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[1]
- We consider two key deep uncertainties in future storm surge hazard:
  - **Model choice** for storm surge[2]
  - **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**[3], (2) global mean **temperature**[3,4,5], (3) global mean **sea level**[6,7], and (4) winter mean North Atlantic Oscillation (**NAO**) **index**[2,8].
- For each candidate covariate ($\phi(t)$), 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 ($\theta \in \{\lambda, \sigma, \xi\}$) following *Grinsted* et al.[3]:

Parameters:		
	λ : Poisson rate	$\lambda(t) = \lambda_0 + \lambda_1 \phi(t)$
	σ : GPD scale (width)	$\sigma(t) = \exp[\sigma_0 + \sigma_1 \phi(t)]$
	ξ : GPD shape (tail)	$\xi(t) = \xi_0 + \xi_1 \phi(t)$

- 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:

$$\textbf{ST}: \lambda_1 = \sigma_1 = \xi_1 = 0, \quad \textbf{NS1}: \sigma_1 = \xi_1 = 0, \quad \textbf{NS2}: \xi_1 = 0$$

- We estimate parameter posterior distributions using Markov chain Monte Carlo, and compute **Bayesian model averaging** weights for each model (M_k), given the tide gauge data ($\boldsymbol{x}$):

$$p(M_k|\boldsymbol{x}) = \frac{p(\boldsymbol{x}|M_k)p(M_k)}{\sum_{j=1}^{m} p(\boldsymbol{x}|M_j)p(M_j)}$$

- We integrate return level estimates in year y_i ($RL(y_i)$) across model structures using the BMA weights $p(M_k|\boldsymbol{x})$:

$$RL(y_i|\boldsymbol{x}) = \sum_{k=1}^{m} RL(y_i|M_k)\, p(M_k|\boldsymbol{x})$$

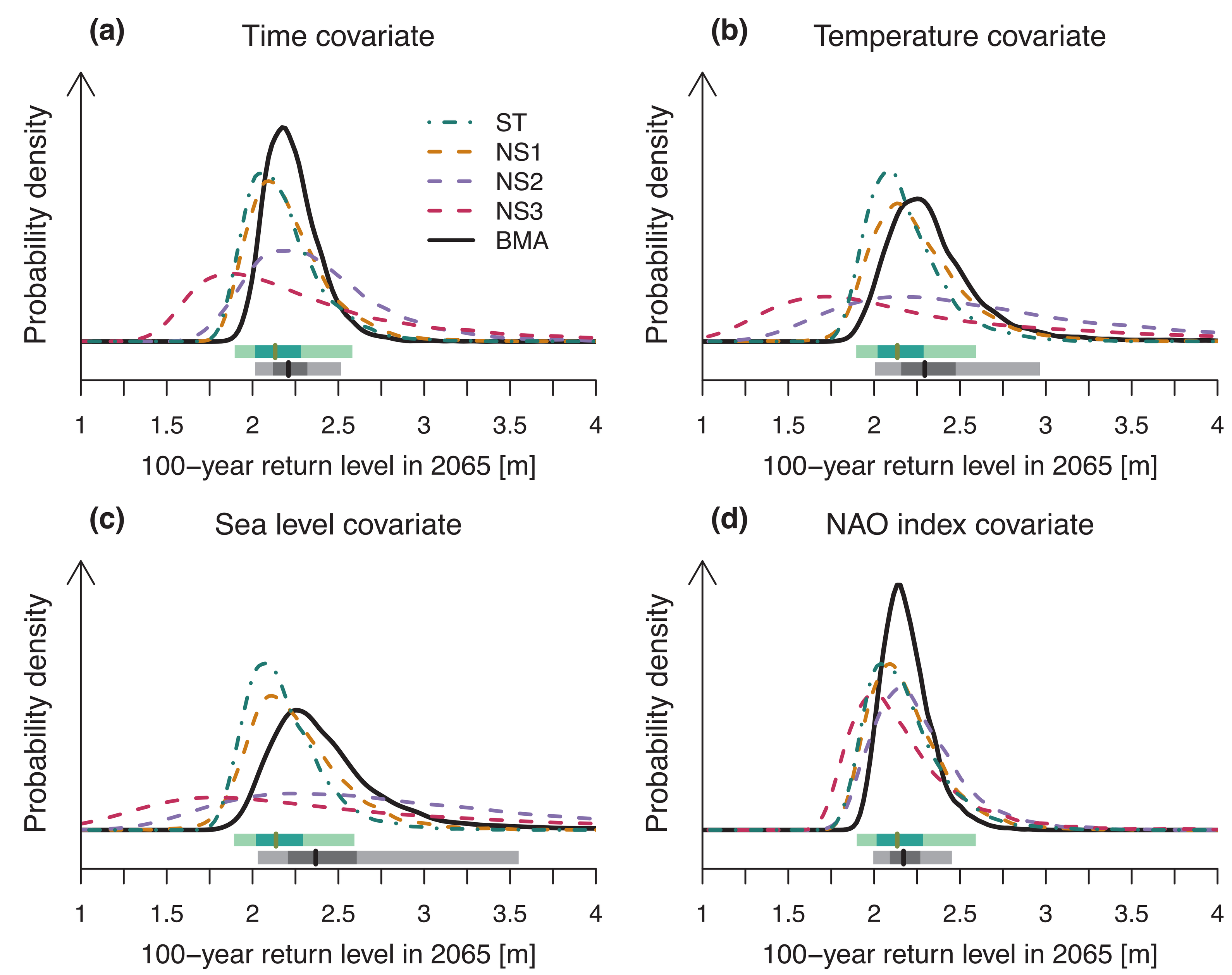
Results

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

BMA weights:

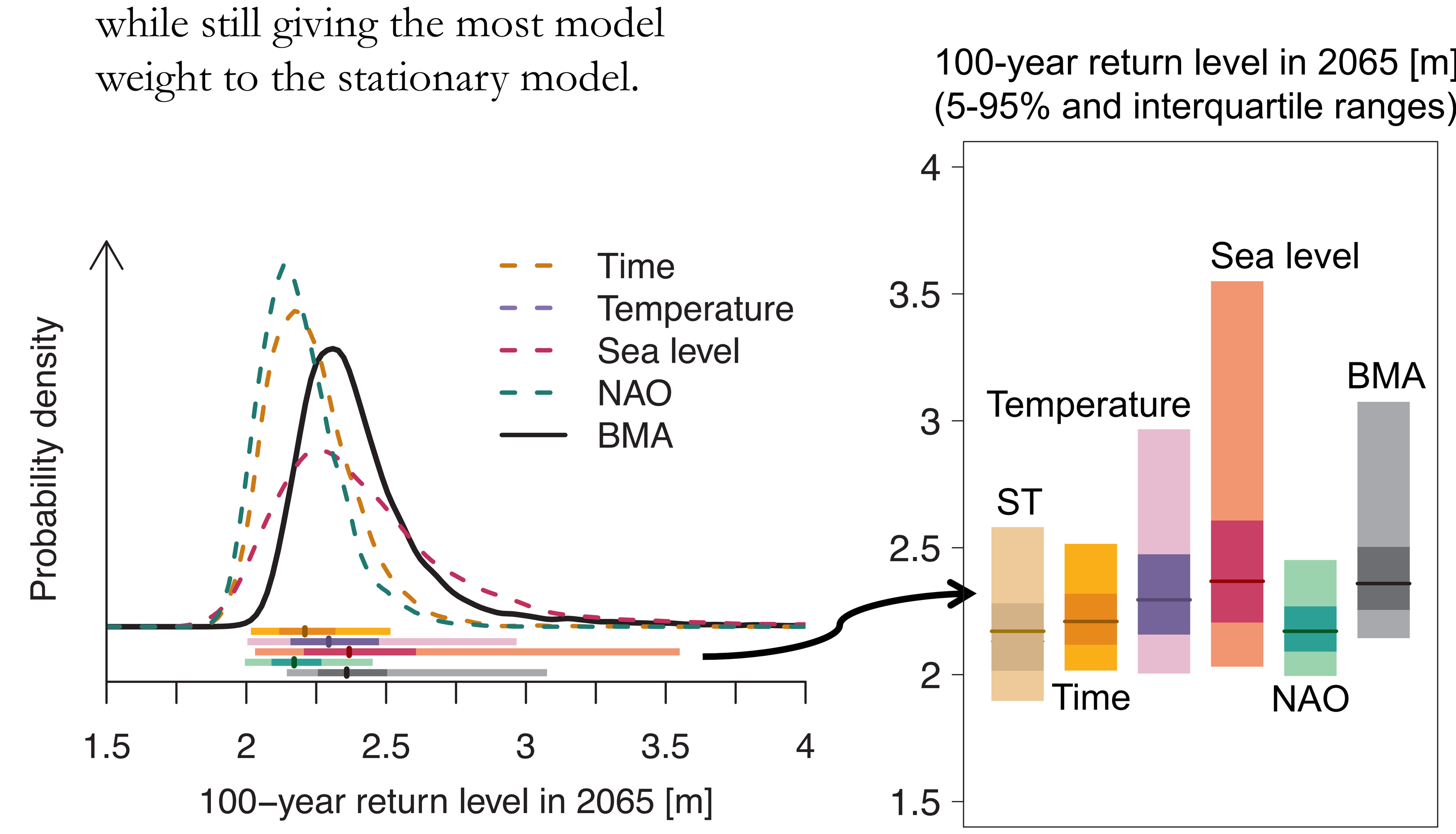
Covariate / Model	ST	NS1 (λ varying)	NS2 (λ, σ varying)	NS3 (λ, σ, ξ varying)
Time	0.52	0.25	0.17	0.06
Temperature	0.55	0.24	0.15	0.06
Sea level	0.55	0.24	0.16	0.06
NOA index	0.55	0.24	0.16	0.05

- **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.



In a final experiment, we combine using BMA a stationary model with all four candidate covariates' three nonstationary models (total of 13 model structures).

- **Key result #3:** Accounting for nonstationarity and uncertain model structure increases the estimated 100-year return level by up to 23 cm, while still giving the most model weight to the stationary model.



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

1. Wong and Keller 2017, doi: 10.1002/2017EF000607
2. Wong *et al.* 2018, doi: 10.1088/1748-9326/aacb3d
3. Grinsted *et al.* 2013, doi: 10.1073/pnas.1209980110
4. Ceres *et al.* 2017, doi: 10.1007/s10584-017-2075-0
5. Lee *et al.* 2017, doi: 10.1002/2017GL074606
6. Arns *et al.* 2013, doi: 10.1016/j.coastaleng.2013.07.003
7. Vousdoukas *et al.* 2018, doi: 10.1038/s41558-018-0260-4
8. Haigh *et al.* 2010, doi: 10.1016/j.csr.2010.02.002

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