Insuring Against Hurricanes: What is to be gained for Caribbean Islands to Join a Cross-Country Insurance Scheme?

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Hurricanes cause considerable losses in the Caribbean and have been shown to be detrimental to economic growth. We investigate the extent to which natural catastrophe risk can be diversified across Caribbean countries in a common pool, and thus the advantages of entering a cross-country risk insurance scheme like the Caribbean Catastrophe Risk Facility. To this end we use over 150 years of historical hurricane track data and a loss estimation model for Caribbean islands to produce a distribution of losses in the region. As the hurricane losses are rare events with heavy tails, we model their dependence across islands by experimenting with various multivariate peaks over threshold (POT) models, identifying their di_erences. The results are then used to evaluate the risk contributions of each of the countries to the overall risk of the pool, and to asses the role that model uncertainty can play in pricing catastrophe risk.

1 Objectives

Extreme climate has resulted in nearly US$3 trillion worth of damages globally over the last 35 years.[1] Worryingly, not only are developing economies the most geographically exposed to these events, but they are also much less resilient to the subsequent losses, having little reserve funds, limited disaster preparation, and scarce access to insurance markets. As a response, a number of cross-country insurance schemes have been introduced to allow countries within certain regions to pool their risk and hence lower the cost of insurance coverage, such the Caribbean Catastrophe Risk Insurance Facility (CCRIF) and the African Risk Capacity (ARC). Despite the general enthusiasm regarding these products and plans to introduce new ones[2], such as the Pacific Catastrophe Risk Assessment and Financing Initiative (PCRAFI), there appears to be little reliable quantitative understanding as to their actual potential for diversification of risk.

In this paper we analyze the extent to which natural catastrophe risk is diversifiable across countries or systemic. To this end we use hurricane losses across islands in the Caribbean. Employing analytical tools from the systemic risk literature, we further evaluate the contribution of each island to the pooled risk of the Caribbean. This calculation could form the basis for setting a premium for each country. Finally, by considering different models of the cross-island dependence of hurricane risk, we empirically assess the possible role that model risk can play in the evaluation of the hurricane risk pooled across the region, in the calculation of insurance premia, and on the pricing of a cat bond written on the risk of the pool.

Arguably, losses due to hurricanes in the Caribbean present an ideal case study for the task at hand. More specifically, the region is subject on average to about six hurricane strength storms per year, and these can cause considerable losses due to their strong winds, storm surge, and associated excessive rainfall. Importantly,

[1] See e.g. World Bank (2013)
[2] See e.g. World Bank (2014)

the small island economies in the Caribbean are particularly vulnerable to such large natural shocks due to their small physical size, geographic isolation, limited natural resources, rapid population growth, high population densities, low economic diversification, and poorly developed infrastructure, and thus would find it expensive to insure against these.[3] At the same time, the islands are spread across a large enough spatial area so that the correlation of losses due to hurricanes is likely to be far from perfect.

Among the requisites of an ideally insurable risk, Schmit (1986) lists having a large number of homogeneous exposure units, independence among them, and the avoidance of catastrophic potential. In this paper we empirically analyze the risks of hurricane destruction in the Caribbean, which violate all three of these requisites: there are only 31 island groups (16 that joined the CCRIF), which are not homogeneous in size nor exposure; the risk is dependent across islands; and moreover the risk is catastrophic, in that events are rare and extreme, and are best described by a distribution with fat tails. The extent to which natural disaster risk can be diversified across a pool is the subject of an ongoing discussion in the literature, see, e.g., Froot (2001) who analyzes potential reasons for the failure of insurance markets in the presence of catastrophe risk. For instance in the case of crop insurance, Miranda & Glauber (1997) argue that systemic weather risk induces dependence and can cause crop insurance markets to fail, whereas in a framework with Gaussian risks, Wang & Zhang (2003) argue that the spatial correlation is not strong enough for such a failure. Duncan & Myers (2000) show how catastrophic risk increases the cost and coverage of crop insurance and can lead to a complete breakdown of the market. More recently, Ibragimov, Jaffee & Walden (2009) show that when independent catastrophic risks have heavy left tails, such as arise under, e.g., power law distributions, insurance markets might fall into a “nondiversification trap”, where insurance providers choose not to offer insurance and not to participate

[3] See Meheux, Dominey & Lloyd (2007).

in reinsurance, even though there is sufficient capacity in the market for full risk sharing.

In this study our first objective is to evaluate how systemic hurricane risk is and whether there is scope for diversification. Obviously, for an investor or insurer with infinitely deep pockets, there is no risk that is systemic. To assess whether risk is diversifiable, one needs to evaluate the capital buffer that is required to cover the risk with a large enough probability. There are many different insurance principles that can be used to compute a premium or a risk contribution, but the most relevant in our context are Value-at-Risk (VaR) and expected shortfall (ES). More precisely, VaR is the quantile of the loss distribution for a low enough threshold probability, and as such, it can be linked to the size of the capital buffer that is required to avoid bankruptcy in case of extreme losses, much in the same way as banks' regulatory capital charges depend on the VaR of their portfolio of assets. In contrast, expected shortfall is a tail expectation, which measures the expected loss conditional on a loss in excess of the VaR.

Our second objective is to evaluate the contribution of each country to the overall risk of a pool of all countries. From the analytical point of view, this question can be answered using methodology proposed recently in the systemic risk literature (for a recent review of this literature, see, e.g., Bisias & Valavanis 2012, Benoit, Colliard, Hurlin & Pérignon 2017). The most prominent examples are the conditional Value-at-Risk (CoVar), proposed by Adrian & Brunnermeier (2016), systemic expected shortfall (SES) and marginal expected shortfall (MES) of Acharya, Pedersen, Philippon & Richardson (2017), and SRISK introduced by Acharya, Engle & Richardson (2012) and Brownlees & Engle (2017). These methods all rely on estimating either the quantile of one contributor, conditional on an extreme aggregate event, to measure how sensitive a contributor is to aggregate risk, or the quantile of the aggregate conditional on an extreme event of each contributor.

Finally, we want to assess the importance of model risk in evaluating the scope for diversification of hurricane damage. This will also give an insight into the pricing of cat bonds, which requires as an input the multivariate distribution of damages across countries. The issue of parameter uncertainty for cat bonds was first considered in a simulation study by Froot & Posner (2002), who find that the sensitivity of the pricing of catastrophe risk to parameter uncertainty is not very large. In contrast, Woodard, Paulson, Vedenov & Power (2011) show how the choice of copula can strongly influence risk analysis for crop insurance. In our setup, model risk stems from the uncertainty about the right dependence model. Different models of dependence will lead to different ways of pricing catastrophe risk, which should lower the valuation of such risks for an ambiguity-averse investor (see, e.g., Kunreuther, Meszaros, Hogarth & Spranca 1995). Our aim here is to estimate a joint distribution of losses due to hurricanes for all countries in the Caribbean. To this end we use a peaks over threshold (POT) model for the distribution of losses in any given country, and copulas to build a joint distribution for these losses. From the methodological point of view this is a multivariate extension of the approach used by Longin & Solnik (2001) to model pairs of stock index returns, which relied on statistical methodology by Ledford & Tawn (1996). The extension from the bivariate to the large-dimensional multivariate case, however, is not an easy step. In particular, it opens the way to a large number of different possible models, all of which might suffer from misspecification. This underlying uncertainty about the correct model can introduce severe model risk, and we will evaluate this explicitly.

2 Methodology and research design

2.1 Risk premium

While there are a number of measures that can be used to assess risks, and the amount of risk reduction that diversification affords, we rely on value-at-risk (VaR) and expected shortfall (ES), also called conditional VaR (CVaR). Classical principles for calculating risk premia include the fair premium, which corresponds to the expected loss, and the standard deviation (variance) principle, where a linear function of the standard deviation (variance) is added to the fair premium; see Brillinger (1993) for a discussion in the context of earthquake insurance, and Grossi & Kunreuther (2005) for a general discussion of risk premium calculation for catastrophe insurance.[4] Some of these alternative ways of assessing risks can be problematic, for instance in the case of risks with fat tails, where even low order moments, such as the average, the standard deviation or the expected utility under the loss might not be defined.[5]

For a threshold probability α, VaR_α is defined as the α-quantile of the risk distribution: $P(L \geq VaR_\alpha) = \alpha$. As shown by Gouriéroux, Laurent & Scaillet (2000), the sensitivity of the VaR of a portfolio $L = \sum_i w_i L_i$ of individual losses L_i to the portfolio weight w_i, of risk i (which, in our case, is 1) can be computed as follows:

$$\frac{\partial VaR_\alpha}{\partial w_i} = E[L_i | L = VaR_\alpha]. \tag{1}$$

Given that VaR is homogeneous of degree one in portfolio weights, using Euler's theorem one can decompose the VaR of a portfolio into the contributions of each constituent to the overall VaR, as follows (see e.g. Hallerbach 2002):

$$VaR_\alpha = \sum_i E[L_i | L = VaR_\alpha]. \tag{2}$$

A similar exercise can be done with ES, which is defined as the expected loss,

[4] VaR has been used in the context of crop insurance by e.g. Wang & Zhang (2003) in the U.S., and more recently by Shen, Okhrin & Odening (2016) in China.

[5] Alternatively, the actuarial literature also uses the probability of ruin as a way of determining premia (for a discussion of different principles for the calculation of risk premia in the actuarial literature, see, e.g., Kaas, Goovaerts, Dhanene & Denuit 2008) or premia can also be computed by specifying preferences and using an expected utility framework, such as with a CRRA assumption. For an example of preference-based flood insurance premia calculations in the Netherlands, see Paudel, Botzen & Aerts (2013).

conditional on a VaR exceedance: $ES_\alpha = E[L|L \geq VaR_\alpha]$. As shown in Gouriéroux et al. (2000), and in Acharya et al. (2017), the ES of a portfolio of individual losses L_i can be decomposed as follows:

$$ES_\alpha = E[L|L \geq VaR_\alpha] = \sum_i E[L_i|L \geq VaR_\alpha], \tag{3}$$

where the Marginal Expected Shortfall (MES) is the sensitivity of the portfolio ES to the weight, w_i of risk i:

$$MES_\alpha = \frac{\partial ES_\alpha}{\partial w_i} = E[L_i|L \geq VaR_\alpha]. \tag{4}$$

As is well-known, ES presents the advantage over VaR that it is a coherent measure, since, unlike VaR, it is sub-additive, which means that the sum of the ES of two portfolios of risks is necessarily greater than the ES of the combined portfolios (see Artzner, Delbaen, Eber & Heath 1999). Moreover, MES, the contribution to the portfolio ES is much easier to compute and analyze than the contribution to the portfolio VaR, since the former conditions on an event that can be observed ($L \geq VaR_\alpha$), while the latter conditions on a null-event ($L = VaR_\alpha$), see Mainik & Schaanning (2014). Our approach is close to that of Huang, Zhou & Zhu (2012), who compute individual banks' marginal contribution to a systemic risk indicator measured by the price of insurance against systemic financial distress. We will compute the contributions to overall VaR and ES by simulation under the different joint distributions of hurricane losses we will estimate; see, e.g., Glasserman (2005), who devises efficient simulation methods for the calculation of risk contributions in a credit risk setting, based on importance sampling.

To assess the scope for diversification, we can compare the VaR and ES of the pool to the sum of VaR and ES of each of the countries in the pool: $\frac{VaR_\alpha(L)}{\sum_i VaR(L_i)}$ and $\frac{ES_\alpha(L)}{\sum_i ES(L_i)}$. Likewise, we can evaluate the benefits of each country from joining the pool by comparing their risk measures to their contribution to the risk measure of the pool: $\frac{E[L_i|L=VaR_\alpha]}{VaR(L_i)}$ and $\frac{E[L_i|L\geq VaR_\alpha]}{ES(L_i)}$.

2.2 Marginal model: peaks over thresholds (POT)

Before modelling the dependence between hurricane damage in the Caribbean, we estimate marginal models for hurricane losses in each island in the Caribbean. It is common practice to model the probabilities of relatively rare occurrences using extreme value theory, see for instance Jagger & Elsner (2006) for hurricane wind modeling. One result of Extreme Value Theory (EVT) is that there are three possible limit distributions for maxima of independent random variables: the Fréchet, the Gumbel and the Weibull, which can all be cast within the Generalized Extreme Value (GEV) family. Depending on the value of their exponent, they have finite tails, exponential or power tails. A standard approach in this regard is the Peaks Over Threshold (POT) model, based on the Pickands Balkema de Haan theorem, which states that for a large class of distributions exceedances over a high threshold m are well approximated by a Generalized Pareto Distribution (GPD), which is characterized by a scale parameter σ and by a shape parameter ζ, whose value corresponds to the tail parameter as the GEV.

We thus consider that for each territory i, the distribution of hurricane losses L_i, can be approximated as follows:

$$P(L_i \leq x) = \begin{cases} (1 - F_{i,n}(m_i)) \left(1 - \left(1 + \zeta \frac{x - m_i}{\sigma_i}\right)_+^{-1/\zeta_i}\right) & \text{whenever } x \geq m_i \\ F_{i,n}(m_i) & \text{whenever } x < m_i, \end{cases} \tag{5}$$

where $z_+ = \max(0, z)$, and $F_n(x) = \frac{1}{n}\sum_j \mathbb{1}_{\{L_{ij}\leq x\}}$ is the empirical distribution, based on the sample $(L_{i1}, \ldots, L_{in})$. A negative value of the shape parameter ζ_i implies that the distribution has an upper bound of $-1/\zeta_i$, while, when $\zeta_i = 0$, the distribution has a thin tail with exponential decay (like e.g. the normal distribution), and when $\zeta_i > 0$, the distribution has a fat tail, with power decay (like, e.g., the Student t).

2.3 Multivariate POT models

Since we are interested in the scope for insurance, it is important to take account of the dependence in extremes that exists between the different islands/territories. Insurance will work best when events across territories are independent or negatively correlated. Copulas are the ideal tool to characterize the dependence between a number of marginal distributions. They rely on the Sklar (1959) theorem, which shows how a joint distribution can be decomposed into the product of the marginals and a copula term that captures the dependence among them. Copulas have been used in the context of systemic risk in contexts with a catastrophic component, see, e.g., Goodwin & Hungerfors (2014) use copula to model the systemic risk in crop insurance.

Our aim is to build a multivariate density of extreme losses for all the islands in the Caribbean. We will consider a number of different parametric copula models to join the individual POT models into a proper multivariate distribution of hurricane losses:

2.3.1 Gaussian copula

This is the first and the simplest dependence model that comes to mind. Even though, from a theoretical point of view, the Gaussian copula cannot obtain as an extreme value distribution, it has been used for multivariate extreme value analysis by Renard & Lang (2007). Padoan, Ribatet & Sisson (2010) also use a Gaussian copula in a bivariate composite likelihood approach for spatial extremes. We can estimate this copula under increasingly general assumptions: equicorrelation, where the correlation between all islands is the same, with a factor structure, or an unrestricted correlation matrix.

2.3.2 Student t copula

The multivariate Student t distribution generalizes the Gaussian. While it is possible to entertain the same assumptions on the correlation as in the Gaussian case, the t allows for dependence in the extremes in the form of tail dependence.

2.3.3 Gumbel copula (logistic model)

This is the classical "work horse" model in the case of bivariate extremes, but it is more difficult to handle in a high-dimensional context. Tawn (1990) shows that in its most general form, the d-dimensional multivariate asymmetric logistic (Gumbel) distribution is a sum over all partitions, B of the set of indices $(1, \ldots, d)$. Stephenson (2009) proposes MCMC estimation methods of the (possibly) high-dimensional asymmetric logistic model. Hofert, Mächler & McNeil (2012) show how to efficiently evaluate a high-dimensional Gumbel copula.

2.3.4 Extreme-Value t copula

The multivariate EV-t copula of Demarta & McNeil (2005) is the theoretical extreme-value limit of the Student t copula.

2.3.5 Vine copulas

Vine copulas decompose a joint distribution into a number of iteratively conditioned bivariate copulas, according to a tree structure. The tremendous flexibility of vine copulas rests on the fact that the tree structure and the bivariate copula building blocks can be chosen arbitrarily and combined at will. This class of models is very large, and seems like a promising avenue for modeling multivariate extremes. Depending on the tree of conditioning, one obtains canonical vines (C-vines), which are based on a pivot country (as in a factor model), the dependence of which is computed with all other countries, or a D-vine, where bivariate copulas are used for dependence among neighboring countries, where countries are placed in a chain. R-vines combine structures from both D-vines and C-vines. D-vines seem especially suited to the structure of our island data, since their tree structure involves modeling dependence between neighbors. They have been used, e.g., by Schulte & Schumann (2015) to model spatial flooding in three locations.

2.3.6 Hierarchical Archimedean copulas

Hierarchical Archimedean copulas (HACs) imply equidependence inside and across groups and are restricted to positive dependence. They are defined on a tree structure, and their specification and estimation has been discussed by Okhrin, Odening & Xu (2013*a*). They were used in the context of insurance by Okhrin, Odening & Xu (2013*b*).

3 Data description

3.1 Study Region

Our study group are the 31 Caribbean islands (groups) located in the North Atlantic Basin. These include both politically independent islands as well as special territories. As can be seen in Figure 1, the islands differ substantially in size and are spread over a relatively wide geographic area.

3.2 Hurricane Data

Our hurricane data is taken from the HURDAT database. which is the most comprehensive database of all tropical cyclones in the Atlantic Ocean, Gulf of Mexico and Caribbean Sea, since 1851 and provides, among other things, information on the location of the storm center and maximum wind speed at 6 hourly intervals. To show the exposure of the region to hurricanes we depict all tropical storms over our sample period, 1851-2014, that reached hurricane strength at least at some point over their life time, in Figure 2. As can be seen, there have been a large number of storms (893) that have traversed the region over the 161 year period. Clearly, however, some islands were more exposed to storms than other. In order to derive a distribution of losses for the islands we make the assumption that the probability distribution that can be derived from the historical storms is stable over time and thus can be seen as representative of the possible distribution of storms today and the intermediate future.[6] Each storm thus presents a possible realization from this distribution and can be used to predict losses across islands given its characteristics.

3.3 Loss Estimation Model

To associate the possible losses that the hurricanes given in HURDAT would induce per island if they were to happen today, we use CCRIF's Second-Generation Hazard and Loss Estimation Model (2G Model). Under this model, for any given storm, first storm and site specific characteristics are used to calculate local (at a 30 arc-seconds cell size) winds and storm surge within islands in response to an event. These are then translated into damages using local exposure data and damage functions. Importantly, the exposure data consists of locally estimated asset values at risk (also at 30 arc-seconds) and thus allows the generation of estimated losses in monetary terms by considering asset exposure and explicit damage functions.[7] More precisely, for each 30 arc-second grid cell the number of dwelling units is computed from population data, land cover information is used to infer construction types and non-residential exposure, and infrastructure is estimated using the

[6]There are of course concerns about hurricanes changing in frequency and intensity with climate change; see Walsh, McBride, Klotzbach, Balachandran, Camargo, Holland, Knutson, Kossin, Lee, Sobel & Sugi (2016). However, using synthetic tracks derived under different climate change scenarios for the North Atlantic Basin, Emanuel (2011) shows that an increasing trend in damage increase is unlikely to emerge before the next 40 to 70 years.

[7]The underlying data sources are remotely sensed land cover, distributed population estimates, and national and sectoral economic data.

density and distribution of building types, while the agricultural component in the loss estimation is estimated using land cover data and agriculture's contribution to a country's GDP. Each asset class (residential, non-residential, and infrastructure) is then subject to a damage function associated with each type. Finally, all asset losses are aggregated at the national level for each storm.

4 Preliminary Results and Expected output

4.1 Some preliminary results

We use the 893 tropical storms that traversed the Caribbean region over our sample period as inputs into the the 2G Hazard and Loss Estimation Model described above. Of these 579 produced positive losses across islands. Estimated total losses were on average 224 million US dollars, with a standard deviation of 889 million. On average each damaging storm affected about 3 islands (standard deviation of 3), with one storm affecting up to 22 islands.

We also investigate the risk profile of individual islands by estimating univariate POT models. To this end, we first determine the threshold above which a loss is considered as extreme. To do so, we follow standard practice and examine mean residual plots, where the different thresholds are plotted against the empirical estimates of tail expectations.[8] Given that there are only relatively few hurricane events, we set the threshold in such a way that we only leave out very small losses. This is roughly in agreement with the MRL plots shown in Figures A.1 to A.3 in Appendix A, which look reasonably linear from the very start. Using these thresholds we next estimated the univariate POT models, the estimates of which are displayed in Table 2. The results show that both hurricane series in most countries have pos-

[8]The idea underlying the use of the MRL plot is to find the threshold after which the plot is linear. This is because the tail expectation of a GPD is linear in the threshold, i.e., $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1\frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds.

itive, although not always significant, shape parameters, which indicates that the hurricane impact series have power tails, which decay slowly, implying that there is a non-negligible probability of extreme events. This is confirmed also by the convexity of the return plots for hurricane shown in Figures 3 to 5.

As a first step, before estimating the multivariate POT models, we investigate the correlation of risk across islands by simply calculating the pairwise dependence between the hurricane losses in the different islands. More specifically, Figure 6 displays the correlation matrix of the cumulative density functions, also known as probability integral (PIT), derived from the marginal POT models. These are the inputs into the multivariate copula model. Using a variant of k-nearest neighbor method, the series have been ordered in such a way that more correlated territories closer to each other. This highlights the underlying dependence structure in the data. As can be seen, some islands have very strong positive dependence, in particularly those that are geographically close. For instance, unsurprisingly, losses in Haiti are strongly positively correlated with those in the Dominican Republic, Jamaica, and Cuba. At the same time, there also exist negative correlation between some pairs of islands, hence scope for diversification. For instance, losses from hurricanes in Trinidad and Tobago, which is the most southern of the islands in the Caribbean, are negatively correlated with most other islands in the region, except for those geographically close, like some islands in the Eastern Caribbean. Nevertheless, distance is not a perfect predictor of correlation, as hurricanes often travel far distances across the Caribbean. For example, despite being nearly 2000 km away, Trinidad and Tobago's losses are positively correlated with those of Jamaica. These few examples readily demonstrate the complex nature of the nature of correlation of hurricane losses across the region.

We have already run some of the dependence models, for instance a hierarchical Archimedean copula (HAC) based on the Gumbel copula. We estimate the optimal structure of the dependence tree and the copula parameters as shown in Okhrin et al. (2013*a*). The structure of the dependence tree and the pairwise rank correlations are shown in Figure 7. Without any prior information about the geography of the islands, the HAC copula model divides the country into the that are the most homogeneous. Unfortunately, the HAC construction cannot handle negative dependence, and as such it is not capable of capturing the negative dependence that might be present between some countries, and which is beneficial in terms of risk mitigation.

4.2 Expected output and tables

We will estimate all the different copulas we mentioned above, and possibly some alternative ones. The output of these will result in a set of tables, although these will not be the main interest of the paper per se. The model estimates will then be used to compute the risk contributions of different country pools. The results of this exercise we will result in several tables such as Table 3, which lists overall VaR and ES for different pools of countries, as well as the risk reduction from pooling, under the different copula models. We will also produce an number tables like Table 4, which lists the risk contributions to VaR and ES of the different countries under the different dependence models.

5 Timeline of delivery

Table 1: Timeline

Completion date	**Task**
Completed	Process historical hurricane data and run Loss Estimation Model
Completed	Estimate Univariate POT models
September 2017	Estimate a number of different copula models. Check which ones are most suitable for large dimension
November 2017	Simulate from the models to estimate contributions to overall risk
February 2018	Define scenarios for different pool compositions
June 2018	First Draft of Paper
October 2018	Final Draft of Paper

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Figure 1: Caribbean Islands

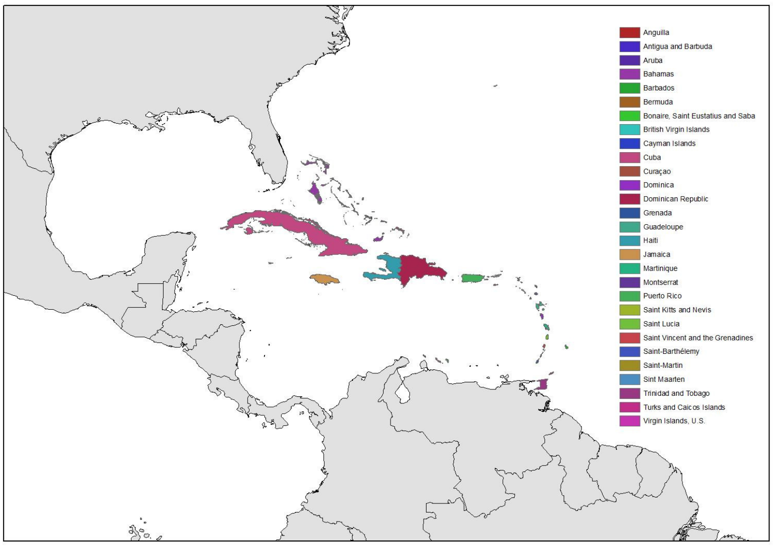


Figure 2: Hurricanes in the Caribbean, 1851-2012

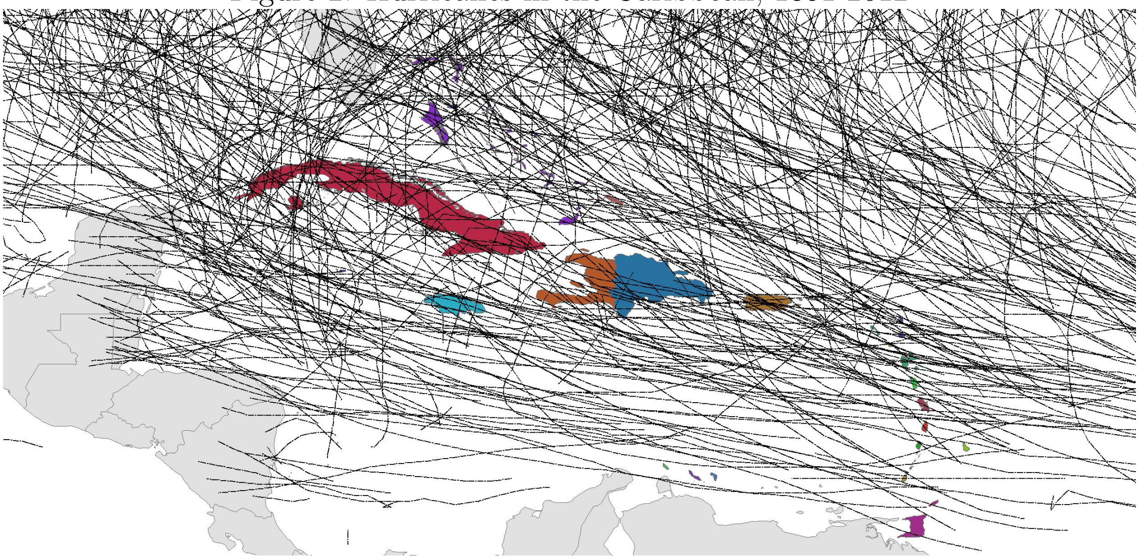


Figure 3: Return plots of peaks over threshold (POT) models, 1/3

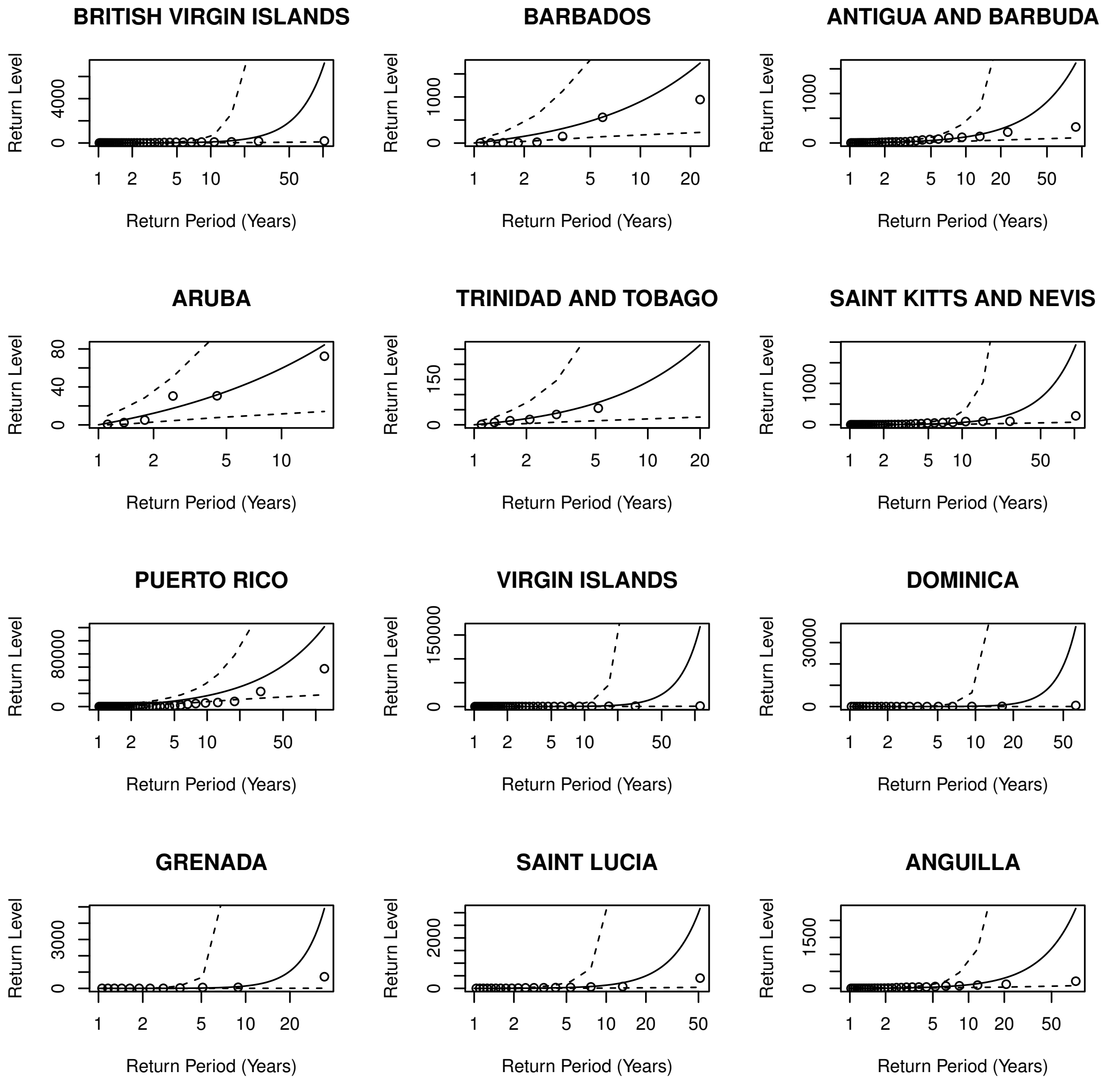


Figure 4: Return plots of peaks over threshold (POT) models, 2/3

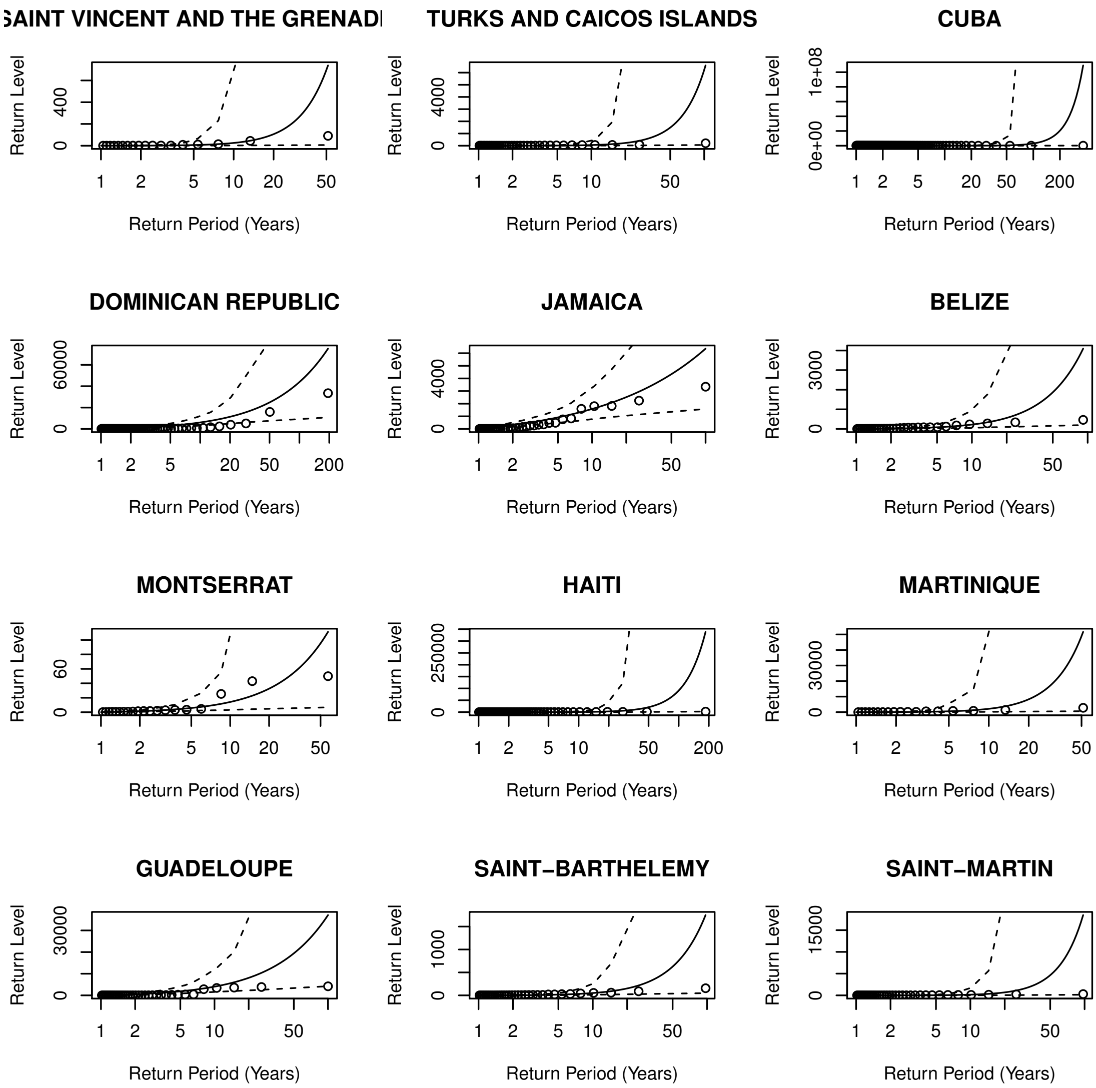


Figure 5: Return plots of peaks over threshold (POT) models, 3/3

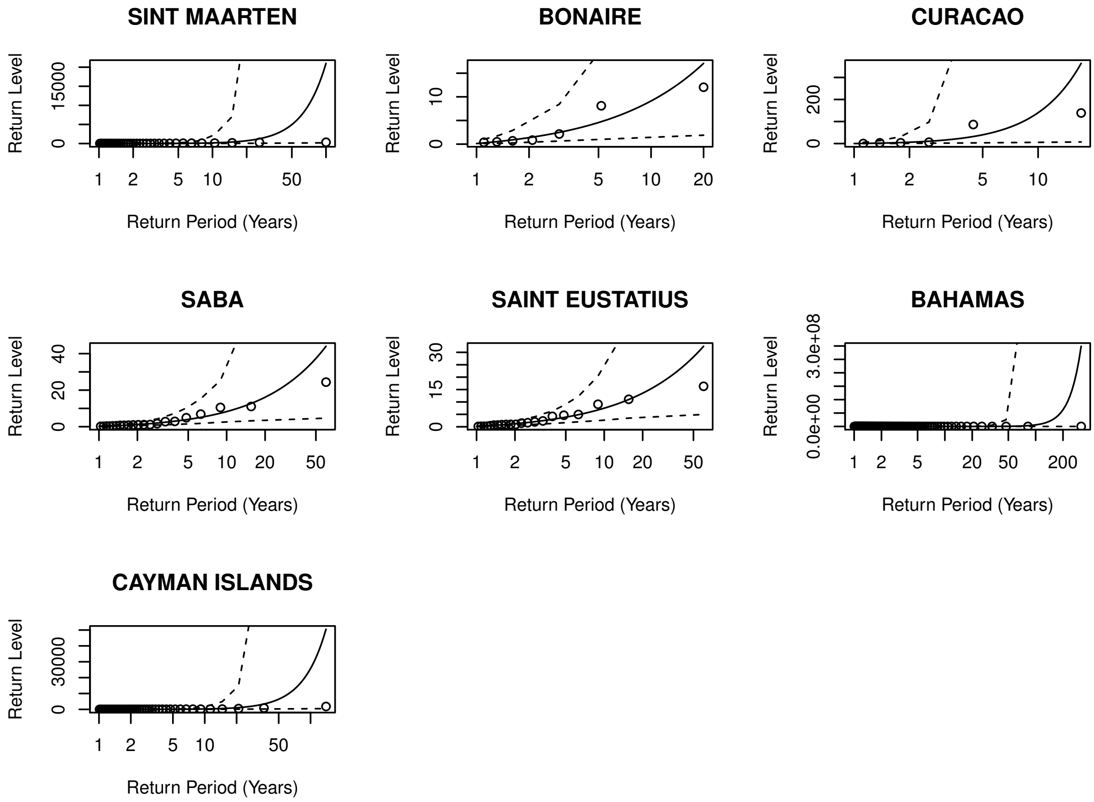
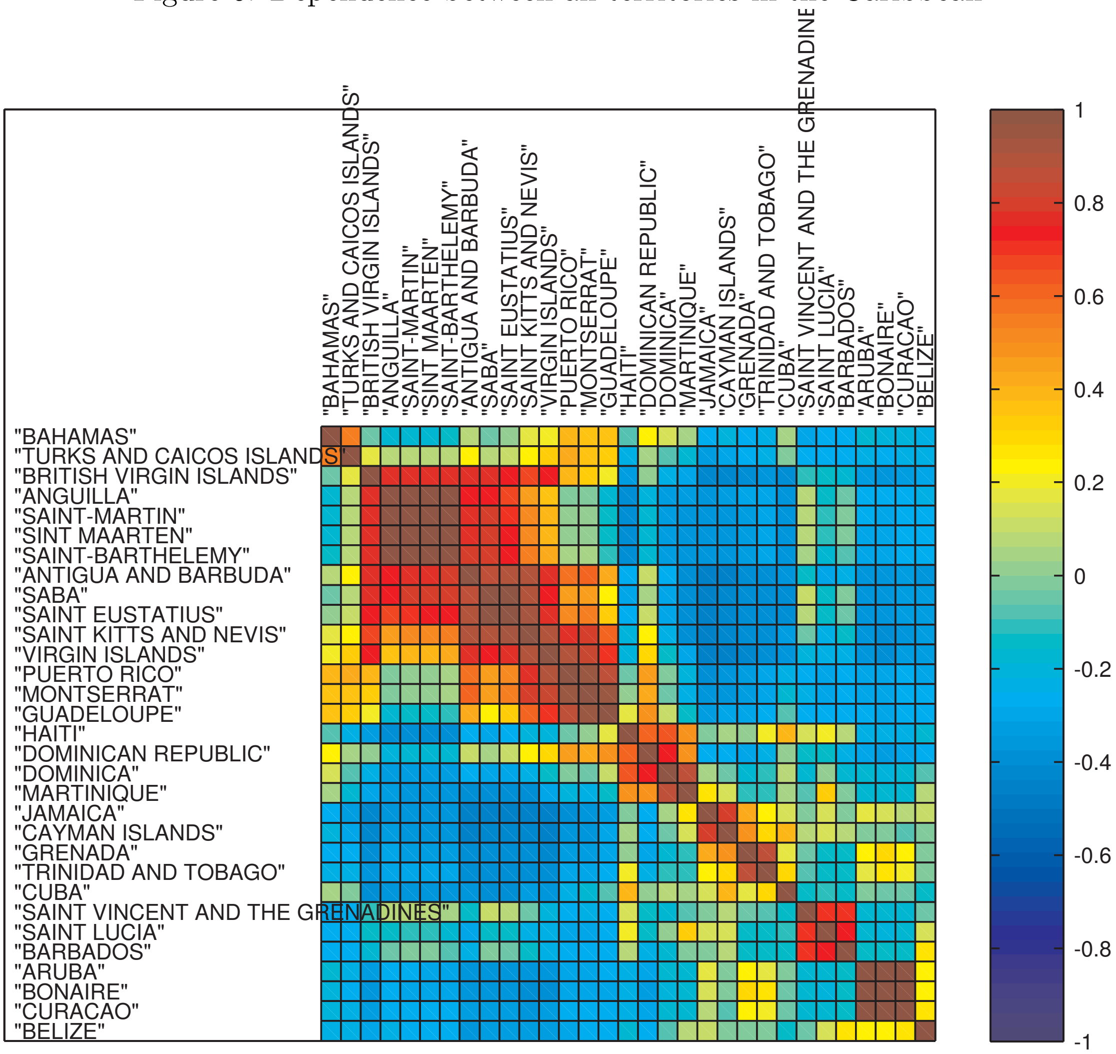
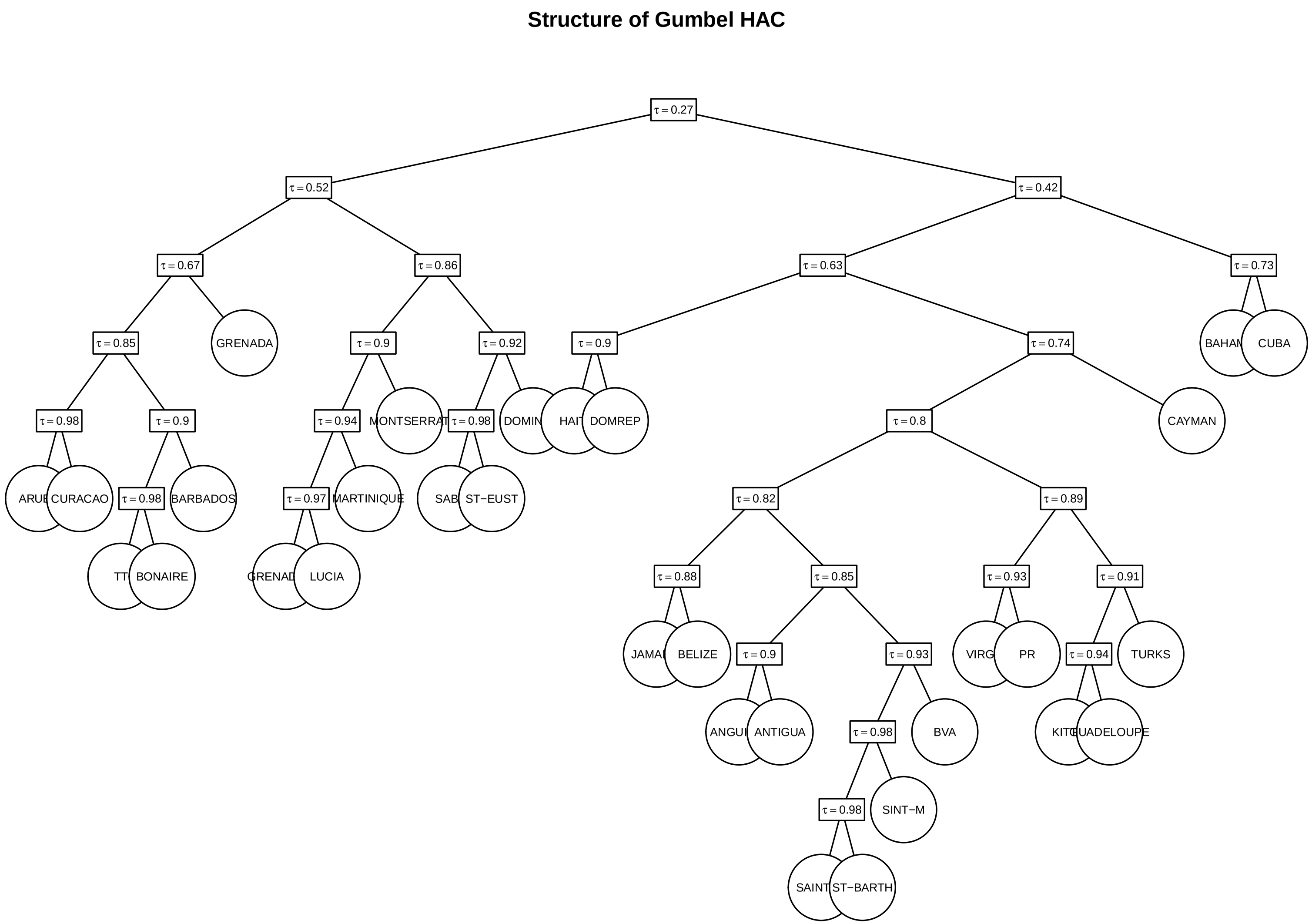


Figure 6: Dependence between all territories in the Caribbean



This figure displays the correlation matrix of the cumulative density functions derived from the marginal POT models. This assists in detecting the underlying dependence structure in the data. Using a variant of k-nearest neighbor method, the series have been ordered in such a way that more correlated territories closer to each other.

Figure 7: Dependence tree from Hierarchical Archimedean (HAC) model with Gumbel copulas, for all countries in the Caribbean



This figure displays the structure of the dependence tree and the pairwise rank correlations are shown of a hierarchical Archimedean copula (HAC) based on the Gumbel copula. We estimate the optimal structure of the dependence tree and the copula parameters as shown in Okhrin et al. (2013*a*).

Table 2: Parameters of the marginal peaks-over-threshold (POT) model

Country	N. exceed.	Prob. exceed.	Scale	Std error	Shape	Std error	LogL
BRITISH VIRGIN ISLANDS	36	0.08	0.00	0.00	1.86	0.51	-135.13
BARBADOS	8	0.02	0.00	0.00	0.66	0.59	-49.16
ANTIGUA AND BARBUDA	31	0.07	0.00	0.00	1.15	0.47	-140.29
ARUBA	6	0.01	0.00	0.00	0.43	1.27	-24.85
TRINIDAD AND TOBAGO	7	0.02	0.00	0.00	0.78	0.67	-34.12
SAINT KITTS AND NEVIS	36	0.08	0.00	0.00	1.50	0.42	-126.96
PUERTO RICO	42	0.10	0.00	0.00	0.73	0.27	-358.93
VIRGIN ISLANDS	39	0.09	0.00	0.00	2.35	0.56	-200.96
DOMINICA	22	0.05	0.00	0.00	2.92	0.93	-75.44
GRENADA	12	0.03	0.00	0.00	2.84	1.12	-39.98
SAINT LUCIA	18	0.04	0.00	0.00	1.96	0.77	-71.51
ANGUILLA	28	0.07	0.00	0.00	1.47	0.57	-116.84
SAINT VINCENT AND THE GRENADINES	18	0.04	0.00	0.00	2.05	0.79	-41.15
TURKS AND CAICOS ISLANDS	36	0.08	0.00	0.00	2.06	0.52	-108.74
CUBA	128	0.30	0.00	0.00	2.77	0.38	-887.03
DOMINICAN REPUBLIC	68	0.16	0.00	0.00	0.79	0.22	-501.67
JAMAICA	35	0.08	0.00	0.00	0.48	0.25	-241.49
BELIZE	32	0.07	0.00	0.00	1.29	0.51	-160.84
MONTSERRAT	20	0.05	0.00	0.00	1.15	0.46	-47.18
HAITI	65	0.15	0.00	0.00	2.13	0.44	-357.98
MARTINIQUE	18	0.04	0.00	0.00	1.94	1.63	-120.26
GUADELOUPE	35	0.08	0.00	0.00	0.91	0.32	-245.18
SAINT-BARTHELEMY	34	0.08	0.00	0.00	1.54	0.53	-114.93
SAINT-MARTIN	34	0.08	0.00	0.00	2.08	0.67	-139.95
SINT MAARTEN	35	0.08	0.00	0.00	2.08	0.64	-146.19
BONAIRE	7	0.02	0.00	0.00	0.80	0.72	-14.72
CURACAO	6	0.01	0.00	0.00	1.75	1.22	-25.41
SABA	21	0.05	0.00	0.00	0.88	0.42	-41.29
SAINT EUSTATIUS	21	0.05	0.00	0.00	0.74	0.44	-40.59
BAHAMAS	111	0.26	0.00	0.00	3.41	0.46	-612.57
CAYMAN ISLANDS	49	0.11	0.00	0.00	2.00	0.49	-226.64

This table displays the number of exceedances in each country, as well as the exceedance probability, the results for univariate POT models in Column (1). All models are estimated with maximum likelihood. The scale and shape parameters are marginal parameters of the POT model, and they correspond to parameters σ and ζ in Equation (5).

Table 3: Pooled risk with different dependence models

Dependence model	Panel A: Overall risk measures							
	Value-at-Risk				Expected shortfall			
	East	West	CCRIF	All	East	West	CCRIF	All
Gaussian								
Student t								
Extreme value Student t								
Hierachical Archimedean								
Vine copula								
etc.								
	Panel B: Ratio of pooled to sum of individual							
	Value-at-Risk				Expected shortfall			
	East	West	CCRIF	All	East	West	CCRIF	All
Gaussian								
Student t								
Extreme value Student t								
Hierachical Archimedean								
Vine copula								
etc.								

This table shows the Value-at-Risk and Expected Shortfall under different dependence models for 4 different pools of countries: (1) countries in the Eastern Caribbean; (2) countries i the Western Caribbean; (3) current members of the CCRIF cross-country insurance scheme; (4) All countries of the Caribbean. Panel A shows the value of the pooled risk measures, while Panel B contains the ratio of the pooled value to the sum of the risk measures of te individual countries.

Table 4: Risk contributions of the different islands under different dependence model

	Contribution to Value-at-Risk					Contribution to Expected Shortfall				
Country	Gaussian	t	EV-t	HAC	vine	Gaussian	t	EV-t	HAC	vine
BRITISH VIRGIN ISLANDS										
BARBADOS										
ANTIGUA AND BARBUDA										
ARUBA										
TRINIDAD AND TOBAGO										
SAINT KITTS AND NEVIS										
PUERTO RICO										
VIRGIN ISLANDS										
DOMINICA										
GRENADA										
SAINT LUCIA										
ANGUILLA										
ST VINCENT & GRENADINES										
TURKS & CAICOS										
CUBA										
DOMINICAN REPUBLIC										
JAMAICA										
BELIZE										
MONTSERRAT										
HAITI										
MARTINIQUE										
GUADELOUPE										
SAINT-BARTHELEMY										
SAINT-MARTIN										
SINT MAARTEN										
BONAIRE										
CURACAO										
SABA										
SAINT EUSTATIUS										
BAHAMAS										
CAYMAN ISLANDS										

This table shows the risk contributions of the different countries to overall VaR and Es under different dependence models.

Appendices

A Peaks over threshold models

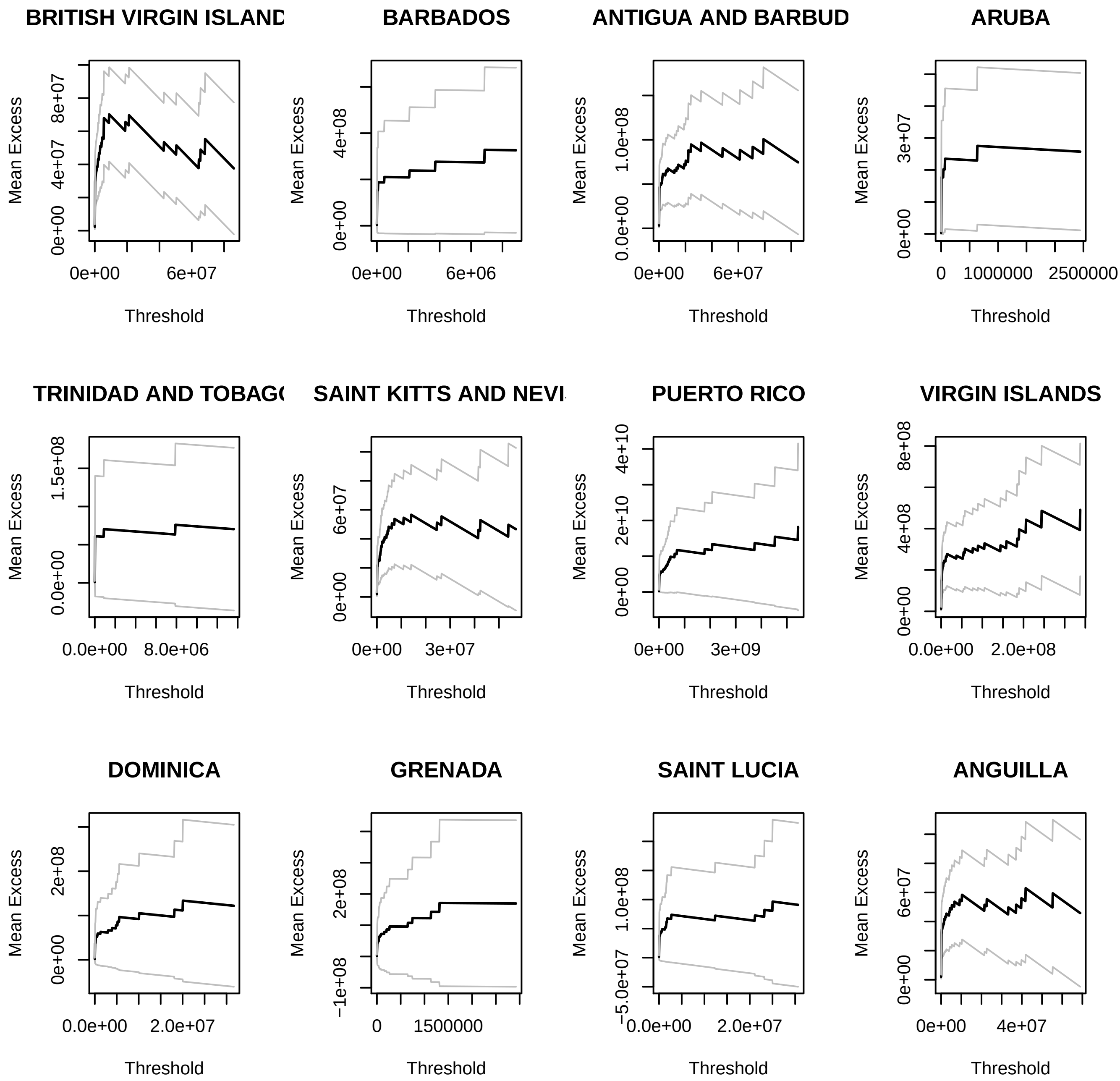


Figure A.1: Threshold choice and mean residue plots, 1/3
This figure shows Mean Residual (MRL) plots for hurricane. The plots show tail expectation $E[Y - m|X > m]$ for different values of the threshold m. The idea underlying the use of the MRL plot is to find the threshold after which the plot is linear, since a defining feature of the GPD is that its tail expectation is linear in the threshold: $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1\frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds.

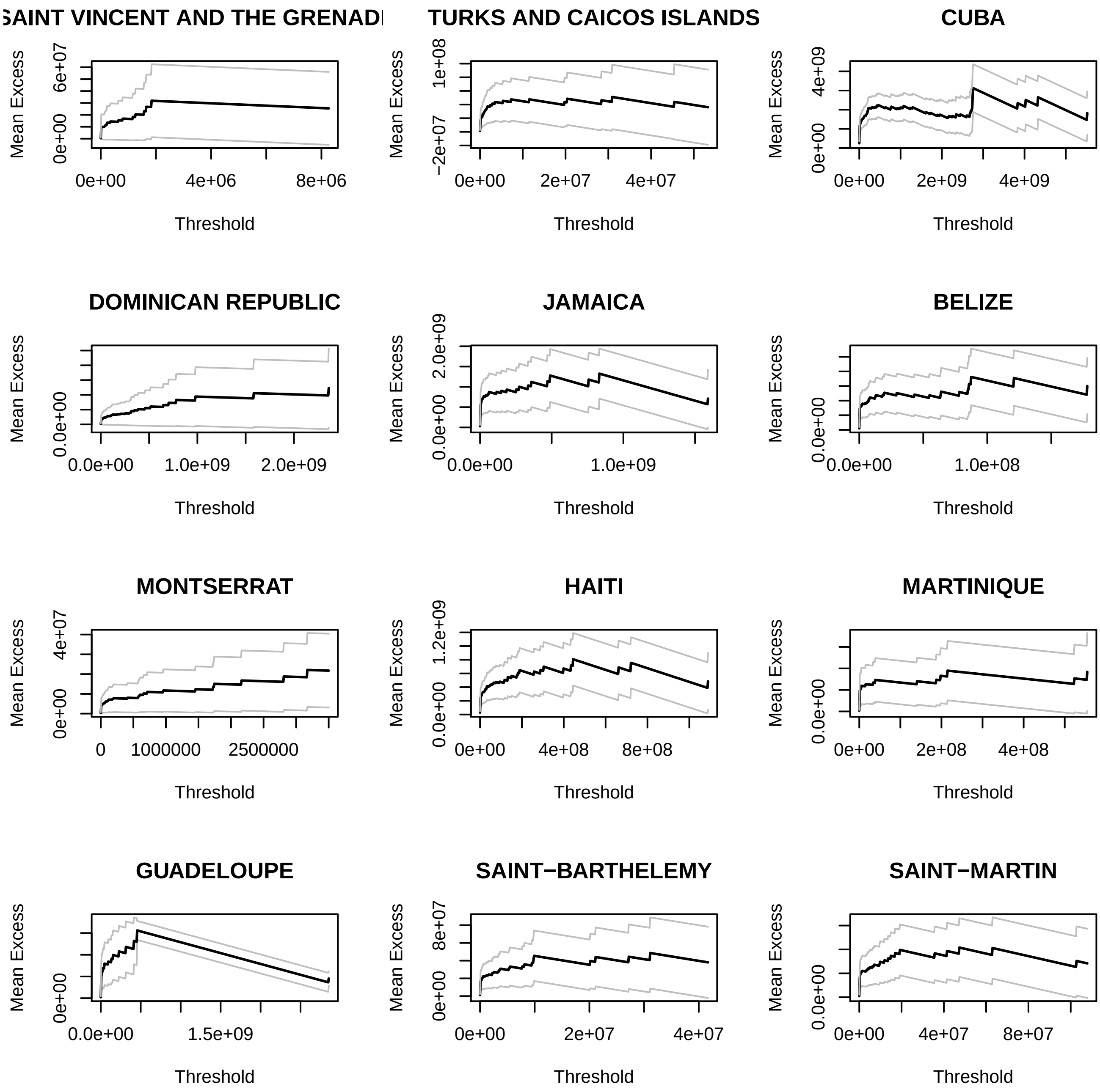


Figure A.2: Threshold choice and mean residue plots, 2/3

This figure shows Mean Residual (MRL) plots for hurricane. The plots show tail expectation $E[Y - m|X > m]$ for different values of the threshold m. The idea underlying the use of the MRL plot is to find the threshold after which the plot is linear, since a defining feature of the GPD is that its tail expectation is linear in the threshold: $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1 \frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds.

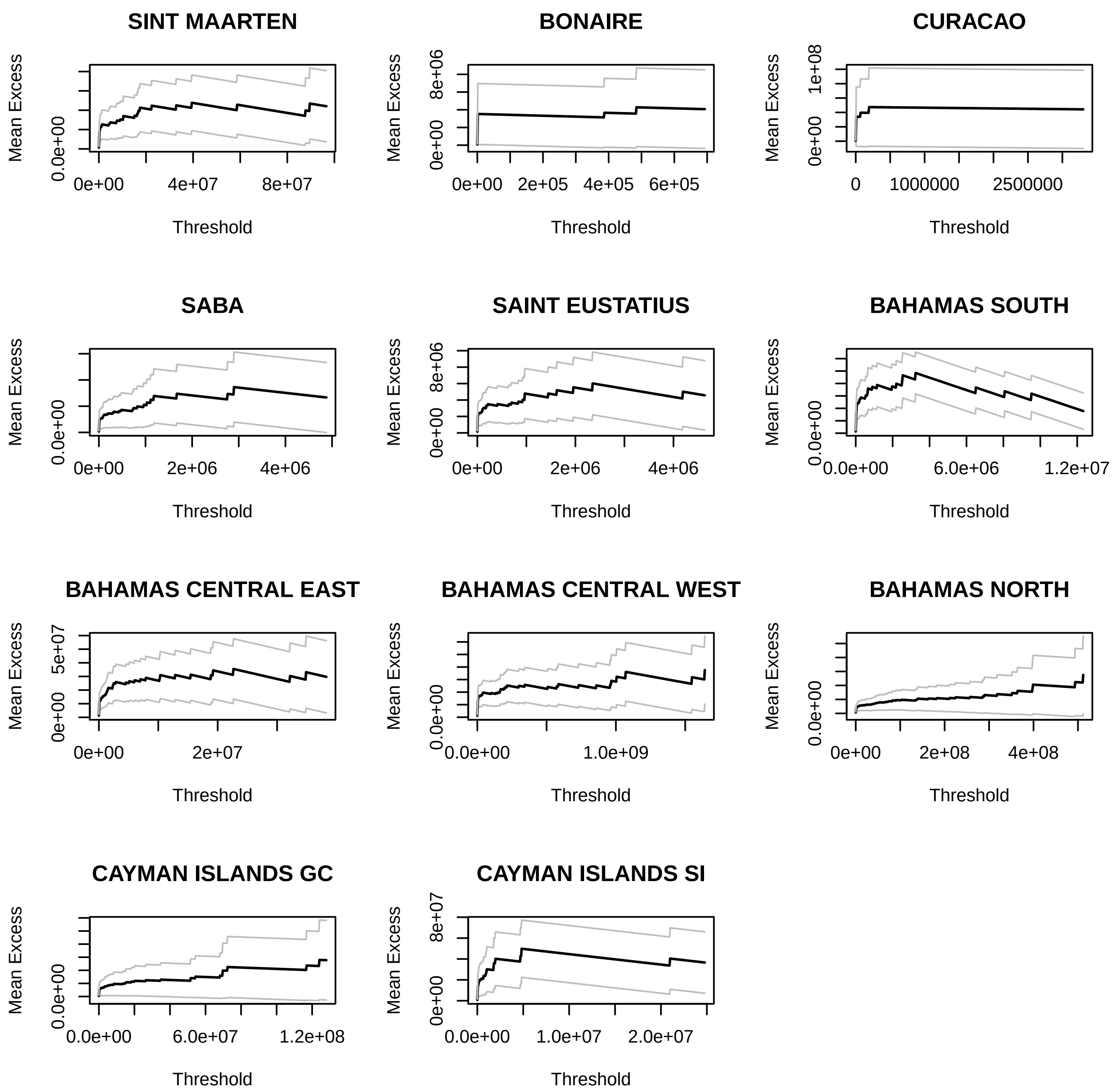


Figure A.3: Threshold choice and mean residue plots, 3/3
This figure shows Mean Residual (MRL) plots for hurricane. The plots show tail expectation $E[Y - m|X > m]$ for different values of the threshold m. The idea underlying the use of the MRL plot is to find the threshold after which the plot is linear, since a defining feature of the GPD is that its tail expectation is linear in the threshold: $E[Y - m_1|Y > m_1] = E[Y - m_0|Y > m_0] + m_1 \frac{\zeta}{1-\zeta}$ where $Y \sim GDP(m_0, \sigma_0, \zeta)$, and $m_1 > m_0$ are thresholds.