An Integration and Assessment of Nonstationary Storm Surge Statistical Behavior

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Introduction

- Storm surge is a key driver of uncertainty in future coastal hazards.
- We consider two key deep uncertainties in future storm surge hazard:
  - Model choice for storm surge
  - Potential nonstationarity in storm surge frequency and intensity
- So we ask:
  1. What are projections of future storm surge hazard?
  2. What are the impacts on these projections from deep uncertainty in storm surge model choice and nonstationarity?

- We use Norfolk, VA as a case study and demonstrate the use of Bayesian model averaging (BMA) as a tool to characterize the deep uncertainty surrounding model structural choice and nonstationarity.

Methods

- We use tide gauge data from Sewells Point (1928-2016) and consider four possible covariates of storm surge behavior:
  1. time
  2. global mean temperature
  3. global mean sea level
  4. winter mean North Atlantic Oscillation (NAO)
- For each candidate covariate, we fit a statistical model in which a Poisson process (PP) governs the arrival of events whose sea level exceeds the 99th percentile of detrended daily mean sea levels, and these exceedances follow a generalized Pareto distribution (GPD).
- Potential nonstationarity in model parameters (θ = {λ, α, ξ}) following Grinsted et al.

Parameters:

- λ: Poisson rate
- α: GPD scale (width)
- ξ: GPD shape (tail)

For each candidate covariate, in addition to the fully nonstationary model above (NS3), we consider a stationary model (ST) and two other potentially nonstationary models:

- ST: λ_t = ξ_t = 0, NS1: λ_t = ξ_t = 0, NS2: ξ_t = 0

- We estimate parameter posterior distributions using Markov chain Monte Carlo, and compute Bayesian model averaging weights for each model (M_j), given the tide gauge data (X):

\[ p(M_j | X) = \frac{p(X | M_j) p(M_j)}{\sum_{j=1}^{M} p(X | M_j) p(M_j)} \]

- We integrate return level estimates in year y (RL(y)) across model structures using the BMA weights (p(M_j | X)):

\[ RL(y | X) = \sum_{j=1}^{M} RL(y | M_j) p(M_j | X) \]

Results

- Key result #1: For any given covariate structure, about half the model weight is associated with nonstationary statistical models.

<table>
<thead>
<tr>
<th>Covariate / Model</th>
<th>ST (λ varying)</th>
<th>NS1 (λ, α varying)</th>
<th>NS2 (λ, α, ξ varying)</th>
<th>NS3 (λ, α, ξ, varying)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>0.52</td>
<td>0.25</td>
<td>0.17</td>
<td>0.06</td>
</tr>
<tr>
<td>Temperature</td>
<td>0.55</td>
<td>0.24</td>
<td>0.15</td>
<td>0.06</td>
</tr>
<tr>
<td>Sea level</td>
<td>0.55</td>
<td>0.24</td>
<td>0.16</td>
<td>0.06</td>
</tr>
<tr>
<td>NOAA index</td>
<td>0.55</td>
<td>0.24</td>
<td>0.16</td>
<td>0.05</td>
</tr>
</tbody>
</table>

- Key result #2: Bayesian model averaging successfully combines flood hazard projections, across uncertain model structures.
  - The additional information (covariates of storm surge nonstationarity) raise the upper tail of projected flood hazard.

Discussion

- Bayesian model averaging (BMA) is a useful tool to combine model predictions when there is disagreement over which model to use.
- We used BMA to address uncertainty in which covariate (if any!) to use, and uncertainty in which (non)stationarity structure to use.
  - The degree to which we believe the nonstationary models/different covariates is informed by the data.
- Provides guidance on how best to incorporate nonstationary processes into flood hazard estimates, and a framework to integrate other locally important climate variables, to better inform coastal risk management practices.

References

7. Voukoukis et al. 2018, doi: 10.1038/s41558-018-0260-4

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