# Spatial stochastic simulation to aid local extreme value analysis of cyclone-induced wave heights when numerical hydrodynamic simulations are scarce

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Teddy

Vicky



## Motivating test case: cyclone-induced extreme waves at Guadeloupe archipelago (French West Indies)



**Objective:** estimate extreme wave heights (Hs) induced by tropical cyclones TC along the Guadeloupe coast

**Difficulty:** historical data are relatively scarce (28 TCs)



### Synthetic TC approach

Randomly generate а large number of synthetic TCs using stochastic generator [1] 2,000 TCs

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the TC-induced Compute wave using heights numerical hydrodynamic simulators (e.g. ADCIRC-SWAN [2])



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Hs maximum Extract values around the coasts of Guadeloupe and perform extreme value analysis [3] to evaluate the return levels of interest (e.g. 100y Hs RL)

### Synthetic TC approach

Randomly generate a large number of synthetic TCs using stochastic generator [1] 2,000 TCs



Compute heights hydrodyna ADCIRC-

The combination random TCs with numerical simulations can face severe difficulties when the computational time cost of each numerical simulation is large (several hours, even days)

In practices, only a few (50-100) numerical simulation results may be available...

Extract

around th

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and perform extreme value analysis [3] to evaluate the return levels of interest (e.g. 100y Hs return level)



Hs (m)

[1]: Emanuel et al. BAMS 2006; [2]: Krien et al., NHESS 2015; [3]: Coles et al., 2001

Return Period (years)



ComputetheTC-inducedmaxmum Hs for the limited numberof available TCs (M=50-100)



. . .





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Compute the TC-induced maxmum Hs for the limited number of available TCs (M=50-100)



-61.7 -61.6 -61.5 -61.4 -61.3 -61.2 -61.1

17.0

16.5

16.0

Map (1)

EOF3

17.0

-62.5

-62.0

-61.5 -61.0



[1] Jolliffe & Richman, 1987

-61.7 -61.6 -61.5 -61.4

-61.3 -61.2 -61.1



2

Compute the TC-induced maxmum Hs for the limited number of available TCs (M=50-100)

Decompose the Hs maps onto

Map(2) =  $\alpha_{1,2}x$ 

suitable basis functions using



-61.7 -61.6 -61.5 -61.4

Etc...

-61.3 -61.2 -61.1

-61.7 -61.6 -61.5 -61.4 -61.3 -61.2 -61.1

-61.7 -61.6 -61.5 -61.4

-61.3





**Learn** the joint statistical law of the expansion coefficients  $\alpha_{k,i}$   $k = 1 \dots n$ ,  $i = 1 \dots M$  with n=the number of EOFs and M the number of maps **Method:** multivariate Gaussian kernel smoothing





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Sample from the joint law and reconstruct the synthetic Hs maps. Then, augment the observations at the location of interest with the synthetic data



#### **Comparison of Return Levels**



With 1971 synthetic TCs (Full Synthetic TC approach)

With 100 synthetic TCs (Sparse Synthetic TC approach)

Data augmentation appears to decrease the bias and the uncertainty (95% Confidence Interval width) With data augmentation using EOF-based reconstructed Hs maps



#### Validation exercise – 100y RL estimates

Use of M=100 randomly sampled TCs among the full dataset of Krien et al. (2015) composed of 1971 TCs (representative of 3,200 years) with n=4 EOFs (replicated 25 times)



100y RL estimates with data augmentation has the lower bias: absolute percentage error ~12.3% (averaged over the Pts) to be compared to 25.5% without

#### Validation exercise – 95% confidence interval (CI) width

Use of M=100 randomly sampled TCs among the full dataset of Krien et al. (2015) composed of 1971 TCs (representative of 3,200 years) with n=4 EOFs (replicated 25 times)



Data augmentation leads to CI width of the same order than the approach with the full dataset



#### Influence of the number of maps – 100y RL estimates

Use of M=50 randomly sampled TCs among the full dataset of Krien et al. (2015) composed of 1971 TCs (representative of 3,200 years) with n=4 EOFs (replicated 25 times)



100y RL estimates with data augmentation has the lower bias: absolute percentage error ~16.2% (averaged over the Pts)

#### Influence of the number of EOFs – 100y RL estimates

Use of M=100 randomly sampled TCs among the full dataset of Krien et al. (2015) composed of 1971 TCs (representative of 3,200 years) with n=3 EOFs (replicated 25 times)



100y RL estimates with data augmentation has the lower bias: absolute percentage error ~12.2% (averaged over the Pts)

#### Influence of the decomposition method – 100y RL estimates

Use of M=100 randomly sampled TCs among the full dataset of Krien et al. (2015) composed of 1971 TCs (representative of 3,200 years) with Partial Least Squares Regression [1] (replicated 25 times)



100y RL estimates with Data augmentation has the lower bias: absolute percentage error ~12.3% (averaged over the Pts)

[1] Martens, 2001

#### **Summary and open questions**

- Estimates of 100 year Return Level imposes the use of a large dataset (1,000-2,000) of computed Hs maps; each of thme corresponding to a synthetic Tropical Cyclone
- To perform the analysis using 50-100 Hs maps, we propose to augment the available database with reconstructed Hs maps using EOFs
- Compared to a crude approach using only 50-100 maps, results suggest that the bias is lowered (~10-15%) as well as the uncertainty estimates (95% confidence interval width)

#### Open questions

- Could a limited number of synthetic tropical cyclones be selected beforehand?
- Does the approach perform well for larger return periods (>100 years)?
- Is the performance equivalent to other procedures like the recently developed STM-E approach [1] or resampling techniques specifically developed for extremes [2]?

[1] Wada et al., Ocean Eng. 2018; [2] Opitz et al., spat. Stat., 2020

