S1 Mangrove damage model

S1.1 Background

The Bay of Bengal is home to the Sundarbans mangrove forest, which provides habitats for over 5,000 plant and animal species (Spalding and Leal, 2024). Alongside habitat provisioning, mangroves provide many ecosystem services—coastal protection, carbon sequestration, and nutrient cycling (Krauss and Osland, 2020)—yet up to 30% of global mangrove extent has been lost in the past 50 years (Goldberg et al., 2020). While the main drivers of global mangrove losses are anthropogenic, natural disasters accounted for 3% of global mangrove losses between 2010 and 2020, almost entirely driven by disasters in Asia. This figure was three times greater than that of the previous decade. While mangroves in the Bay of Bengal mangroves are of less concern than mangrove systems elsewhere (Spalding and Leal, 2024), understanding the risk to these vital ecosystems remains important.

In terms of natural disasters, storms are a major driver of mangrove damage and dieback (Taillie et al., 2020; Goldberg et al., 2020; Bhatia et al., 2018). Mangrove forests sustain damages during storms via a range of interacting environmental, biological, and geophysical mechanisms (Mo et al., 2023; Taillie et al., 2020).

In recent studies, cumulative precipitation and maximum wind speed have been identified as strong predictors of storm damage to mangrove forests (Mo et al., 2023; Taillie et al., 2020; Amaral et al., 2023).

S1.2 Method

To simulate data under the independence assumption an independent standard uniform random variable is sampled for each pixel in the domain and this is transformed to data space using the probability integral transform from Sect. **??**. The sampling procedure is repeated 914 times to generate an event set for the independence assumption. For the total dependence assumption, a percentile u_n is generated for each of a set of return periods RP_n according to,

$$u_n = 1 - \frac{1}{\lambda \mathrm{RP}_n}.$$

The u_n value is broadcast across both the space (ij) and climate field (k) dimensions and the return level at each (ijk)-combination is calculated using the PIT for that variable.

The mangrove vulnerability function is formulated as follows: we define a mangrove patch as "damaged" if it experiences a drop in enhanced vegetation index (EVI) greater than 20% in the wake of a storm. The logistic regression model is fitted to predict the probability of damage based on the maximum wind and cumulative precipitation near the mangrove patch during that storm. The fitted model achieves a precision score of 64%, recall of 70%, and a critical success index of 50%. The regression coefficient was 0.2961 for wind speed and 0.0975 for precipitation, indicating a strong and mild influence on damages by wind and precipitation, respectively. The historical climate fields in this model are derived from IBTrACS data, hence it is likely there will be some underestimation of damages when combining this model with ERA5 simulations, though this is somewhat alleviated by the damaged/not damaged binary model. Figure S1 visualises the bivariate response surface of the model. Mangrove presence data from Bunting et al. (2022) provides a shapefile of mangrove presence in the region. The Python 'xagg' package (Schwarzwald and Geil, 2024).

The mangrove vulnerability function can now be applied to the historical ERA5 and synthetic storm footprints to predict damage probability fields for each wind storm event. To get the expected damage area (EDA)—the expected area of mangrove forest experiencing a drop in EVI greater than 20%—the damage probability field is multiplied by the area of mangroves present in each grid cell. Letting p be the probability the mangroves in a grid cell are damaged and assuming uniformity of damage probability within pixels,

$$\mathbb{E}[\text{damaged area}] = p \cdot [\text{mangrove area}] + (1 - p) \cdot [0] = p \cdot [\text{mangrove area}].$$

By linearity of the expectation function, we can also express the expected total area damaged (ETDA) for each storm as
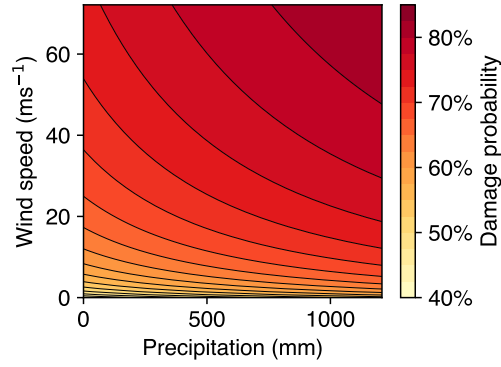
Figure S1. Bivariate response surface from logistic regression showing mangrove damage probability as a function of wind speed and precipitation, where mangrove damage is defined as a drop in EVI exceeding 20% in the wake of a storm.

$$\mathbb{E}[\text{total damaged area}] = \mathbb{E}\Big[\sum_{i,j}\text{damaged area}_{ij}\Big] = \sum_{i,j}\mathbb{E}\big[\text{damaged area}_{ij}\big].$$

We can now calculate the empirical distribution function $\hat{F}$ over the set of ETDAs for each storm footprint. To obtain empirical return periods for each ETDA, we use the event occurrence rate $\lambda \approx 1.81$ to calculate return periods according to

$$\text{RP} = \frac{1}{\lambda\big(1 - \hat{F}\left(\text{ETDA}\right)\big)}$$

45   where RP corresponds to a RP-year return period.

S2   Figures

S2.1   Precipitation and sea-level pressure footprints
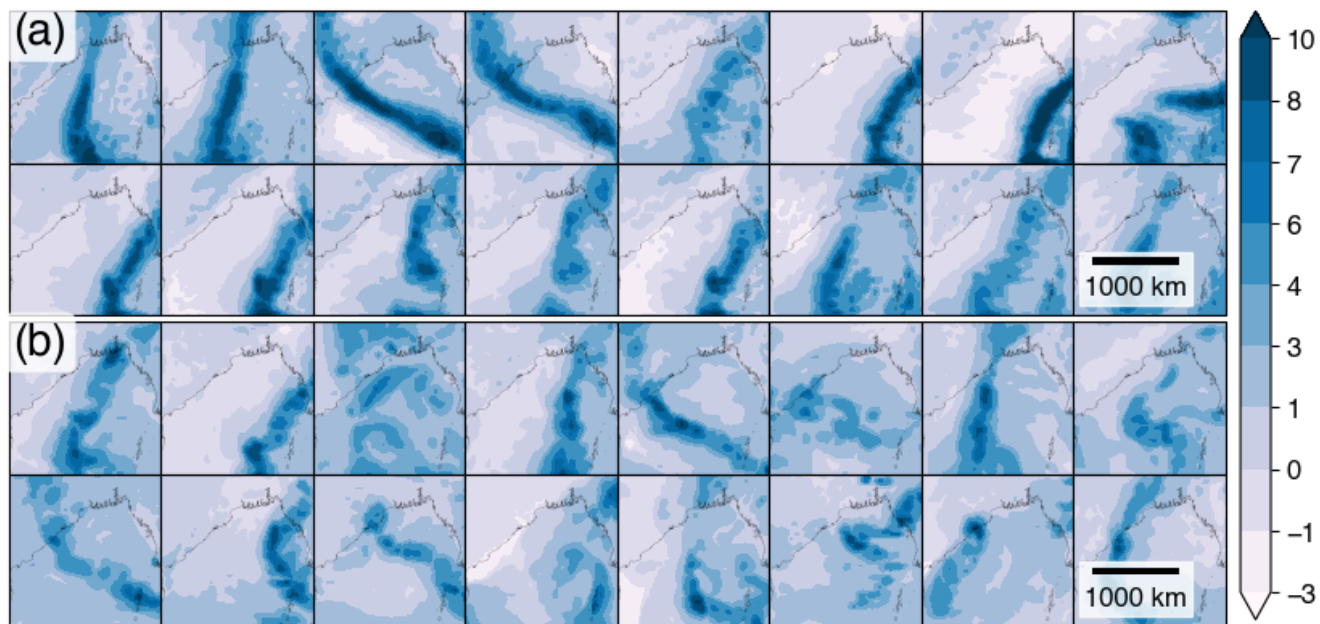
Figure S2. Comparison of generated (a) and training (b) precipitation fields over the Bay of Bengal in Gumbel space.
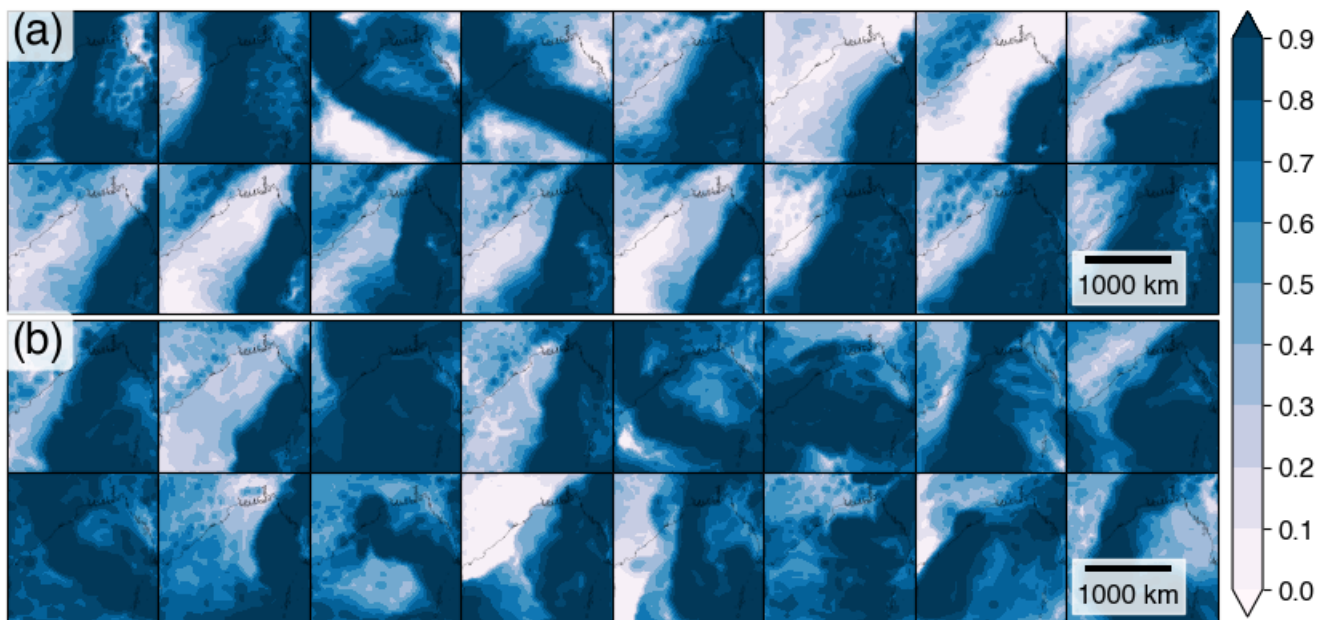
Figure S3. Comparison of generated (a) and training (b) precipitation fields over the Bay of Bengal in uniform space.
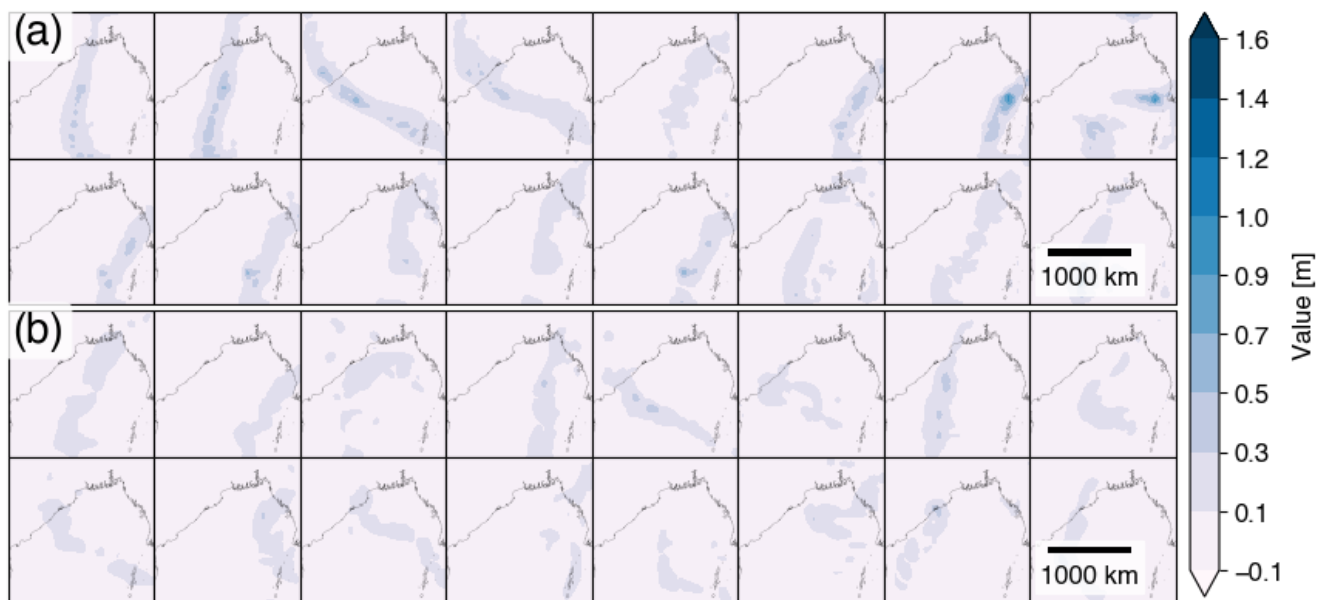
Figure S4. Comparison of generated (a) and training (b) precipitation fields over the Bay of Bengal in the data space.
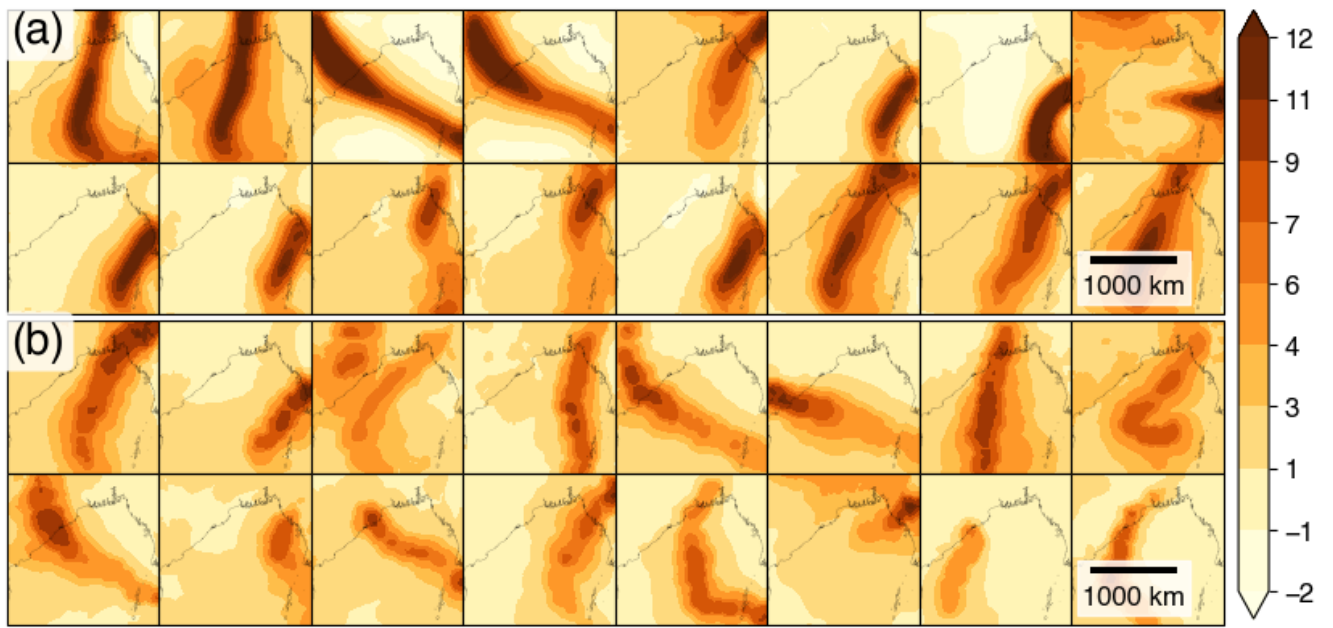
Figure S5. Comparison of generated (a) and training (b) low pressure fields in Gumbel space.
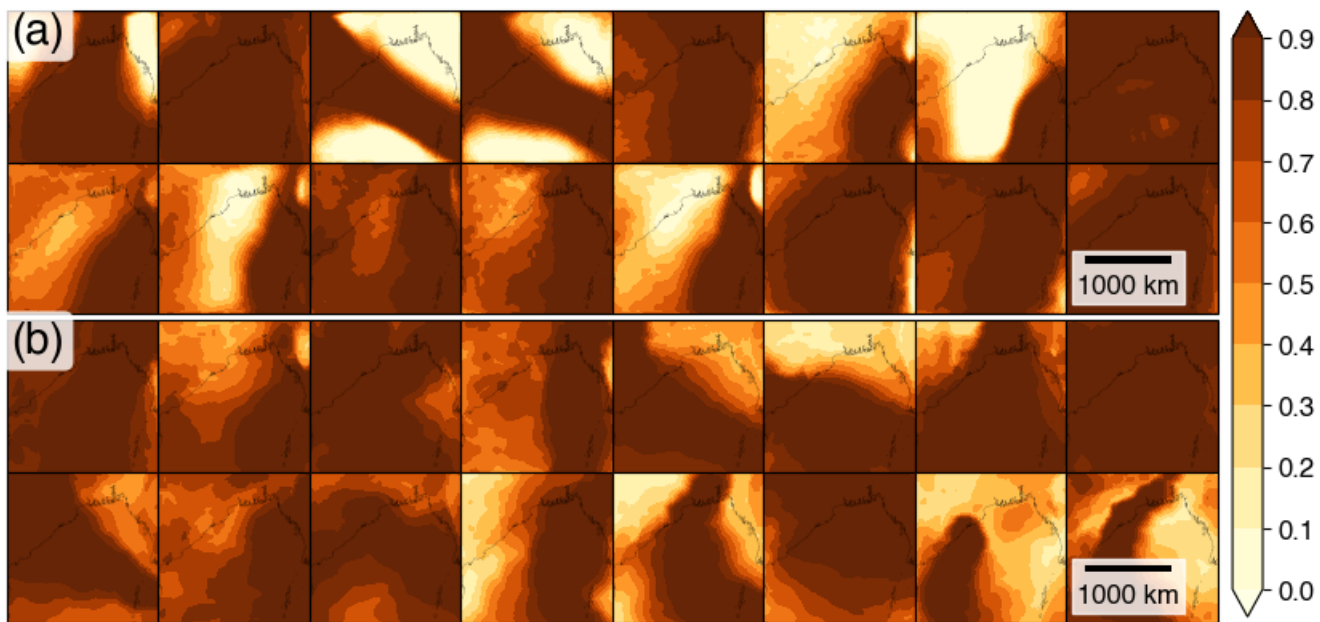
Figure S6. Comparison of generated (a) and training (b) low pressure fields in uniform space.
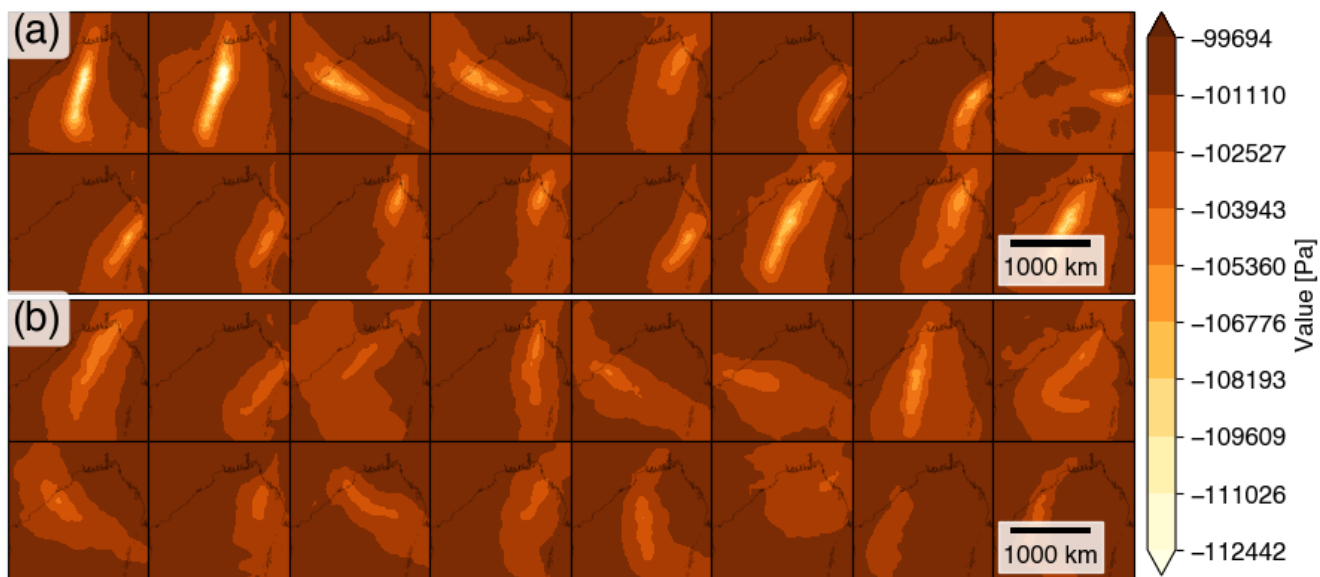
Figure S7. Comparison of generated (a) and training (b) low pressure fields in the data (**??** data spaces.

References

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