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MS08: Risk and Reliability for Maritime and Ocean Engineering Applications
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Temporally Coherent Modeling of Tropical-Cyclone Compound Flooding for Reliable Coastal Hazard Estimation

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Contents

Motivation

Challenges in Coastal & Ocean Engineering

- Coastal infrastructure designed using **rare design water levels** (e.g., 100-year return level)
  - Tropical cyclone-induced extreme water levels (flooding)

- Limited historical data of tropical cyclones
  - Insufficient to estimate long-period return levels empirically

→ Statistical extrapolation becomes necessary

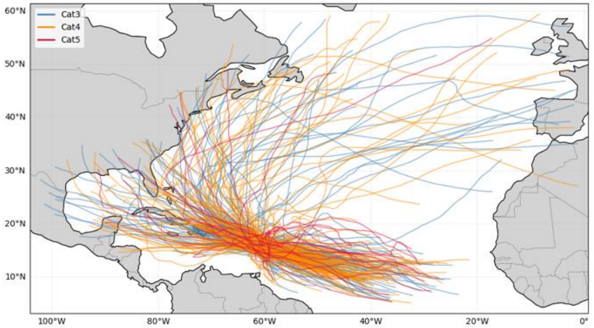


Fig. 1. Historical tropical cyclone trajectories

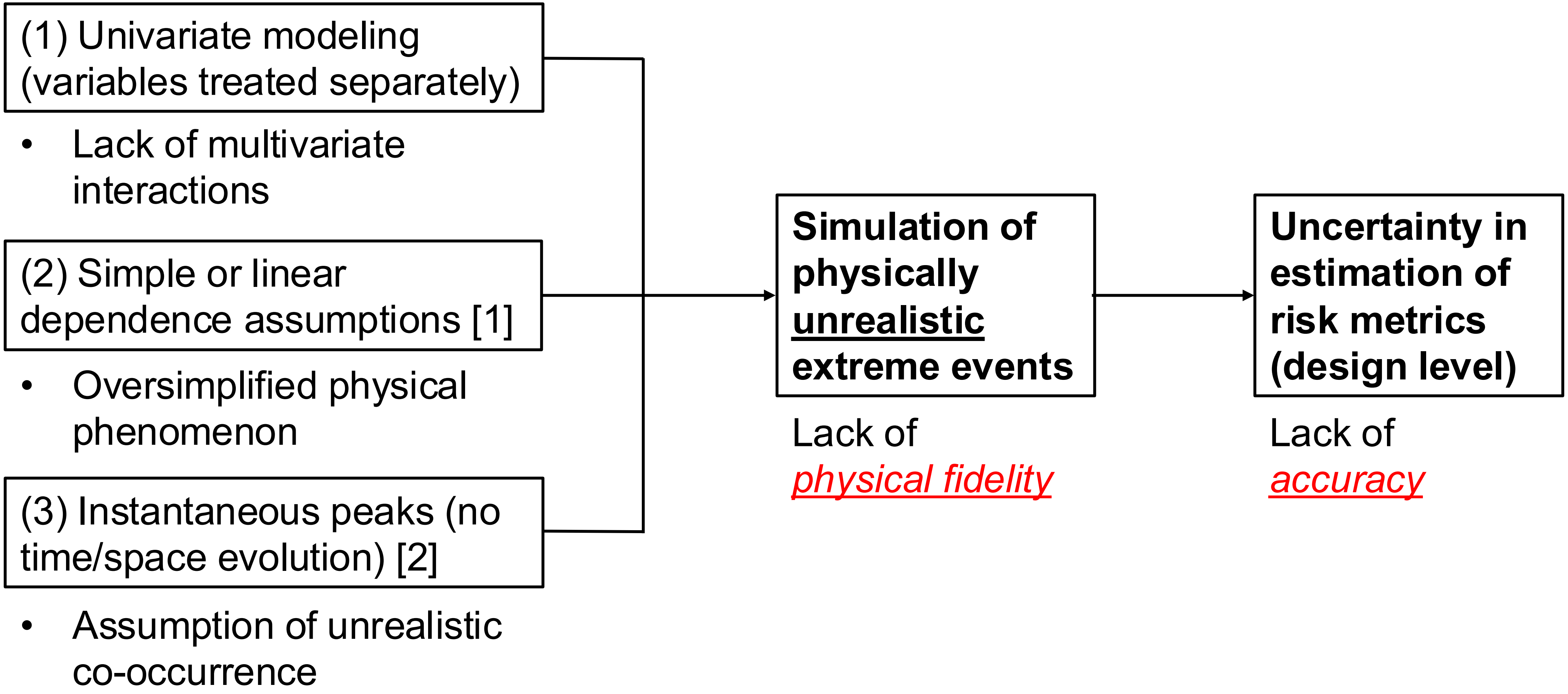
Uncertainties in Statistical Extrapolation

- Compound behavior of TC-induced flooding
- Caused by interaction of:
  - Sea surface height (surge)
  - Offshore wave projection (wave run-up)

(1) Data limitation of rarely observed joint extremes
(2) Complex modeling of multivariate dependence
(3) Distinct spatio-temporal structure of each variable

→ Reliable estimation of extreme *compound* event required

Challenges in Conventional Approaches



(1) Univariate modeling (variables treated separately)

- Lack of multivariate interactions

(2) Simple or linear dependence assumptions [1]

- Oversimplified physical phenomenon

(3) Instantaneous peaks (no time/space evolution) [2]

- Assumption of unrealistic co-occurrence

Simulation of physically unrealistic extreme events

Lack of *physical fidelity*

Uncertainty in estimation of risk metrics (design level)

Lack of *accuracy*

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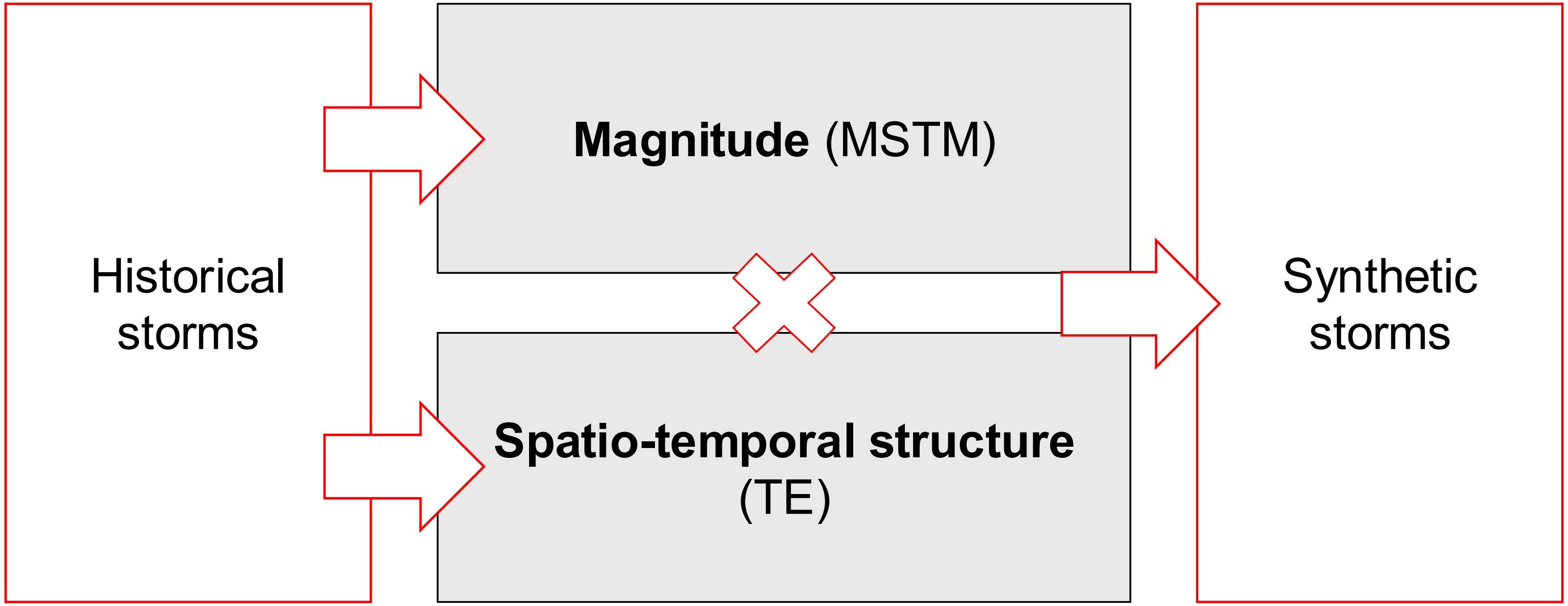
[1] Coles, S (2001). An introduction to statistical modeling of extreme values. Springer, London, UK,

[2] Heffernan, J.E. and Tawn, J.A. (2004), A conditional approach for multivariate extreme values (with discussion). Journal of the Royal Statistical Society: Series B (Statistical Methodology).

Prior Research

Multivariate Spatio-Temporal Maximum and Temporal Exposure (MSTM-TE) [3]

- An extreme-value framework incorporating spatial and temporal exposure (relative intensity)


Historical storms

Magnitude (MSTM)

Spatio-temporal structure (TE)

Synthetic storms

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[3] Sando, K., Wada, R., Rohmer, J., & Jonathan, P. (2024). Multivariate spatial and spatio-temporal models for extreme tropical cyclone seas. Ocean Engineering

Research Objectives

Research Questions:	**Objectives**:
(1) Can preserving spatio-temporal coherence improve the reliability of extreme compound event estimation under limited observations?	(1) To evaluate the role of temporal structure in improving reliability of probabilistic estimation of compound extremes
(2) What can temporally coherent simulated storms reveal about the compound nature of extreme events?	(2) To identify how joint behavior and temporal exposure govern the mechanisms of compound extremes

Contents

1. **Research Background and Objectives**
2. **Methodology**
3. **Results & Discussion**
4. **Conclusion**

Study Domain and Dataset

Study Domain and Locations

- Guadeloupe region
  - Northeastern Caribbean Sea (60.5°W-62.5°W; 15°N-17°N)
- Four study locations on the main island

Dataset

- **1000-year** period containing **685 TCs** that pass within a 300 km radius of the archiopelago
  - Clustered into East (466 storms) and West (219 storms) based on the location of maximum wave height to fulfill the modeling assumption [3]
- 18,890 node spatial mesh
- High-resolution time series of key metocean variables

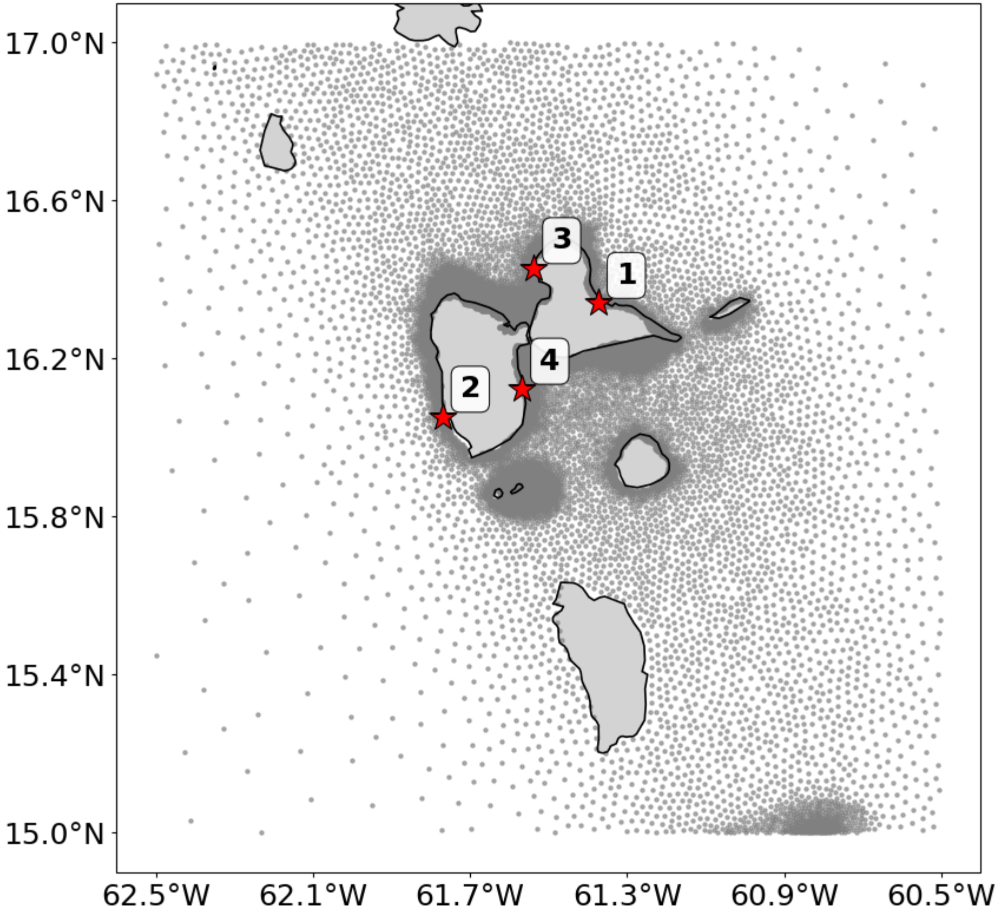


Fig. 2. Map of the Guadeloupe region showing the mesh grid nodes (grey dots) and the four study locations (red stars).

[3] Sando, K., Wada, R., Rohmer, J., & Jonathan, P. (2024). Multivariate spatial and spatio-temporal models for extreme tropical cyclone seas. Ocean Engineering, 309, 118365.

Risk Assessment Metric & Variables

Risk assessment metric (Total Water Level)

$$TWL = Ssh + R$$

- Sea surface height (Ssh)
- Wave run-up (R)

Wave run-up [4]

$$R = 1.1\left[0.35\beta_f\sqrt{\frac{9.81H_sT_p{}^2}{2\pi}} + \sqrt{\frac{9.81H_sT_p{}^2}{2\pi}\left(0.563\beta_f{}^2 + 0.0004\right)}\right]$$

- $\beta_f = 0.1$: foreshore slope [5]
- H_s: significant wave height
- T_p: peak wave period

Variables

Risk metric as a function of:

- Sea surface height (Ssh)
- Significant wave height (H_s)
- Peak wave period (T_p)

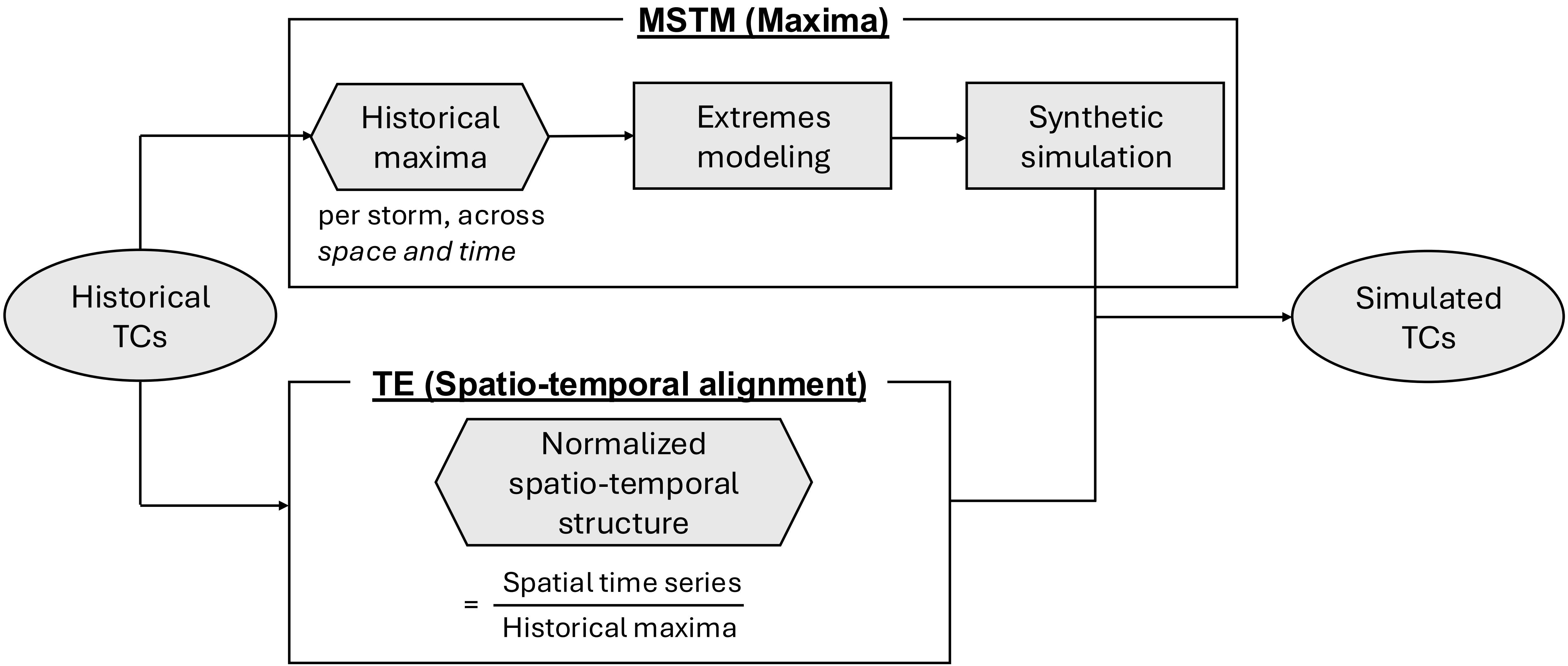
Modeling Configurations

1. Trivariate: Ssh, H_s, T_p (each metocean variable)
2. Bivariate: Ssh (storm surge), $H_sT_p{}^2$ (wave run-up)

[4] Stockdon, H. F., Holman, R. A., Howd, P. A., & Sallenger, A. H., Jr. (2006). Empirical parameterization of setup, swash, and runup. Coastal Engineering,

[5] Melet, A., Meyssignac, B., Almar, R., & Le Cozannet, G. (2018). Under-Estimated Wave Contribution to Coastal Sea-Level Rise. Nature Climate Change

Methodology Overview [6]



$$= \frac{\text{Spatial time series}}{\text{Historical maxima}}$$

[6] Chung, M., Wada, R., Rohmer, J., & Jonathan, P. (2026). Temporally Coherent Modeling of Tropical Cyclone Compound Flooding for Reliable Coastal Hazard Estimation. EGUsphere [preprint]

Extremes Modeling

Marginal modeling

- Behavior of *each variable* at its most extremes
- Generalized Pareto Distribution

Conditional modeling

- Dependence structure *among variables*
- Heffernan-Tawn model
  - Behavior of $Y_{d'}$ and remaining variables $Y_d > \psi_d$ (where ψ_d: dependence threshold)

Generalized Pareto Distribution

$$F(y) = 1 - \left(1 + \frac{\xi y}{\sigma}\right)^{-\frac{1}{\xi}}, y > 0$$

- σ: scale parameter
- ξ: shape parameter

Heffernan & Tawn Model [2]

$$Y_{d'}|(Y_d = y) \approx \alpha_{d'|d} y + y^{\beta_{d'|d}} Z_{d'|d}$$

- $\alpha_{d'|d} \in [-1,1]$: conditional linear parameter
- $\beta_{d'|d} \in (-\infty, 1]$: conditional scale parameter
- $Z_{d'|d}$: residual term

[2] Heffernan, J.E. and Tawn, J.A. (2004), A conditional approach for multivariate extreme values (with discussion). Journal of the Royal Statistical Society: Series B (Statistical Methodology).

Synthetic Simulation

Conditioning variable selection

- Reflects how often each variable dominates in the historical dataset

Peak value simulation

- Sampled from historical storms matching the dominant variable

Conditional variable generation

- Generated using parameters from conditional extremes modeling

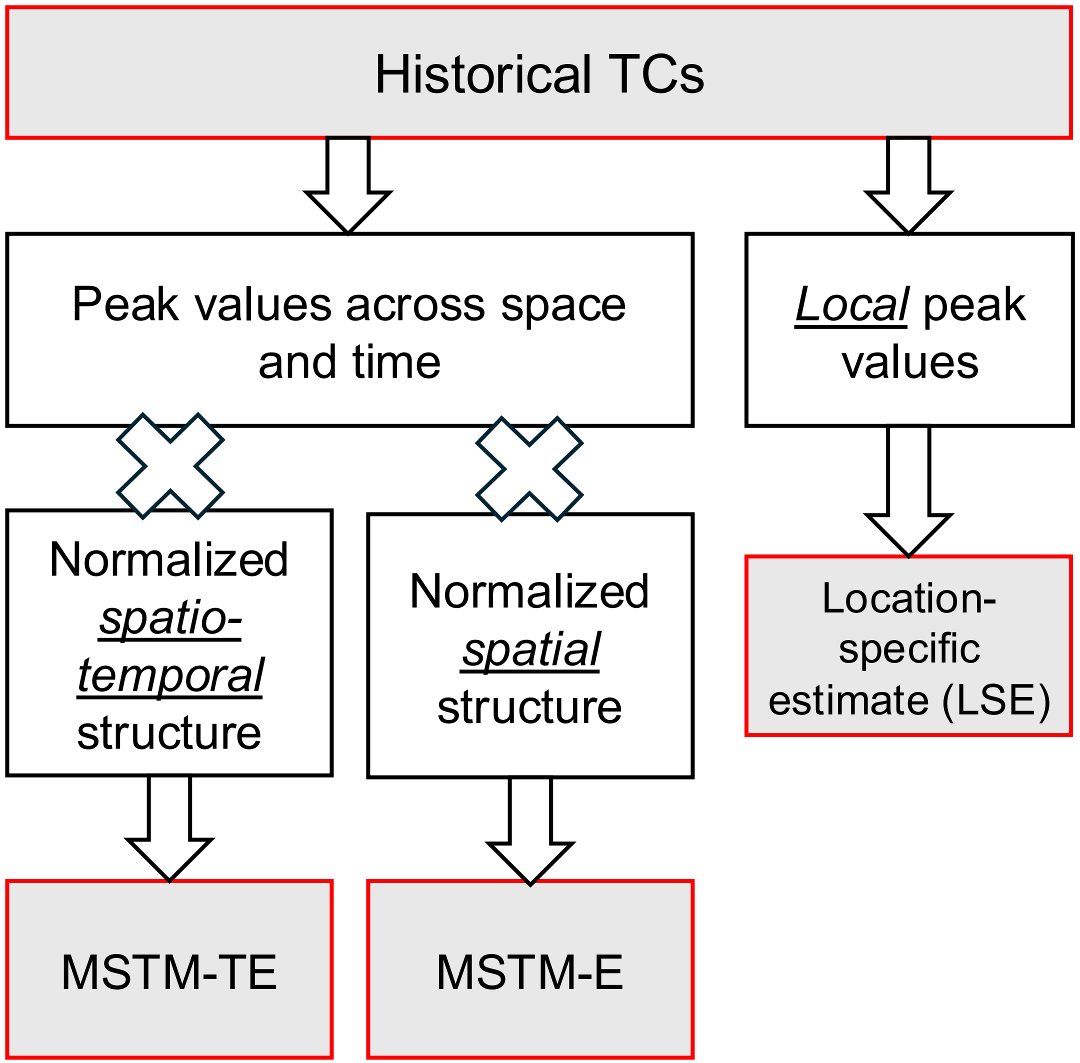
Historical temporal exposure pattern attachment

- Randomly attached
  - Independence between MSTM and TE sets tested

Simulated TC peak values/time series

Performance Evaluation

Performance evaluated across four frameworks:



Historical TCs

Peak values across space and time

Local peak values

Normalized *spatio-temporal* structure

Normalized *spatial* structure

Location-specific estimate (LSE)

MSTM-TE

MSTM-E

	MSTM-TE	MSTM-E	LSE
Spatial preservance	✓	✓	✗
Temporal preservance	✓	✗	✗

Evaluation metrics:

- **Bias**: difference between simulated return levels and ground truth
- **Variance**: how much the return level estimates fluctuate across simulations

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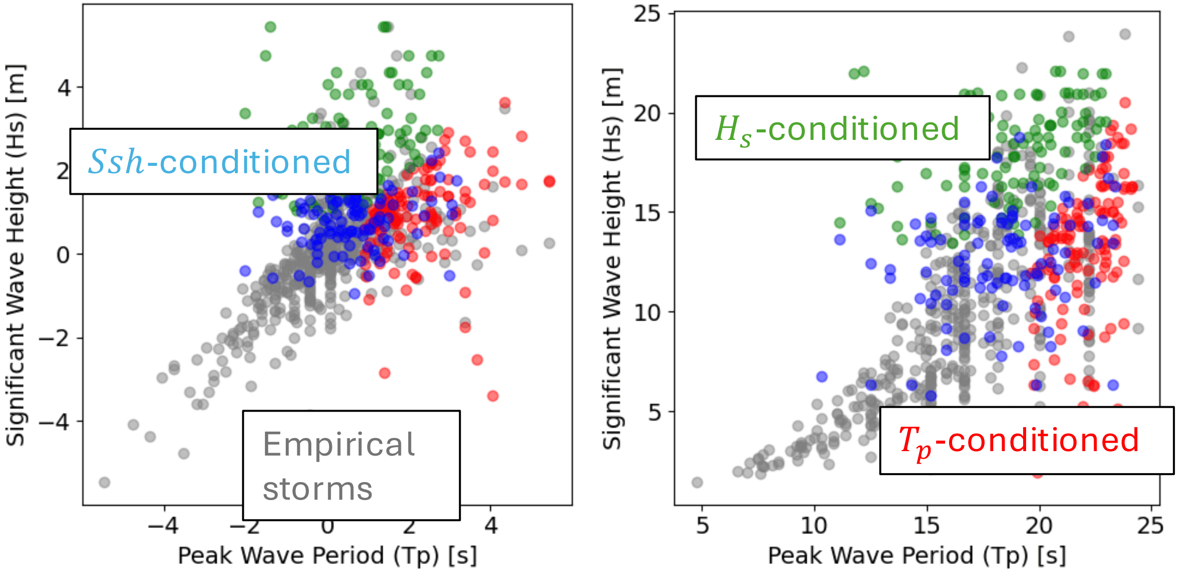
3. Results & Discussion

Simulated MSTM & Time Series

Trivariate configuration (T_p, H_s, Ssh)

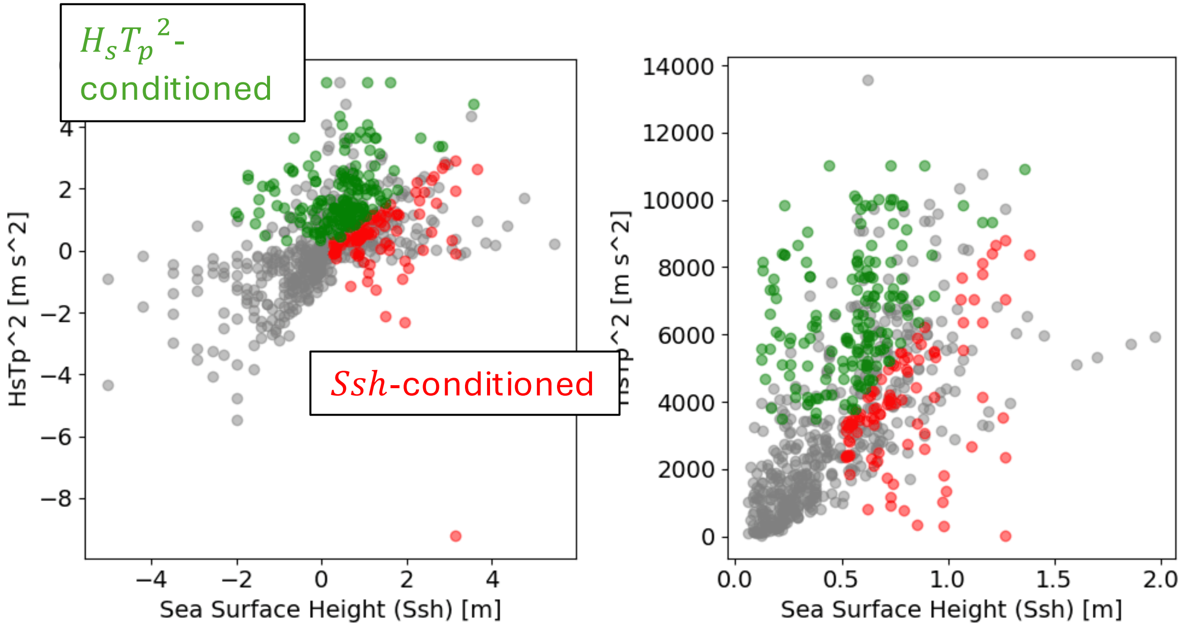


(a) Laplace scale

(b) Physical scale

Fig. 3. Sample visualization of the simulated MSTM vectors for East cluster storms.

Bivariate configuration $(H_sT_p{}^2, Ssh)$



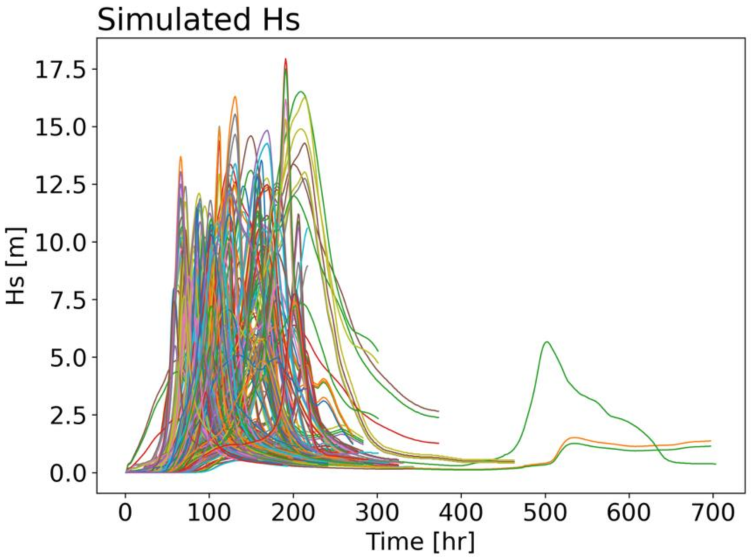
(a) Laplace scale

(b) Physical scale

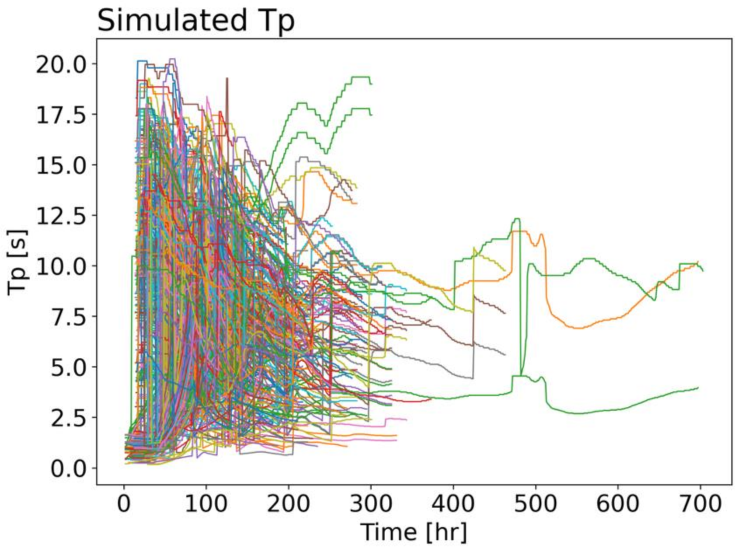
Fig. 4. Sample visualization of the simulated MSTM vectors for East cluster storms.

3. Results & Discussion

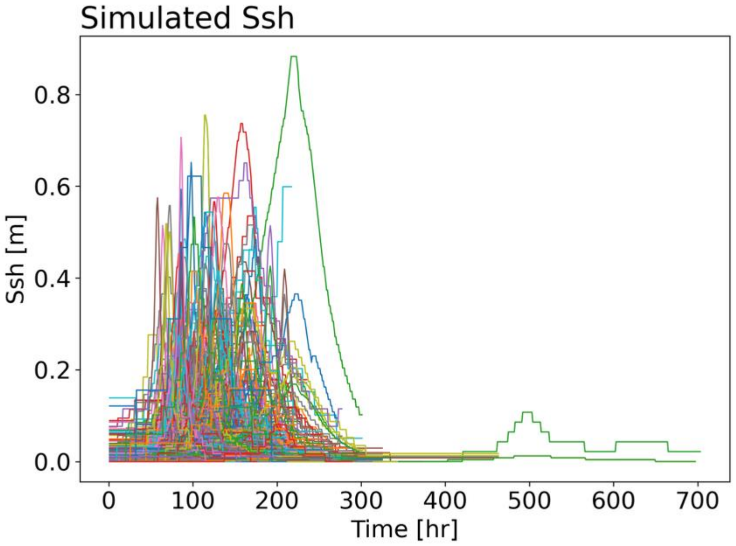
Simulated Time Series



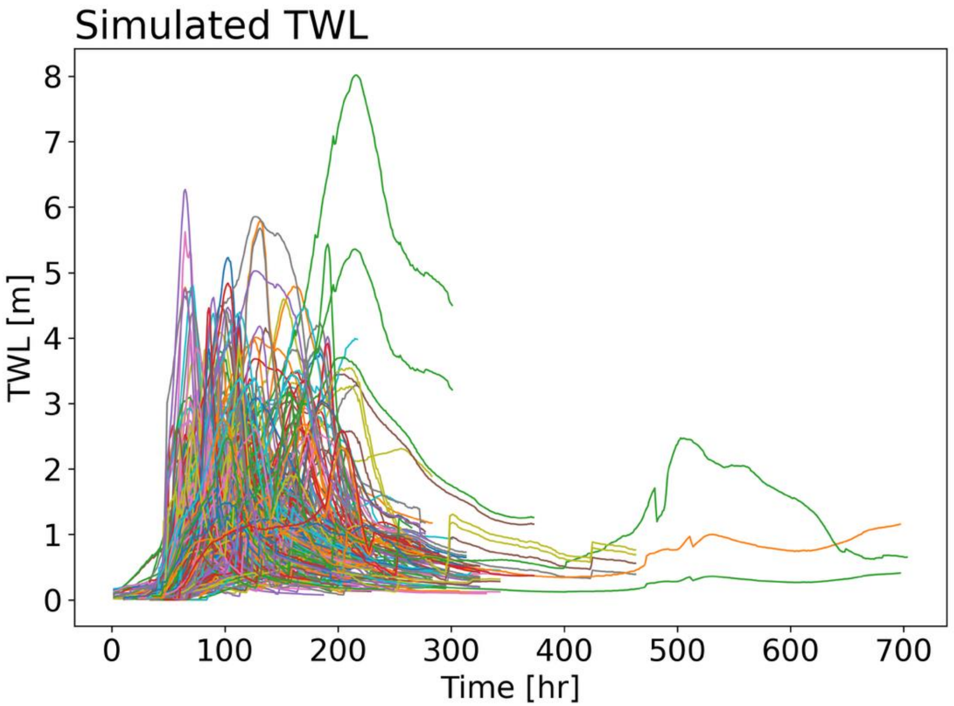
(a) H_s time series



(b) T_p time series



(c) Ssh time series



(d) TWL time series

Fig. 5. Full time series of the simulated variables for the East cluster at Location 1

Return Value Estimation

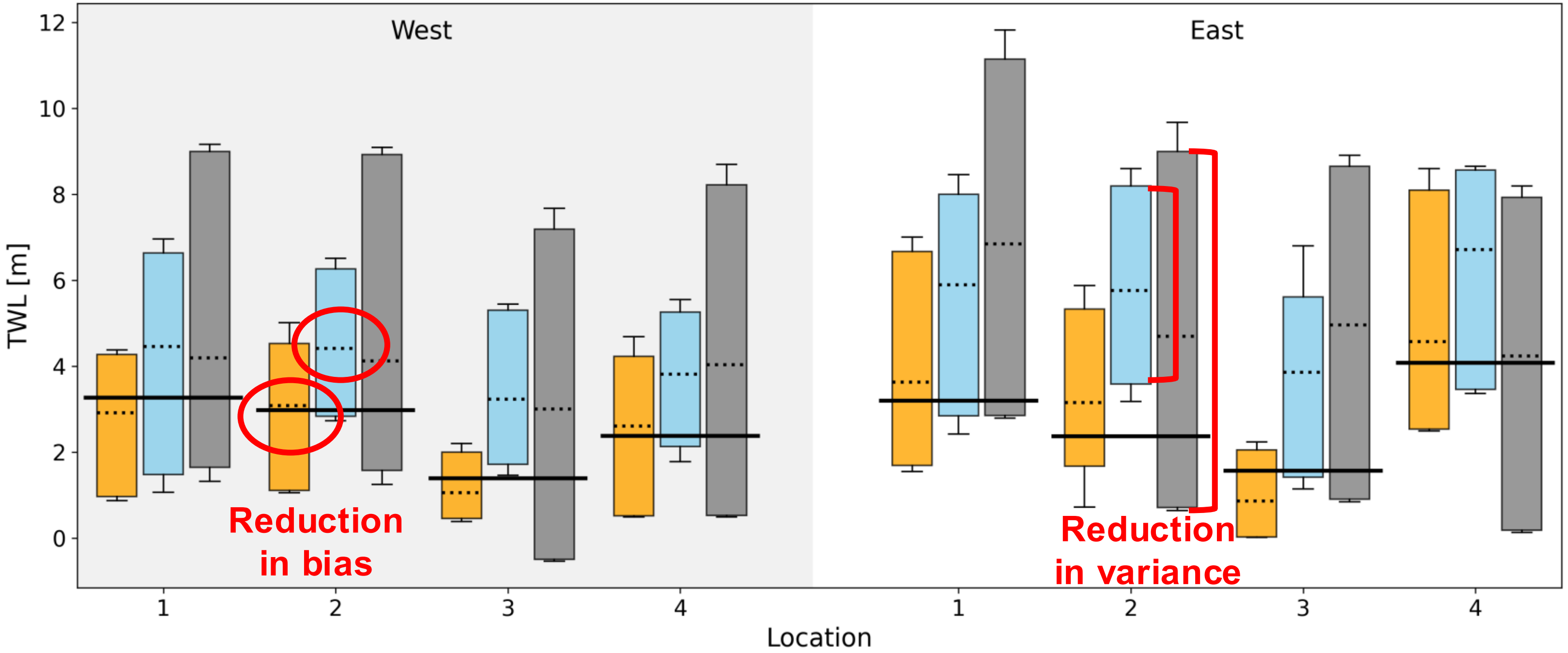


Fig. 6. Box–whisker plots of TWL return-level estimates for a 100-year return period modeled by west-cluster storms (left) and east-cluster storms (right). The black horizontal: the ground truth. The horizontal dotted line within each box: the mean value.

Across all study locations:

MSTM-E (blue)

- Reduces *variance* compared to LSE (grey)

MSTM-TE (yellow)

- Reduces *bias* compared to MSTM-E (blue)

→ Spatio-temporal coherence improves return level accuracy

3. Results & Discussion

Identification of Governing Mechanisms

Empirical storms

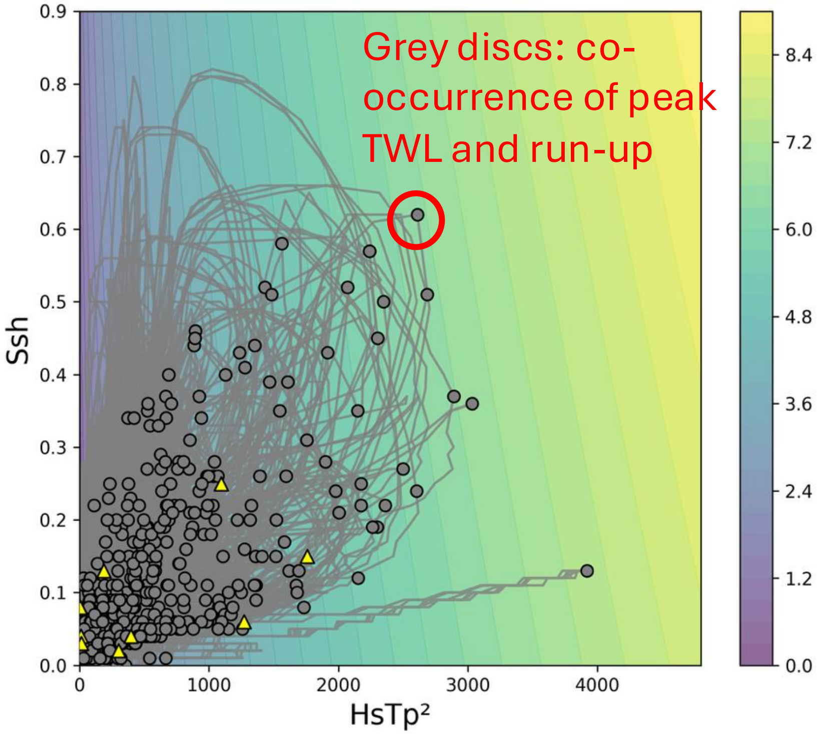


Fig. 7. Joint time series trajectory of empirical storms (east cluster) for **Location 1.**

9 ”timing-offset” storms

Simulated storms

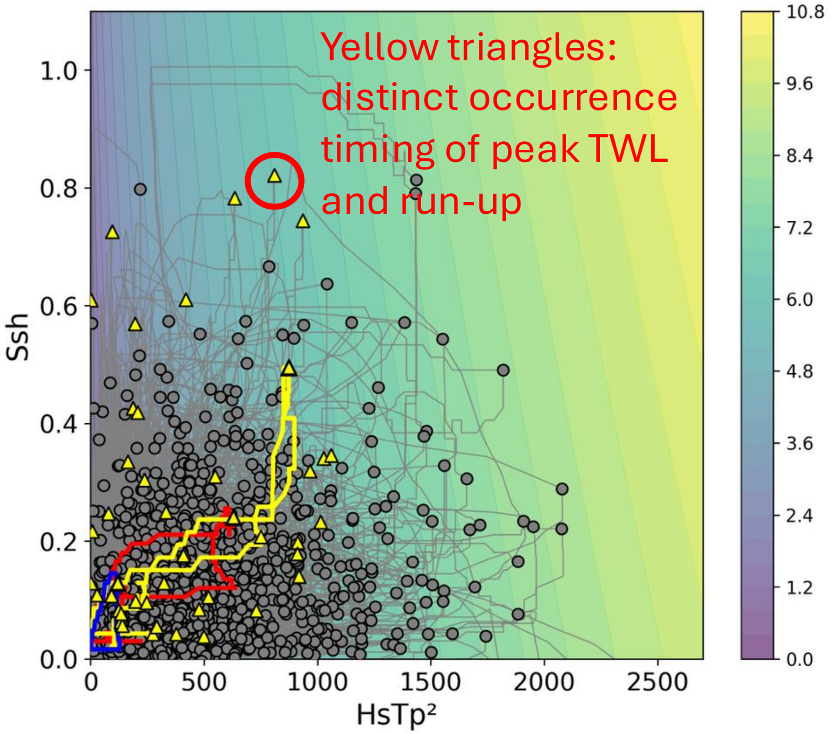


Fig. 8. Joint time series trajectory of simulated storms (east cluster) for **Location 1.**

42 ”timing-offset” storms

Consistent co-occurrence of peak TWL and peak run-up (via ${H_s T_p}^2$)

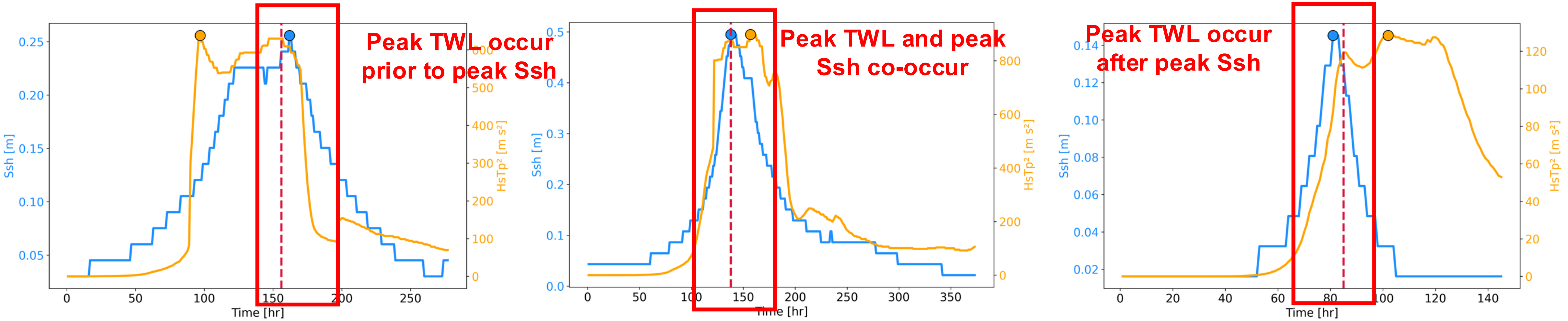
→ Extreme TWL dominantly driven by extreme wave run-up

→ Enable extended analysis of the rare behavior

3. Results & Discussion

Behavioral Pattern of Rare Events

Time series of storms in which peak TWL and peak run-up do not co-occur



Peak TWL occur prior to peak Ssh

Peak TWL and peak Ssh co-occur

Peak TWL occur after peak Ssh

(a) Red-highlighted storm

(b) Yellow-highlighted storm

(c) Blue-highlighted storm

Fig. 9. Full time series of the **simulated Ssh (blue) and $H_sT_p{}^2$ (yellow)** for each of the highlighted storms in Fig. 8. **Red dashed line represents the timing of peak TWL.**

__All__ "timing-offset" storms show that extreme TWL occurs when elevated surge levels interact with high (but not necessarily maximal) wave energy

Simplification of Simulation Framework

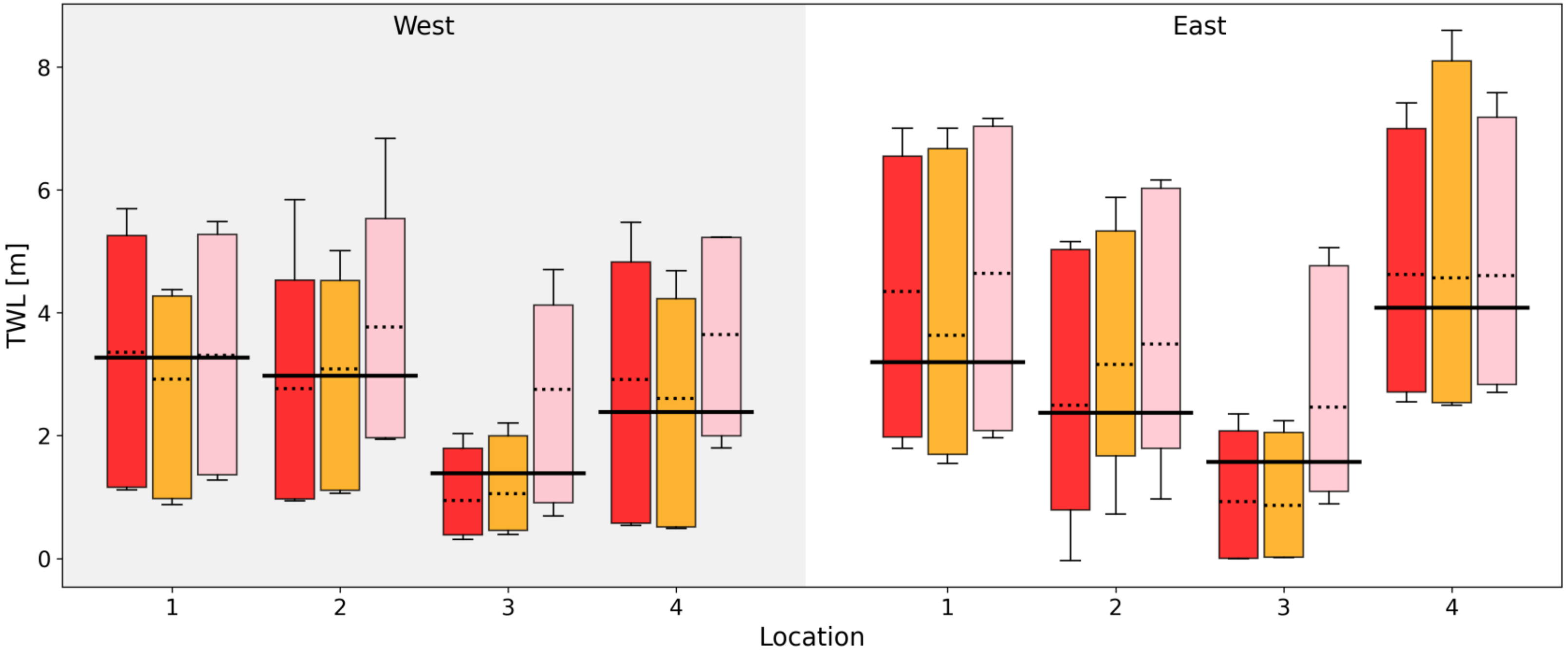


Fig. 10. Box–whisker plots of TWL return-level estimates for a 100-year return value estimates of TWL obtained from the **simplified timing-aligned framework (red)**, the MSTM-TE framework under **the trivariate configuration (yellow),** and the **bivariate configuration (pink)**.

Comparison across:

1. Extraction of TWL at the time of peak wave run-up (red)
   - $f\left(Ssh\left[\max H_s {T_p}^2\right], \max H_s {T_p}^2\right)$

2. MSTM-TE (trivariate)
   - $\max f(Ssh, H_s, T_p)$ (yellow)

3. MSTM-TE (bivariate)
   - $\max f(Ssh, H_s {T_p}^2)$ (pink)

Similar trends (bias and variance) shown as MSTM-TE simulated return-level estimates

Contents

Conclusion

RQ1. Can preserving temporal coherence improve reliability?

Temporal coherence is essential for reliable design-level hazard estimation
- Reduced bias and variance

RQ2. What can temporally coherent simulated storms reveal?

The time series simulations reveal the governing mechanisms of compound extremes
- Systematic investigation of statistically rare behavior

→ Enable development of simplified framework

Reliable estimation of compound extremes:
- Requires preserving temporal coherence
- Enables systematic understanding of the statistical pattern of underlying physics