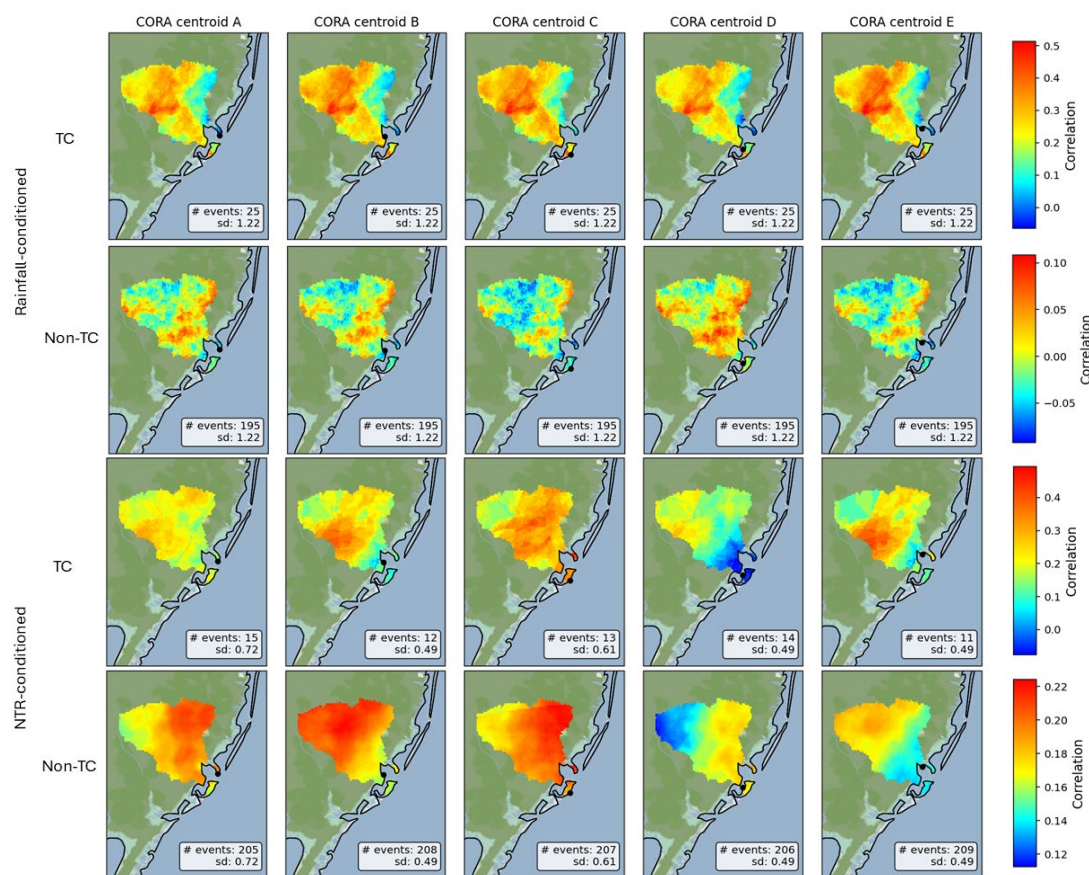


Figure 3: Spatial distribution of Kendall's τ correlation coefficients across the watershed for the five CORA centroids. Each panel reports the mean number of events and the standard deviation (sd) of the number of events in the samples. Separate color scales are used for each row owing to differences in the range of correlation coefficients.

4.1.3 Water level as the coastal forcing

Figure 4 shows the correlations within the conditional samples when coastal forcing is represented by WL. The corresponding correlations using NTR, presented in Figure 3, are included for comparison. For TC events, adopting WL as the coastal forcing substantially reduces the spatial correlation compared with NTR. This reduction is expected since WL includes astronomical tides, which introduces additional variability unrelated to the large-scale meteorological processes associated with TC-driven rainfall. In contrast, NTR isolates the meteorologically driven component of WL and therefore retains a stronger relationship with TC-influenced rainfall patterns. In the non-TC samples, correlations between rainfall and both WL and NTR are weak ($|r| < 0.08$). Differences between the two



are generally small and may reflect sampling variability rather than a systematic physical effect.

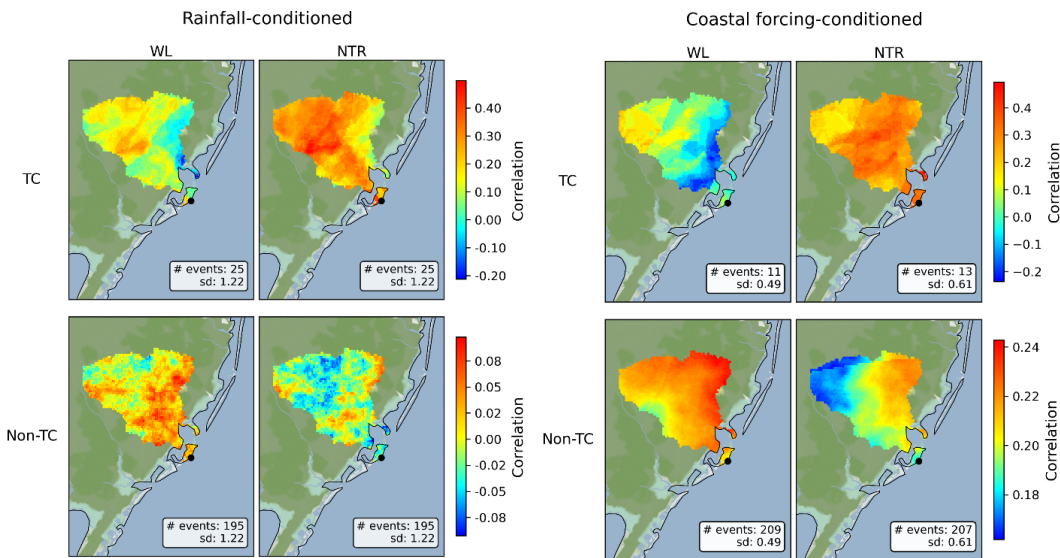


Figure 4: Spatial variability of Kendall's τ correlation coefficients over the catchment for samples conditioned on rainfall (left panel) and on the coastal forcing either WL or NTR (right panel). Note the colorbar scale varies between panels.

4.1.4 Joint return periods

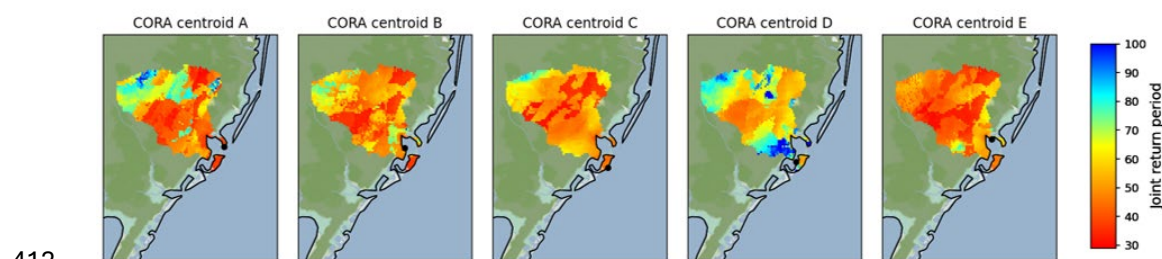
The joint return periods of the 10-year rainfall, 10-year NTR events are shorter than the 100-year return period expected under the assumption that the drivers occur independently (Figure 5). Across all the centroids, 87 of AORC – CORA pairs (0.7%), yielded joint return periods exceeding 100-years. Of these 87 sites, 31 (35.6%) contain at least one sample with a negative correlation that contributes to the joint return period. At the remaining 56 (64.4%) sites, where retained correlations were positive, exceedances instead reflect a limitation of the two-sided conditional sampling approach. Specifically, the approach fits two marginal distributions to each variable depending on its conditioning role: a GPD when the variable is the conditioning variable, and a non-extreme distribution when it is the conditioned variable (see Section X). Because these two fits are not required to be consistent with one another, the resulting joint return period can exceed the nominal 100-year threshold implied by the GPD-derived 10-year events.

Joint return periods are sensitive to CORA centroid choice. A return period close to or greater than 100 years is more widespread across the northwest edge of the watershed for CORA centroid A, and is in the north and south of the watershed when adopting CORA



centroid D. For centroid C, joint return periods fall between 30 and 60 years across 85% of the watershed with a minimum of 28 years and a maximum of 87 years.

411



412

413 *Figure 5: Joint return period of an event comprising the 10-year rainfall, 10-year NTR.*

414 Recall that, for each storm type, only the highest AEP among the conditional samples is
415 retained in the joint return period calculation. The top row of Figure 6 shows the
416 correlations for conditional samples that contribute an AEP used in the joint return period
417 calculation at CORA point C. For both TCs and non-TCs, the AEP is most often contributed
418 by the sample conditioned on NTR.

419 The middle row of Figure 6 shows the correlations for cases where the conditional sample
420 contributing the AEP has a stronger correlation than the alternative conditional sample for
421 the same storm type. For non-TC events, the conditional sample contributing to the AEP
422 almost always has stronger correlation (99.6% of locations), in contrast, for TC events this
423 occurs at only 49.7% of locations.

424 The bottom row of Figure 6 shows the correlations for cases where the conditional sample
425 contributing to the AEP has weaker correlation than the alternative conditional sample. For
426 TC rainfall-conditioned samples, some samples contribute to the joint return period
427 calculation despite having Kendall's τ correlation coefficients of up to 0.22 lower than the
428 corresponding sample that does not contribute to the AEP. This indicates that differences
429 in the dependence structure, rather than dependence strength alone, govern the
430 contribution of conditional samples to the joint return period.

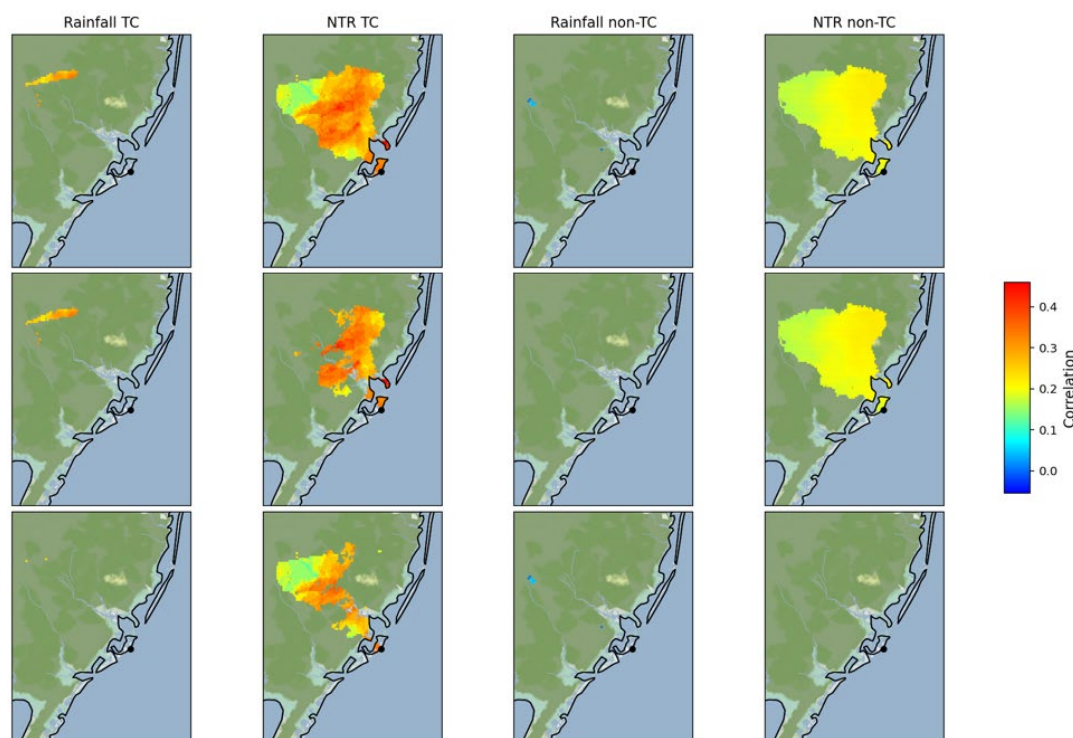


Figure 6: Kendall's τ correlation coefficients of samples contributing to AEPs. Top: all contributing samples. Middle: Kendall's τ of the contributing conditional sample, shown only for samples where it exceeds the τ of the non-contributing conditional sample, for each storm type. Bottom: Kendall's τ of the contributing conditional sample, shown only for samples where it is less than the τ of the non-contributing conditional sample, for each storm type.

The shape and magnitude of the dependence structure is captured by the fitted copulas. The copula families selected for the conditional samples contributing to the AEP are shown in Figure 7. Considerably greater spatial variability in the selected copula family is evident for TC events than for non-TC events among the cases that drive the AEP. In contrast, the dependence structure of non-TC samples is relatively uniform across the study area, with the Tawn type 1 copula selected for the small number of rainfall-conditioned samples and the NTR-conditioned samples over most locations.

Across the watershed, TC samples contribute an average of 73% of the joint AEP (Figure S2), indicating that the joint return period is controlled primarily by the dependence structure of TC events. A similar percentage contribution from TCs was found for Gloucester City, PA, and St. Petersburg, FL, by Maduwantha et al. (2024). For the NTR-conditioned TC samples, although the survival Gumbel copula is selected for 62% of



locations, there is also pronounced spatial clustering in copula selection. Frank copulas are common in the northwestern and western parts of the watershed, Joe and survival Clayton copulas form a central band, and Gaussian copulas are primarily selected in the eastern coastal region. This systematic spatial organization indicates that the dependence structure between rainfall and NTR varies across the watershed rather than occurring randomly between locations.

The copula family, and specifically its representation of upper-tail dependence, is a stronger determinant of joint return periods than Kendall's τ alone (Figure 7). The shortest joint return periods are generally associated with locations where copulas exhibiting upper-tail dependence, i.e., Joe and survival Clayton copulas are selected for the AEP dominant TC NTR-conditioned sample. These copulas assign relatively high probability to the joint occurrence of extreme rainfall and NTR, resulting in smaller AEPs and consequently shorter joint return periods. In contrast, locations where Gaussian, survival Gumbel or Frank copulas are selected generally exhibit longer joint return periods. These copulas exhibit weak or no upper-tail dependence and, despite having similar values of Kendall's τ at some locations, assign lower probabilities to concurrent extremes.

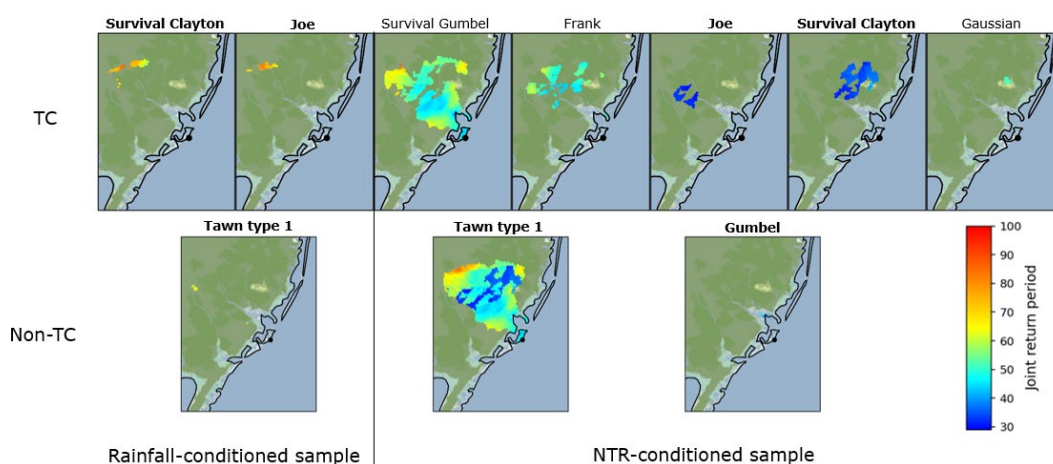


Figure 7: Spatial distribution of the best-fitting copula families for the conditional samples. Copula families with upper tail dependence are indicated by bold titles, and the color scale represents the corresponding joint return period (years).

4.2 Point-Based vs. Aggregated Methods

4.2.1 Comparison of Methods

Figure 8 shows the joint return period of the 10-year rainfall and 10-year NTR events, along with the uncertainty in AORC–CORA point-pair estimates. The 95% confidence interval of



473 these estimates ranges from 27.5 years at centroid E to 47.8 years at centroid D. Method 1
474 (point-to-point pairing) generally performs poorly, with estimates falling outside the 95%
475 confidence interval for three of the five centroids. This is because the AORC grid point
476 paired with each tide gauge is located near the coast, where joint return period estimates
477 are amongst the shortest in the catchment, and the method therefore consistently
478 underestimates the basin-wide median joint return period.

479 Method 2 (30 km composite record) falls within the 95% confidence interval and is closest
480 to the mean of the AORC–CORA point-pair estimates at all centroids. Method 3 (basin
481 average) predicts consistently shorter joint return periods than the median of the AORC–
482 CORA point-pair estimates, falling within the 95% confidence interval for four of the five
483 centroids. The shorter return periods arise because, when basin-averaged rainfall is used,
484 the correlation in the TC sample conditioned on NTR, the dominant contribution to the AEP,
485 is higher than the corresponding correlation at most individual AORC–CORA pairs (Figure 2,
486 middle row, 24-hour panel).

487 Based on these results, using an aggregated rainfall record from locations within the
488 vicinity of the tide gauge (30 km; Method 2) provides the most reliable estimates, followed
489 by the basin-average approach, which leads to underestimation of the joint return periods.
490 While pairing the tide gauge with the nearest grid point (Method 1) is the least reliable
491 approach, this is likely due to the inability of a single grid point to represent the spatial
492 rainfall variability across the watershed.

493

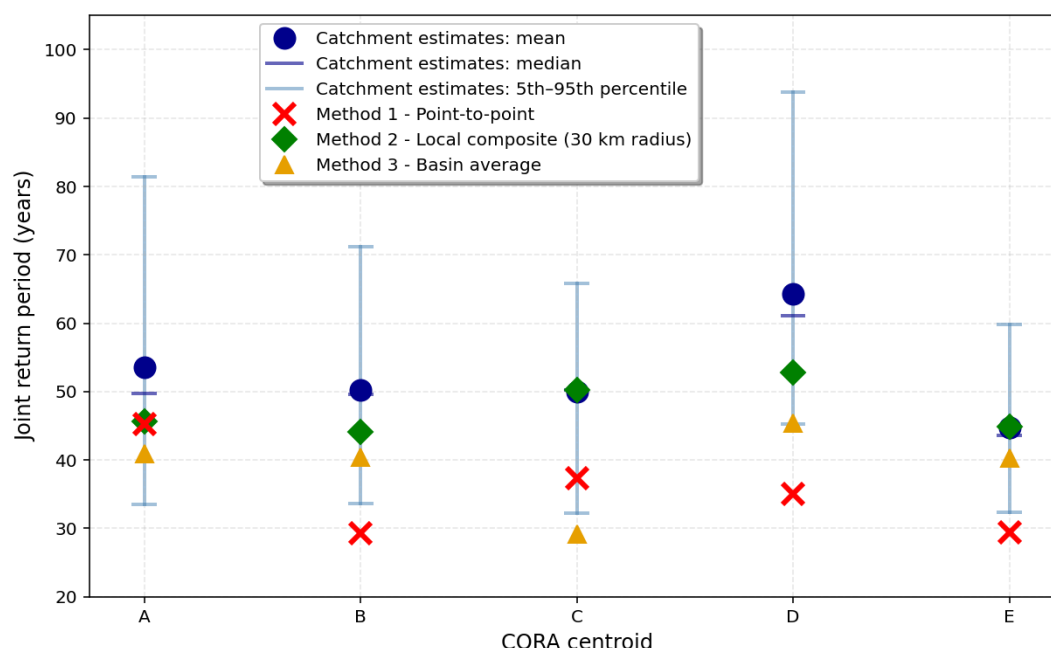


Figure 8: Joint return periods estimated using three watershed-scale rainfall characterization approaches, compared with the distribution of basin-wide AORC-CORA point pair estimates.

4.2.2 Sensitivity of Joint Return Period to Rainfall Aggregation Radius

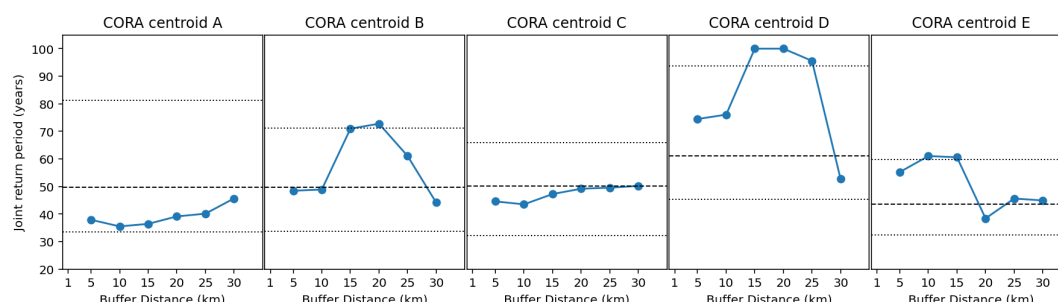
The sensitivity of the joint return period to the radius used to construct the composite, spatially averaged rainfall record was tested for radii of 5– to 30 km (Figure S3). For CORA centroids A, B, C, and E, joint return period estimates remain within the 95% confidence interval across all tested distances (Figure 9). The estimates for centroids A, B and E are within 20 years of the median basin-wide AORC-CORA point pair estimates for all distances. For centroid C the choice of radius has little effect on the estimated joint return period.

Centroid D is a notable exception to the general joint return period vs buffer distance trend. Joint return period rises sharply from ~60 years at a 5 km radius to a peak of approximately 90–100 years near 15–20 km, before declining again by 30 km. Figure 5 shows that centroid D sits adjacent to a compact, localized zone of elevated joint return period (approaching 100 years) that is distinct from the surrounding lower values (30–50 years) found through most of the basin. At small buffer radii, the basin average is therefore dominated by this concentrated zone of high joint return periods; as the radius grows, increasing amounts of the surrounding area of lower joint return periods are incorporated, pulling the average back down. Centroid B experiences a similar non-monotonic pattern due to a similar



514 localized zone of elevated joint return periods (approaching 80 years); however, it remains
515 within the 95% confidence interval.

516 While the extent of rainfall averaging is largely inconsequential for basin-wide estimates in
517 areas with relatively homogeneous joint return period, it becomes more influential where
518 fine-scale spatial heterogeneity exists near the representative coastal point, as is the case
519 at centroid D. At 30 km, however, centroid D's estimate returns to a range consistent with
520 the other four centroids, supporting this distance could be a reasonable minimum for
521 representing rainfall in compound flood hazard assessments in medium-sized catchments.



522

523 *Figure 9: Variability in joint return period with buffer radius distance at the five CORA*
524 *centroids. Solid lines show the median, and dashed lines show the 95% confidence*
525 *interval of the joint return periods, calculated across all grid points within the watershed for*
526 *each CORA centroid.*

527 4.3 Validation of probabilistic event generation framework

528 This section assesses whether the framework outlined in Sections 3.1 and 3.3 generates a
529 synthetic population of events that reflects the key characteristics and dependence
530 structure of the observed event population. Validation is performed using a parametric
531 bootstrap procedure, whereby the entire time-varying event generation process is repeated
532 to produce synthetic samples of the same size as the original dataset, enabling
533 comparison between the synthetic and observed event populations. Specifically, the
534 synthetic events are evaluated in terms of the dependence between total event rainfall and
535 NTR peak (Section 4.3.1), total event rainfall volumes (Section 4.3.2), and peak water levels
536 (Section 4.3.3). Where discrepancies between the synthetic and observed event
537 populations are identified, potential explanations for these differences are also examined.

538 4.3.1 Dependence

539 The Maduwantha et al. (2026) framework's dependence modeling involves fitting copulas
540 to peak basin-average rainfall for this study over a 24-hour accumulation time and peak
541 NTR, conditioning on one of the drivers, after stratifying by storm type. Because the



542 synthetic events are derived from a copula fit to the basin-average time series, any bias
543 between basin-average-rainfall and grid-point-NTR correlation is expected to propagate
544 into the synthetic-event correlations. This is confirmed by comparing the bias between
545 basin-average-rainfall-NTR and grid-point-rainfall-NTR correlation (Figure 10) against the
546 bias between synthetic-event and grid-point-rainfall-NTR correlation (Figure 11): the two
547 show a similar spatial pattern of opposite sign, as expected given that synthetic-event
548 correlation closely tracks basin-average correlation (Figure S4). This indicates that bias in
549 the synthetic events is largely inherited from the spatial structure of the basin-average
550 correlation bias, rather than introduced independently by the event-generation process
551 itself.

552 Using 24-hour basin-average rainfall leads to an overestimation of the rainfall–NTR
553 correlation across much of the catchment for TC events, and a slight underestimation for
554 non-TC events (Figure 10). This pattern is reflected in the box plots of observed-minus-
555 synthetic-event bias in Figure 11: for TC events, the median bias is -0.02 and -0.07 , with
556 interquartile ranges of 0.11 and 0.14 , for the rainfall- and NTR-conditioned samples
557 respectively, confirming that the synthetic, basin-average correlation tends to overestimate
558 local observed correlation. This overestimation is strongest in the east for the rainfall-
559 conditioned sample and in the northwest for the NTR-conditioned sample, though the
560 magnitude is somewhat reduced relative to the basin-average bias in Figure 10. A small
561 number of locations with weakly negative basin-average bias become positive in the
562 synthetic-event bias, even though the median remains negative. For non-TC events, bias is
563 smaller in magnitude and more mixed in sign, with a median of 0.03 for the rainfall-
564 conditioned sample and less than 0.01 for the NTR-conditioned sample, and an
565 interquartile range of 0.03 for both. These patterns reflect the greater spatial variability in
566 correlation for TC events across the catchment, described in Section 4.1.2, whereas the
567 more spatially homogeneous non-TC correlation is better represented by a single basin-
568 average value. This confirms that basin-averaged rainfall systematically misrepresents the
569 local dependence structure, particularly for TC events.

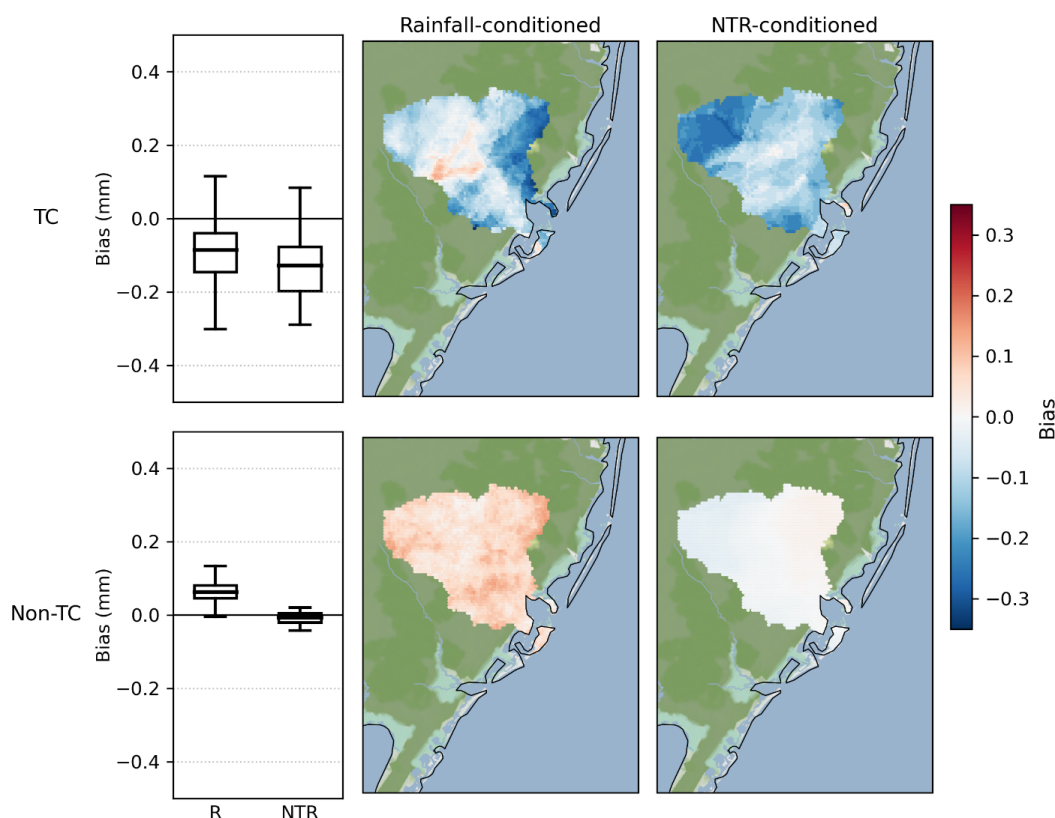


Figure 10: Bias in Kendall's τ , calculated as the correlation between point rainfall and NTR minus the correlation between basin-averaged rainfall and NTR, for the rainfall- and NTR-conditioned samples, stratified by storm type (TC and non-TC). Box plots (left) show the distribution of bias across all AORC grid points in the catchment; maps (right) show the corresponding spatial distribution of bias at each grid point.

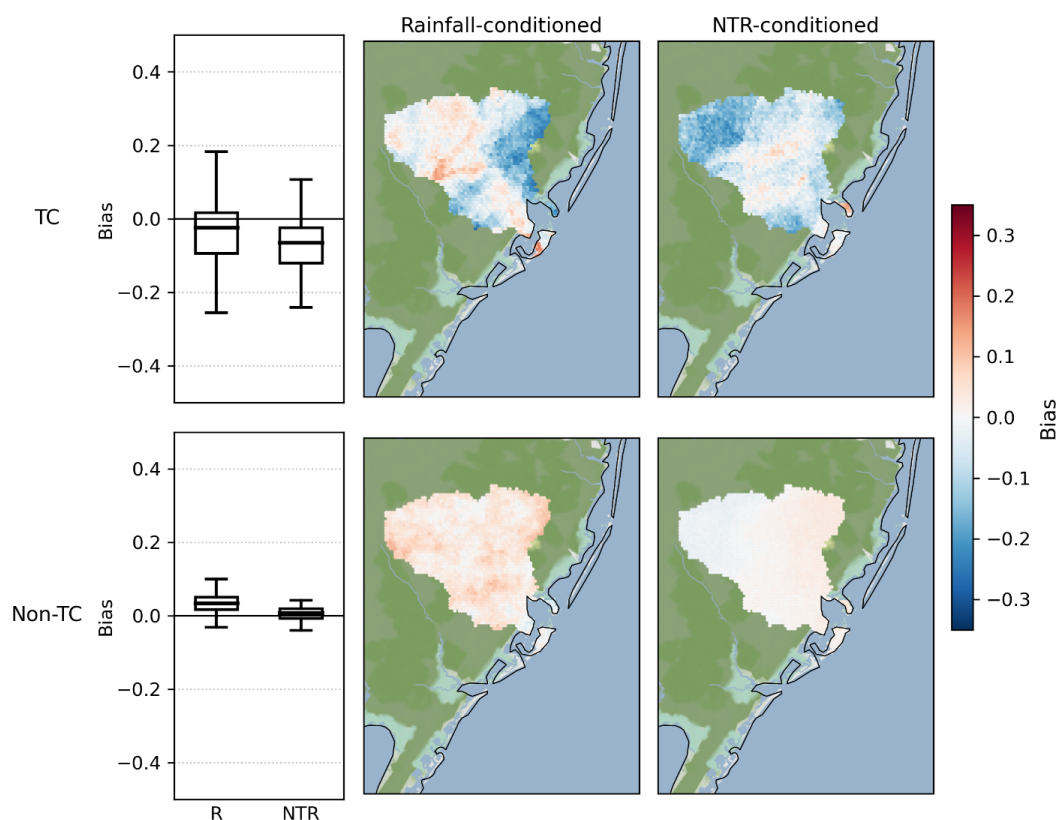


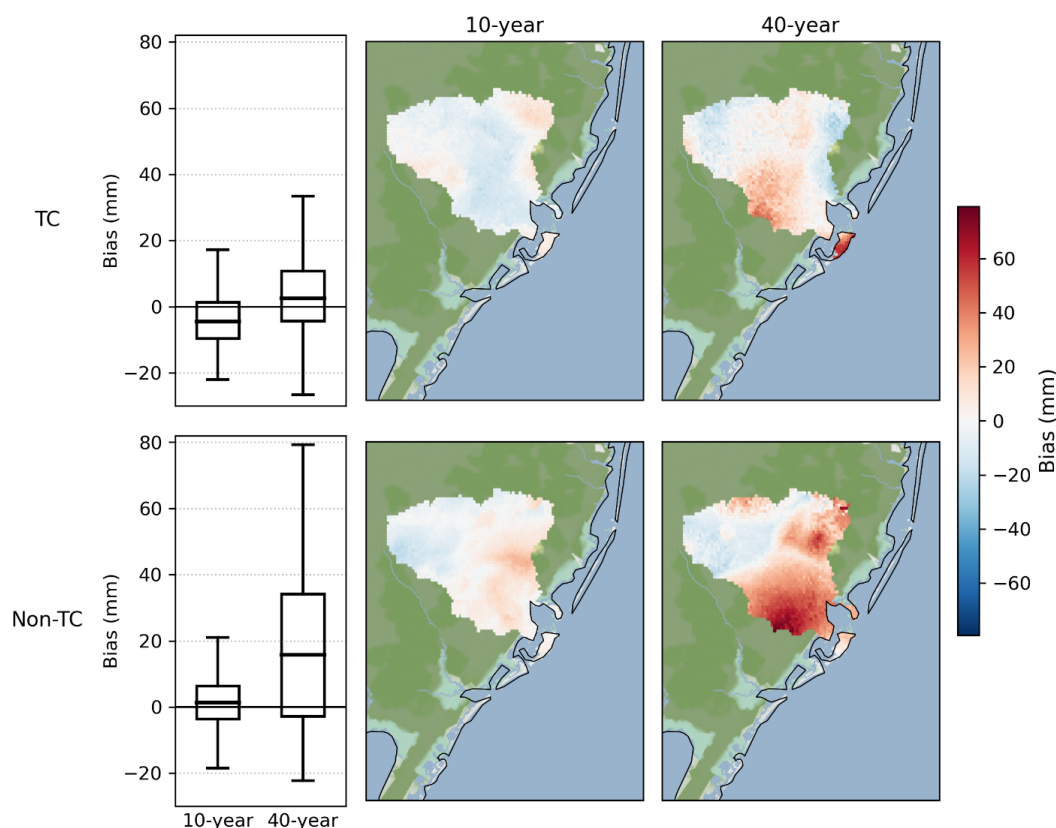
Figure 11: Bias in Kendall's τ , calculated as the correlation between point rainfall and NTR at each grid point minus the correlation between rainfall and NTR in the synthetic events generated for that storm type and conditioning variable. Box plots (left) show the distribution of bias across all AORC grid points in the catchment; maps (right) show the corresponding spatial distribution of bias at each grid point.

4.3.2 Rainfall

Figure 12 compares return level estimates derived from rainfall fields associated with synthetic events generated by conditioning on rainfall against the corresponding empirical estimates at each AORC grid point. Event rainfall totals are estimated at the 10- and 40-year return levels, which can be robustly estimated given the length of the available AROC record. Median bias in event rainfall totals is generally small for TC events. For non-TC events, a small positive median bias is evident at the 10-year return level and increases at the 40-year return level, indicating systematic underestimation at higher return levels. The spread of the bias also increases with return period for both event types, indicating reduced consistency in the ability of the model to generate synthetic events that reproduce the observed marginal behavior of extreme rainfall return levels. While interquartile ranges



are similar across storm types at the 10-year return period, they diverge substantially at the 40-year return period. For TC events, the relatively narrow interquartile range indicates that synthetic estimates exhibit more consistent bias behavior across the catchment than the non-TC events. In contrast, non-TC events exhibit a wider interquartile range indicating greater variability in model performance and a broader distribution. No bias values fall beyond the $1.5 \times$ interquartile ranges whiskers, indicating that no statistical outliers are present according to the boxplot criterion.



605

606 *Figure 12: Bias in simulated rainfall return levels relative to observed values for TC and non-*
607 *TC events, at 10- and 40-year return periods. Box plots (left) show the distribution of bias*
608 *(mm) across all AORC grid points in the catchment; maps (right) show the corresponding*
609 *spatial distribution of bias at each grid point.*

The maps in Figure 12 demonstrate that biases in the return level estimates are spatially structured rather than uniform across the catchment. At the 10-year return level, bias is generally small. For TC events, simulations modestly overestimate return levels in much of the central portion of the catchment and underestimate them towards the east and west



614 catchment perimeter. For non-TC events, modest overestimation is observed in parts of the
615 northeast while underestimation is more common in the west. At the 40-year return level,
616 bias grows, particularly for non-TC events: simulations underestimate totals in the south
617 and west portions of the catchment, while small overestimation occurs in the northeast
618 quadrant. For TC events, the trend seen for the 10-year return level reverses, with
619 simulations underestimating return levels in the central portion of the catchment and more
620 modest overestimation around the catchment perimeter. For the 40-year non-TC events,
621 underestimation can exceed 75 mm in localized areas. Because rainfall return levels vary
622 relatively little across the catchment (Figure S5), this spatial pattern is similarly reflected in
623 the relative error distributions (Figure S6). For the 40-year return level the catchment
624 average relative bias is -1.2% for TC events and 4.9% for non-TC events, the absolute
625 relative bias never exceeds 20%.

626 4.3.3 Water level

627 There is good agreement between observations and simulations for NTR peaks (Figure 13a,
628 b) for both TC and non-TC events. WLs sampled within ± 72 hours of an NTR peak similarly
629 show good agreement between observations and simulations for both TC and non-TC
630 events (Figure 13c, d). For peak total WLs, good-agreement is seen for TC events (Figure
631 13e); however, there is a systematic underestimation of low return period (< 1 -year) non-TC
632 events (Figure 13f).

633 To investigate this discrepancy, we decomposed the highest WLs in the record (assuming 5
634 events per year) into tide and NTR components, identifying which events fall outside the
635 ± 72 -hour window used to construct the NTR-conditioned sample (Figure 14).
636 Approximately 19% of TC-associated high-water-level events and 42% of non-TC high-
637 water-level events do not occur within ± 72 hours of an NTR peak; for the ± 36 -hour window
638 used in storm declustering, the corresponding figures are 19% and 44%. The peak WL
639 events that are not in the NTR samples are caused by large spring tides which require only a
640 smaller surge than moderate tides to produce an extreme. Within the implemented
641 methodology, each tide in a sampled month is equally likely to be sampled, despite the
642 spring tides disproportionally generating the most extreme WLs.

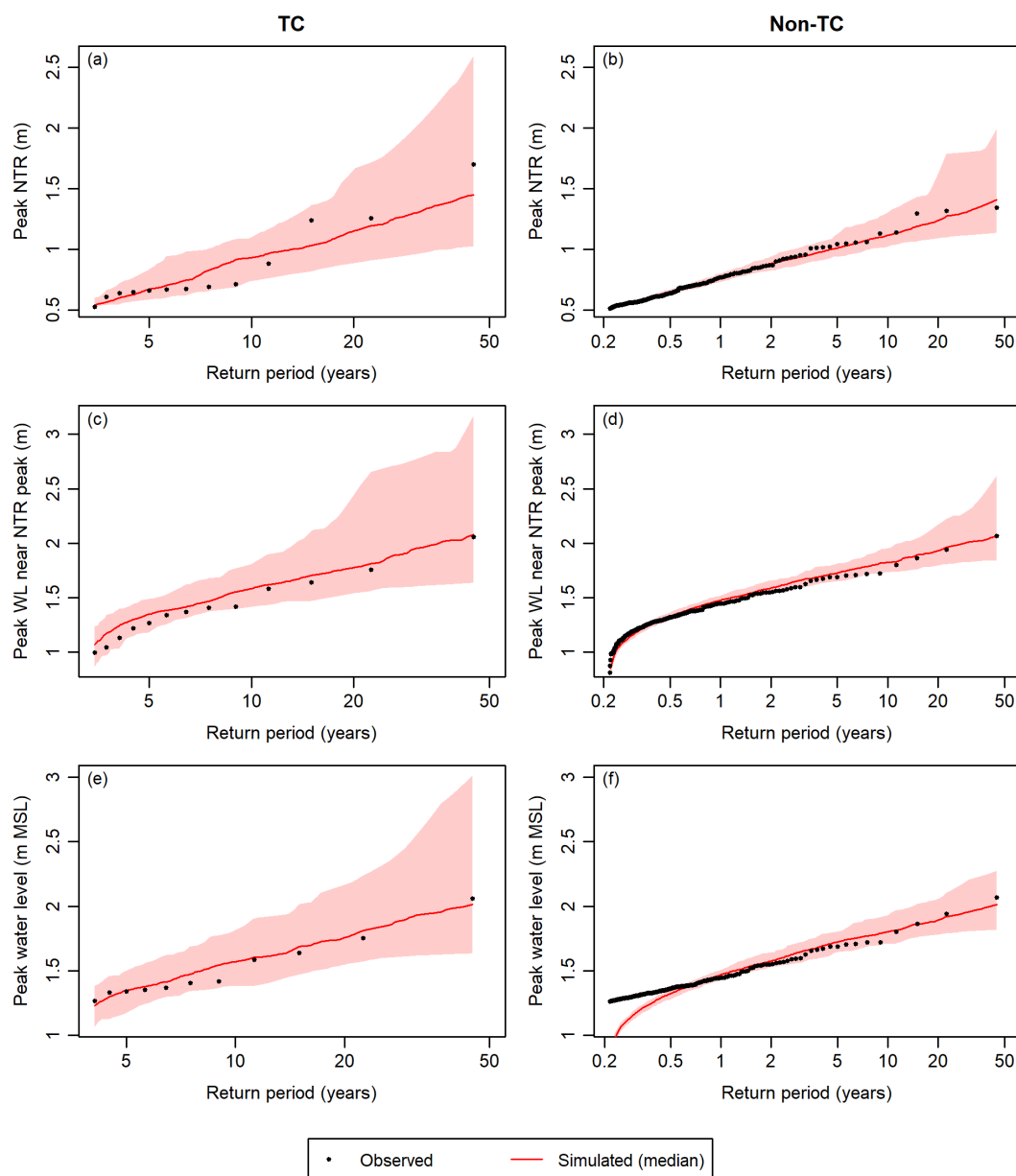
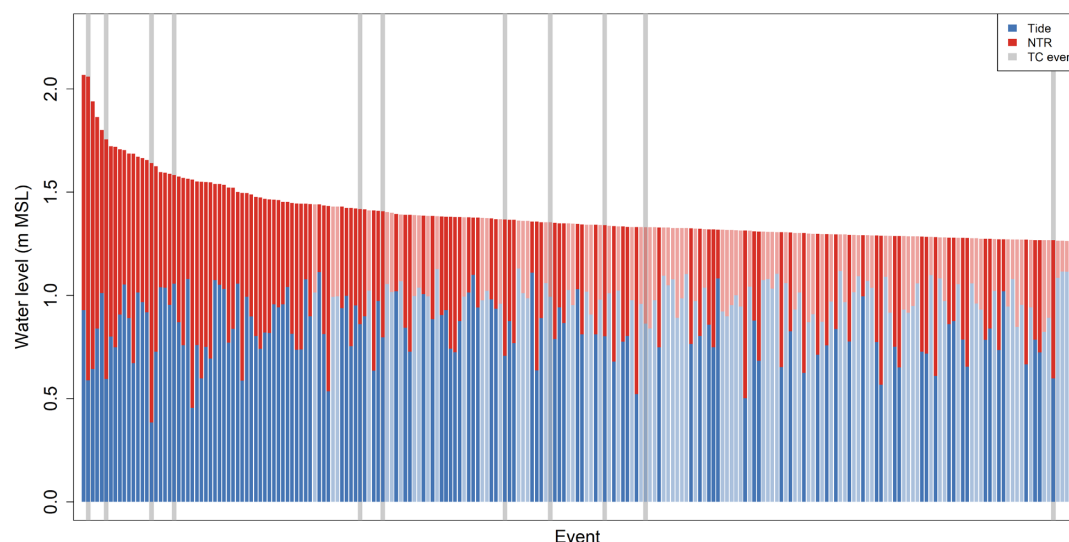


Figure 13: Observed (black dots) and simulated (red line, median; shaded band, 95% CI) return level estimates for TC (left) and non-TC (right) events: NTR peaks (a, b), peak water levels (c, d) and peak water levels within ± 72 hours of an NTR peak (e, f).



648

649 *Figure 14: The highest water level events decomposed into tidal and NTR components,*
650 *ordered by total water level. Shaded grey bars indicate TC events. Transparent bars indicate*
651 *events that do not coincide with an NTR peak within ± 72 hours and are therefore not*
652 *represented in the NTR-conditioned sample.*

653 5. Conclusion

654 In the Mullica River watershed, spatially variable correlation in the conditional samples is
655 stronger for TC than for non-TC or pooled samples, consistent with other recent studies,
656 and is more spatially variable for TC events than for non-TC events. This correlation is
657 relatively insensitive to the choice of CORA centroid, except when located behind a barrier
658 island. Using total water level rather than NTR to represent the coastal forcing may produce
659 weaker correlations than NTR and, in turn, underestimate the severity of the compounding
660 flood hazard. TC events contributed a greater proportion of AEP, on average 73%,
661 compared with non-TC events. Joint return periods themselves are more strongly governed
662 by the shape of the dependence than the strength of correlation: at locations where the
663 copula used to model dependence in the TC sample exhibits upper tail dependence, joint
664 return periods are 15 years (66 vs 51) shorter than at sites that do not.

665 Among the three methods tested for characterizing rainfall, the local composite
666 representation of aggregated rainfall produced estimates of joint return period closest to
667 the mean of the AORC–CORA point-pair estimates. Sensitivity to the buffer radius varies
668 with the spatial variability of the joint return period; nonetheless, a 30 km buffer radius
669 offers a reasonably robust default choice across cases. Basin-average aggregation



670 systematically overestimated the joint return period, and pairing a single rain gauge with
671 the tide gauge record overestimated it to an even greater degree.

672 The framework implemented for generating temporally varying rainfall fields and water level
673 hydrographs systematically generates a synthetic population of events consistent with the
674 observed population in terms of marginal distributions. The correlation structure inherited
675 from using basin-averaged rainfall in the joint probability analysis introduces systematic
676 bias, particularly for TC events. There was some systematic underestimation of event
677 rainfall totals at the 40-year return level for non-TC events, with a discernible geographic
678 pattern; however, this bias was relatively minor, on average approximately 5% of the
679 observed 40-year rainfall estimate. In terms of coastal forcing, peak water levels for short-
680 return-period non-TC events were also underestimated, a limitation attributable to the
681 framework's design, which prioritizes simulating the most extreme NTR events rather than
682 the most extreme water levels directly. This distinction is important for applications
683 focused on non-TC-driven flooding, where NTR extremity and total water level extremity do
684 not necessarily coincide.

685 Future work should focus on refining the synthetic event generation framework to ensure
686 that large spring tides, which can generate large total water levels without correspondingly
687 large NTR, are appropriately captured, and on identifying an alternative to basin-averaged
688 rainfall to reduce correlation bias. One candidate is a storm-centered rainfall
689 representation, in which the spatial averaging window is defined relative to each event's
690 own rainfall centroid rather than a fixed geography, which may better preserve the
691 dependence structure of individual storms. Based on the local composite results, a 30 km
692 radius offers a reasonable initial default for such an approach. Additionally, implementing
693 this approach in other, larger catchments would help generalize the local composite
694 approach to coastal regions with differing storm climates.

695 Code availability

696 Statistical modelling was undertaken using the MultiHazard R package (Jane et al., 2026),
697 which is available on Github (<https://github.com/rjaneUCF/MultiHazard>). The remaining
698 code are available in GitHub at [https://github.com/CoRE-Lab-UCF/MACH-Mullica-River-](https://github.com/CoRE-Lab-UCF/MACH-Mullica-River-Watershed)
699 Watershed (last access: 25 September 2026) (zenodo doi).

700 Data availability

701 The AORC (1 km) version 1.1 data can be obtained from NOAA at
702 <https://registry.opendata.aws/noaa-nws-aorc> (National Oceanic and Atmospheric



703 Administration, National Weather Service, 2026a). The Coastal Ocean Reanalysis dataset
704 can be accessed through NOAA at <https://tidesandcurrents.noaa.gov/cora.html> (National
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709 Supplement.

710 The supplement related to this article was uploaded along with this preprint.

711 Author contributions

712 The study was conceived by TW and RJ. RJ developed the methodology, undertook the
713 analysis, and wrote the first draft of the paper under the guidance of TW, PM, and GV. All
714 authors co-wrote the final paper.

715 Competing interests

716 The contact author has declared that none of the authors has any competing interests.

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