

Topographic Enhancement of Tropical Cyclone Precipitation (TCP) in Eastern Mexico

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Abstract

Tropical Cyclone Precipitation (TCP) is one of the major triggers of flash flooding and landslide in eastern Mexico. The interactions between the topography of the Sierra Madre Occidental and the TCP of storms from the Gulf of Mexico are still poorly understood. We apply multiple statistical techniques to a 99 year daily TCP record and an elevation data with high spatial resolution. Correlation analysis for the whole dataset is dominated by the strong inland-to-ocean gradient of both TCP and topography. Clusters defined by grids' distances to the coast show significant positive correlations between TCP variables and topographic complexity variables (Range, Standard Deviation, and Slope). The quantile analysis demonstrates that the most extreme TCPs are more likely to locate in grids with higher amounts of topographic complexity (Range and Standard Deviation) than the median and the trivial TCPs. The Random Forest (RF) model is an excellent tool to disentangle complex relationships between TCP and topography. The models show that the grid's location and aspect of the slope aspect are the two most important variables that affect the TCP statistics. TCP in eastern Mexico is sensitive within two zones: (1) Low lying coastal regions with lower elevation and less topographic complexity. (2) The mountainous region with higher elevation and topographic complexity, especially with the slope facing the windward direction to the Gulf. All results support that the topography in eastern Mexico has an enhancing effect on the TCP.

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1 **Topographic Enhancement of Tropical Cyclone Precipitation (TCP) in Eastern**
2 **Mexico**

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7

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9 **Key Points:**

- 10 • Topographic enhancement of Tropical Cyclone Precipitation is analyzed based on a 99-
11 year climatology.
- 12 • Clustered locations show strong correlation between topographic complexity and
13 Tropical Cyclone precipitation.
- 14 • Random Forest models can identify the most important topographic variables and their
15 sensitivities in the Tropical Cyclone Precipitation.
16

17 **Abstract**

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19 in eastern Mexico. The interactions between the topography of the Sierra Madre Occidental and
20 the TCP of storms from the Gulf of Mexico are still poorly understood. We apply multiple
21 statistical techniques to a 99 year daily TCP record and an elevation data with high spatial
22 resolution. Correlation analysis for the whole dataset is dominated by the strong inland-to-ocean
23 gradient of both TCP and topography. Clusters defined by grids' distances to the coast show
24 significant positive correlations between TCP variables and topographic complexity variables
25 (Range, Standard Deviation, and Slope). The quantile analysis demonstrates that the most
26 extreme TCPs are more likely to locate in grids with higher amounts of topographic complexity
27 (Range and Standard Deviation) than the median and the trivial TCPs. The Random Forest (RF)
28 model is an excellent tool to disentangle complex relationships between TCP and topography.
29 The models show that the grid's location and aspect of the slope aspect are the two most
30 important variables that affect the TCP statistics. TCP in eastern Mexico is sensitive within two
31 zones: (1) Low lying coastal regions with lower elevation and less topographic complexity. (2)
32 The mountainous region with higher elevation and topographic complexity, especially with the
33 slope facing the windward direction to the Gulf. All results support that the topography in eastern
34 Mexico has an enhancing effect on the TCP.

35 **1 Introduction**

36 Tropical Cyclone Precipitation (TCP) is one of the major triggers of flooding and
37 landside over the land. Various studies (Emanuel, 2017; Knutson et al., 2019; Risser & Wehner,
38 2017; Trenberth et al., 2018) have argued that anthropogenic global warming may increase the
39 chance of extreme TCP events like Hurricane Harvey in 2017. Some have attributed those

40 increases to energy support from the heated oceans (Trenberth et al., 2018). For those Tropical
41 Cyclones (TCs) that made landfall, the surface-atmosphere interaction is quite different from that
42 when they are over the oceans. The TCP processes over land can be quite complex and are
43 influence by many factors, including the moisture and energy that the storm brought from the
44 ocean, the size, translation speed, and intensity of the storm, surface conditions of the land
45 (moisture and energy), land use and cover, interactions with other weather systems, and the
46 topographic features (Arndt et al., 2009; Kimball, 2008; Tuleya, 1994; Zhang et al., 2018).

47 Although the influence of topographic features on different kinds of precipitation systems
48 have been extensively discussed by different pieces of literature, Houze (2010) reviewed
49 orographic effects on all types of precipitation systems and concluded that the mechanism of
50 how TCP is affected by mountains is understudied. Research on this topic can be categorized as
51 theoretical modeling, observational data analysis, and numerical modeling of storm cases. Early
52 numerical simulations indicate that the topographic features not only alter the structure and
53 energy inside of the storm but also affect the basic flow that steers the TCs (Bender et al., 1985,
54 1987). Most current theoretical TCP models (Langousis & Veneziano, 2009; Lu et al., 2018) are
55 based on the calculation of water vapor flux of the low-level convergence of horizontal wind.
56 One very important parameter in those theoretical TCP models is the surface drag coefficient,
57 which describes the surface roughness that influences the low-level convergence and the TCP
58 intensity (Kepert, 2001; Langousis & Veneziano, 2009; Shapiro, 1983). However, the current
59 theoretical parametric TCP model usually does not consider the influence of topography on the
60 surface roughness, which can significantly alter the rainfall pattern.

61 Advances in remote sensing helped the understanding of interactions between TCs and
62 topography in much more details. Radar has been used to observe the wind and rain field in

63 landfalling TCs with strong interactions with the orography. Wind profiler radar shows that the
64 wind has been deflected with a strength that may cause a secondary circulation or block the
65 previous storm circulation system in two typhoons that interacted with the Central Mountain
66 Range (CMR) of the Taiwan Island (Pan et al., 2008). Yu and Cheng (2008) used Doppler radars
67 to observe Orographic enhanced precipitation in Typhoon Xangsane in 2000. They discovered
68 that background storm precipitation and profile of the mountains are both important to the
69 enhancement with larger precipitation observed over the narrower and lower barrier. R. B. Smith
70 et al. (2009) used multiple sources of observation from remote sensing and gauges as well as a
71 linear model to study the enhancement of the precipitation in Hurricane Dean in Dominica. They
72 conclude that the enhanced precipitation is not likely from the new convection triggered by the
73 land but more possible to be due to the seeder-feeder mechanism. This mechanism is happening
74 at a faster speed than the inland convections with falling raindrops of TCs gathering cloud-water
75 sourced from the complex terrains (Bergeron, 1968; Ronald B. Smith, 1979).

76 Various simulations based on dynamic weather models also demonstrated the mechanism
77 of how topography enhances TCP. Wu et al. (2002) used a Mesoscale Model (Penn-State MM5)
78 to simulate rainfall from the Typhoon Herb and discovered that a significant forced lifting of
79 airflow associated with the interaction between the storm's circulation and the CMR of the
80 Taiwan island. Similarly, Lin et al. (2002) proved that the topography is a major forcing of
81 rainfall in the mountains of Taiwan than the original rain bands. Li et al. (2007) demonstrated
82 that the condensational heating is an important process in the southeastern China terrains and
83 drastically increased the precipitation in Typhoon Aere in 2004 by using a Regional Eta-
84 coordinate Model. Severe TC Larry in Australia was also simulated in both no topography and
85 topography scenarios (Ramsay & Leslie, 2008). Localized maximum precipitation exists in

86 elevated regions in the simulation with topography. And precipitation in the simulation without
87 topography is more symmetric. More recently, Huang et al. (2020) used an idealized Weather
88 Research and Forecasting (WRF) model to test the sensitivity of TCP to vortex core size,
89 intensity, and steering wind speed for TCs passing CMR in Taiwan. They concluded that the
90 influence between topography and TCP is a complex interaction of vortex track, landfall
91 position, and the structure of the vortex circulation. The mountain range in Taiwan can deflect or
92 even block the westward-moving TC systems in the Pacific (Lin et al., 2005). Houze (2012)
93 provided a physical mechanism for the lifting effect of tropical cyclones by the orography. While
94 TCs are over the ocean they tend to be moist neutral and the uniform warm ocean boundary
95 makes the flow slightly unstable. The lifting over the mountainside releases this instability and
96 triggers the convective cells on the windward side and then interact with the gravity wave on the
97 lee side of the mountain.

98 Mexico is a country prone to attacks of TCs on both sides of coasts facing the Pacific
99 Ocean and the Gulf of Mexico. TCP can contribute 0 to 40% of the annual precipitation across
100 Mexico, which is estimated from the satellite precipitation product TMPA 3B42 from 1998 to
101 2013 (Agustín Breña-Naranjo et al., 2015). Franco-Díaz et al. (2019) used the same product and
102 estimated that TCs contribute 10 to 30% of total precipitation from July to October and are
103 associated with 40 to 60% of daily extreme rainfall (> 95th percentile) in the coastal area.
104 Extreme TCP events are triggers of severe flooding with massive disruption to the society and
105 intense economic losses (Agustín Breña-Naranjo et al., 2015). One example is the incident of
106 two TCs (Tropical Storm Manuel in the Pacific and Hurricane Ingrid in the Gulf of Mexico)
107 strike Mexico between September 13 and 20 in 2013. Flooding from extreme precipitation has
108 damaged 45,000 homes with \$900 million of insured losses and \$5.7 billion in total economic

109 losses. Mexico is a mountainous country with complex topography. Some existing studies have
110 looked at the influence of orography to precipitation system like North American Monsoon
111 (Vivoni et al., 2007), and general precipitation in Mexico (Mascaro et al., 2014; Pineda-Martinez
112 & Carbajal, 2009). Several theoretical and case studies (Farfán & Cortez, 2005; Farfán &
113 Zehnder, 2001; Zehnder, 1993) have been focused on the orographic effect on TCs on the Pacific
114 coast of Mexico, from the Sierra Madre mountains. There is a lack of study that is focused on
115 how orography influences the precipitation of landfall TCs from the Gulf of Mexico on the
116 eastern coast of Mexico. Our approach is different from most of the previous studies for this
117 topic, which are mostly based on single or several cases of TCs. We will systematically look at
118 this topic by using a 99-year daily gridded record of TCP derived from a large number of rain
119 gauges. It is possibly the longest climatological record we can find for the TCP with acceptable
120 spatial details. Topographic characteristics are calculated for each 0.25° grid box from the
121 Digital Elevation Model (DEM) with a high spatial resolution (1 km). The relationships between
122 TCP and different topographic characteristics will be analyzed. We will not only focus on only
123 the general TCP but also the most extreme TCP and its probability. We will use several
124 statistical techniques to explore the relationships in the data: including traditional techniques of
125 the correlation analysis, k-means clusters, and quantile comparison, as well as the new non-
126 parametric machine learning model Random Forest.

127 The article is organized as follows. Section 2 will introduce the data and methods of
128 analysis with more details. In Section 3, we will present the results with three focuses. The first
129 will be the general statistical analysis including the correlations and quantile comparisons based
130 on the whole dataset. The second will be on the Random Forest modeling of TCP variables based
131 on locational and topographic variables. We will also develop models only using topography

132 variables to explain their influences independently. The third focus will be on the most intense
133 TCP cases in Mexico's 99-year history of climatology. We will compare the topography of the
134 locations for those most extreme cases with that for locations for those median TCPs and see
135 whether there are systematic differences. We will summarize and discuss our findings in Section
136 4.

137 **2 Data and Methods**

138 **2.1. Precipitation**

139 The TCP is extracted from two major pieces of information: daily rain gauges and
140 locations of the TCs. We have already updated the collection of daily rain gauge observations for
141 both the U.S. and Mexico from 1920 to 2018 from two sources in another study (Zhu & Quiring,
142 2017). The Daily Global Historical Climatology Network (GHCN-D) covers both the U.S and
143 Mexico with 35161 gauges. The density of gauges is good for the spatial interpolation to even
144 grids at 0.25° in the U.S, but not dense enough for Mexico. Therefore, we collect a second source
145 of daily gauge precipitation for Mexico from the National Weather Service of Mexico, which
146 contains a total of 2526 gauges. Daily TCP is collected from rain gauges within the daily TC
147 boundary, which is defined by connected moving circles with a radius of 800 km. The center
148 locations of those circles are defined by the storm center locations with a 6-hour interval
149 provided by the International Best Track Archive for Climate Stewardship (IBTrACS). We
150 correct the possible wind introduced under-catch in the rain gauge and optimize the Inverse
151 Distance Weighting (IDW) parameters for the spatial interpolation. Those are finished by
152 comparing our gridded TCP data with the Tropical Rainfall Measuring Mission (TRMM) Multi-
153 satellite Precipitation Analysis (TMPA) product 3B42 (Zhu & Quiring, 2017). The final daily
154 TCP grids with 0.25° spatial resolution are clipped by daily boundaries defined by the connected

155 500 km radius. We use 800 km circles for the step of TCP gauge collection to avoid bias on the
156 edges of 500 km circles when we are doing the IDW spatial interpolation. It yields 4373 TCP
157 days for the whole North American Continent. If we only look at TCP received by Mexico
158 locations, there are 1442 TCP days between 1920 and 2018. The daily TCPs are also aggregated
159 into storm total accumulated TCP, which yield 399 TCP events in the same time span. In the
160 detailed analysis in the Section 3, we also calculate percentile precipitations (e.g., 95 Percentile
161 or P95) and probabilities that exceed certain percentile TCP for different TCP samples for
162 comparison purposes.

163 **2.2. Topography and Location**

164 We obtain the raw elevation data from the Global 30 Arc-Second Elevation (GTOPO30)
165 offered by the Earth Resources Observation and Science (EROS) Center of the United States
166 Geological Survey. The GTOPO30 has a 1 km resolution and was derived from a variety of
167 sources, which was finished in 1996. We first use the shapefile of Mexico's boundary to subset
168 the whole data in ArcGIS by the Environmental Systems Research Institute (ESRI). Then the
169 statistics of elevations are calculated for each precipitation grid box ($0.25^\circ \times 0.25^\circ$) that contains
170 ~ 750 elevation points. We calculate seven variables from the GTOPO30 elevation data to
171 describe the topographic feature of each 0.25° grid. Basic elevation statistics include the mean,
172 maximum, minimum, range, and standard deviations of the elevation sample in each box. All
173 those elevation statistics have the unit of meter. The slope and its' aspect are calculated by the
174 algorithm (Burrough et al., 2015) provided by the ESRI ArcGIS zonal statistics package. The
175 slope describes the ratio between the rise and the run ($\tan \theta$) and the aspect describes a slope's
176 major orientation angle from the normal (north as 0°). We also calculate the sphere distance from

177 each 0.25° grid to the nearest coastline of the Gulf of Mexico since there is normally a decaying
178 of TCP from coast to inland.

179 **2.3. Statistical Methods**

180 To explore the relationships between TCP variables and the topographic and location
181 variables, we apply the pairwise correlations (Spearman's ρ) and report all p-values (<0.01 and
182 <0.05) (Best & Roberts, 1975). Because of the strong coast to inland gradient in the TCP, we
183 used the K-means clustering technique to group all grids into six categories based on their
184 distances to the Gulf coast. Analysis within K-means groups can reveal more distinctive
185 relationships between TCP and topography. We also apply percentile analysis for samples of the
186 TCP data from both the whole dataset and the extreme case studies. For example, we find the
187 locations with TCP that are larger than the 99.9 Percentile ($P_{99.9}$, the most extreme cases of the
188 TC.P) as well as the locations with TCP that are between 49.95 and 50.05 Percentile ($P_{49.95}$ and
189 $P_{50.05}$, the cases with the median amount of TCP). We then compare the two groups of locations'
190 topographic features and find whether there are some significant differences between the sample
191 medians by using the Mann-Whitney U-test (Mann & Whitney, 1947).

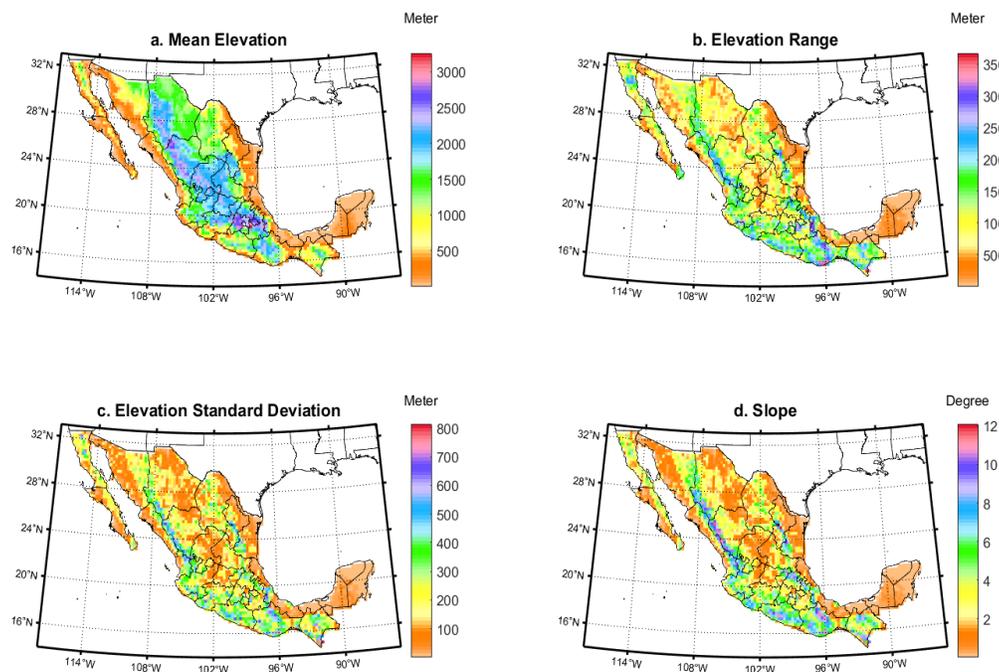
192 Both the correlation and the quantile analysis can provide us some insights into how
193 topography features influenced TCP quantitatively. However, those traditional statistical
194 techniques have the shortcomings of normally focusing on one topographic variable for each
195 comparison and can't deal with the combined effects from multiple topographic variables to
196 TCP. It is also very challenging to explain variables with special distributions like latitude and
197 longitude or slope aspect with a cyclic change from 0 to 360° . The Random Forest (RF) Model is
198 a powerful machine learning technique that is based on ensembles of decision trees (Breiman,
199 2001; Breiman et al., 1984). It has a much less stringent requirement for distribution or type of

200 independent variable. Since the orographic influence on TCP is a complex process with multiple
 201 factors working together, and some of our explanatory variables are not normally distributed, we
 202 believe the RF model is the best candidate to explore the relationships between topographic
 203 variables and TCP extracted from many storms in a long term climatology. The RF models can
 204 also rank the importance of individual variables in the model and reveal relationships and
 205 sensitivities between independent variables and response variables (Greenwell, 2017).

206 **3 Results, or a descriptive heading about the results**

207 **3.1. Spatial Distribution**

208 Seven different topographic characteristics are calculated for each 0.25° grid box from
 209 the 1km resolution DEM. They are Mean, Max, and Minimum elevations, elevation Range and
 210 Standard Deviations, Slope, and Slope Aspect. Figure 1 shows the map for four major
 211 topographic features. We can observe that Mexico has mountainous areas with > 3000 meters

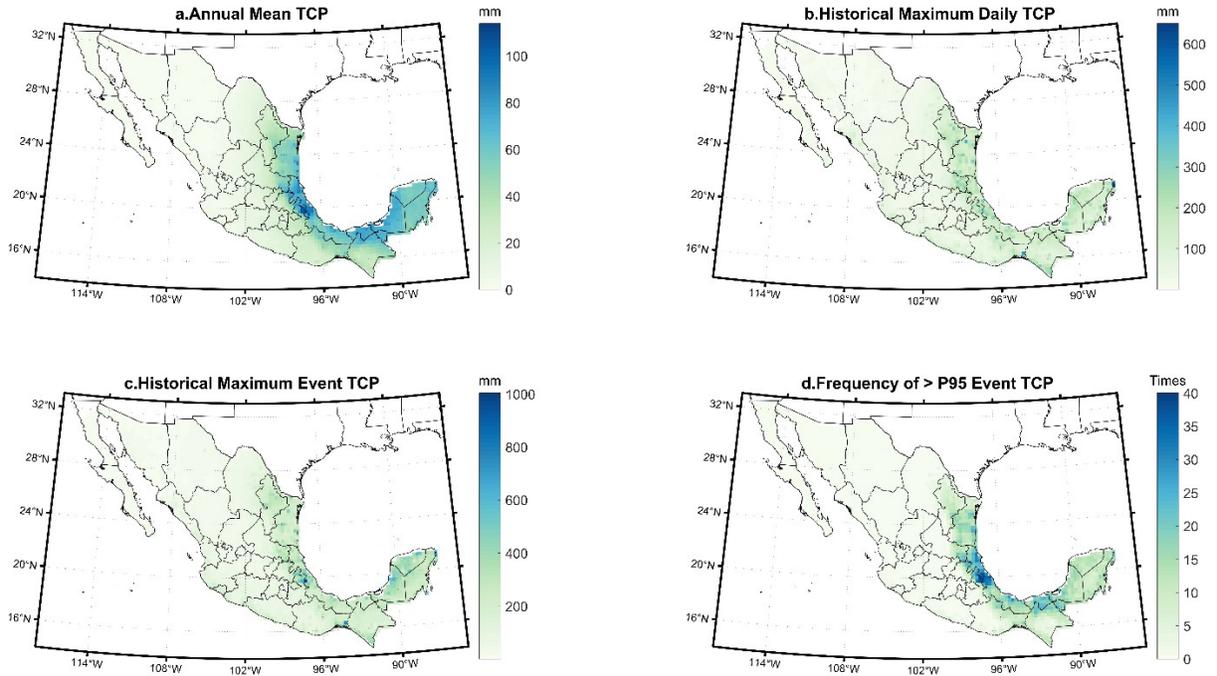


212
 213

Figure 1. Elevation characteristics in Mexico calculated for 0.25° grids.

214 Mean elevation in the central and > 500 meters elevations on the coast (1a). The elevation
215 Range (1b), Standard Deviation (1c), and Slope (1d) are demonstrating more complex spatial
216 variations and they share some similarities. Particularly, on the windward side of the Gulf of
217 Mexico, all three topographic variables are demonstrating abrupt changes from the coastal to
218 more inland areas, which might lead to uplifts or seed-feeder effect of the cloud and strengthen
219 convective precipitation like TCP.

220 TCP can be characterized in many ways. Based on the available spatial and temporal
221 resolution of the data, we define five TCP variables for the analysis. The Annual Mean TCP
222 (AMTCP) is calculated by dividing all aggregated daily TCP by 99 years at each grid. The
223 Maximum Daily TCP (MaxDTCP) is calculated by picking the highest daily TCP from 99 years
224 for each grid. The Maximum Event TCP (MaxETCP) identifies the 99 year maximum of the
225 event total TCP. Then we calculate the 95 percentile (P_{95}) thresholds of both daily and event
226 TCPs for entire Mexico in 99 years. The Probability that TCP exceeds the P_{95} value is calculated
227 as the times the P_{95} value has been exceeded divided by 99 years. We calculate it for all grids for
228 both the daily TCP dataset (DTCPGP95 for Daily TCP Greater than P_{95}) and the event dataset
229 (ETCPGP95 for Event TCP Greater than P_{95}). Figure 2 displays the spatial distributions of
230 AMTCP, MaxDTCP, MaxETCP, and ETCPGP95. The AMTCP is showing a decreasing pattern
231 from the coast to inland, with some high values in the central east Mexico and the neck of the
232 Yucatan Peninsula. The decreasing gradient from the coast to the inland is not as strong as the
233 AMTCP for the MaxDTCP, MaxETCP, and ETCPGP95. Some inland locations are showing the
234 maximum values. There are local maximums clustered in central-east Mexico for the MaxETCP
235 and ETCPGP95.



236

237

Figure 2. Four TCP variables for Mexico based on a 99 year climatology.

238

239 3.2. Correlation and Quantile Analysis

240 The correlations for pairs of topographic variables and TCP variables are shown in Table

241 1. Since the TCP is very sensitive to the distance from the location to the coastal line, we

242 calculated the distance from every grid to the nearest coastal line that is facing the Gulf of

243 Mexico (the “Distance” variable in Table 1). The Distance demonstrates the strongest negative

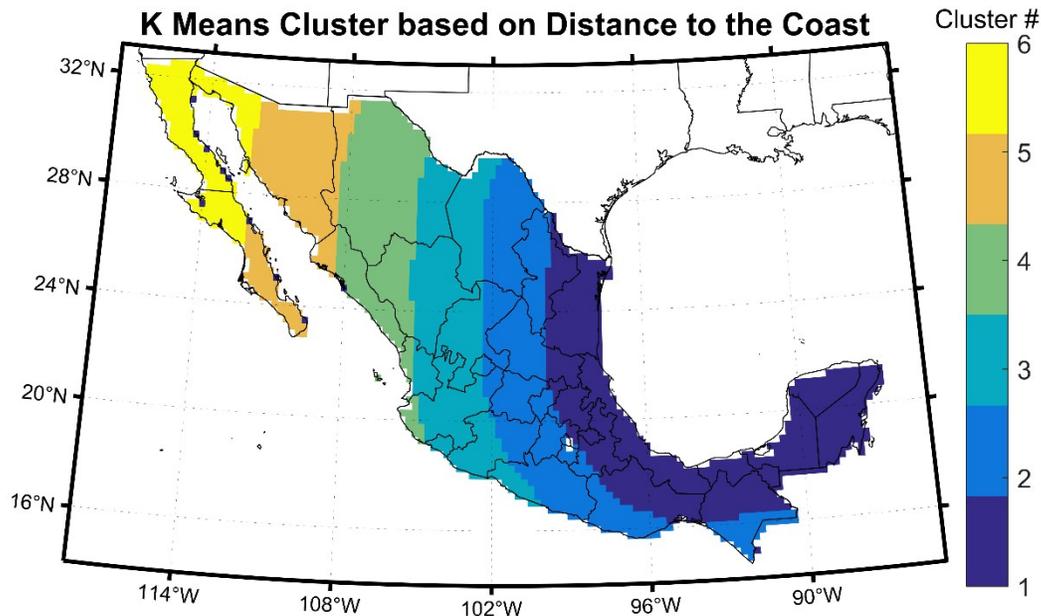
244 **Table 1.** Correlation between TCP variables and Environmental Variables for all Grids.

Variables	Mean	Max	Min	Range	Std	Slope	Aspect	Distance
AMTCP	-0.39**	-0.38**	-0.38**	-0.18**	-0.15**	-0.17**	-0.24**	-0.74**
MaxDTCP	-0.39**	-0.34**	-0.40**	-0.09**	-0.06**	-0.07**	-0.22**	-0.66**
MaxETCP	-0.41**	-0.38**	-0.41**	-0.13**	-0.11**	-0.11**	-0.22**	-0.68**
DTCPGP95	-0.44**	-0.38**	-0.42**	-0.18**	-0.12**	-0.11**	-0.24**	-0.59**
ETCPGP95	-0.44**	-0.41**	-0.43**	-0.16**	-0.14**	-0.18**	-0.23**	-0.59**

245 ** indicates $p < 0.01$, * indicates $p < 0.05$, Distance is for Distance from each grid to the nearest coastal line of Gulf of
 246 Mexico.
 247

248 correlations to all TCP variables indicating the strong gradient of TCP from the coast to inland.
 249 All other topographic variables are showing statistically significant negative correlations with the
 250 TCP variables. We believe that those negative relationships are strongly influenced by the
 251 Distance variable because the elevation generally rises with more complexity as we move from
 252 the coast to the inland in eastern Mexico. We are not able to find any signal for the topographic
 253 enhancement of TCP by simply correlating the two because they are contrarily determined by the
 254 location.

255 To further demonstrate the relationship between topography and the TCP, we must
 256 compare them within a region of grids with a similar distance to the coastal line. Therefore, we
 257 used the Distance as the criteria for a K-Means clustering, which divides the whole set of grids
 258 into six clusters according to each grid's distance to the nearest coastal line (Figure 3). We are



259
 260 **Figure 3.** K-Means Clusters of grids calculated based on their distances to the nearest coastal
 261 line that is facing the Gulf of Mexico.

262 only focusing on Cluster 1 and 2 here since they are where most of TCP from Atlantic TCs are
 263 located in Mexico (Figure 1). The Cluster 1 and Cluster 2 grids are within 93.50 and 340.18 km
 264 to the coastal line, respectively. We calculated the paired correlations between topographic
 265 variables and TCP variables for both clusters. The correlation coefficients in Table 2 and 3 are

266 **Table 2.** Correlation between TCP variables and Elevation variables for grids in cluster #1
 267 (Coastal Grids).

Variables	Mean	Max	Min	Range	Std	Slope	Aspect
AMTCP	-0.30**	-0.14*	-0.32**	0.21**	0.18**	0.23**	0.24**
MaxDTCP	-0.43**	-0.17**	-0.47**	0.30**	0.24**	0.36**	0.21**
MaxETCP	-0.58**	-0.21**	-0.65**	0.44**	0.34**	0.48**	0.25**
DTCPP95	-0.46**	-0.25**	-0.49**	0.25**	0.22**	0.36**	0.18**
ETCPP95	-0.50**	-0.34**	-0.50**	0.18**	0.14*	0.35**	0.18**

268 ** indicates p value<0.01, * indicates p value<0.05

269

270 **Table 3.** Correlation between TCP variables and topographic variables for grids in cluster #2

271 (Inland Grids near Coast).

Variables	Mean	Max	Min	Range	Std	Slope	Aspect
AMTCP	-0.28**	-0.05	-0.35**	0.36**	0.29**	0.36**	0.03
MaxDTCP	-0.48**	-0.24**	-0.50**	0.31**	0.23**	0.39**	-0.02
MaxETCP	-0.50**	-0.22**	-0.54**	0.39**	0.31**	0.42**	-0.03
DTCPP95	-0.49**	-0.23**	-0.51**	0.33**	0.24**	0.37**	0.01
ETCPP95	-0.37**	-0.13*	-0.38**	0.31**	0.21*	0.32**	0.02

272 ** indicates p value<0.01, * indicates p value<0.05

273

274 showing a very different pattern than Table 1. Only the Mean, Max and Min elevations have a
 275 negative correlation with TCP variables. The dominating impacts from the distance to the coast
 276 have been largely removed. The Range, Standard Deviation, and Slope are all demonstrating
 277 statistically significant positive correlations with the TCP variables. It indicates that the TCP is
 278 enhanced at the locations where elevation is changing fast. Particularly, in cluster 2, where the
 279 topography is more complex than cluster 1, the positive correlations are showing more stable
 280 with higher average values than Cluster 1. The MaxETCP has the highest mean correlations with

281 the Range, Standard Deviation of the Elevation and the Slope for both Clusters 1 and 2. It
 282 indicates that regions with abrupt changes in elevation have stronger enhancing effect for TCP.

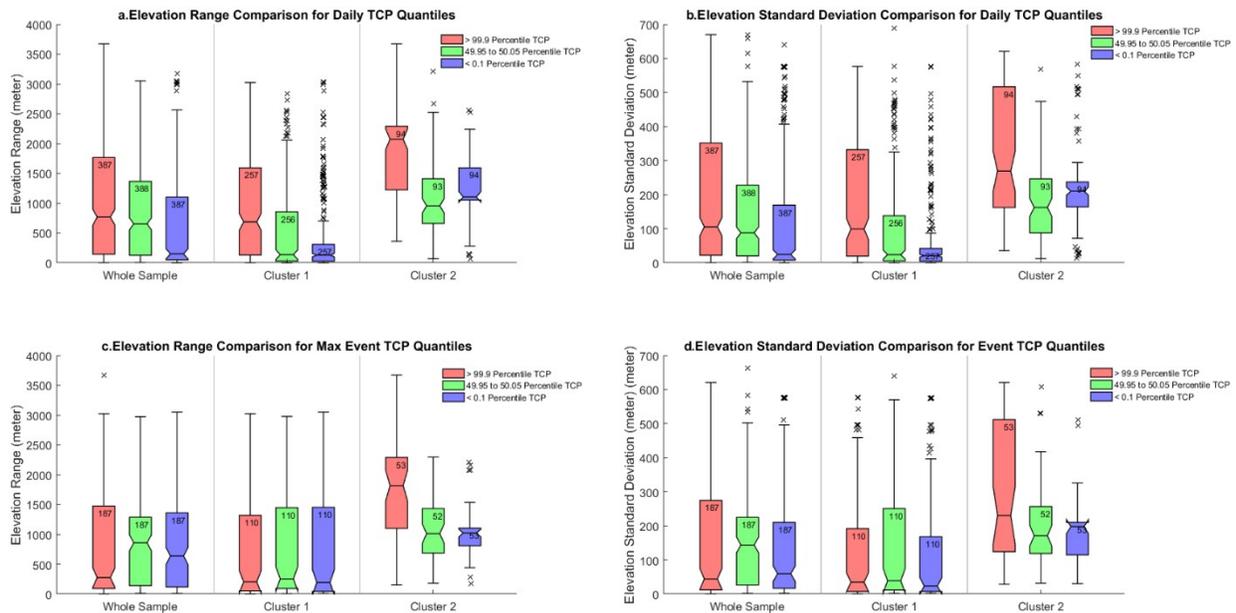
283 The most extreme TCP events are the most important parts of the whole dataset because
 284 they can generate a massive amount of rain-water into mountain ranges and watersheds and
 285 introduce a higher risk of flash flooding and landslide. Here we select the most extreme TCPs
 286 (precipitation $> P_{99.9}$), the median TCPs (precipitation between $P_{49.95}$ and $P_{50.05}$) and trivial TCPs
 287 (precipitation $< P_{0.01}$) and compare the topographic variables for their locations. We want to show
 288 how topographic characteristics differ between the most extreme precipitation locations and the
 289 median and trivial ones. We pick the Elevation Range and Standard Deviation for the
 290 comparison because they both show high positive correlations with TCP variables. The
 291 comparisons are repeated for the whole data, cluster 1, and cluster 2. Large differences between
 292 the most extreme TCP ($P_{99.9}$) and median TCP (P_{50}) can reach 167.62 mm for daily comparison
 293 and 337.05 mm for Event comparison. Box plots (Figure 4a and 4b) and Man-Whitney U-test
 294 (Table 4 and Supplement 1) show that the most extreme daily TCP locations have significantly
 295

296 **Table 4.** Comparison of quantile TCPs and their associated elevation Range

Category	Daily TCP						Event TCP					
	$P_{99.9}$ TCP	Elev Range	P_{50} TCP	Elev Range	$P_{0.1}$ TCP	Elev Range	$P_{99.9}$ TCP	Elev Range	P_{50} TCP	Elev Range	$P_{0.1}$ TCP	Elev Range
Whole	164.15	767	7.99	654 ⁺	0.01	152 ⁺	318.09	276	15.30	861	0.04	638
Cluster 1	176.50	687	8.88	138 ⁺	0.01	130 ⁺	357.48	205	20.43	255	0.03	195
Cluster 2	122.49	2074	7.38	983 ⁺	0.04	1106 ⁺	220.49	1818	13.20	1013 ⁺	0.07	1025 ⁺

297 “+” indicates the current elevation Range sample median is smaller than the elevation Range sample for the $P_{99.9}$ TCP in the same
 298 category, using the Mann-Whitney U-test at the 5% significance level. TCP has a unit of mm and Elevation Range has a unit of
 299 meter.
 300

301 larger elevation range and standard deviation than the median TCP and trivial TCP locations. It
 302 indicates that the most extreme daily TCPs tend to happen more frequently at locations with
 303 more complex topography. Those patterns are weaker for the event TCP (Figure 4c and 4d). No



304

305 **Figure 4.** Comparison for Elevation Range and Standard Deviation between the most extreme

306 TCPs ($>P_{99.9}$), median TCPs (between $P_{49.95}$ and $P_{50.05}$), and trivial TCPs ($<P_{0.1}$)

307 distinct difference in elevation ranges and standard deviations are observed for the comparison

308 for the whole sample and Cluster 1 grids. Only Cluster 2 demonstrates a significantly higher

309 elevation range and standard deviation for the extreme TCP locations than those for other TCP

310 locations (Table 4 and Supplement 1). Cluster 2 grids are located more inland than Cluster 1

311 grids with a more complex topography and less probability of extreme TCPs. But those extreme

312 TCP cases are more sensitive to the topography changes.

313 3.3. Random Forest Modeling

314 RF models are developed for all five TCP variables using locations and topographic

315 information as independent variables to understand they influence TCP collectively and their

316 importance. We develop two models for each TCP variable, the Total models have the complete

317 10 independent variables including both location and topographic characteristics; the

318 Topographic (Topo) models only contain 7 topographic features. We want to understand the
 319 most important variables for TCP globally as well as the most important topographic variables.

320 Table 5 is showing statistics for the 3 Total Models and 3 Topo Models we have chosen
 321 to represent all 10 models. Statistics for the other 2 total and 2 topo models are shown in
 322 Supplement 2. All Total Models demonstrate a very high amount of explained variance (>85%),
 323

324 **Table 5.** Information about Random Forest Models developed for three TCP variables: AMTCP,
 325 MAXETCP and ETCPGP95. The importance is calculated as the percentage of increased MSE
 326 (%IncMSE) if the variable is removed

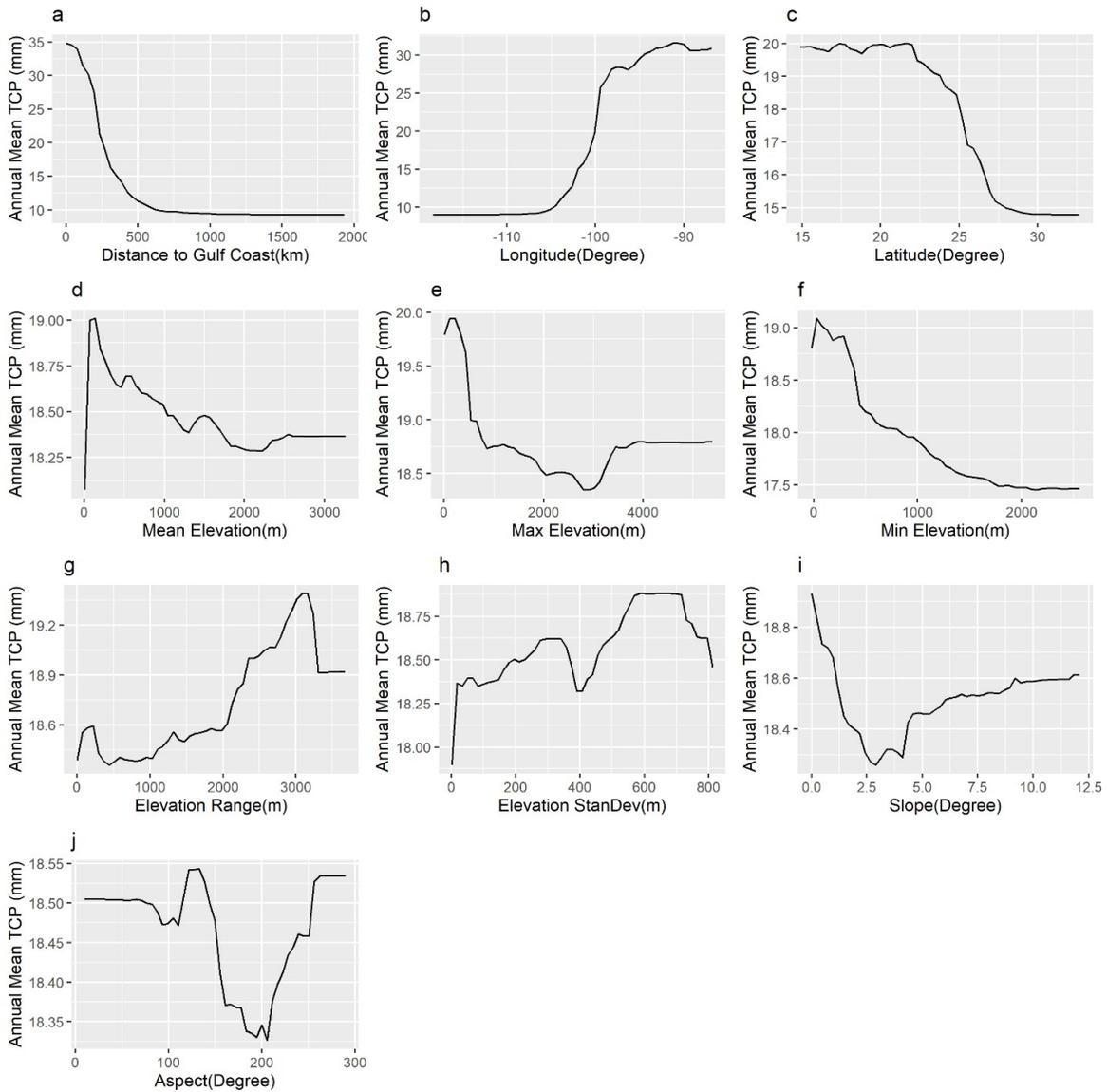
		AMTCP Total Model		AMTCP Topo Model		MaxETCP Total Model		MaxETCP Topo Model		ETCPGP95 Total Model		ETCPGP95 Topo Model	
Variance Explained		96.66%		59.18%		86.09%		51.25%		90.91%		54.15%	
Importance Rank	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE	
1	Dist	38.99	Asp	69.57	Lat	42.55	Asp	49.59	Dist	41.31	Asp	64.64	
2	Lon	36.69	Slope	56.39	Lon	37.56	Range	32.68	Lat	38.96	Slope	41.19	
3	Lat	30.00	Range	37.90	Dist	29.15	Std	32.22	Lon	27.82	Range	30.30	
4	Min	19.18	Max	34.81	Range	20.33	Slope	29.79	Min	20.95	Std	28.18	
5	Slope	16.58	Std	32.82	Slope	16.65	Max	25.80	Max	18.04	Mean	22.84	
6	Max	15.05	Min	29.27	Std	16.64	Mean	16.60	Mean	17.18	Max	21.98	
7	Mean	14.07	Mean	27.38	Max	15.7	Min	11.83	Std	16.85	Min	21.89	
8	Asp	11.71			Min	14.91			Asp	16.18			
9	Range	11.28			Asp	14.26			Slope	15.76			
10	Std	10.80			Mean	11.9			Range	15.32			

327
 328

329 which is caused by the more complete information in their independent variables. The Distance,
 330 Longitudes, and Latitudes are the three most important variables in all Total Models. Longitudes
 331 and Latitudes control the relative position between each grid to storm tracks. The proximity to
 332 the storm will determine how much precipitation each grid will receive. The distance has a high
 333 importance rank in Total models. We have already shown a very strong negative relationship
 334 between the Distance and TCP in the previous section. The minimum elevation has the highest
 335 importance rank among all topographic variables. Variables that describe the topographic

336 complexity, such as the elevation Range and Slope, are showing high importance rank in some
 337 Total models (MaxETCP).

338 The partial dependence plot describes the marginal effect (sensitivity) from individual
 339 independent variables to the dependent variable (Breiman, 2001) in RF models. It shows that the
 340 sensitivity of AMTCP drops as the Distance increases or the longitude becomes more toward the
 341 west (Figure 5a and b). It generally matches the spatial distributions of the TCP. The lower



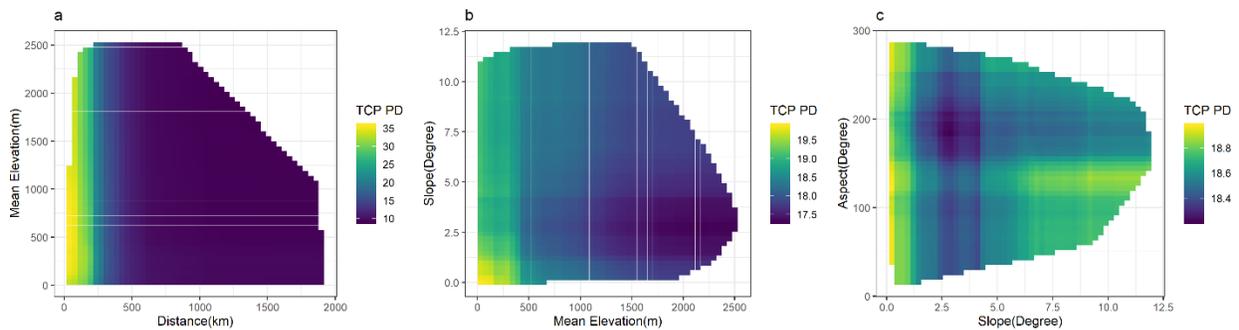
342

343 **Figure 5.** Partial Dependence Plot for variables in the total RF model for the Annual Mean TCP.

344 latitude observes higher sensitivity of TCP values (Figure 5c), which is due to that lower latitude
345 normally observes higher frequency of TC tracks. There is a general decreasing TCP sensitivity
346 when elevations are increasing (Figure 5d, e, f). However, unlike the monotonous change in plots
347 for location variables, the Mean and Max elevation show more non-linear TCP sensitivity
348 changes. Particularly, we can observe suddenly rise of TCP sensitivity when the mean elevation
349 is at 500 meters and 1500 meters (Figure 5g). There is also an elevated TCP sensitivity plateau
350 when the maximum elevation is greater than 3000 meters. This is an interesting pattern and
351 might be related to the topographic enhancement of TCP by mountains. Figure 6 demonstrates
352 the TCP sensitivity responses to selected couples of independent variables for the Total model of
353 AMTCP. There is a strong influence of TCP sensitivity from the Distance. The highest
354 sensitivity of TCP is located within 200 km of the coastal line and between 50 to 1200 m in
355 mean elevation (6a).

356 Higher values of elevation Range and Standard Deviation generally lead to higher TCP
357 sensitivity (Figure 5g and 5h). The TCP becomes more sensitive when the elevation Range is
358 larger than 2000 m and the elevation Standard Deviation is between 400 and 800 meters. The
359 TCP sensitivity is high at a very shallow Slope, drops sharply and reach to the lowest at slope
360 value of 2.5° , and increases with steeper slope values (Figure 5i). Coastal areas have very
361 shallow steep slopes but high spatial variabilities in TCP, the cloud lifting effect increases
362 gradually when it moves to more inland with steeper slopes. This pattern is also shown in Figure
363 6b, where the highest TCP sensitivity is demonstrated in a region with very low mean elevation
364 and shallow slope. But the TCP sensitivity increases again when the Slope becomes steeper ($>$
365 5°). Finally, the slope Aspect is demonstrating an interesting pattern for the TCP sensitivity in
366 Figure 5j. When the slope is facing the Gulf of Mexico (with aspect between 0 to 180), there is a

367 much higher TCP sensitivity. Particularly, the TCP sensitivity peaks at the aspect angle of 120°.
 368 This is an angle that is vertically intersected with the mean translation direction of landfalling
 369 Atlantic TCs if we consider the β effect of the TC motion in the northern hemisphere (Chan,
 370 2005). But when the slope is facing the lee side (with aspect between 180° to 360°), particularly
 371 between 150° to 250°, the TCP is much less sensitive to the slope with the minimum reached
 372 when the Aspect is $\sim 200^\circ$. When the Aspect is greater than 250°, the sensitivity increases again,
 373 which might be caused by those occasionally stalled TCs moving from the north to south. This
 374 pattern can also be observed in Figure 6c. Particularly, we can observe a stripe of enhanced TCP
 375 sensitivity when the Aspect is between 110° to 150°, it is even strengthened when the Slope is
 376 steeper ($> 5^\circ$). Figure 6c also shows the dipole of high TCP sensitivity for both shallow and steep
 377 regions of the Slope ($< 1^\circ$ or $> 5^\circ$).

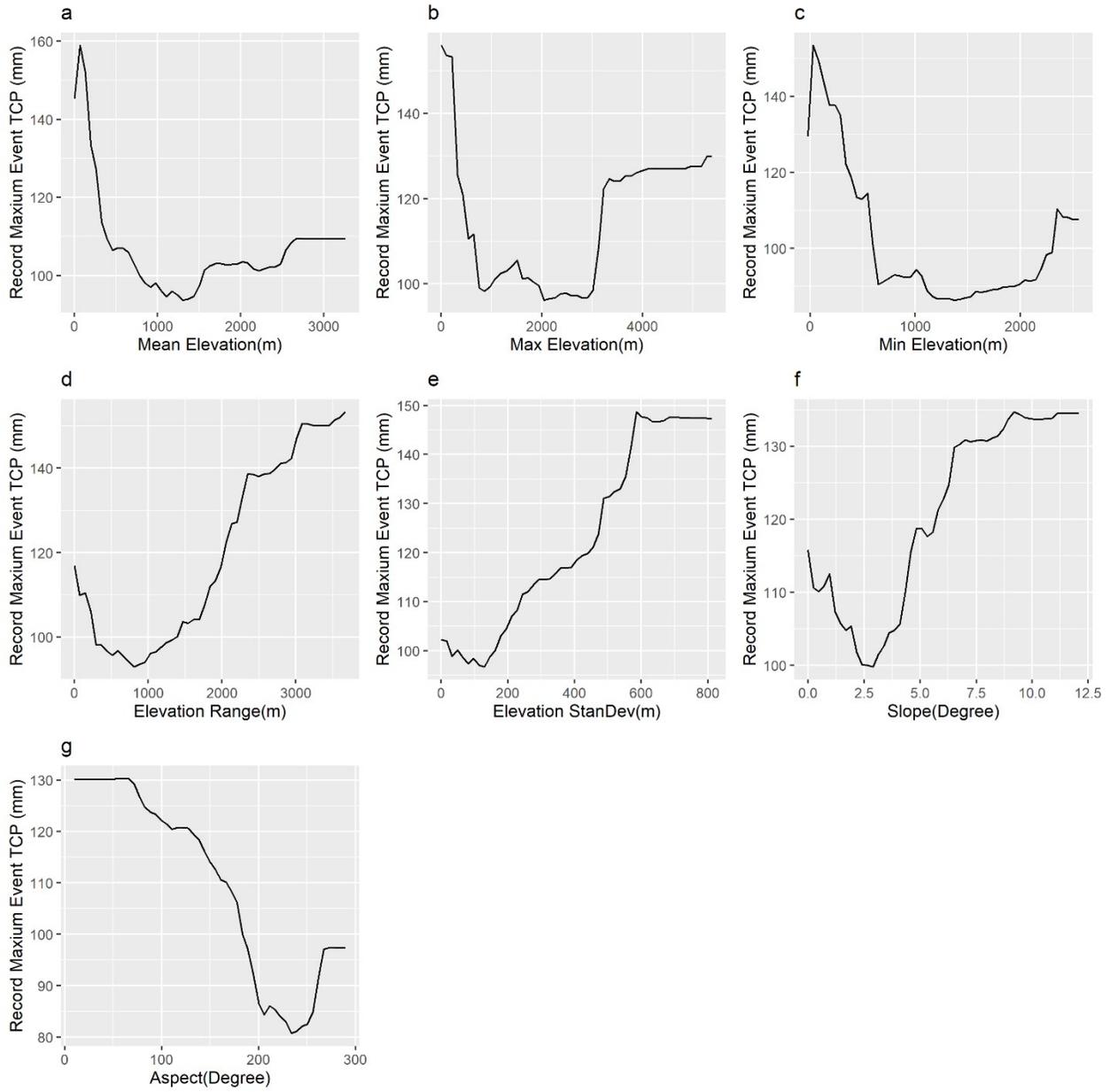


378

379 **Figure 6.** Selected Partial Dependence (PD) Plots for coupled variables in the Total RF model
 380 for the Annual Mean TCP.

381 The Topo models also show high explained variance ($>50\%$ on average), there are some
 382 changes in the variable importance rankings (Table 5, Supplement 2). The Aspect ranks as the
 383 most important variable in all the topographic models. The topography complexity variables
 384 (Slope, Standard Deviation, and Range) rank higher than other topographic variables including
 385 the Mean, Max and Minimum. The patterns of TCP marginal changes in partial dependence plots

386 are similar to those for total models and show the same directions of changes (Figure 7,
 387 Supplement 3, 5, 8, 10). Here we are demonstrating the plot for the MaxETCP as an example.



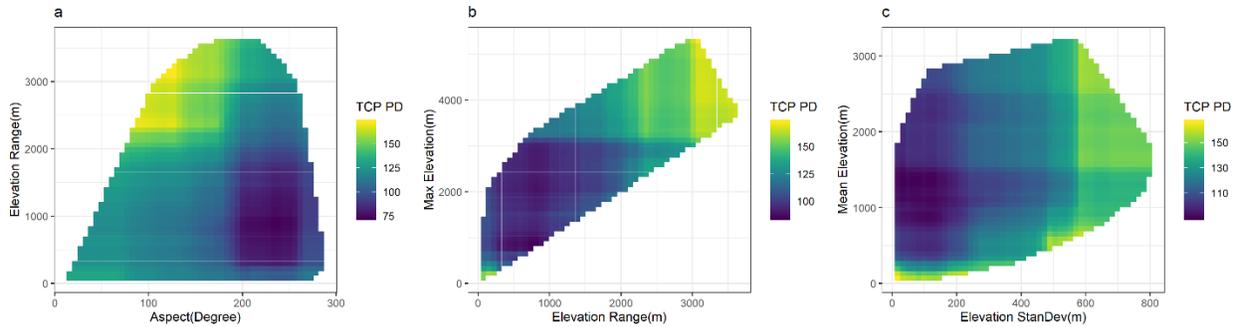
388

390 **Figure 7.** Partial Importance Plot for variables in the topographic RF model for the Maximum
 391 Event TCP

392

393 Lower Mean, Max, and Min elevation generally correspond to higher TCP sensitivity and the
394 sensitivity decreases with elevation increases in smaller ranges. TCP sensitivities start to increase
395 at higher elevations and then keep stable. For example, there are sudden rises of TCP sensitivity
396 at ~1300 meters and 2400 meters for the mean elevation (Figure 7a) and at 2800 m for the
397 maximum elevation (Figure 7b). The MaxETCP has similar TCP sensitivity responses to the
398 elevation Range and Standard Deviation (Figure 7d and e) with those in the AMTCP Total
399 Model. After a small dip in the lower value regions, the TCP sensitivity starts to rise
400 monotonously from a ~ 1000 meters Range and a 170 meters Standard Deviation. The “U” shape
401 of the TCP sensitivity curve for the Slope (Figure 7f) is also showing a similar pattern with the
402 Total model of ANTCP (Figure 5i). However, steeper slope ends are observing higher TCP
403 sensitivity than the shallower slopes. And higher TCP sensitivity at steeper Slope appears in the
404 partial dependence plots for most of the other Total and Topo TCP models, except the Total
405 model for the ANTCP (Figure 5i). Based on both the importance of the Slope variable in those
406 models and these recurring patterns, we conclude that steeper Slopes generally lead to higher
407 chances of modification of TCP in Mexico. The partial importance of the Aspect (Figure 7g)
408 follows the same pattern with the Total model but with more distinct drops of TCP sensitivity
409 when the Slope starts to turn to the lee direction to the Gulf of Mexico (Aspect > 180°). The
410 coupled variable TCP partial dependence plots (Figure 8) are showing even more clear-cut
411 patterns than those for the total models. Figure 8a has the highest TCP sensitivity for that the
412 Aspect is between 90° to 180° and the Range is greater than 2000 m. The high TCP sensitivity
413 zone for the high Range appears again in Figure 8b, together with the Max elevation is greater
414 than 2000 m. Except for a high zone under ~ 300 m mean elevation, the TCP sensitivity
415 generally increases with higher elevation standard deviation (Figure 8c). The highest TCP

416 sensitivity is reached when the standard deviation is greater than 700 m and the mean elevation is
 417 greater than 1500 m.



418

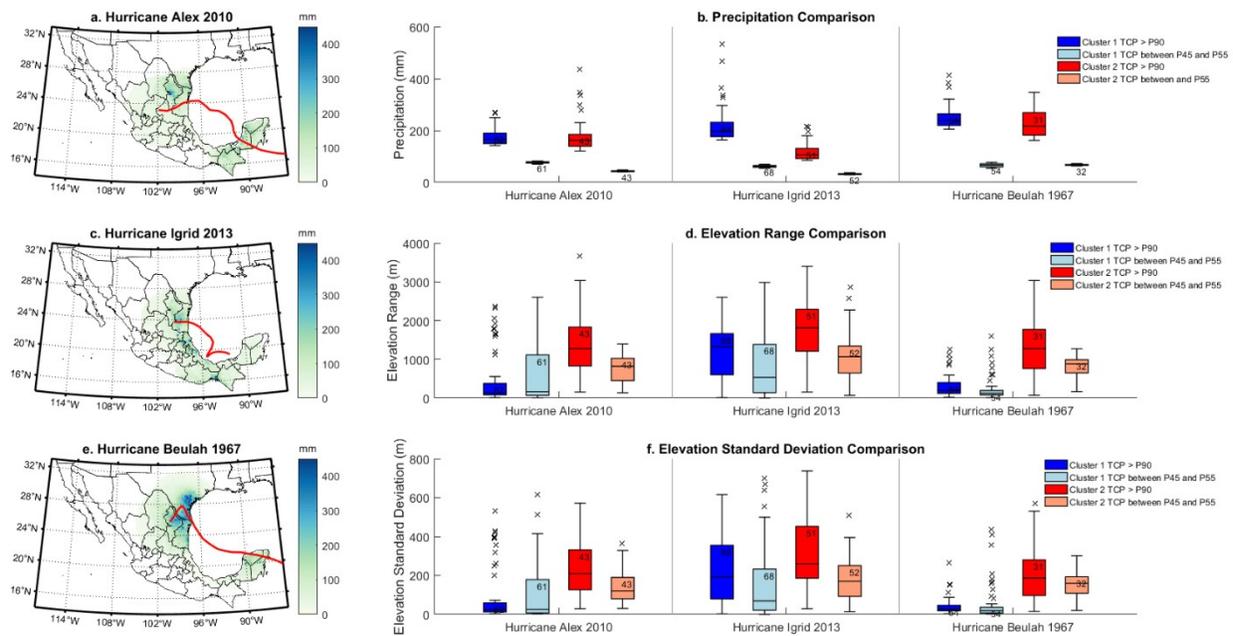
419 **Figure 8.** Selected Partial Dependence (PD) Plots for coupled variables in the topographic RF
 420 model for the Maximum Event TCP.

421 We use the partial dependence plots for the Total model of ANTCP and the Topographic
 422 model of MaxETCP as two examples. Partial dependence plots for all other models are displayed
 423 from supplement 3 to 10. Generally, the sensitivities of TCP variables behave in a consistent way
 424 to the changes of independent variables across different models. That gives us confidence that
 425 the RF can accurately capture the complex relationships between environmental variables
 426 (particularly topographic ones) and TCP characteristics based on the long climatology. They
 427 provide us a quantitative evaluation of which variable is most important to variations of the TCP
 428 and how the TCP is sensitive to different ranges of the topographic variables. That is very
 429 helpful for us to identify thresholds of changes when we study details about how topography
 430 influences the TCP from other methods in the future.

431 **d. Extreme Cases**

432 The final section of the data analysis is focused on the case study of three storms that
 433 produced the most intense TCP in the 99 years of Mexico climatology. They are Hurricane Alex
 434 in 2010, Hurricane Igrid in 2013 and Major Hurricane Beulah in 1967. Alex and Igrid are
 435 originated from tropical disturbances from the Gulf of Mexico or the Caribbean Sea and

436 experience rapid intensification in a short translation distance before they made the landfall.
 437 Beulah is originated from the Atlantic Ocean and gathered a large amount of energy through its
 438 long translation distance before it became the major hurricane that made landfall first in Texas.
 439 We can observe large areas of extreme TCP for Hurricane Beulah for both Southern Texas and
 440 northeastern Mexico (Here we display all TCP without country border in the maps but calculate
 441 the statistics only for grids in Mexico). All three storms have produced > 400 mm precipitation at
 442 some locations (Figure 9 a, c, and e) and those extreme precipitations caused massive flooding
 443 and landslides with large losses of lives and infrastructures.



444
 445 **Figure 9.** The total precipitation for the three most intense TCP events for Mexico and
 446 comparison of topographic variables between locations with extreme TCP (>P₉₀) and median
 447 TCP (between P₄₅ and P₅₅)

448 Here we process the topography comparison for the quantile event TCP again for each
 449 storm. We choose those greater than 90 percentile (P₉₀) TCP as the extreme values and those
 450 between 45 (P₄₅) and 55 (P₅₅) percentile TCP as the median values because the sample size of

451 grids for a single storm is much smaller than the whole dataset. Figure 9b, d, and f compare the
452 precipitation, elevation Range, and Standard Deviation for grid locations grouped by quantile
453 TCPs for Cluster 1 and 2 separately. Table 6 and Supplement 11 are statistics of their median
454 with the Mann-Whitney U-test. The P_{90} TCPs are much larger than the median TCP in most
455 cases with at least 150 mm difference (Figure 9b and Table 6). Those big differences in
456 precipitation are very closely related to differences in topographic complexity. In Figure 9d,
457 most extreme TCP associated elevation Range samples have larger medians than the samples
458 associated with median precipitation for all three storms. Particularly, those differences are even
459 larger for the comparison for Cluster 2 (red and orange boxes). The same information is also
460 demonstrated in Table 6, where most of the Mann-Whitney U-test for the sample median
461 comparisons are statistically significant (with “+” sign in table 6). One exception is in the
462 comparison for Cluster 1 in Hurricane Alex. Hurricane Alex has a large area of extreme
463 precipitation over the Yucatan Peninsular for its first landfall and Yucatan is mostly covered by
464 flatter terrains. The comparison for the elevation Standard Deviation is demonstrating the similar
465 patterns (Figure 9f) as the elevation range. Four out of six comparisons show that the extreme
466 TCP associated Elevation Standard Deviations is significantly larger than those with the median
467 TCP (Supplement 11).

468 The extreme case study shows us that even there are lots of uncertainty and variability in
469 the individual storm, the most extreme storms still demonstrate a very strong topographic
470 enhancing effect for the TCP. This effect is existing in both coastal areas (Cluster 1 grids) the
471 inland areas that are close to the coast (Cluster 2 grids). Cluster 2 grids have more distinctive
472 patterns for this topographic enhancing effect. Directly from the precipitation maps in Figure 9,

473 we can observe that in all three storms, clusters of maxima of precipitation are located in some
474 inland areas in addition to locations on the coast where storms just made landfall.

475 **4 Discussions and Conclusions.**

476 The interactions between TCs and the topographic features over the land is a challenging
477 topic because they are affected by so many factors together, and it becomes even more complex
478 if we are focused on precipitation generated by TCs. There are many variations in storms,
479 include their energy and moisture budget, storm size, tracks, etc. All those storm elements will
480 have impacts on the locations and intensities of TCP. When TCs are translating from the ocean
481 to the land, the boundary layer condition will significantly be changed and influence the behavior
482 of TCs. The increase of surface roughness is believed to be an important contributor to the
483 enhanced advection in the TC system, which introduces more TCP (Arndt et al., 2009; Kimball,
484 2008; Tuleya, 1994; Zhang et al., 2018). The complex terrain is one of the most important
485 surface roughness factor that contributes to enhanced precipitation from the clouds, including
486 those from the TCs (Houze, 2010, 2012).

487 Mexico is a country prone to strikes of TCs and its complex terrain has already triggered
488 intense precipitation events that led to massive flooding events. However, how the terrains are
489 interacting with the TC systems and influence their precipitation patterns has not been studied
490 thoroughly, particularly for the windward side of the Sierra Madre Oriental. Our analysis is
491 based on the longest available record of gauge observed TCP for Mexico since 1920 and we use
492 both traditional and modern statistical data-mining techniques to discover relationships between
493 the TCP and the topographic features. Our results demonstrate that locations (latitudes and
494 distance to the coast) are the most dominant controller of the TCP variations in Mexico. The
495 direct correlation between topography features and TCP variables does not reveal much

496 information about the orographic enhancement because there is also a strong relationship
497 between topography variables and their locations. Negative correlations are dominating between
498 TCP and topography variables for the whole dataset. The spatial comparison between
499 topographic variables and TCP shows that there are isolated and clustered inland locations with
500 enhanced TCP statistics. A lot of those locations are also demonstrating a high amount of
501 elevation variabilities.

502 To quantify the relationship between TCP and topography, we divided the whole grids set
503 into six subgroups (clusters) using the K-Means clustering based on each grid's distance to the
504 nearest coastal line. The correlation analysis demonstrates a significant change compared with
505 the result of the whole data. Elevation variance variables (Range, Standard Deviation, and Slope)
506 are showing statistically significant positive relationships with TCP variables, while other
507 elevation variables (Mean, Max, and Min) are still demonstrating negative relationships. Cluster
508 2 (inland grids that nearest to the coast) is showing stronger average positive correlations
509 between elevation variance variables and the TCPs than the Cluster 1 (coast). If we look at the
510 most extreme cases of TCP, they tend to happen at locations with a higher amount of elevation
511 variance. The most extreme TCP locations have a much higher elevation Range and Standard
512 Deviation than the median and trivial TCP locations. The comparisons for the daily TCP are all
513 statistically significant. On the event scale, only the Cluster 2 comparisons are statistically
514 significant. This result agrees with many previous theoretical and modeling studies based on TC
515 cases. R. B. Smith et al. (2009) found that the Hurricane Dean had the orographic precipitation
516 enhancement within 92 km of Dominica, they are more likely from the seeder-feeder accretion
517 mechanism in a nearly stationary spiral rainband. The uplifting phenomenon is more common
518 when the TCs meet larger mountain ranges. In a simulation study for an Australia TC (Ramsay

519 & Leslie, 2008), the TCP reduced immediately after landfall but was enhanced when the storm
520 met the steep coastal orography and the wind field has been substantially modified. The
521 mountain lifting of TCs was extensively studied for the CMR of Taiwan Island. TCs are
522 modified in their 3-D flows, precipitation, or even tracks while they are passing the CMR (Chang
523 et al., 2013; Lin et al., 2002; Wu et al., 2002; Yu & Cheng, 2008). The deflection of storm tracks
524 by mountains has also been investigated in Taiwan island (Lin et al., 2005) and the Sierra Madre
525 Occidental of western Mexico (Farfán & Zehnder, 2001; Zehnder, 1993). The result from our
526 analysis shows that the complex topography has a strong enhancing effect to the TCP in this
527 area. Based on the size of the Sierra Madre Oriental and the statistical analysis, we believe this
528 enhancement is more likely to be the cloud uplifting effect. But it will need more observations
529 and numerical simulations to prove it.

530 The RF model has been proved to be an effective tool to explore the relationships
531 between environment variables (both location and topography) and the TCP. The RF model
532 explains more variances than the traditional statistical models. Multivariate regression models
533 can obtain an explained variance between 31% to 75% of the annual precipitation in different
534 mountainous areas around the world (Basist et al., 1994). Our RF models are showing 47% to
535 96% variances of different TCP characteristics based on the fact that the TCP has more
536 uncertainties than the annual mean precipitation. The correlation analysis or multiple regression
537 models can only show influence from one or several environment variables to the TCP because
538 of the nature of the statistical methods and the distribution of the variables. The RF model excels
539 in including different explanatory variables with different kinds of distribution and revealing
540 their relationships with the response variable collectively. Our result demonstrates that the
541 location variables (particular the distance to the coast) are the most important factor in

542 influencing the TCP in all total models and the aspect of the Slope is the most important factor in
543 all topography models. The mountain ranges that are in the windward of the Gulf are
544 demonstrating higher sensitivity in the amount of TCP and the probability in extreme TCP,
545 particularly between 120° to 180°. The TCP sensitivity has non-linear responses to some
546 topographic variables. Some TCP variables are demonstrating a dipole pattern in their sensitivity
547 responses to several elevation variables. The first high sensitivities of TCP appear at regions with
548 very low elevation and shallow Slopes due to the high variability in the TCP dynamics right after
549 landfall. Another high TCP sensitivity zone is also pronounced at regions with higher elevation
550 (max elevation > 3000 m) and more complex terrains (elevation range > 2000 m, slope > 5°, and
551 Elevation Standard Deviation > 500 m), which is very likely to be the topographic enhancing
552 effect of TCP. The RF model can capture these two separate processes with big impacts on the
553 TCP very well.

554 The interaction between individual TC and topography is complicated by the storm's
555 track, landfall positions, storm size, intensity, amount of moisture, and influences from other
556 weather systems over land. We have selected three storms that have produced the largest amount
557 of total TCP between 1920 and 2018. All of them made landfall near the northeastern corner of
558 Mexico with some degree of deflections in their tracks. Although some previous research
559 mentioned that storm tracks can be deflected by the orography (Chang et al., 2013; Farfán &
560 Zehnder, 2001; Lin et al., 2002; Wu et al., 2002), we need more numeric experiments and
561 observations to fully understand the mechanisms for storms in our study. The deflection does
562 extend the time that a storm staying at one location and increases the possibility of orographic
563 enhancement of precipitation in three storms we have chosen. Similar to the maps for the TCP
564 statistics of the whole dataset, the maps for the TCP of the maximum cases also show maximum

565 TCPs over mountainous areas with complex topography. Those most extreme TCP events have a
566 median of ~ 200 mm with the possibility of exceeding 400 mm occasionally. That intensity of
567 precipitation could trigger severe flash flooding and landslide in those areas (Salinas-Jasso et al.,
568 2020). Our result shows that the locations with the most intense TCP in those three storms have a
569 statistically significant larger elevation Range and Standard Deviation than those with median
570 TCPs. The topographic enhancing effect of TCP is very strong at the storm level, shown by the
571 three most extreme TCP cases. This effect is more pronounced in Cluster 2 grids, which have
572 higher mean elevation and more complex terrains.

573 Our analysis is based on long term gauge observed precipitation at the daily interval and
574 1km resolution DEM data. We have clearly shown very strong statistical relationships between
575 TCP variables and topographic features, which indicates the enhancing effect of the Sierra Madre
576 Oriental to the TCP from the TCs on the Gulf side. The same effect has been shown by the whole
577 dataset as well as the most extreme TCP cases. The RF models can provide certain ranges of
578 topographic variables (elevation Range, Slope, and Aspect) that have particularly high sensitivity
579 of TCP. The study is limited by the dimension of the observation and the temporal resolution of
580 the data. The orographic effects on rainfalls are closely related to the directions of 3-D flows, as
581 well as the energy, temperature, and moisture distribution at different altitudes. Rain gauges can
582 only provide precipitation observation at the surface level for a long period. We need more 3-D
583 observations to understand the more detailed precipitation mechanisms for each storm in the
584 future. The finest tempo-resolution for our data is daily, which might not be able to capture some
585 rapid precipitation processes at the sub-daily or even finer time scales. The spatial distribution of
586 rain gauges may occasionally be not enough to capture the detailed spatial distribution of TCP,
587 which leads to under-sampling issues while we are processing the IDW spatial interpolation. In

588 the future, we can refer to TRMM Multi-satellite Precipitation Analysis (TMPA) or the newest
589 Integrated Multi-Satellite Retrievals (IMERG) for Global Precipitation Measurement (GPM) for
590 much detailed rain ratios in most recent TCs. We also plan to set up numerical models (both
591 regional and global) to test the statistical relationships we have found from the observations.

592 **Acknowledgments**

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595 Gauge observations are derived from the Daily Global Historical Climatology Network (GHCN-

596 D) (<https://www.ncdc.noaa.gov/ghcnd-data-access>) and obtained from the National Weather

597 Service of Mexico by requiring. Tropical cyclone tracks are obtained from International Best

598 Track Archive for Climate Stewardship (IBTrACS) (<https://www.ncdc.noaa.gov/ibtracs/>). The

599 DEM data is obtained from the USGS EROS Archive - Digital Elevation - Global 30 Arc-

600 Second Elevation (GTOPO30) ([https://www.usgs.gov/centers/eros/science/usgs-eros-archive-](https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-second-elevation-gtopo30?qt-science_center_objects=0#qt-science_center_objects)

601 [digital-elevation-global-30-arc-second-elevation-gtopo30?qt-science_center_objects=0#qt-](https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-second-elevation-gtopo30?qt-science_center_objects=0#qt-science_center_objects)

602 [science_center_objects](https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-30-arc-second-elevation-gtopo30?qt-science_center_objects=0#qt-science_center_objects))

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738

Supplement Materials for “ Topographic Enhancement of Tropical Cyclone Precipitation (TCP) in Eastern Mexico”

Supplement 1. Comparison of elevation Standard Deviation for quantile TCP

Category	Daily TCP						Event TCP					
	P _{99.9} TCP	Elev Std	P ₅₀ TCP	Elev Std	P _{0.1} TCP	Elev Std	P _{99.9} TCP	Elev Std	P ₅₀ TCP	Elev Std	P _{0.1} TCP	Elev Std
Whole	164.15	105.88	7.99	88.24 ⁺	0.01	24.67 ⁺	318.09	45.14	15.30	144.29 [*]	0.04	71.34
Cluster 1	176.50	100.03	8.88	24.17 ⁺	0.01	20.94 ⁺	357.48	34.85	20.43	38.97	0.03	23.73
Cluster 2	122.49	269.30	7.38	163.43 ⁺	0.04	210.34 ⁺	220.49	235.84	13.20	171.28 ⁺	0.07	205.26 ⁺

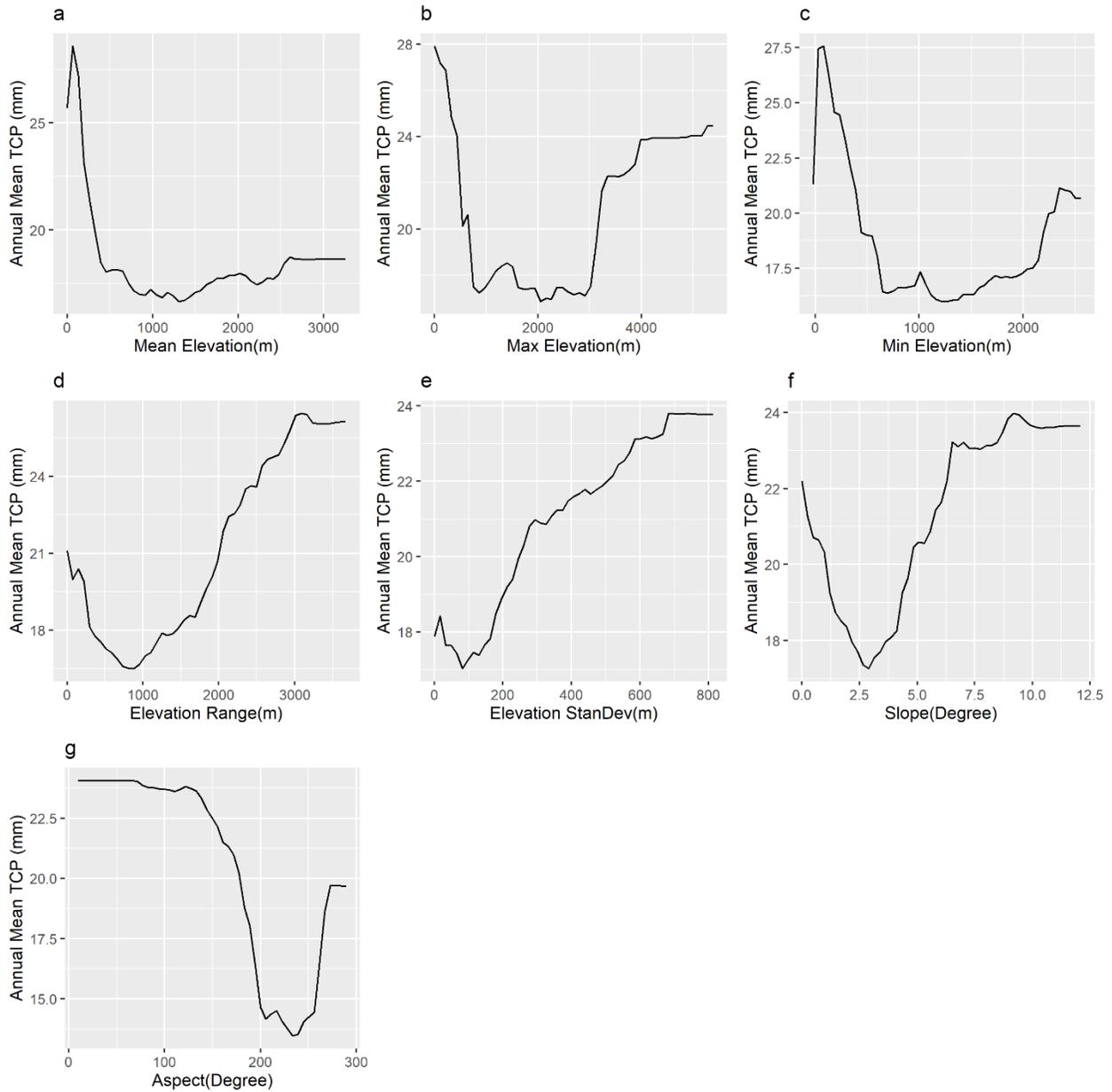
“+” indicates the current Elevation Standard Deviation sample median is smaller than the Elevation Standard Deviation sample for the P_{99.9} TCP in the same category, using the Mann-Whitney U-test at the 5% significance level. “*” indicates the current Elevation Standard Deviation sample median is greater than the Elevation Standard Deviation sample for the P_{99.9} TCP in the same category, using the Mann-Whitney U-test at the 5% significance level.

Supplement 2. Information about Random Forest Models developed for three TCP variables:

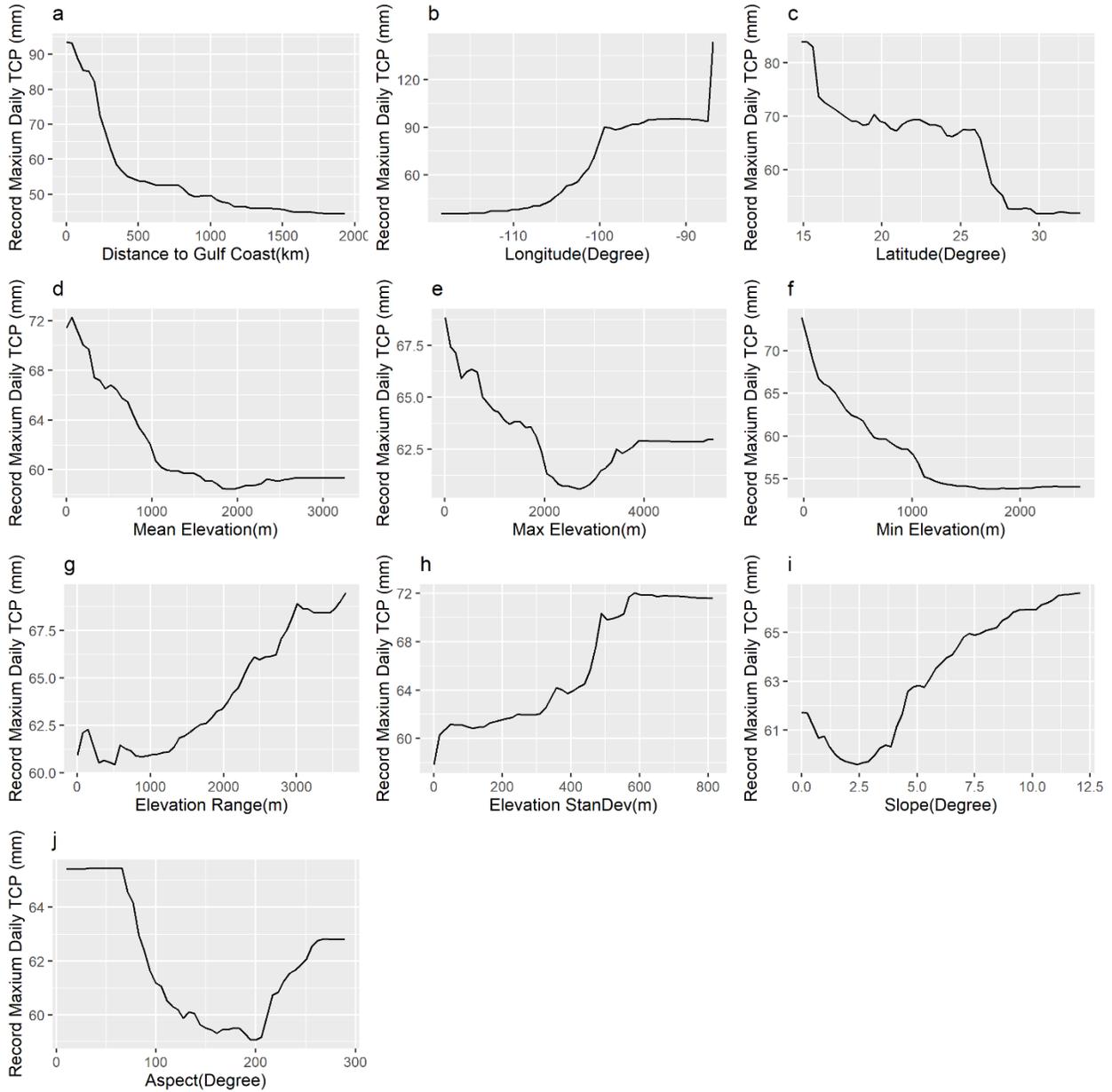
MaxDTCP and DTCPGP95. The importance is calculated as the percentage of increased MSE

(%IncMSE) if the variable is removed

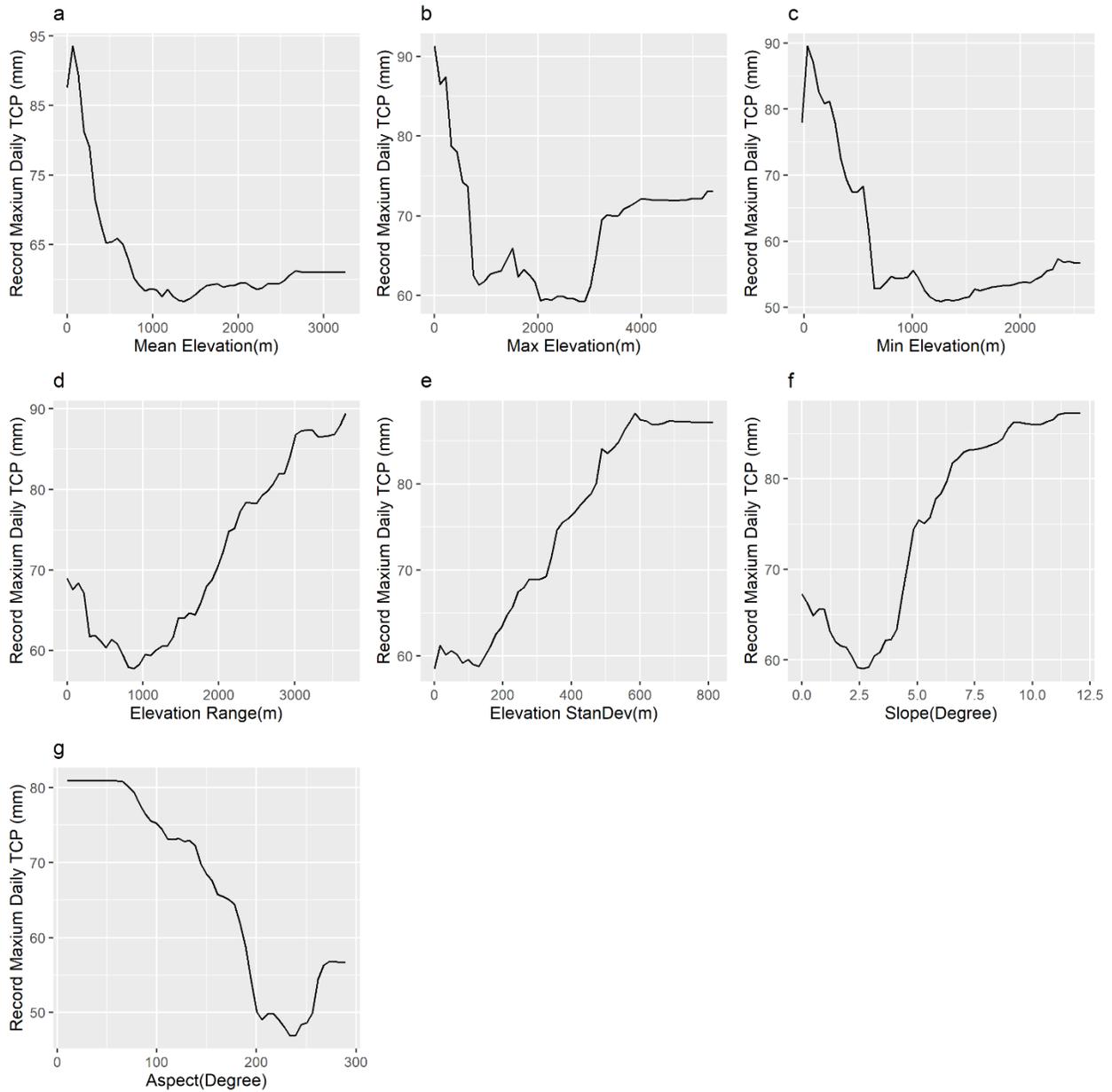
Variance Explained	MaxDTCP		MaxDTCP		DTCPGP95		DTCPGP95	
	Total Model		Topo Model		Total Model		Topo Model	
	80.28%		47.43%		91.05%		52.06%	
Importance Rank	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE	Var Name	%Inc MSE
1	Lon	41.38	Asp	49.22	Lat	45.05	Asp	71.94
2	Lat	40.76	Slope	37.83	Dist	39.21	Slope	41.62
3	Dist	31.80	Range	29.55	Lon	37.83	Std	33.33
4	Min	26.10	Std	29.22	Min	18.79	Range	28.53
5	Mean	23.23	Min	27.88	Range	16.94	Max	24.55
6	Slope	18.85	Mean	27.82	Max	15.91	Mean	22.85
7	Max	18.23	Max	24.23	Std	15.57	Min	20.80
8	Std	17.16			Slope	14.94		
9	Range	16.48			Mean	14.14		
10	Asp	11.44			Asp	14.06		



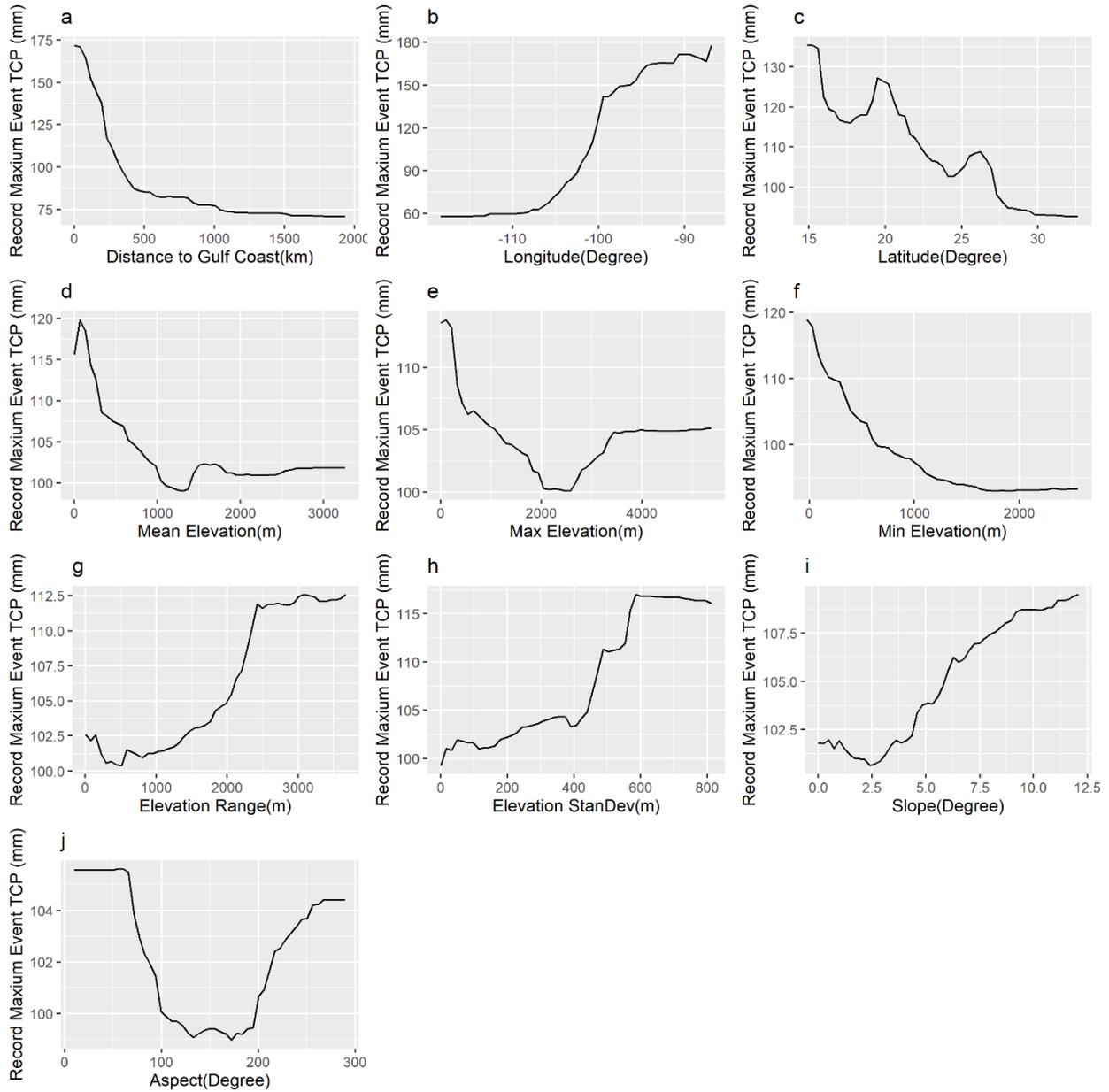
Supplement 3. Partial Importance Plot for variables in the topographic RF model for the Annual Mean TCP.



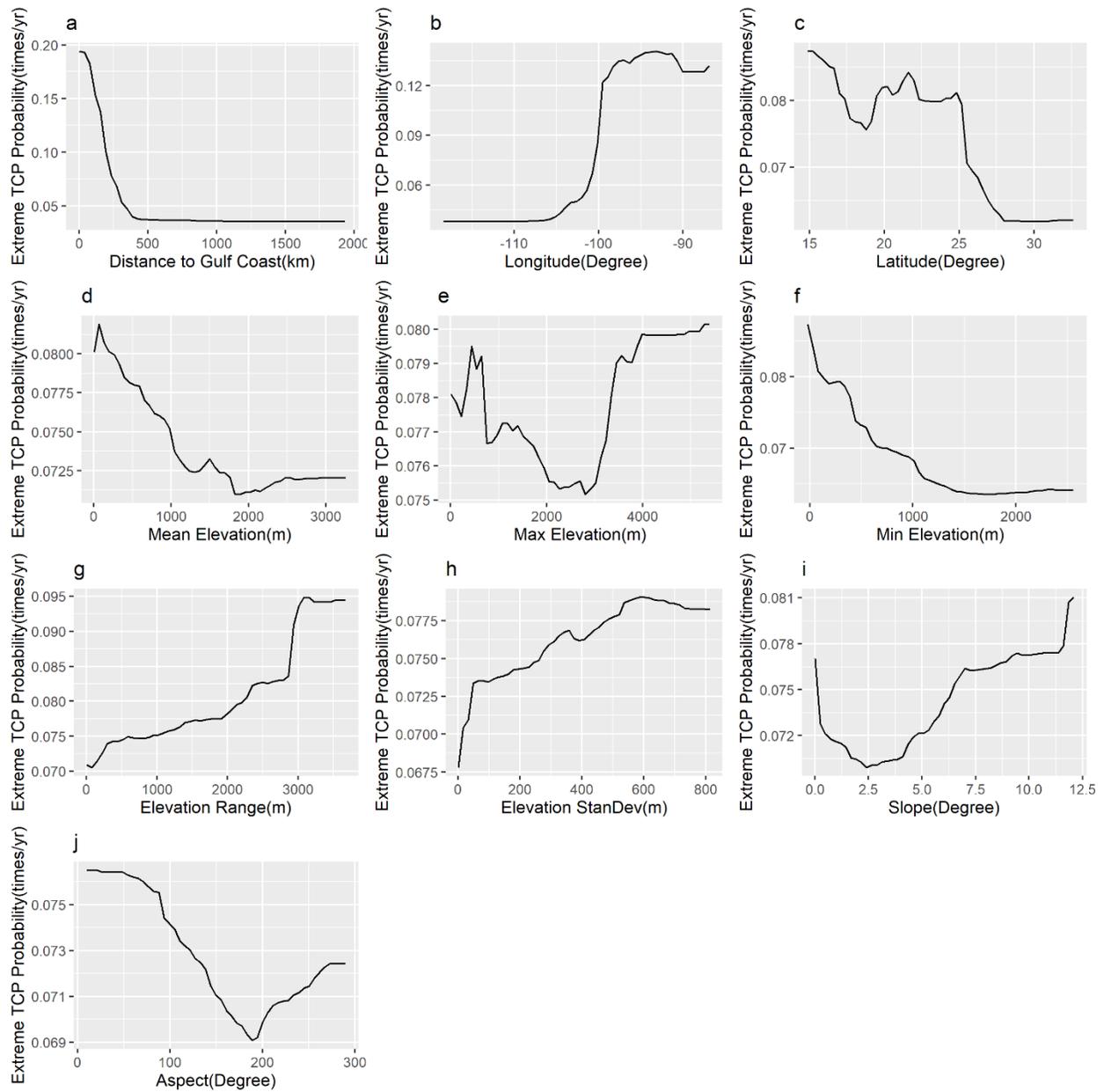
Supplement 4. Partial Importance Plot for variables in the total RF model for the Maximum Daily TCP.



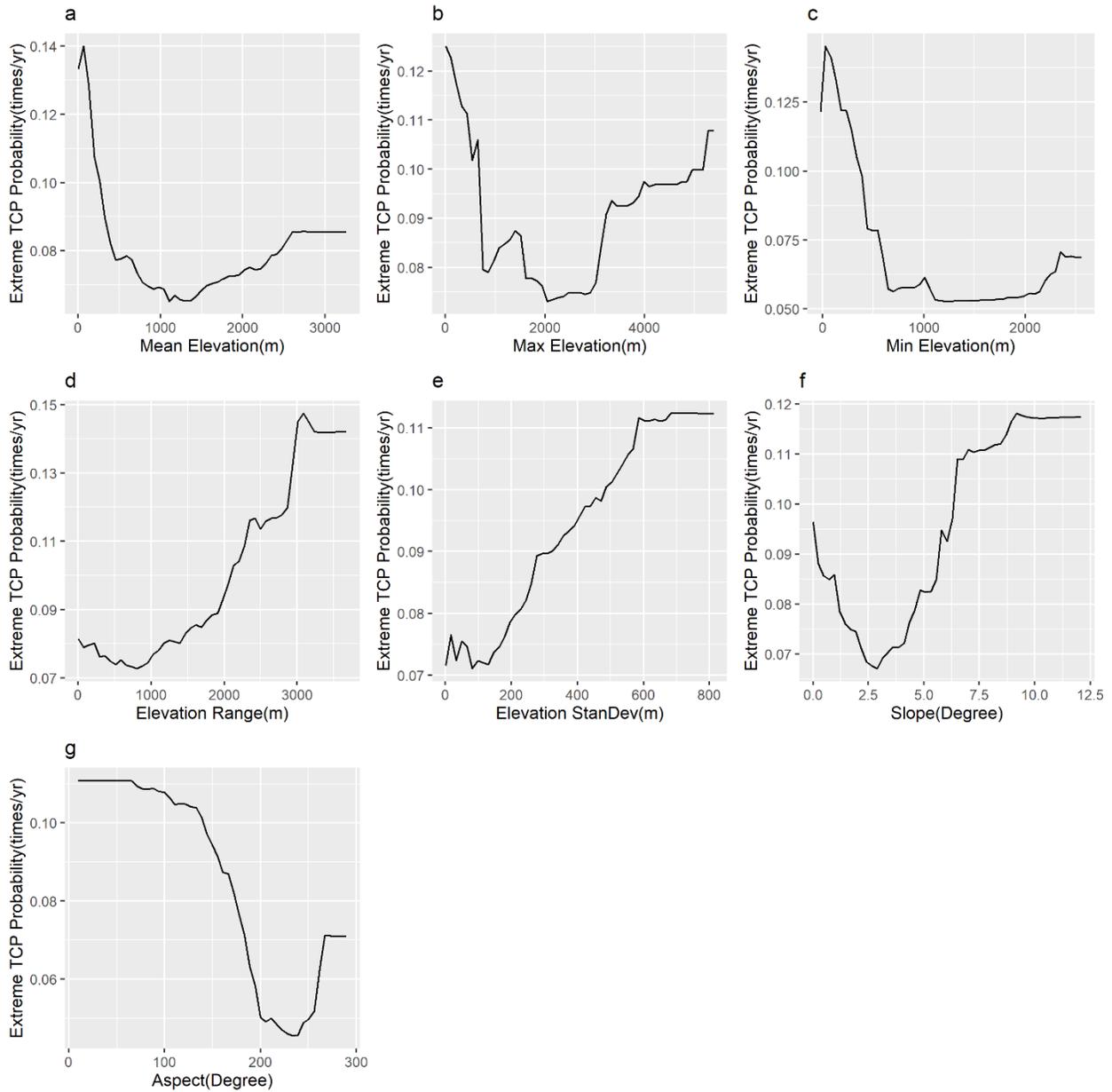
Supplement 5. Partial Importance Plot for variables in the Topographic RF model for the Maximum Daily TCP.



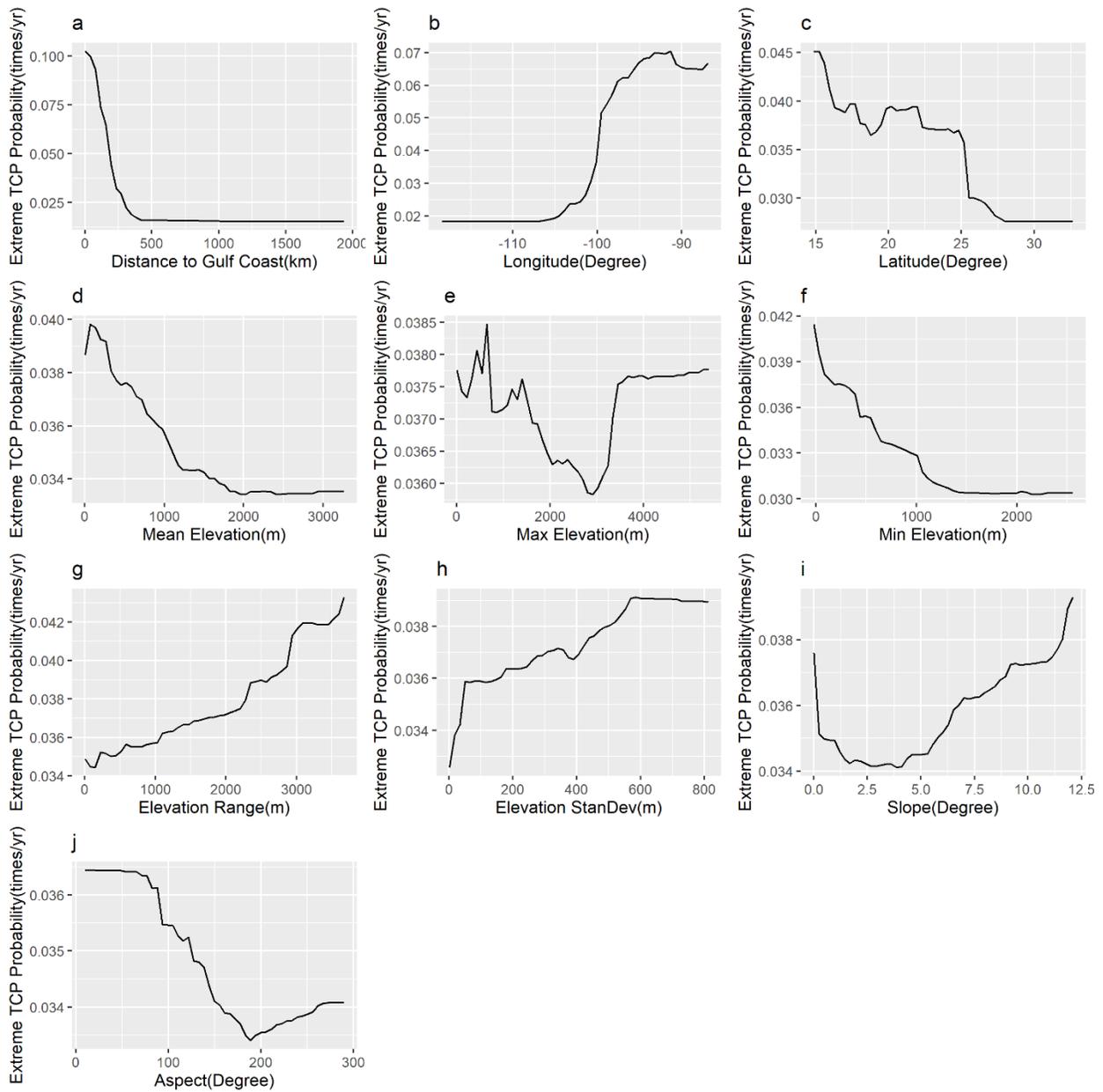
Supplement 6. Partial Importance Plot for variables in the Total RF model for the Maximum Events TCP.



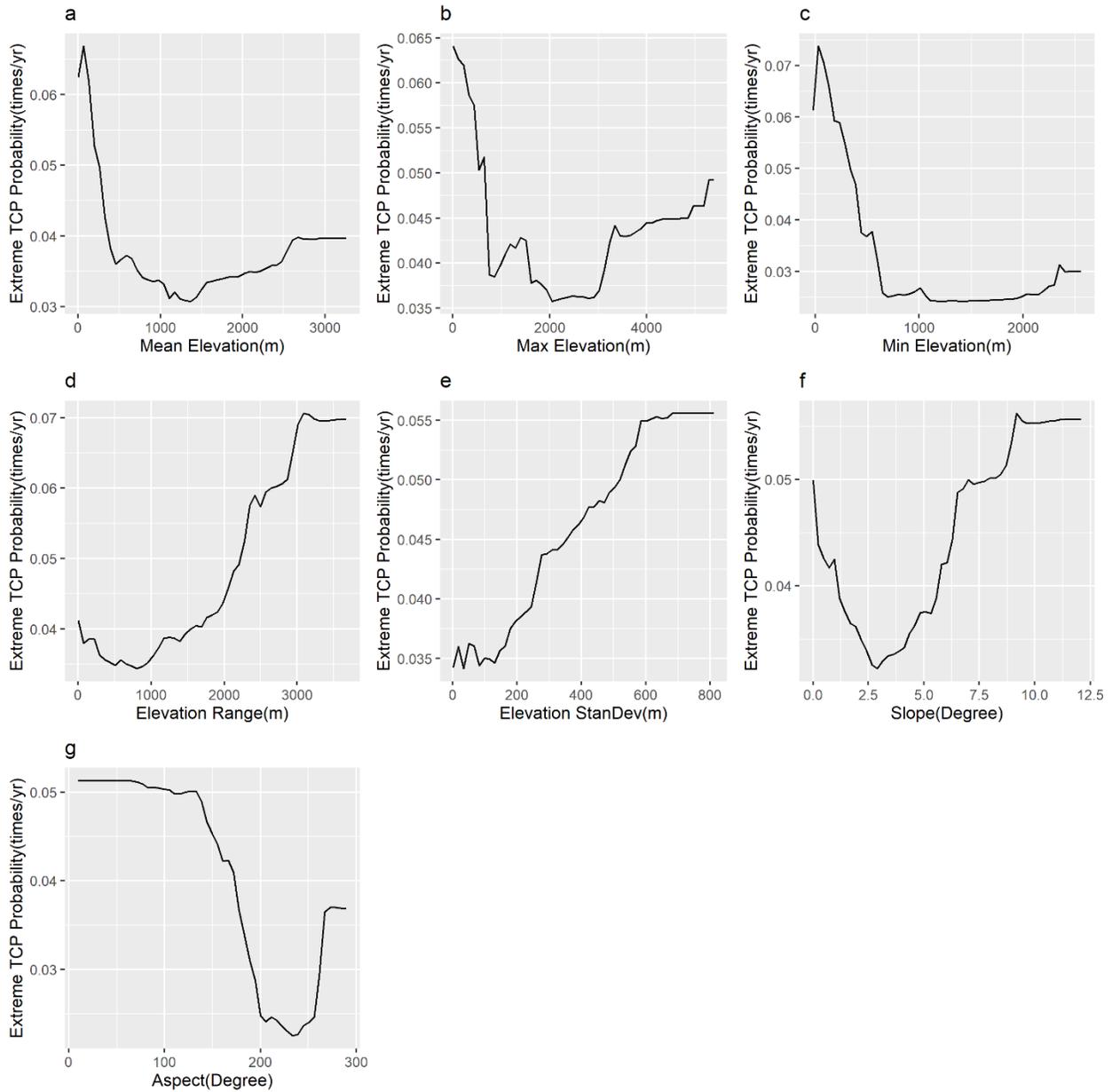
Supplement 7. Partial Importance Plot for variables in the Total RF model for the Probability of Daily TCP with greater than the P_{95} .



Supplement 8. Partial Importance Plot for variables in the Topographic RF model for the Probability of Daily TCP with greater than the P_{95} .



Supplement 9. Partial Importance Plot for variables in the Total RF model for the Probability of Event TCP with greater than the P_{95} .



Supplement 10. Partial Importance Plot for variables in the Topographic RF model for the Probability of Event TCP with greater than the P_{95} .

Supplement 11. Comparison of elevation standard deviation for quantile locations TCP for three most intense storms

Storm	Hurricane Alex				Hurricane Igrid				Hurricane Beulah			
	P ₉₀ TCP		P ₄₅ to P ₅₅ TCP		P ₉₀ TCP		P ₄₅ to P ₅₅ TCP		P ₉₀ TCP		P ₄₅ to P ₅₅ TCP	
Category	TCP	Elev Std	TCP	Elev Std	TCP	Elev Std	TCP	Elev Std	TCP	Elev Std	TCP	Elev Std
Cluster 1	164.89	23.50	76.80	26.48	197.41	192.13	62.02	68.65 ⁺	238.84	27.85	217.70	18.71 ⁺
Cluster 2	162.87	217.64	43.66	121.08 ⁺	107.69	263.22	31.95	169.46 ⁺	66.71	189.11	67.02	159.51

“+” indicates the Elevation Range sample median for P₄₅ to P₅₅ TCP locations is smaller than the Elevation Range sample for the P₉₀ TCP locations, using the Mann-Whitney U-test at the 5% significance level. TCP has unit of mm and Elevation Range has unit of meter