Article

Explaining the Flood Behavior for the Bridge Collapse Sites

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**Abstract:** Given the increasing intensity and frequency of flood events, and the casualties and cost associated with bridge collapse events, explaining the flood behavior for the collapse sites would be of great necessity. In this study, annual peak flows of two-hundred and five watersheds, associated with two hundred and ninety-seven collapse sites, are analyzed. Generalized Extreme Value distribution together with other statistical analyses are used to derive and analyze shape parameters of the distributions which represents the extremeness of flood events. Random forest mechanism is employed in order to identify the predictor variables (and the associated importance levels) for the shape parameters. Peak flows are also classified in order to find the extremes, and the associated return periods. The results indicate that most of the bridge collapse sites across different physiographic regions, Appalachian Highland, Central Lowland, Coastal Plain, and Interior Highlands, exhibit common characteristics such as similar extremeness of flood events, hydrologic heterogeneity, human interference, and frequent occurrence of extreme flows. These results indicate a commonality in flood behavior, as stem from specific settings, for the collapse sites studied. The findings instigate re-visiting the bridge design practices and guidelines, and provide some basis to assess the risk of future collapse.

**Keywords:** Flood Behavior; Bridge Collapse; Shape Parameter; Extreme Flows

1. Introduction

Floods, scour, and other hydraulic events are perceived to be the most common causes of total or partial bridge collapse in the United States (US) [1]. About 62.23% of over-water bridge collapses correspond to hydraulic events [[**1**](https://www.mdpi.com/2073-4441/12/1/52/htm#B1-water-12-00052)] with an annual hydraulic collapse frequency of approximately 1/5000 [1,2]. Scour–particularly scour during floods–alone has been estimated to cause the collapse of 20-100 bridges per year in the US [1,3-4]. Flood-induced scouring is of particular concern due to the intensity and frequency of recent floods in the different states of the USA. More frequent or intense flooding are linked with climate and land use change [5]; the associated high risk is linked with the direct and indirect costs, casualties, and user delays [1, 3-4,6]. The 2021 American Society of Civil Engineer’s (ASCE) Report Card noted that $22.7 billion annual investment is needed to substantially improve the current bridge conditions [7].

In response to reducing collapse risk due to floods, engineers primarily aim at determining the magnitude and frequency of design floods. Guidelines to determine the flood magnitudes with return periods, include TR-55 [8], Bulletin 17C [9], and StreamStats [10], among several others. Methods commonly used for estimating the return period of a flood event include block maxima approaches, in which a series of annual peak flows is used to define an extreme value distribution. The generalized extreme value distribution (GEV) is widely used model for extreme events [11]. The major benefit of the GEV model is its ability to fit highly skewed data since it combines three distributions: Gumbel, Frechet, and Weibull [11]. The GEV distribution has three parameters, namely the location and scale parameters that are mostly related to the magnitude of flow [12] and the shape parameter that determines the behavior (or shape) of the tail of the distribution [12].

Although in engineering design the distribution parameters are seldom analyzed, recent hydrologic research has focused on explaining the parameters of the GEV distribution of streamflow extremes [13-19] to investigate the properties of flood events. The shape parameter is of particular interest when investigating the extremeness (or behavior) of the flood events. High-level quantiles in the peak flow distribution are usually of great interest in water resources management. However, no conclusive remark can be made in explaining the shape parameters since the results of different studies are not directly comparable because of the data coming from different regions. Some studies suggest that the shape parameter depends on climate indices, while other attributes of the catchments are less important [13-14,20-21]. Other studies find unclear (slightly significant) relationships between the shape parameter and other basin attributes [12, 22-24].

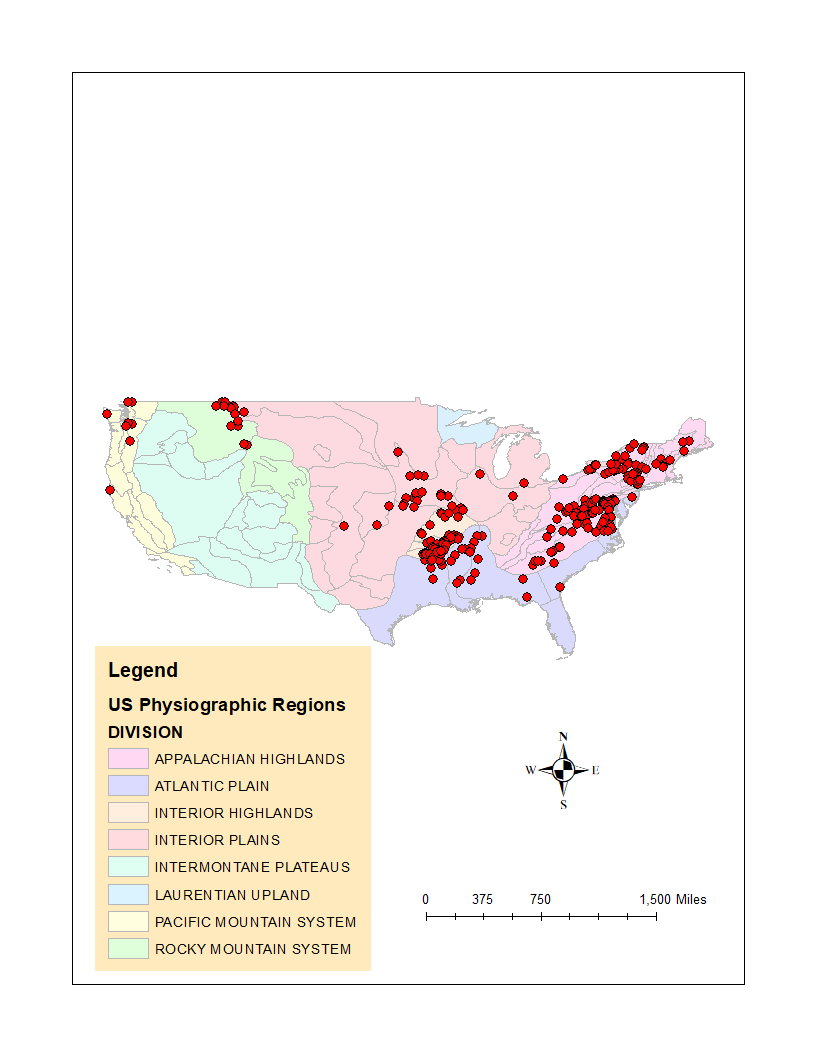
The goal of the study is to explain flood behavior for 297 bridge collapse sites in relation to the shape parameters of the GEV distribution given that the studies of historical streamflow data have yielded mixed results in terms of current trends in annual peak flows and the existence of abrupt changes [25-28]. To attain the goal, three objectives are identified: (1) To derive shape parameters of GEV distribution using annual peak flow data, (2) to identify predictor variables for the shape parameter, and (3) to identify extreme flows with associated return periods. Values of shape parameters would reveal the overall extremeness of the flood events. The predictor variables would help to identify important hydrological signatures in relation to extremeness of the flood events. Finally, the identification of extreme flows with return periods would help to identify the uniqueness of the flood events for the collapse sites, if any. Results can reveal any anomaly and/or trend in the behavior of peak floods for the bridge collapse sites, and can support the understanding of the mechanism behind the generation of collapse inducing floods. Since analyzing peak flow distribution parameters is not a common practice in bridge design procedures, such analysis can provide preliminary data to assess future collapse risk as it can be highlighted that the flood event occurrence should be expected within a specific context. Concerning the bridge collapse sites, the findings of the present study are also original in comparison to previous studies in which the shape parameters were examined.

2. Methods

2.1. Selection of sites

The New York State Department of Transportation (NYSDOT) bridge failure database is used here to identify 297 bridge collapse sites (Figure 1). NYSDOT is the only US-wide database of bridge collapses. The recorded information includes NYSDOT failure database ID, identifier in National Bridge Inventory (NBI), failure cause, the location of the collapsed bridge, the feature under the bridge, the year of construction, the date or year of collapse, the bridge material and structure type, the type of collapse (total or partial), the number of casualties related to the collapse, and other comments. The selected bridges were located in Appalachian Highland (140 sites), Coastal Plain (47 sites), Central Lowland (42 sites), Interior Highlands (54 sites), Pacific Mountain (8 sites), and Rocky Mountain (8 sites). The sites were sought according to the following criteria:

* Existence of a stream gauge listed in the US Geological Survey (USGS) National Water Information System Database at the bridge location, near the bridge location (on the same tributary of the river or on the different tributary), or at a further distance (not the same tributary, but on the same river or within the same watershed).



**Figure 1.** 297 bridge collapse sites across different physiographic regions in U.S.

* Bridges were apparently collapsed (complete or partial collapse) due to hydraulic reasons including floods, scour, hurricane, washout, and debris. It should be noted that one or more hydraulic events can occur together. For instance, flood events can be associated with both scour and washout. Similarly, a hurricane event can cause flood induced scour and washout. With the presence of debris, effect of any hydraulic event can become exaggerated.

Retrieved information of the selected bridge collapse sites (with associated USGS stations) can be found at <https://github.com/fahmidah/Shape-Parameter-Bridge-Collapse-Sites/tree/main/List%20of%20Collapse%20Sites>

2.2. Shape parameters

Shape parameters are retrieved for the GEV distribution using *extRemes R* package. Annual peak flow data, retrieved from United States Geological Survey (USGS), are used to fit with the GEV distribution. The cumulative distribution function of the GEV distribution is given by the following equation [[29](https://www.mdpi.com/2073-4441/12/1/52/htm#B24-water-12-00052)-33].

Here μ is the location parameter, σ is the scale parameter, and *k* is the shape parameter. The shape parameter is of critical significance in that it proscribes the type of distribution: Gumbel (shape parameter = 0), Frechet or heavy-tail (shape parameter >0) and Weibull (shape parameter <0) for fitting to block maxima series of data. Therefore, the shape parameter is related to how extreme the floods are. The higher values of k result in heavier tails.

2.3. Predictor variables

Random forests mechanism [13] is used to derive physiography-based predictor variables and the associated importance levels. Pacific Mountain and Rocky Mountain System were excluded from the physiography-based study because of the low number of sites. The methodology is then also implemented considering all the collapse sites together across different physiographic regions in U.S. The methodology is implemented with the aim to find predictor variables for the shape parameters for a dataset that comprises information about streamflow and forcing, climatic indices, topographic, land cover, soil, geology, population infrastructure, dam, and watershed characteristics of 205 U.S. gauge basins (associated with 297 collapse sites) with varying human interference in the watershed. The dataset was published by USGS [34] and is available to public at the <https://water.usgs.gov/lookup/getspatial?gagesII_Sept2011>.

2.4. Classification of peak flows

This study employs Jiang classification scheme [35] to categorize annual peak flows into heavy-tail and light-tail flows. Heavy tail distribution implies that flows in the heavy-tail increase more than the exponential order as compared to the flows in the light-tail and such high flows are expected to be with higher return periods. With Jiang classification scheme [35], the minimum heavy-tail flow would be identified. To retrieve the return periods of minimum and maximum heavy-tail flows, the annual peak flow data are fitted with GEV distribution and the task is performed by implementing the *extRemes* R package [36].

3. Results

3.1. Shape parameters

For physiographic regions studied, as shown in Figure 2, shape parameters do present fairly normal distributions (p value of the Shapiro-Wil normality test > 0.05). The extremeness of the flood behavior is quite similar acroass the study regions, as evident by the similar shape parameter values (mean and median). In fact, the median value of the shape parameter (Table 1) within each physiographic region is close to the median value of 0.19 as obtained for the watersheds with a diversity of climate types [13]. The site with the largest shape parameter value (= 0.74) is located with Central Lowland (USGS station# 6108000) (Table 1), that is combatively heavier tail for the peak flow distribution, which implies the higher likelihood of getting extreme peak flows. On the other hand, sites within Coastal Plain can experience much broader fluctuations (e.g., three or more standard deviations from the mean) in peak flows; such finding is evident by the value of the kurtosis ( > 3) in Table 1. A distribution is said to be leptokurtic when the kurtosis is greater than 3 implying that there is a greater potential for extreme fluctuations in the observed values. All the shape parameters values for 205 stations can be retrived from <https://github.com/fahmidah/Shape-Parameter-Bridge-Collapse-Sites/tree/main/Shape%20Parameters>.

|  |  |
| --- | --- |
| D:\peak\Appalachian his.tiff | D:\peak\central.tiff |
| 1. Appalachian Highland | 1. Central Lowland |
| D:\peak\interior his.tiff | D:\peak\coastal.tiff |
| 1. Interior Highland | 1. Coastal Plain |
| C:\Users\Ruma\Desktop\PEAK\Main\All sites.tiff | |
| 1. All sites | |

**Figure 2.** Normal distributions of the shape parameters derived from GEV estimates of the annual peak flows for the bridge collapse sites

**Table 1.** Descriptive statistics of the shape parameter values for the bridge collapse sites

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Physiographic Region** | **Range** | **Mean** | **Median** | **Standard**  **deviation** | **Kurtosis** | **Shapiro-Wil Normality**  **Test** |
| Appalachian Highland | -0.21 - 0.61 | 0.21 | 0.20 | 0.19 | 2.58 | 0.16 |
| Central Lowland | -0.31 - 0.74 | 0.20 | 0.19 | 0.25 | 2.96 | 0.65 |
| Interior Highland | -0.11 - 0.43 | 0.18 | 0.17 | 0.14 | 2.43 | 0.53 |
| Coastal Plain | -0.32 – 0.63 | 0.18 | 0.2 | 0.21 | 3.28 | 0.64 |
| All Sites | -0.32 – 0.74 | 0.20 | 0.19 | 0.19 | 3.02 | 0.85 |

3.2. Predictor variables

Six types of predictor variables are found for each of the physiographic regions studied, and also when all the sites are considered together (Figure 3). Among all the predictor variables, climate variables are found in a greater number across all regions (Figure 3). For Appalachian Highland, there are a total of 36 predictor variables (with positive importance levels) identified: climate (13), watershed (7), soils (6), topography (3), dams (4), and population infrastucture (3). Certain cliamte variables are found to be the most important predictor variables; 9 out of 10 variables (ranking between 1 to 10) are climate variables (Table 2). For Interior Highlands, 29 predictor variables (with positive importance levels) are identified: climate (10), soils (6), watershed (4), dams (4), population infrastucture (3), and topography (2). Certain climate, dam, and soil properties are found to be most important (Table 2). Finding dam properties as the important predictor variables (3rd, 6th, 8th) (Table 2) might be noted here specifically as it suggests the apprent importantce of the human interference within the watershed. The importance of human interference is also apparent within Central Lowland with the rankings of certain variables: population density (2nd), percentage of impervious area (3rd), percentage of developed area in the watershed (4th), and road density (7th) (Table 2). In total, 32 predictor variables (with positive importance levels) are identified for Central Lowland: climate (13), watershed (5), soils (4 ), topography (4), dams (3), and population infrastucture (3). Certain topography, population infrastructure, and climate variaables are found to be most important (Table 2). For Coastal Plain, 32 predictor variables (with positive importance levels) are identified: climate (13), watershed (6), soils (6), dams (3), population infrastucture (3), and topography (1). Certain soil and climate variables are found to be the most imortant (Table 2). When considering all sites together, 39 predictor variables (with positive importance levels) are identified: climate (15), topo (5), soils (6), population infrastructure (3), dams (3), and watershed (7). The finding, considering all sites together, is quite similar to the Appalachian Highland; 9 out of 10 important variables are found to be climate type. Figures representing all predictor variables with associated importance levels are provided in Appendix A. Description of all predictor variables (with associated importance levels) can be found at <https://github.com/fahmidah/Shape-Parameter-Bridge-Collapse-Sites/tree/main/Predictor%20Variables%20Description>.

Figure 3. Types of predictor variables across different physiographic regions

Table 2. Types of most important (ranking 1 to 10) predictor variables across different physiographic regions.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Ranking** | **Appalachian Highland** | **Interior Highlands** | **Coastal Plain** | | **Central Lowland** | | **All Sites** | |
| 1 | WDMIN\_BASIN | FST32F\_BASIN | AWCAVE | | ELEV\_MEAN\_M\_BASIN | | WD\_BASIN | |
| 2 | WD\_BASIN | LST32F\_BASIN | SANDAVE | | PDEN\_2000\_BLOCK | | LST32F\_BASIN | |
| 3 | WDMAX\_BASIN | DDENS\_2009 | PERMAVE | | IMPNLCD06 | | WDMAX\_BASIN | |
| 4 | SLOPE\_PCT | BDAVE | PLANTNLCD06 | | DEVNLCD06 | | PPTAVG\_BASIN | |
| 5 | T\_MIN\_BASIN | T\_MIN\_BASIN | SILTAVE | | T\_MAXSTD\_BASIN | | FST32F\_BASIN | |
| 6 | T\_AVG\_BASIN | STOR\_NID\_2009 | PRECIP\_SEAS\_IND | | LST32F\_BASIN | | ELEV\_MEAN\_M\_BASIN | |
| 7 | LST32F\_BASIN | T\_AVG\_BASIN | LST32F\_BASIN | | ROADS\_KM\_SQ\_KM | | RH\_BASIN | |
| 8 | T\_MAX\_BASIN | STOR\_NOR\_2009 | PPTAVG\_BASIN | | RH\_BASIN | | T\_MIN\_BASIN | |
| 9 | SNOW\_PCT\_PRECIP | PET | ELEV\_MEAN\_M\_BASIN | | ELEV\_STD\_M\_BASIN | | T\_AVG\_BASIN | |
| 10 | PET | CLAYAVE | ROADS\_KM\_SQ\_KM | | FST32F\_BASIN | | PET | |
|  |  |  |  | |  | |  | |
|  |  | Climate | |  | | Watershed | |
|  |  |  | |  | |  | |
|  |  | Soils | |  | | Dams | |
|  |  |  | |  | |  | |
|  |  | Population Infrastructure | |  | | Topography | |

Predictor variables, ranking between 1 to 10, have more importance levels for Central Lowland as compared to the other physiogrpahic regions except for soil and 4 other distincy variables (major dam density, mean watershed slope, percentage of cultivated land in watershed, and drainage area) (Figure 4). Soil variables (ranking 1 to 10) are found to be relatively more important for Coastal Plain (Figure 4). For all topography and watershed variables (Ranking 1 to 10), Interior Highlands have the least impotance levels (Figure 4). Higher importance levels imply higher predictability of the flood behavior for Central Lowland compared to other regions. Since the system has a higher predictability, accurate forecasts based on current observations (predictor variables with higher importance levels) would be compatively easier.

|  |
| --- |
|  |
| 1. Climate variables |
|  |
| 1. Population Infrastructure |
|  |
| 1. Soils |
|  |
| 1. Topography |
|  |
| 1. Watershed |
|  |
| 1. Dams |

**Figure 4**. Importance levels for the six types of important predictor variables (ranking 1 to 10) as retrieved for different physiographic regions

There is a total of 40 distinct predictor variables identified for the collapse sites within different regions: climate (15), watershed (7), soil (6), topography (5), population infrastructure (4), and dams (3). Among them 10 predictor variables are found common across all regions (Table 3); climate (6), soil (2), population sturcture (1), and watershed (1). Each of the common variables is found to be important for one or more than one physiographic regions (Table 3) except for the variable ‘T\_MIN\_STD\_BASIN’, and ‘FRAGUN\_BASIN’. Only one common variable ‘LST32F\_BASIN’ is found to be important (ranking between 1 to 10) for all regions.

**Table 3.** Common predictor variables for all of the study regions. Superscripts indicate the regions for which the corresponding variable is noted as important predictor (ranking between 1 and 10)

|  |  |  |
| --- | --- | --- |
| Variables | Variable Type | Variable Explanation |
| LST32F\_BASINABCD | Climate | Watershed average of mean day of the year of last freeze |
| T\_MIN\_BASINCD | Climate | Watershed average of minimum monthly air temperature (degrees C) |
| T\_AVG\_BASINCD | Climate | Average annual air temperature for the watershed |
| SNOW\_PCT\_PRECIPD | Climate | Snow percent of total precipitation estimate |
| CLAYAVEC | Soils | Average value of clay content |
| ROADS\_KM\_SQ\_KMAB | Population Infrastructure | Road density |
| FST32F\_BASINC | Climate | Watershed average of mean day of the year of first freeze |
| T\_MINSTD\_BASIN | Climate | Standard deviation of minimum monthly air temperature |
| SANDAVEB | Soils | Average value of sand content |
| FRAGUN\_BASIN | Watershed | Fragmentation Index of "undeveloped" land in the watershed. High numbers = more disturbance by development and fragmentation; a very pristine basin with a lot of contiguous undeveloped land cover would have a low number |
| ACentral Lowland BCoastal Plain CInterior Highlands DAppalachian Highland | | |

*3.3 Extreme peak flows*

Most of the USGS stations (172 out of 195) associated with the collapse sites are found to be exhibiting ‘heavy-tail’ distribution (Figure 5, Table 4) for peak flows, that is shape parameter value is greater than zero. Heavy tail distribution flows are expected to be with higher return periods. However, most of the heavy tail flows exhibit lower return periods, less than 50 years (Figure 5, Table 4). The minimum return periods for heavy tail flows ranges from 1 to 3 years across different regions (Table 4). The median values for the return periods are found to be less than 50 years for all of the physiographic regions studied (Table 4). On the other hand, the maximum return periods for the heavy tail flows range from 213 to about 897 years (Table 4). Comparing all the regions, the likelihood of having extremes (outliers) is higher for Appalachian Highland as implied by the larger kurtosis value of 47. The calculated return periods for the heavy tail flows (for 205 USGS stations) can be retrived from <https://github.com/fahmidah/Shape-Parameter-Bridge-Collapse-Sites/tree/main/Return%20Periods>.

|  |
| --- |
|  |
| (a) Appalachian Highland |
|  |
| (b) Central Lowland |
|  |
| (c) Coastal Plain |
|  |
| (d) Interior Highlands |

**Figure 5.** Classification of annual peak flows for the bridge collapse sites

**Table 4.** Return periods and associated information for heavy-tail flows for the bridge collapse sites

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Physiograhic Region | # of sites with heavy tail flows (total sites) | # of sites with different retuen Periods (years) | | | | Minnimum/ Maximum  Return Periods (years) | Mean/Median | Kurtosis |
| < 50 years | 50 – 100  years | 100 - 500  years | > 500  years |
| Appalachian Highland | 100 (111) | 80 | 9 | 10 | 1 | 3 / 897 | 45.58 / 13.57 | 47.0 |
| Central Lowland | 23 (26) | 18 | 1 | 4 |  | 2 / 465 | 55.37 / 10.12 | 10.41 |
| Coastal Plain | 28 (33) | 22 | 1 | 5 |  | 2 / 213 | 45.38 / 14.81 | 2.05 |
| Interior Highlands | 21 (25) | 15 | 3 | 2 | 1 | 1 / 627 | 75 / 18.41 | 9.30 |

4. Discussion

The key findings are discussed here.

1. *Normal distribution of shape parameters does not imply climate variables as the most important predictor variables.* Some studies suggest that the shape parameter depends on climate indices, while other attributes of the catchments are less important [13-14,20-21]. With such attributes, the GEV shape parameter is most preferably modelled by a normal distribution with a common mean across all sites [13-15,[37](https://www.mdpi.com/2073-4441/12/1/52/htm#B35-water-12-00052),[38](https://www.mdpi.com/2073-4441/12/1/52/htm#B38-water-12-00052)]. However, it is claimed that this may be a result of an insufficient summary of the catchment attributes by the implemented indices [39]. For the study, the retrieved values of shape parameters does agree with recent studies [[12](https://www.mdpi.com/2073-4441/12/1/52/htm#B29-water-12-00052),21-24,[40](https://www.mdpi.com/2073-4441/12/1/52/htm#B43-water-12-00052)] in that the values follow fairly normal distribution for each physiographic region. However, for the study sites, the distinct association with climate variables is not evident except for Appalachian Highland.
2. *There are different types of important predictor variables across all study regions*. Although there is an over-representation of climate variables, important predictor variables (ranking 1 to 10) include more than one type across all regions. Important predictor variables include climate and topography for Appalachian Highland; climate, dam, and soil for Interior Highlands; topography, population, and climate for Central Lowland; and soil, climate for Coastal Plain. The results suggest the hydrological heterogeneity of the collapse sites supporting the claim that the hydrological heterogeneity is implicitly reflected in the shape parameter [21]. In fact, the median value of the shape parameters obtained for each region is very close to the median value of 0.19 obtained for the sites with hydrological heterogeneity, that is a large diversity of climate types [13].
3. *Predictor variables associated with human interference are found across all regions*. For all regions ‘population infrastructure and ‘dams’ variables are obtained as the predictor variables. For Interior Highlands, Coastal Plain, and Central Lowland, the importance of human interference (ranking between 1 to 10) is apparent with higher importance levels as compared to other predictor variables. In fact, reconnaissance studies throughout the mid-west revealed the extensive human disturbance which together with easily erodible soils has produced thousands of miles of highly unstable streams [41,42].
4. *Extreme heavy tail flows occur frequently for the bride collapse sites*. The persistence of lower return periods, as low as 1 to 3 years, of the heavy-tail peak flows implies that extreme heavy-tail flows occur more frequently than expected for the bridge collapse sites. Such finding is in accordance with a recent study of the bridge collapse sites [43] where the prevalence of collapse inducing floods with lower return periods has become evident. Such findings instigate re-visiting the guidelines specifying use of a “100-year flood,” or a flood with an annual probability of exceedance of 1%, for modern interstate bridges receiving federal funding [44]. Such practices assume that extreme floods occur rarely which can cause partial or complete bridge collapse.

5. Conclusions

In the study, analysis of shape parameters, retrieved from the GEV distribution of annual peak flows, are performed for 205 USGS watersheds (or stations) associated with 297 bridge collapse sites across different physiographic regions. Annual peak flows are also analyzed in relation to the heavy-tail flows and their return periods. Certain unique findings become apparent for all of the collapse sites in relation to each physiographic region (Appalachian Highland, Central Lowland, Interior Highlands, and Coastal Plain): (a) normal distribution of shape parameter with a mean across all sites, (b) hydrologic heterogeneity, (c) human interference, and (d) frequent occurrence of extreme peak flows. Such findings, common to each physiographic region studied, necessitate re-visiting bridge design and bridge collapse risk study in relation to not only the magnitude and frequency of floods but also the behavior of the floods as stemming from specific settings.

**Author Contributions:** Conceptualization, F.U.A., H.T., and G.P.; methodology, F.U.A., H.T., and G.P.; formal analysis, F.U.A., H.T., and G.P.; data curation, F.U.A.; writing—original draft preparation, F.U.A.; writing—review and editing, H.T., and G.P.; funding acquisition, F.U.A. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** Dataset including all variables used to retrieve the predictor variables can be found at <https://water.usgs.gov/lookup/getspatial?gagesII_Sept2011>.

**Conflicts of Interest:** The authors declare no conflict of interest

**Appendix A**

**Figure A1**. Importance levels for the predictor variables of the shape parameters for Appalachian highland

**Figure A2**. Importance levels for the predictor variables of the shape parameters for Coastal Plain

**Figure A3**. Importance levels for the predictor variables of the shape parameters for Interior Highlands

**Figure A4**. Importance levels for the predictor variables of the shape parameters for Central Lowland

**Figure A5**. Importance levels for the predictor variables of the shape parameters considering all sites

References

1. Cook, W.; Barr, P.J.; Halling, M.W. Bridge failure rate. *J. Perform. Constr. Facil*. **2015**, 29. <https://doi.org/10.1061/(ASCE)CF.1943-5509.0000571>
2. Nowak, A.S.; Collins, K.R. *Reliability of structures*, 2nd ed*.*; CRC Press: 2012.
3. Briaud, J. L.; Brandimarte, L.; Wang, J.; D’Odorico, P. Probability of scour depth exceedance owing to hydrologic uncertainty. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*. **2007**, 1(2), 77–88.
4. Stein, S. M.; Sedmera, K. *Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations*; NCHRP Report No. 107: 2006
5. Meyer, M. D.; Flood, M.; Keller, J.; Lennon, J.; McVoy, G.; Dorney, C.; Leonard, K.; Hyman, R.; Smith, J. *Climate change, extreme weather events and the highway system: a practitioner’s guide*; NCHRP: 2013
6. Neumann, J. E.; Price, J.; Chinowsky, P.; Wright, L.; Ludwig, L.; Streeter, R.; Jones, R.; Smith, J. B.; Perkins, W.; Jantarasami, L.; Martinich, J. Climate change risks to US infrastructure: impacts on roads, bridges, coastal development, and urban drainage. *Climatic Change*. **2014**, 131, 97–109
7. ASCE. *A Comprehensive Assessment of America’s Infrastructures*; ASCE: 2021
8. National Resources Conservation Service. *Urban Hydrology for Small Watersheds*; TR-55; USDA: Washington, DC, USA, 1986
9. Hydrology Subcommittee. *Bulletin 17C Guidelines for Determining Flood Flow Frequency*; USGS Interagency Advisory Committee on Water Data: Reston, VA, USA, 2019
10. Atkins, J.B.; Hummel, P.R.; Gray, M.; Dusenbury, R.; Jennings, M.E.; Kirby, W.H.; Riggs, H.C.; Sauer, V.B.; Thomas, W.O., Jr. The national streamflow statistics program: A computer program for estimating streamflow statistics for ungaged sites. In *Hydrologic Analysis and Interpretation. Section A: Statistical Analysis*; Ries, K.G., Ed.; USGS: Washington, DC, USA, 2007
11. Eljabri, S.S.M. New Statistical Models for Extreme Values. Ph.D. Thesis, The University of Manchester, Manchester, UK, 2013
12. Northrop, P.J. Likelihood-based approaches to flood frequency estimation. *J. Hydrol*. 2004, 292, 96–113
13. Tyralis, H.; Papacharalampous, G.A.; Tantanee, S. How to explain and predict the shape parameter of the generalized extreme value distribution of streamflow extremes using a big dataset. *J. Hydrol*. **2019**, 574, 628–645
14. Lima, C.H.R.; Lall, U.; Troy, T.; Devineni, N. A hierarchical Bayesian GEV model for improving local and regional flood quantile estimates. *J. Hydrol*. **2016**, 541, 816–823
15. Morrison, J.E.; Smith, J.A. Stochastic modeling of flood peaks using the generalized extreme value distribution. *Water Resour. Res.* **2002**, 38, 41-1–41-12
16. Kuzuha, Y.; Tomosugi, K.; Kishii, T.; Komatsu, K. Coefficient of variation of annual flood peaks: Variability of flood peak and rainfall intensity. *Hydrol. Process*. **2009**, 23, 546–558
17. Veneziano, D.; Langousis, A. Scaling and fractals in hydrology. In *Advances in Data-Based Approaches for Hydrologic Modeling and Forecasting*; Sivakumar, B., Berndtsson, R., Eds.; World Scientific: Singapore, 2010
18. Blöschl, G.; Sivapalan, M. Process controls on regional flood frequency: Coefficient of variation and basin scale. *Water Resour. Res*. **1997**, 33, 2967–2980
19. Vogel, R.M.; Sankarasubramanian, A. Spatial scaling properties of annual streamflow in the United States. *Hydrol. Sci. J*. **2000**, 45, 465–476
20. Wallis, J.R.; Schaefer, M.G.; Barker, B.L.; Taylor, G.H. Regional precipitation frequency analysis and spatial mapping for 24-hour and 2-hour durations for Washington State. *Hydrol. Earth Syst. Sci*. **2007**, 11, 415–442
21. He, J.; Anderson, A.; Valeo, C. Bias compensation in flood frequency analysis. *Hydrol. Sci. J***. 2015**, 60, 381–401.
22. Villarini, G.; Smith, J.A. Flood peak distributions for the eastern United States. *Water Resour. Res*. **2010**, 46
23. Villarini, G.; Smith, J.A.; Serinaldi, F.; Ntelekos, A.A. Analyses of seasonal and annual maximum daily discharge records for central Europe. *J. Hydrol*. **2011**, 399, 299–312
24. Villarini, G.; Smith, J.A.; Baeck, M.L.; Krajewski, W.F. Examining Flood Frequency Distributions in the Midwest, U.S. *J. Am. Water Resour. Assoc*. **2011**, 47, 447–463
25. Lins, H.; Slack, J. Streamflow trends in the United States. *Geophysical Research Letters*. **1999**, 26(2), 227–230
26. Mallakpour, I.; Villarini, G. The changing nature of flooding across the central United States. *Nature Climate Change.***2015**, 5(3), 250–254
27. Villarini, G.; Serinaldi, F.; Smith, J. A.; Krajewski, W. F. On the stationarity of annual flood peaks in the continental United States during the 20th century. *Water Resources Research.* **2009**, 45(8), W08417
28. Kundzewicz, Z. W.; Kanae, S.; Seneviratne, S. I.; Handmer, J.; Nicholls, N.; Peduzzi, P.; Mechler, R.; Bouwer, L. M.; Arnell, N.; Mach, K.; Muir-Wood, R.; Brakenridge, G. R.; Kron, W.; Benito, G.; Honda, Y.; Takahashi, K.; Sherstyukov, B. Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal*. **2014**, 59(1), 1–28
29. Coles, G.S. *An Introduction to Statistical Modeling of Extreme Values*; Springer: New York, NY, USA, 2001
30. Dey, D.K.; Roy, D.; Yan, J. Univariate Extreme Value Analysis. In *Extreme Value Modeling and Risk Analysis, Methods and Applications*; Dey, D.K., Yan, J., Eds.; CRC Press: Boca Raton, FL, USA, 2016; pp. 1–2
31. Stedinger, J.R.; Vogel, R.M.; Foufoula-Georgiou, E. Frequency Analysis of Extreme Events. In *Handbook of Hydrology*, 1st ed.; Maidment, D.R., Ed.; McGraw Hill Education: New York, NY, USA, 1993; pp. 18.1–18.66
32. Hosking, J.R.M.; Wallis, J.R. *Regional Frequency Analysis*; Cambridge University Press: New York, NY, USA, 1997
33. Koutsoyiannis, D. Statistics of extremes and estimation of extreme rainfall: I. Theoretical investigation. *Hydrol. Sci. J*. **2004**, 49, 575–590
34. Falcone, J. *GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow;* U.S. Geological Survey: Reston, Virginia, USA, 2011
35. Jiang, B. A New Classification Scheme for Data with a Heavy-Tailed Distribution. *The Professional Geographer*. **2012**, 65(3).
36. Gilleland, E.; Katz, R.W. extRemes 2.9: An extreme value analysis package in R. *J. Stat. Softw*. **2016**, 72
37. Gupta, V.K.; Waymire, E. Multiscaling properties of spatial rainfall and river flow distributions. *J. Geophys. Res*. **1990**, 95, 1999–2009
38. Burlando, P.; Rosso, R. Scaling and multiscaling models of depth-durationfrequency curves for storm precipitation. *J. Hydrol*. **1996**, 187, 45–64
39. Addor, N.; Nearing, G.; Prieto, C.; Newman, A.J.; Le Vine, N.; Clark, M.P. A ranking of hydrological signatures based on their predictability in space. *Water Resources Research*. **2018**. <https://doi.org/10.1029/2018WR022606>
40. Gvoždíková, B.; Müller, M. Evaluation of extensive floods in western/central Europe. *Hydrol. Earth Syst. Sci*. **2017**, 21, 3715–3725
41. Simon, A.; Rinaldi, M. Channel instability in the loess area of the mid-western United States. *Journal of the American Water Resources Association*. **2000**, 36(1), 133-150
42. Johnson, P.A. Physiographic Characteristics of Bridge-Stream Intersections. *River Research and Applications*. **2006**, 22(6), 617-30
43. Flint, M.; Oliver, F.; Billington, S. L.; Freyberg, D.; Diffenbaugh, N.S. Historical Analysis of Hydraulic Bridge Collapses in the Continental United States. *Journal of Infrastructure Systems*. **2017**, 23(3)
44. US Code of Federal Regulations. *Bridges, Structures and Hydraulics*; US Code of Federal Regulations: 2009