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Reask *Metryc:* A Probabilistic Wind Gust Model for Tropical Cyclone Event Response with Global Coverage

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Abstract
Estimating ground level winds during a Tropical Cyclone (TC) landfall is a time sensitive and uncertain exercise. The ability to quickly identify areas of highest risk provides critical insight to first responders and for event mitigation activities. While national agencies around the world are trusted to provide good estimates of location and intensity of a TC at landfall, other key drivers of wind risk, such as the location of maximum wind intensity or the size and shape of the wind field, remain uncertain. This article introduces *Metryc*, a probabilistic modelling system designed to capture the distribution of spatial wind risk at landfall in terms of local-scale wind gusts. Following a similar philosophy to Monte Carlo based risk assessment samplers, *Metryc* simulates 100 different scenarios with a range of estimates for (1) the location of maximum winds, (2) the shape of the wind field and (3) the impact of local terrain. The article reviews the methods and datasets used in developing each model component, as well as the operational set up required to deploy *Metryc* in real-time. By deploying *Metryc* for all historical landfalls globally since 1945, we also introduce an extensive global database of over 929 historical gust footprints that can be used for retrospective analysis and impact model development. For 22 important events of the last decade, *Metryc* wind footprints are evaluated against surface gust observations and made available via an interactive web application.

Key Points
1. The *Metryc* system supports the generation of windspeed footprints for both historical and real-time tropical cyclones.
2. *Metryc* offers a global catalogue of over 929 historical tropical cyclone wind speed footprints at 1 km spatial resolution, covering the period from 1945 to present.
3. *Metryc* provides a probabilistic view of wind gust based on 100 ensemble simulations, primarily capturing uncertainty in observed storm size.

1. Introduction

Strong winds from landfalling tropical cyclones (TCs) cause severe impact to both coastal and inland populations worldwide each year. In the United States alone, tropical cyclones have resulted in nearly 7,000 deaths since 1980 and remain the most destructive weather-related disasters, with total losses amounting to US$1.3 trillion—an average of US$22.8 billion per event (Smith, 2025). Rapidly estimating the threat posed by a TC at landfall is critical for first responders as well as for other public and private bodies trying to plan for the aftermath of the event.

Tropical cyclone advisories issued by national meteorological agencies provide valuable information on storm track and intensity; however, impacts at landfall depend strongly on the spatial structure and extent of the wind field, information that is generally not fully captured by operational advisories (Chen and Chavas, 2022). A comprehensive real-time risk assessment would integrate a dense network of remote and in-situ observations, supplemented by gap-free satellite coverage. However, observational coverage remains inconsistent across regions, and real-time access to relevant data is often unreliable.

Moody's RMS HWind, initially developed by the National Oceanic and Atmospheric Administration's (NOAA) Hurricane Research Division (HRD), provides tropical cyclone wind analyses using data from multiple observational platforms. While HWind delivers valuable surface wind insights, its real-time effectiveness is constrained by observational density and coverage, which are primarily limited to the Atlantic, Eastern Pacific, and Central Pacific basins (Powell *et al*., 2010; Lockwood *et al*., 2024).

An alternative to purely observation-based risk assessment is leveraging models to optimise available data and address coverage gaps. These models integrate the physical principles governing TC behaviour at landfall with statistical relationships characterising key risk parameters. To reconstruct the physical evolution of a TC, models incorporate inputs from national reporting agencies, when available, to estimate position and intensity. Other critical parameters, such as the radius of maximum winds and radial wind decay, are also estimated to simulate the spatial distribution of wind speeds over time, identifying regions experiencing the strongest winds (Holland, 1980; Willoughby, 2006).

While national reporting agencies generally provide accurate TC location and intensity estimates, significant uncertainty remains in other key inputs, such as the radius of maximum wind and empirical parameters that define wind field shape (e.g., the B parameter in the Holland model). Failure to account for this uncertainty can lead to inaccurate risk assessments and misplaced confidence in risk communication to emergency personnel.

To address this uncertainty, we introduce a probabilistic modelling system called *Metryc*. Unlike traditional deterministic models that rely on a single "best guess" estimate, *Metryc* explicitly samples distributions of uncertain input parameters (see Section 3.2), enabling the simulation of a more comprehensive risk profile. Within 12 hours of a tropical cyclone landfall, *Metryc* generates a hazard layer representing the estimated peak wind risk at 1 km spatial resolution for the affected area. This process is applied for each storm globally. Currently, *Metryc* supports several parametric insurance products worldwide for both private and public sectors (e.g., Swiss Re, 2022; PCRIC, 2024), providing local wind speed estimates to facilitate insurance contract settlements. Additionally, *Metryc* has been applied to all historical TC landfalls globally since 1945, producing a dataset of historical wind footprints valuable for evaluation and retrospective analysis, as well as development of impact models.

Following an overview of *Metryc*'s sub-components, this paper outlines the framework used to deploy the tool globally with input track data. We then evaluate *Metryc*'s performance by analyzing a subset of the most impactful landfalling events of the past decade, comparing model outputs with available surface wind observations. Results from this evaluation exercise are made available via the interactive web application (https://apps.reask.earth/metryc-app/).

2. *Metryc* sub-models

Metryc simulates tropical cyclone (TC) wind risk at landfall by integrating wind parameter models from Bruneau *et al*. (2024, hereafter BR24) with a wind field model based on Loridan *et al*. (2017, hereafter LO17), retrained on 1 km resolution data from the InCyc database (see BR24 and below). All sub-models employ quantile regression forests (Meinshausen, 2006) to capture conditional probability distributions, enabling ensemble-based uncertainty quantification.

The models are trained on InCyc, a global database of high-resolution (1-km) WRF tropical cyclone simulations spanning 1980-2020 across all basins (Bruneau *et al*., 2024). The InCyc simulations employed a three-domain nested configuration (27 km, 9 km, 1 km) with Thompson microphysics, MYNN PBL scheme, and RRTMG radiation. Cases were systematically selected to form a representative sample of each basin's historical climatology, capturing the full spectrum of intensities (tropical storm to category 5), environmental conditions (tropical to extratropical transition), and geographic variability. This sampling strategy ensures the models learn physically realistic TC features across different regions and storm configurations. Evaluation of 58 simulated events across the North Atlantic and western North Pacific shows good agreement with observations, including correlation coefficients of 0.7 for central pressure (mean bias ~2 hPa, RMSE 21 hPa) and 0.65 for maximum winds (mean bias 2.6 m s^{-1}, RMSE 13 m s^{-1}), with track displacement errors below 100 km. When applied to TC track and intensity parameters at fixed intervals, the machine learning models (BR24, LO17) generate a spatial simulation of the wind field structure surrounding the system. Additionally, a terrain correction model (detailed in Appendix 1) adjusts wind speeds to account for local gust conditions. Figure 1 presents the workflow of the different sub-models.

2.1. Wind parameters

BR24 provides machine learning-based predictive models for key tropical cyclone parameters:

- Radius of maximum winds (*Rm*)
- Azimuth of maximum winds relative to storm heading direction (*Am*)
- Central pressure (*Cp*)
- Maximum 1-min sustained winds (*Vm*)
- Conversion factors between *Cp* and *Vm*

The BR24 QRF (Quantile Regression Forest) models use track-based predictors including TC position, translational speed, heading, central pressure, maximum winds, and their temporal evolution (6-hour changes and tendencies). By training on the InCyc database, the models learn relationships between readily available track parameters and more uncertain structural characteristics (*Rm*, *Am*). The BR24 models leverage learned relationships between track parameters to infill missing values. For instance, when *Vm* and *Rm* are unavailable, *Cp* can serve as a predictor to estimate them, and vice versa. Cross-validation using leave-one-storm-out evaluation across 58 cases demonstrates predictive skill, with high correlations for maximum winds (*Vm*) and generally unbiased median predictions. Prediction errors are typically in the range of 10-20 km for *Rm* and 5 m s^{-1} for *Vm*, performing favourably compared to traditional parametric approaches.

A key advantage is the ability to simulate parameter distributions conditioned on other TC characteristics, allowing physically consistent representation of variability across different storm configurations. For example, the *Rm* distribution for an intense, slow-moving system in the deep tropics is typically skewed toward smaller values compared to a weaker, faster-moving system in the mid-latitudes (Smith *et al*., 2015). BR24 therefore quantifies storm size, intensity, and peak wind location uncertainties used by *Metryc*.

2.2. Wind field shape

The wind parameters at each track point are input into the LO17 wind field model to simulate the distribution of wind shape parameters (Wi). The LO17 framework decomposes WRF-simulated wind fields (the target) using Principal Component Analysis (PCA), representing each normalised wind field as:

$$\text{TARGET} = \text{MFLD} + W_1 \times PC_1 + W_2 \times PC_2 + W_3 \times PC_3$$

where MFLD is the mean field and PC_i are spatial patterns. The first three principal components collectively explain over two-thirds of wind field variability.

QRF models predict the conditional distributions of W_1, W_2, and W_3 using a sequential structure: W_2 is predicted conditional on W_1, and W_3 conditional on both W_1 and W_2, capturing dependencies between radial structure and asymmetric patterns.

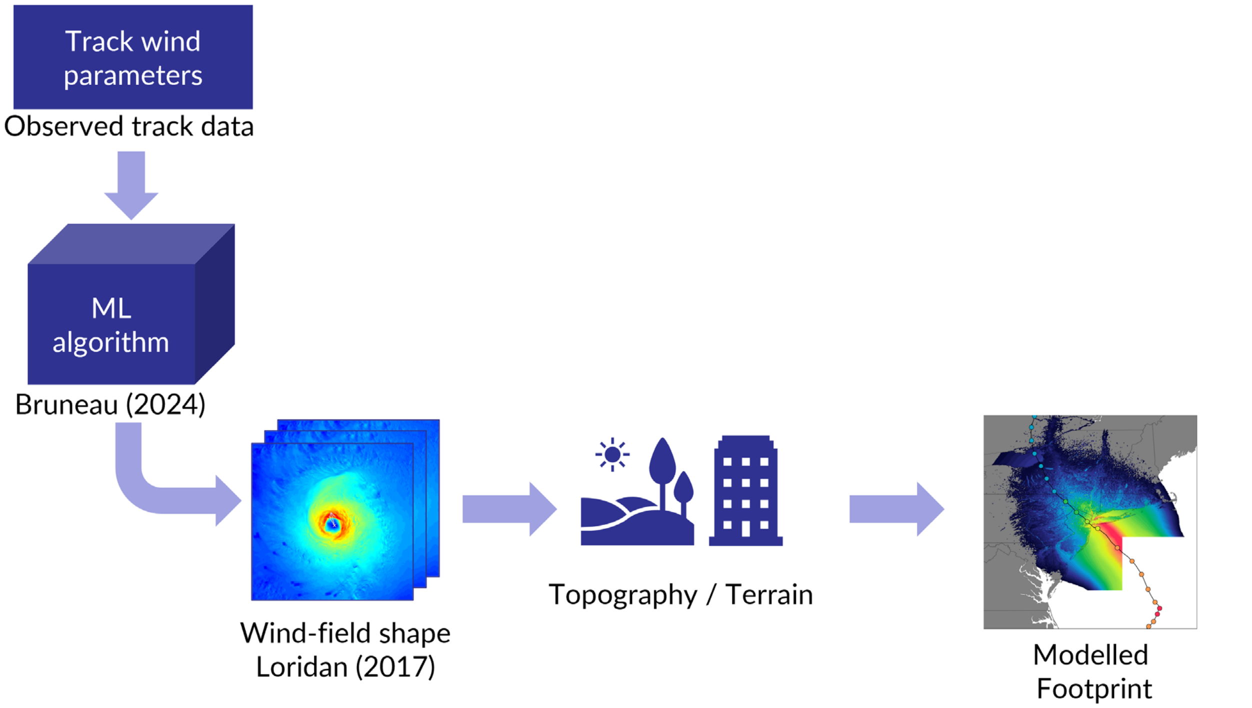

Figure 1: *Workflow of Metryc sub-models.*

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Predictor variables include storm structure (*Rm*, *Am*, *Vm*, *Cp*), track characteristics (position, motion, heading). Cross-validation using leave-one-storm-out testing shows that 89-92% of observed weights fall within the models' 90% confidence intervals (W_1: 92.3%, W_2: 89.1%, W_3: 91.3%), with approximately 50-55% captured by the 50% intervals, confirming the models successfully predict wind field variability with well-calibrated uncertainty estimates. These parameters account for radial decay in wind speeds (W_1) and dominant modes of wind asymmetry, including along-track asymmetry (W_2) and across-track asymmetry (W_3). This framework captures the diverse range of TC wind structures observed globally, including pronounced asymmetries during extratropical transition in the western Pacific (Loridan *et al*., 2014).

The combination of BR24 and LO17 models simulates the spatial distribution of winds around a TC, estimating 10 m 1 min sustained winds over water consistent with the InCyc training data.

2.3 Terrain correction

The final sub-model included in *Metryc* captures the influence of terrain on wind speed estimates and allows conversion of the over-water equivalent sustained winds simulated by LO17 into 3 second wind gusts over land. This terrain model (detailed in Appendix 1) is designed to capture the impact of topography and changes in surface roughness both locally and upwind, using 8 directional sectors. This model is run at a resolution of 1 km and enables the estimation of a 3-sec gust that is most representative of the local conditions on the ground. As a result, locations sheltered in valleys or surrounded by rough terrain, such as forests or densely populated urban areas, will experience relatively weaker winds than open terrain regions.

3. Deployment framework

The three sub-models described in Section 2 allow conversion of track information (i.e., point data), into a 1 km gridded map of wind gust speeds at ground level. This section reviews how the models are initialised and deployed in real time. To illustrate key concepts, Hurricane Laura 2020 is used as an example.

3.1. Data source and modelling philosophy

For real-time event response, *Metryc* can ingest tropical cyclone track data from multiple operational sources, including:

- **NCAR TCGP (Tropical Cyclone Guidance Project) real-time B-deck data**, which incorporate tracks from the U.S. National Hurricane Center (NHC) for the North Atlantic, Eastern Pacific, and Central Pacific basins, and from the Joint Typhoon Warning Center (JTWC) for other global basins.

- **WMO-designated Regional Specialized Meteorological Centers (RSMCs)**, which provide official operational track data from centers such as JMA (Japan Meteorological Agency), IMD (Indian Meteorological Department), and BOM (Bureau of Meteorology).

- **RAMMB (Regional and Mesoscale Meteorology Branch of the Cooperative Institute for Research in the Atmosphere, CIRA)**, which hosts real-time track data consistent with the above NHC- and JTWC-based inputs.

This multi-source integration allows users to select the track dataset most appropriate for their application while maintaining flexibility across basins and operational contexts. For historical events (Section 4), *Metryc* uses best-track data from IBTrACS, which aggregates multiple authoritative sources, including NHC, JTWC, and WMO-RSMCs.

When deployed in real time, *Metryc* is run when the first landfalling point has been analysed and reported, with the goal of making wind estimates available 12 hours after landfall. Figure 2 shows an example set up for Hurricane Laura 2020, with the last over ocean point before landfall marked as "anchor point" (see section 3.2).

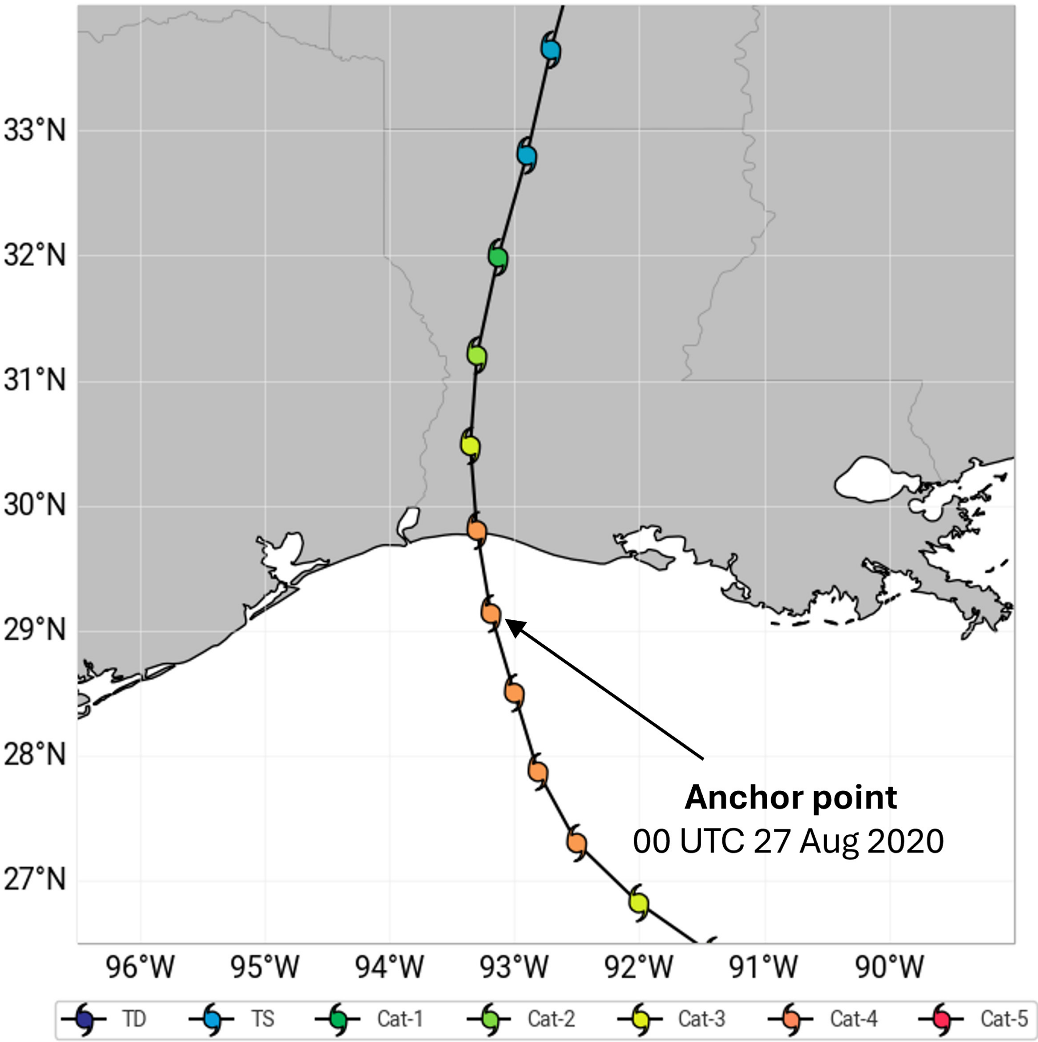

Figure 2: *The observed track of Hurricane Laura (2020). The anchor point, marked on the track, corresponds to the final over ocean observed position before landfall (00 UTC on 27 August 2020). It represents the location at which the Metryc system is initialised (see section 3.2).*

The automated deployment of the system follows these principles:

1. **Track Data Reliability:** *Metryc* primarily uses track data from the NHC and JTWC, the authoritative agencies providing reliable estimates of TC track location and intensity, including 1 minute sustained maximum surface winds and central pressure. However, *Metryc* also offers flexibility to choose track data from WMO recognised RSMC.

2. **Uncertainty in Wind Field Parameters:** Key wind parameters as described in section 2.2 —radius of maximum wind (*Rm*), azimuth of maximum winds (*Am*), and wind field shape (Wi)—are highly uncertain, particularly over land (Sampson *et al*., 2017). Sampling this uncertainty is important in assessing surface wind risk.

3. **Ensemble Simulation Approach:** To explicitly account for these uncertainties, *Metryc* simulates 100 different versions of the event landfall (i.e., 100 ensemble members). Each simulation maintains the same track trajectory and intensity but samples different values for *Rm*, *Am*, and Wi from their respective distributions based on BR24 and LO17 machine learning models.

4. **Peak Wind Gust Mapping:** For each of the 100 ensemble members, *Metryc* produces a 1 km resolution map of peak 3-second wind gusts, representing the highest gust experienced at each grid cell over the storm's lifetime.

5. **Probabilistic Wind Risk Assessment:** The 100 resulting gust footprint maps provide a distribution of gust estimates for each 1 km cell in the landfall region. These distributions enable the extraction of probabilistic metrics to characterise the spatial profile of wind risk. Typically, the 50th percentile gust at each cell is summarised into a single map, as shown in Figure 3, but other metrics such as the 90th percentile or exceedance probability levels can also be made available.

The footprint of peak gusts (50th percentile) simulated in real-time by the *Metryc* system for Hurricane Laura (2020) is shown in figure 3. As Laura made landfall near Cameron, Louisiana, as a Saffir-Simpson category 4 hurricane, it produced extreme wind gusts, with maximum recorded gusts of approximately 150mph near the point of landfall. These gusts were strong enough to destroy the National Weather Service radar in Lake Charles, along with other automated weather stations in the region (Redmon, 2020; Erdman, 2020). Table 1 summarises peak gusts reported by the NHC and NOAA's Global Surface Summary of the Day (GSOD) during the storm. Only a limited number of stations remained operational and recorded maximum gusts. Notably, the NHC reported a malfunctioning station in South Sulphur, Louisiana, located north of the highest recorded wind gusts. This station was excluded from further *Metryc* evaluation, as it did not meet the criteria for peak gust comparison (Appendix 2). This underscores the challenges of relying solely on ground-based observations to capture hurricane wind gusts, and highlights the advantages of using *Metryc* for comprehensive analysis.

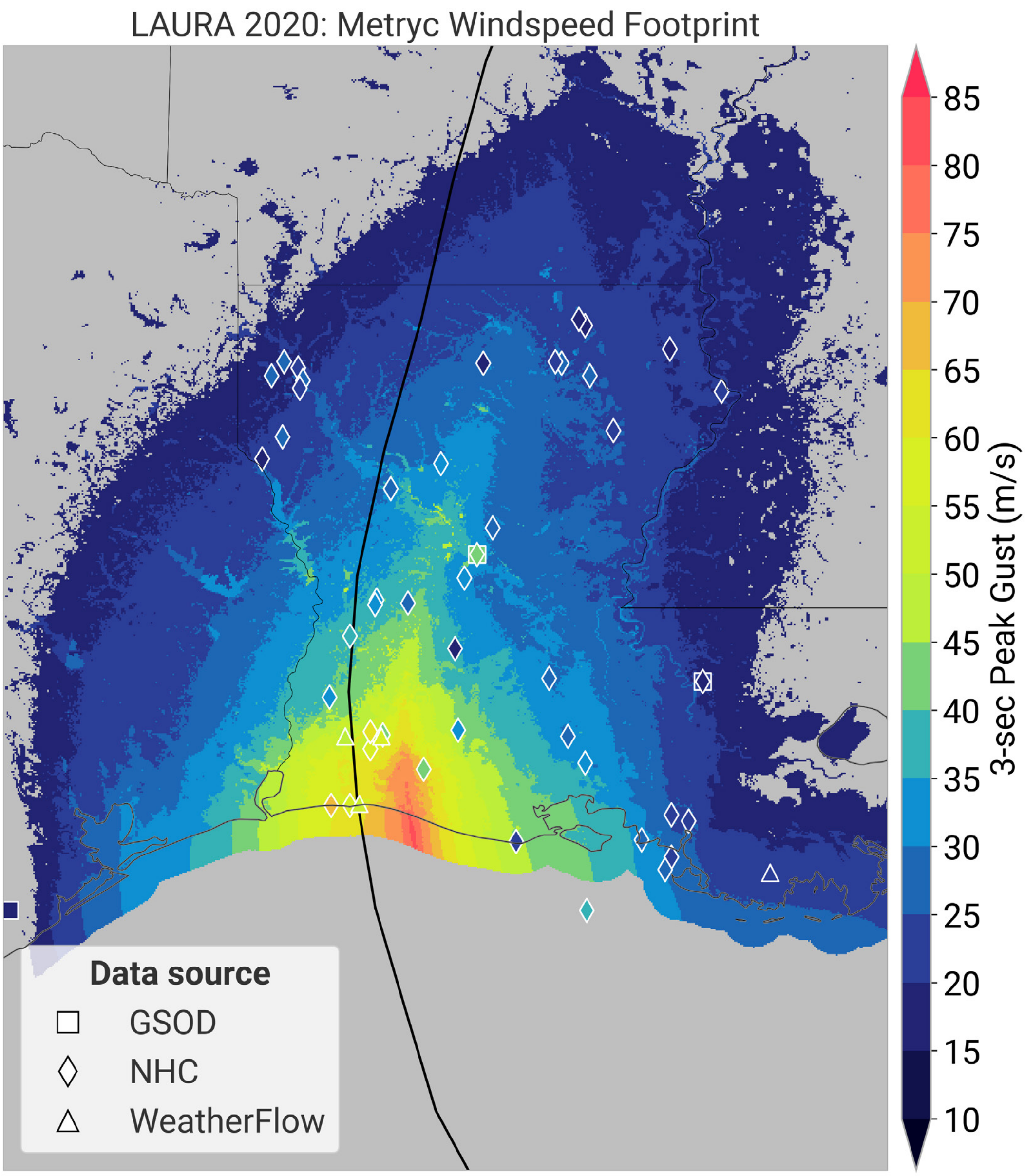

Figure 3: *3-second peak gust footprint of Hurricane Laura (2020) generated by Metryc (50th percentile). The black line represents the storm track from IBTrACS. Coloured markers indicate observation stations from NOAA GSOD (squares), NHC reports (diamonds), and WeatherFlow (triangles), overlaid on the modelled gust footprint. The details on observational sources are given in the appendix table A2.*

Table 1: Observed wind gusts reported during Hurricane Laura (2020), along with corresponding *Metryc*-simulated wind gusts at each station location and their percent difference from observed values. The meteorological station Sulphur (KUXL) (marked with *) represents a malfunctioning station that was excluded from the analysis. Note that only high wind gusts are listed here for illustration.

Station Name	Source	Longitude	Latitude	Observed Wind Gust (m/s)	Metryc Wind Gust (m/s)	Percent Difference (%)
Holly Beach - Mike Theiss, Reed Timmer, Jon Bowser	NHC	-93.46	29.77	68.4	57.2	16.3
Lake Charles 901 Lakeshore Drive	NHC	-93.22	30.23	61.2	52.8	13.7
Lake Charles Municipal Airport (KLCH)	NHC	-93.22	30.12	59.7	57.2	4.1
FCMP T1 Sulphur (UF1T)	WeatherFlow	-93.15	30.2	59.2	55.3	6.5
Calcasieu Pass (CAPL1)	NHC	-93.34	29.77	57.1	61.9	8.4
Cameron (XCAM)	WeatherFlow	-93.29	29.78	52.0	61.1	17.5
FCMP T3 Lake Charles (UF5T)	WeatherFlow	-93.37	30.2	49.4	50.8	-2.8
USW00093915	NOAA	-92.56	31.33	42.9	31.1	27.5
Lacassine (LACL1)	NHC	-92.89	30	42.7	63.9	49.6
Chenault Airpark (KCWF)	NHC	-93.14	30.21	41.7	56.1	34.5
Alexandria International Airport (KAEX)	NHC	-92.55	31.33	40.1	31.1	-22.4
Sulphur (KUXL) *	NHC	-93.38	30.13	28.8*	55.3	92.0*

3.2. Operational workflow

The following workflow and sampling procedure are used to implement the *Metryc* methodology as illustrated in schematic flow chart figure 4.

1. **Track Data Acquisition:** Collect TC track location, intensity, and size estimates from sources described in section 3.1

2. **Data Processing:** Compute all derivatives required by the BR24 and LO17 models, including hourly changes, tendencies, headings, and translational speed (see Table 2 in LO17).

3. **Storm Size/Shape Distribution Modelling:** Model the distribution of *Rm* (radius of maximum winds) and *Am* (azimuth of maximum winds) conditional on track parameter estimates at anchor point (see Figure 1). To ensure a physically consistent initialisation, *Metryc* uses the final over-water position as anchor point rather than the landfall point, as estimates of storm size and wind-field structure (e.g., *Rm* and *Am*) are far more reliable before land interaction. Over land, these parameters become highly uncertain due to rapid structural changes and reduced observational constraints; initialising the BR24 models at the last over-water point therefore provides a more robust basis for ensemble sampling.

   - Use the *Rm* estimate available from the source track data at anchor point; locate this *Rm* value within modelled *Metryc* distribution and store the corresponding quantile (q_{anchor}).
   - If *Rm* estimates are unavailable in the source data, initialise the system to a climatological state and set qanchor=0.5.
   - For *Am*, the system defaults to a climatological state (q_{anchor} = 0.5). When available, RAMMB Aircraft-Based Tropical Cyclone Surface Wind Analyses are used to force the BR24 model at the anchor point, providing a more observationally constrained initialisation. In the current version of *Metryc*, this capability is available for North Atlantic hurricanes over the 2017–present period, for which aircraft reconnaissance data are routinely collected (e.g., Hurricane Ian 2022 had strongest winds left of track before its Florida landfall, see Figure 5a).
   - For *Wi,* the system defaults to a climatological state (q_{anchor}= 0.5).

4. **Sampling Window Definition:** Define a sampling window for quantiles at each track point post anchor to account for increased uncertainty:

$$q_{min} = q_{anchor} - 0.125 + 0.025 \times is.over.land$$

$$q_{max} = q_{anchor} + 0.125 + 0.025 \times is.over.land$$

Where *is.over.land* = 1 if the TC center is over land, otherwise 0. Both *q_min* and *q_max* are constrained between 0.01 and 0.99.

5. **Ensemble Initialisation (100 Members):**

Generation of 100 ensembles that are identical in terms of track and intensity but vary in *Rm*, *Am*, and *Wi*:

- Randomly sample a *Rm* quantile within [*q_min, q_max*] and generate the corresponding *Rm* estimate.
- Add the *Rm* estimate to the parameter list, model the *Am* distribution, and repeat Step 5.1 to sample and estimate *Am*.
- Repeat the process for *Wi* parameters.

6. **Time-Stepping Simulation:** Repeat Step 5 for all subsequent track points, adjusting the quantile sampling window as described in Step 4.

7. **Interpolation:** Interpolate all track parameters including *Rm, Am* and *Wi* to a 1 minute *Metryc* model time step.

8. **Wind Field Computation:** Apply time-stepping wind field calculations and directional terrain model coefficients to compute surface wind gusts at 1 minute intervals.

9. **Peak Gust Mapping:** For each 1 km grid cell, store the maximum gust recorded throughout the storm's passage to generate a gust footprint for each ensemble member.

10. **Probabilistic Footprint Generation:** Extract the median wind speed estimate among the 100 ensemble members for each 1 km grid cell to produce the 50th percentile gust footprint as shown in figure 3.

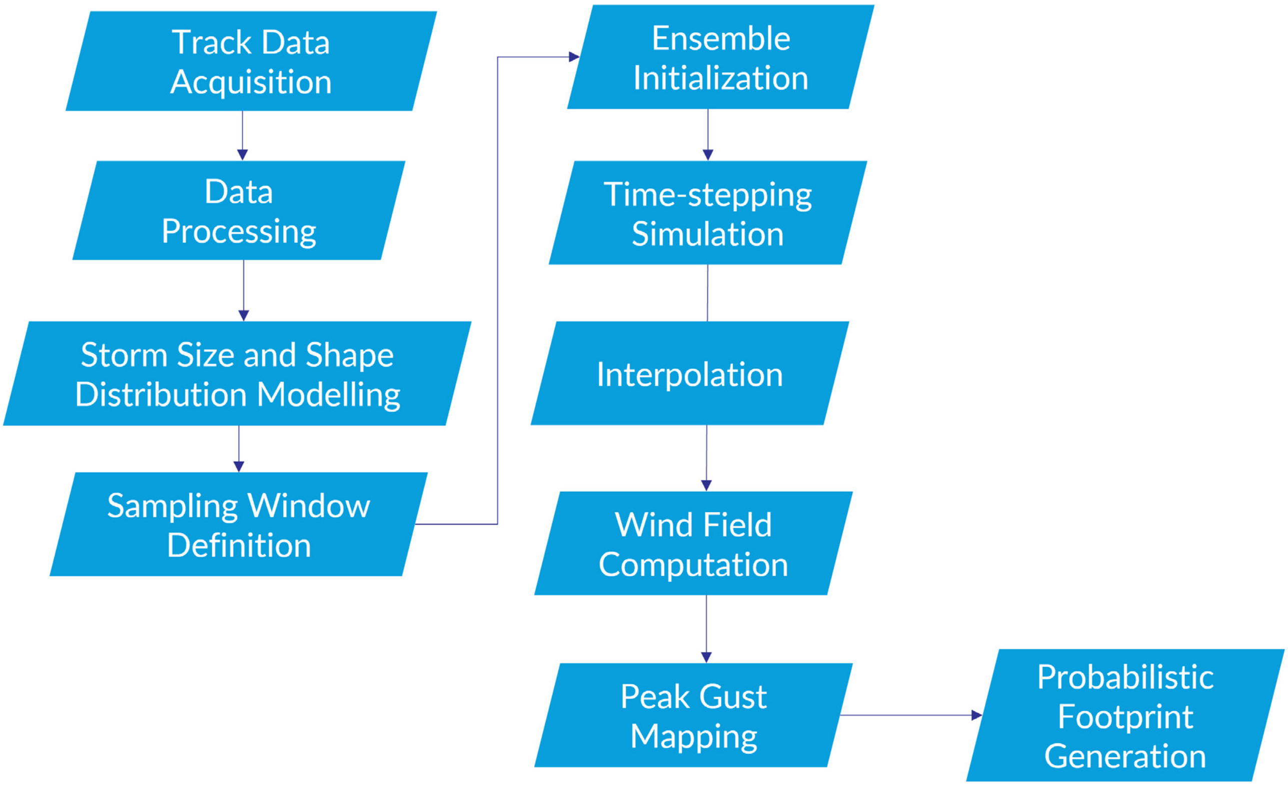

Figure 4: *Metryc system operational workflow*

4. Global catalogue of historical events and model evaluation

In this section we deploy *Metryc* on historical track information and introduce a global catalogue of simulated gust footprints dating back to 1945. We also present some results from an evaluation exercise focused on major events that occurred in the U.S., Japan and Australia during the 2016-2023 period (22 events).

Gathering a clear picture of surface wind distribution from observation networks is very challenging, and simply impossible for older historical events. By running *Metryc* using best-track data from IBTrACS as input we have two main goals:

- **Performance benchmark:** A thorough evaluation against available surface observations for events in the most recent years of the IBTrACS database provides a benchmark for the accuracy of the model. In this evaluation exercise we only use information from IBTrACS that is available all the way back to 1945 (i.e., storm position and intensity).

- **Consistent deployment back to 1945:** Evaluating *Metryc* against recent, well-observed storms demonstrates that the system reliably and consistently converts track and intensity information into realistic gust footprints. Because the same calibrated statistical relationships, sampling strategy, and terrain-interaction models are applied uniformly across the entire archive, the behaviour of the *Metryc* system remains consistent when deployed back to 1945. Thus, while earlier decades inevitably carry some uncertainty in the underlying best-track intensity estimates, this uncertainty stems from the input data rather than from the *Metryc* methodology itself. As a result, the historical footprints remain suitable and robust for large-sample climatological analyses, trend studies, and impact-model development, benefiting from a globally consistent modelling framework across all events.

4.1 Model evaluation

By comparing *Metryc* estimates to available surface wind gust observations we can test model accuracy over a range of locations. One challenge in this exercise is the difference in scale between what *Metryc* simulated wind gusts represent and what a surface measurement instrument likely samples, especially in complex terrain conditions.

- Wind estimates from *Metryc* are designed to represent the average gust to expect over a 1 km2 cell (i.e., the local, or neighbourhood scale, (Grimmond and Oke, 2002)). For cells with large variability in land use and/or topography setup, this will result in a gust value that can't be explicitly measured from any one location within the cell. Yet this is an appropriate metric to characterise the average surface experience of a neighbourhood.
- Observation instruments on the other hand will typically be sited so that their source area samples flat and smooth terrain conditions (e.g., airports). In complex terrain conditions like Japan this is not always possible and the source area for measurement might show higher variability in land use and elevation.

In this setup, the two dimensions described above will only match in cases where the 1 km^2 cell is flat, very homogeneous in land cover, and the source area from the observation instrument samples the same conditions (ideally located at the centre of the grid). In most cases however there will be an intrinsic difference between what *Metryc* is modelling and what the station is reporting. Model performance on any one particular observation is therefore of limited value. The analysis is instead targeting the overall model performance using a large number of data points, with a focus on identifying potential systematic biases.

For that purpose, we have assembled and quality controlled a dataset of over 500 surface observations for events occurring between 2016 and 2023 (see Table 2 and appendix 2). We here compare the peak 3 s gusts measured by the instruments over the lifetime of the events to the value modelled by *Metryc* for the 1 km^2 cell in which the instrument is sited.

Our aim with this evaluation exercise is not to minimise any given error metric, but rather to check that the *Metryc* system can capture the overall spatial trends in observed winds with limited systematic biases.

The evaluation is focused on major events from the 2016-2023 period. Table 2 lists the historical cases considered. Footprints from all Table 2 cases are accessible via our interactive web application (https://apps.reask.earth/metryc-app/), and we here only present a couple of illustrative cases along with evaluation statistics over the full 22 event dataset.

Table 2: Historical cyclone cases used for validation.

Region	Historical cases	Observational data source
U.S.	Idalia 2023, Ian 2022, Ida 2021, Delta 2020, Laura 2020, Sally 2020, Zeta 2020, Michael 2018, Florence 2018, Harvey 2017	• NHC reports • NOAA's Global Summary of the Day (GSOD) • WeatherFlow • Other airport stations
Japan	Nanmadol 2022, Hagibis 2019, Faxai 2019, Trami 2018, Jebi 2018, Cimaron 2018, Jongdari 2018, Lan 2017, Noru 2017 and Malakas 2016	• AMeDAS • Other Airport stations
Australia	Ilsa 2023, Debbie 2017	• GSOD • SWIRLNet • Bureau of Meteorology (BoM)

Figure 5 shows four examples of *Metryc* simulated peak wind gust footprints with surface observation reports. In most cases the *Metryc* footprints are able to capture the peak recorded winds with less than 10 m/s difference, with the exception of Cyclone Debbie (2017, Figure 5d) where *Metryc* underestimates the peak observation reported over Hamilton island (58.5 m/s modelled vs 73 m/s measured). However, a closer look into the location of that measurement station indicates a siting on a hill, close to marine exposure (Kloetzke *et al*., 2017). The wind gusts sampled by that station are therefore not aligned with the scale modelled by the *Metryc* model, and understandably higher. This is a good example of the discussion above regarding scale mismatch.

When it comes to the overall extent of the wind field, observations collected further away from the peak are mostly in line with modelled values. This confirms the ability of the model to capture radial decay and wind asymmetries in these cases. For Hurricane Ian (2022) for instance, modelled wind speeds decay from 70 m/s around Fort Myers down to 15 m/s in northern Florida, which agrees with evidence from surface observations. *Metryc* maximum estimates also align closely with observed peak gusts ranging from 50 to 70 m/s, with an atypical asymmetry pattern for the Northern Hemisphere where highest winds occur to the left of the storm track.

In some cases, *Metryc* wind speeds are lower than those observed far away from the track. This is the case for Typhoon Nanmadol (2022, Figure 5c) for instance, where several coastal stations in southern Japan are reporting much stronger winds that modelled. These locations lie more than 2.5 times the radius of maximum wind from the storm center, where localised mesoscale or convective wind features embedded within the broader tropical-cyclone environment may dominate. Such transient and non-axisymmetric processes are not explicitly captured by *Metryc* and likely explain the higher observed gusts at these sites.

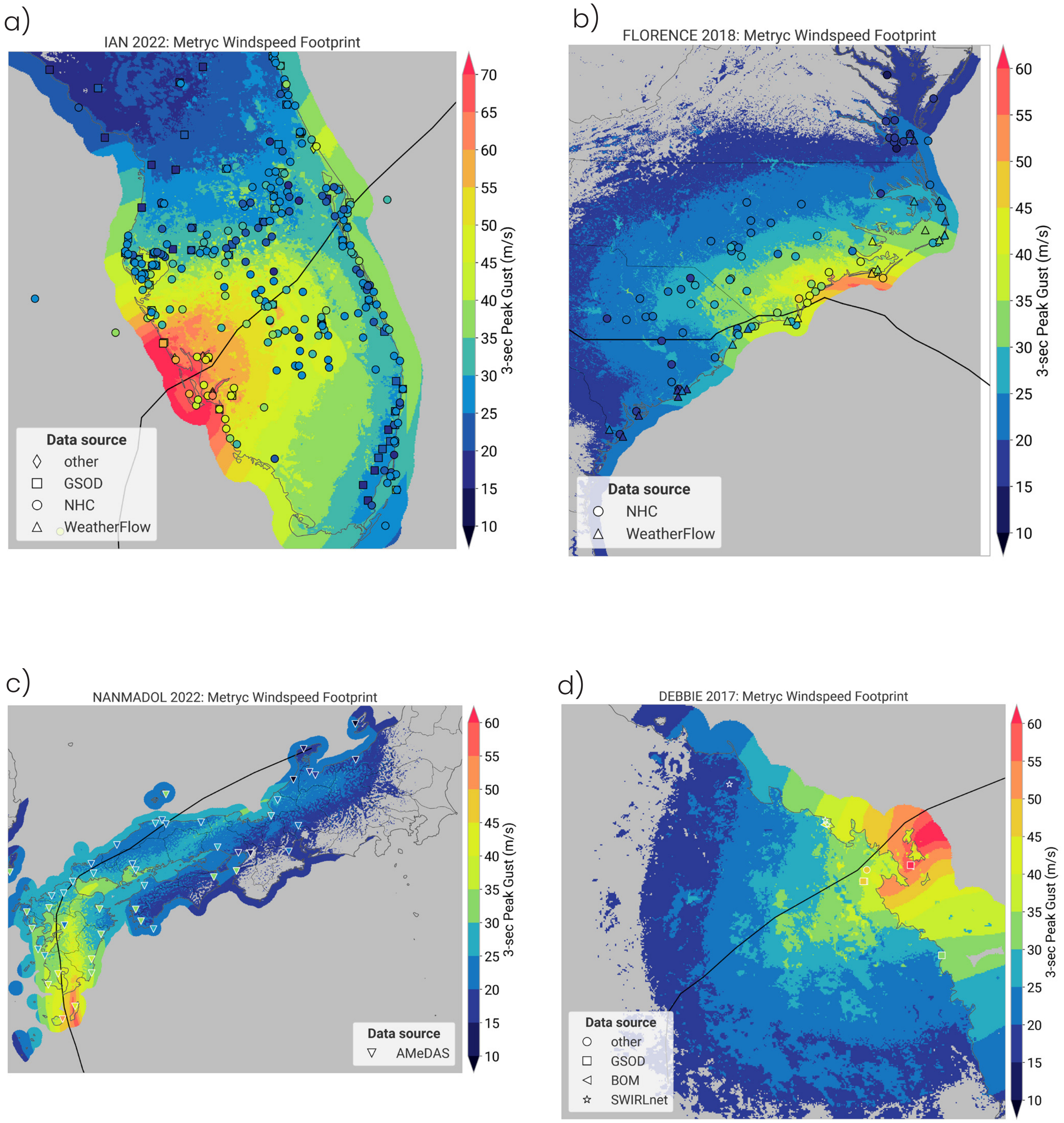

Figure 5: *Metryc peak gust footprints (m/s) for (a) Hurricane Ian (2022), (b) Hurricane Florence (2018), (c) Typhoon Nanmadol (2022), and (d) Cyclone Debbie (2017). Coloured markers represent station observations, with different symbols denoting different data sources.*

To analyse model behaviour beyond individual cases, we here look at the data for all 10 U.S. cases presented as a box-whisker diagram (Figure 6), where the distribution of modelled wind gust is compared to observations. For this analysis, observed gusts are binned in 5 m/s intervals. The median values of the modelled wind gust (see text and y-axis on Figure 5) compare very well with the observed bins (x axis). This provides confidence that *Metryc* modelled wind gusts can be seen as a good predictor of what a surface observation would record. Importantly it confirms the model captures the mean trend in observations with little biases.

Finally, Figure 7 summarises the evaluation of the 10 U.S. (panel a) and 10 Japanese (panel b) storms, with observed and modelled gusts presented as a scatter plot. Due to a small number of available observations, the two Australian storms are not shown.

For the U.S. cases, a slight positive bias is observed for wind speeds exceeding 45 m/s. However, the density of observations above 45 m/s is low and often flagged as incomplete in NHC reports with likely instrument failure (e.g., Ian 2022, Laura 2020, Michael 2018). The root mean square error (RMSE) and mean absolute error (MAE) for the 10 U.S. landfalling cases are 6.66 m/s and 5.01 m/s respectively. Importantly, *Metryc* shows an absolute difference of less than 10 m/s against observations for 89% of stations analysed.

For the 10 Japanese cases, Figure 7b shows a slight underestimation of *Metryc* gusts, particularly for locations more than 150 km away from the storm track. We mostly attribute this bias to frequent mismatch between measurement stations sited in complex terrain and what *Metryc* 1 km2 gust represent. The overall *Metryc* performance is similar to the U.S. with an absolute difference of less than 10 m/s in 87% of cases analysed with RMSE 6.38 m/s and MAE 4.93 m/s.

4.2 Global catalogue and impact modelling applications

To date we have assembled a global catalogue of over 929 historical TC wind footprints post 1945. The methods and type of input data used to assemble this catalogue are fully consistent with what was described in the evaluation exercise of section 4.1. This ensures a comparable level of quality for the resulting footprints, even when the system is deployed in regions and/or decades with very little observations available. This global dataset can be used on its own for retrospective analysis or in conjunction with other sources to allow development and calibration of impact prediction models.

Additionally, the consistency in the generation methodology between the footprints in the global catalogue and those provided immediately after landfall (section 3) allow for a very robust impact modelling framework:

1. **Impact model development:** *Metryc* wind gust can provide value when used as predictors of other impact metrics. Impact datasets such as claim reports, damage to properties, emergency calls or injury reports can be overlaid on top of the historical *Metryc* estimate to assess correlation and build predictive models (e.g., Bolliger and Minnoni, 2025).
2. **Out-of-sample historical back testing:** Thanks to the very large amount of events in the catalogue, out-of-sample model building and evaluation can be efficiently implemented. This is key to avoid overfitting issues.
3. **Model deployment:** Once an impact prediction model based on *Metryc* wind gust is built and validated (steps 1 and 2) it can be confidently deployed immediately at landfall to get fast impact estimates. This is only possible because the methods used to assemble the historical catalogue are the same as for the landfall footprint generation.

Current examples of use cases for the framework above include insurance claim predictions where policy providers seek to quickly assess their resource needs and impact immediately after a landfall, as well as impact based parametric insurance triggers where rapid and standardised impact reporting is critical. Currently, *Metryc* supports several parametric insurance products worldwide for both private and public sectors (e.g., Swiss Re 2022, AXA Climate 2024, Descartes 2022, and Pacific Catastrophe Risk Insurance Company (PCRIC) 2024), providing local wind speed estimates to facilitate insurance contract settlements. *Metryc* also underpins a people-focused parametric insurance scheme for the member states of the Pacific Catastrophe Risk Insurance Company (PCRIC 2024), with payouts that scale to the number of people impacted, ensuring swift liquidity for disaster-relief efforts across the region's vulnerable small-island nations.

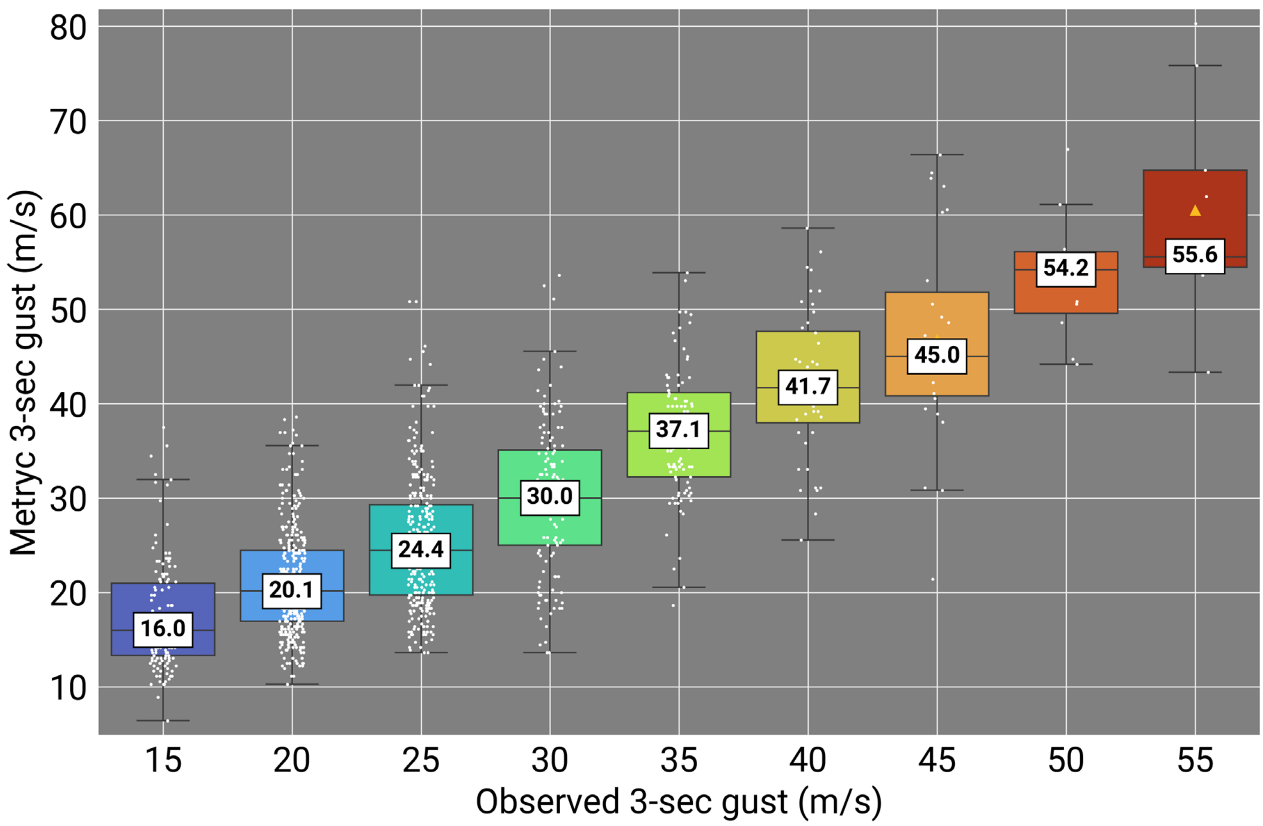

Figure 6: *Distribution of Metryc modelled wind gust against binned observations. The box shows the modelled 25th–75th percentiles (raw modelled values in white dots); the bar represents the 1st–99th percentiles while the value gives the modelled median and the triangle marker indicates the modelled mean.*

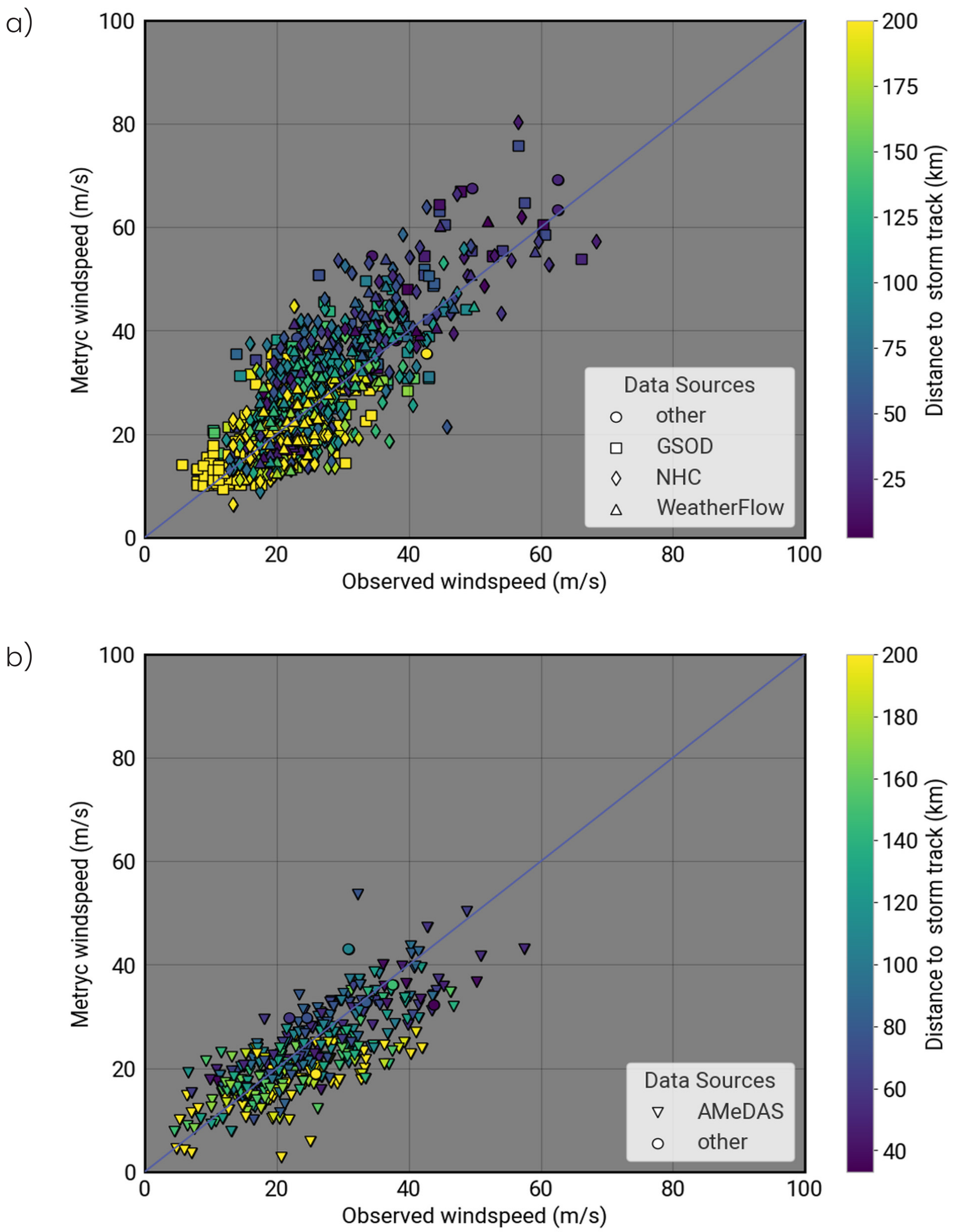

Figure 7: *Scatter plot of observed and Metryc simulated peak wind gust for (a) the 10 U.S. and (b) 10 Japanese storms listed in Table 2.*

5. Summary and Discussion

Gathering rapid estimates of surface wind speeds during the landfall of a major tropical cyclone is challenging. Many of the key drivers of wind risk remain highly uncertain at landfall, and observation networks are often too sparse to provide a complete assessment. This paper introduces an alternative approach called *Metryc*, which leverages machine learning to generate a probabilistic view of surface wind risk. *Metryc* is routinely deployed to produce 1 km resolution estimated gust maps within hours of landfall, offering complete global coverage. It is currently implemented as part of several parametric insurance products worldwide, providing localised wind speed estimates to facilitate the settlement of parametric insurance contracts.

Following a brief review of the core components of the system, this paper describes the real-time deployment of *Metryc* using Hurricane Laura (2020) as a case study. The model's performance is evaluated against surface wind observations from landfalling storms over the past decade, demonstrating strong agreement with available data across the world. For nearly 90% of cases in both the U.S. and Japan, modelled wind gusts and observations differ by no more than 10 m/s. All footprints from this analysis are made available via our interactive web application: (https://apps.reask.earth/*metryc*-app/).

Using the IBTrACS database as input, a catalogue of over 929 historical wind gust footprints was also assembled (this includes category 1+ landfalls). This vast global catalogue allows development of impact prediction models that can be consistently deployed to estimate immediate impact during a TC landfall. This is of particular interest for the humanitarian and parametric insurance use cases where swift and reliable triggers of action are important.

Metryc deliberately focuses on structural uncertainties (radius of maximum winds, azimuth of maximum winds, wind field shape) while treating track position and intensity as fixed inputs from authoritative agencies (NHC, JTWC, RSMCs). This design reflects the operational use case and the recognition that structural parameters represent the dominant uncertainty for spatial wind risk at landfall, particularly over land where observational constraints are weakest (Sampson *et al*., 2017). However, intensity estimates themselves carry uncertainty, particularly in basins outside the Atlantic. Incorporating intensity uncertainty is a priority for future development.

The anchor point initialisation assumes the last over-water structural configuration providing a reliable baseline. Storms undergoing rapid structural changes precisely at landfall (e.g., eyewall replacement cycles) may challenge this assumption.

Our validation is limited to well-observed regions (U.S., Japan, Australia). *Metryc* has been deployed operationally for all global landfalls since 2020, including data-sparse regions, with qualitative feedback from insurance and disaster response partners indicating general consistency with observed damage patterns (e.g., Bolliger and Minnoni, 2025). However, comprehensive quantitative validation in underrepresented regions remains constrained by observational availability and represents a priority as networks expand. Additionally, scale mismatch between 1 km^2 neighborhood-scale estimates and microscale station measurements inherently limits point-wise validation, particularly in complex terrain.

Despite these limitations, *Metryc* represents a significant advance in rapid, probabilistic tropical cyclone wind risk assessment, successfully combining physics-based simulations, machine learning, and operational track data to produce actionable wind footprints within hours of landfall. The strong validation performance, global historical catalogue, and operational deployment experience demonstrate *Metryc*'s value for parametric insurance, disaster response, and impact assessment applications.

Appendix 1: Terrain interaction model

Overview

The models described in section 2.1 and 2.2 allow generation of 10 m elevation winds that are representative of (a) over-water surface conditions and (b) 1 minute sustained estimates. The aim of the terrain interaction model is to provide grids of correction factors that allow conversion to (a) over land surface conditions and (b) 3-second wind gust.

These grids can then be used as part of *Metryc* to ensure wind estimates are representative of the ground level risk, including the contribution from terrain topography and land surface roughness (section 2.3).

The full conversion from over-water sustained winds to over land gusts is achieved in two separate steps and using two separate sets of land correction grids. First, the over-water equivalent sustained winds (*sustained_water*) are modified to account for the impact of topography and terrain roughness on the sustained component of the winds. The factors used for this step are referred to as site coefficients (*sc_grid*). The second step then converts the over-land sustained wind estimates (*sustained_land*) into a 3-sec gust (*gust_land*). These coefficients are referred to as gust factors (*gf_grid*).

Since the wind at a given location is influenced by terrain characteristics both at that location and upwind, we developed eight different grids for each of the two steps. Each grid captures terrain influence assuming the wind is blowing from one fixed sector (i.e., E, NE, N, NW, W, SW, S or SE).

As a result, the following set of conversions allows computation of over land gusts from knowledge of 1 minute sustained estimates over water and wind directions.

$$sustained_{land}[k]=sustained_{water}[k] \times sc_{grid}[k,s] \tag{1}$$

$$gust_{land}[k]=sustained_{land}[k] \times gf_{grid}[k,s] \tag{2}$$

where k is the index for a 1 km grid cell and s is one of the eight wind sectors (E, NE, N, NW, W, SW, S, SE).

Model development

To develop models capable of populating all 16 directional terrain correction grids globally, we followed a framework analogous to LO17 and BR24. Site coefficient and gust factor models were developed using (1) a database of high-resolution numerical simulations and (2) machine learning (quantile regression forests, Meinshausen 2006) to generalise key relationships.

Training simulations: A series of historical landfalling tropical cyclones were simulated using WRF (Skamarock *et al.*, 2019) at 1 km resolution: Katrina 2005 (U.S.), Sandy 2012 (U.S.), Jebi 2018 (Japan), and Debbie 2017 (Australia). These cases were selected to represent diverse terrain types including coastal plains, complex mountainous terrain, and varied urban-rural landscapes. Each simulation employed the highest resolution land use and topography datasets available for the region, along with state-of-the-art topography and roughness parameterisation schemes (e.g., Jiménez and Dudhia 2012).

Gust parameterization: The gust estimates used for training were derived by post-processing WRF outputs following Stucki *et al.*, (2016), who developed a physically based parameterisation that diagnoses the planetary boundary layer (PBL) height and mixes higher winds from aloft into the surface layer to represent 3-second gusts. This approach addresses scale limitations inherent in 1 km resolution atmospheric modeling, where individual turbulent eddies cannot be explicitly resolved. Our resulting gust factors therefore represent the expected relationship between sustained winds and gusts at the local (neighborhood) scale as defined by Grimmond and Oke (2002), capturing terrain-driven variability across 1 km^2 grid cells rather than microscale turbulence patterns.

Training targets: To match the framework in Equations 1 and 2, WRF-simulated sustained winds over land were normalised by their over-water-equivalent values to produce site coefficients (Equation 1), while simulated over-land gusts were normalised by over-land sustained winds to produce gust factors (Eq. 2). These normalised ratios constitute the training targets for the machine learning models.

Feature engineering: To model terrain effects on these correction factors, relevant surface features were identified and computed in two steps:

1. **Source area computation:** For each grid cell and wind direction, this module identifies the upwind cells that most influence local wind conditions based on terrain characteristics and flow dynamics.

2. **Feature computation:** Detailed terrain roughness and topography characteristics are computed both locally and along the upwind source area (Table A1). The directional terrain correction factors are then trained from these features.

Table A1: Terrain features computed at cell location and along source area upwind to be used to train the site coefficient and gust factor models

Feature	Description
Z0.LOC, Z0.S1	Roughness length (m) at the cell location (Z0.LOC) as well as for the cell immediately adjacent in the source area (Z0.S1).
Z0.UW.MU	Roughness length (m) averaged for all cells up to 3 km upwind along the source area.
Z0.LOC.MU	Roughness length (m) averaged for all cells adjacent to the location of interest.
HGT.LOC	Terrain elevation (m) at the cell location.
VAR.UW.MU	Variance in terrain elevation averaged 3 km upwind along the source area.
LP.LOC, LP.UW	Normalized Laplacians (Jimenez and Dudhia, 2012) for the cell location (LP.LOC) as well as upwind along the source area (LP.UW).

Machine learning architecture: Three sequential machine learning sub-models capture and generalise terrain impacts:

1. **Source area model:** Learns to identify the most likely upwind cells of influence from location, wind direction, and terrain characteristics.
2. **Site coefficient model:** Predicts site coefficients based on terrain elevation and roughness at the location and along the upwind source area (Table A1). The normalised Laplacian metric (Jiménez and Dudhia 2012) quantifies topographic exposure, whether the location sits atop a hill or in a sheltered valley, and whether flow has channeled through valleys. Terrain ruggedness is assessed using variance in elevation along the source area.
3. **Gust factor model:** Estimates gust factors from the site coefficient, local roughness length, and roughness of all adjacent cells, emphasising the effect of local roughness on turbulence and gust generation.

Model deployment and grid generation

Once trained using the high resolution WRF simulations the models described above can be deployed for any region in the world. Two data sources are required as input:

- A Land Use Land Cover (LULC) database, with gridded terrain classes at high resolution. Figure A1 shows an example of such a product for the U.S. (National Land Cover Database 2016, Yang *et al*., 2018) available at 30 m resolution. We use products of similar resolution in regions where they are available and revert to the global 500 m GLCNMO product (Global Land Cover by National Mapping Organizations, Tateishi *et al*., 2011) as a backup in other places.
- A high-resolution terrain elevation database: We use the SRTM 90 m resolution product globally (Reuter *et al*. 2007).

The input datasets are then aggregated to our 1 km resolution grid, keeping track of sub grid information about the variance in topography and the proportion of each land use category within the cell. Roughness length values for each 1 km cell are assigned based on the mapping table available in WRF. From this we can compute all terrain characteristics needed by the ML models (Table A1).

Examples of these gridded fields are provided in Figure A2 for the New Orleans region (i.e., same region as in Figure A1). The site coefficients and gust factors shown are for the easterly wind sector. Note the ability of the model to capture the impact of urban areas (lower site coefficients and higher gust factors) as well as hill tops (higher site coefficients, lower gust factors).

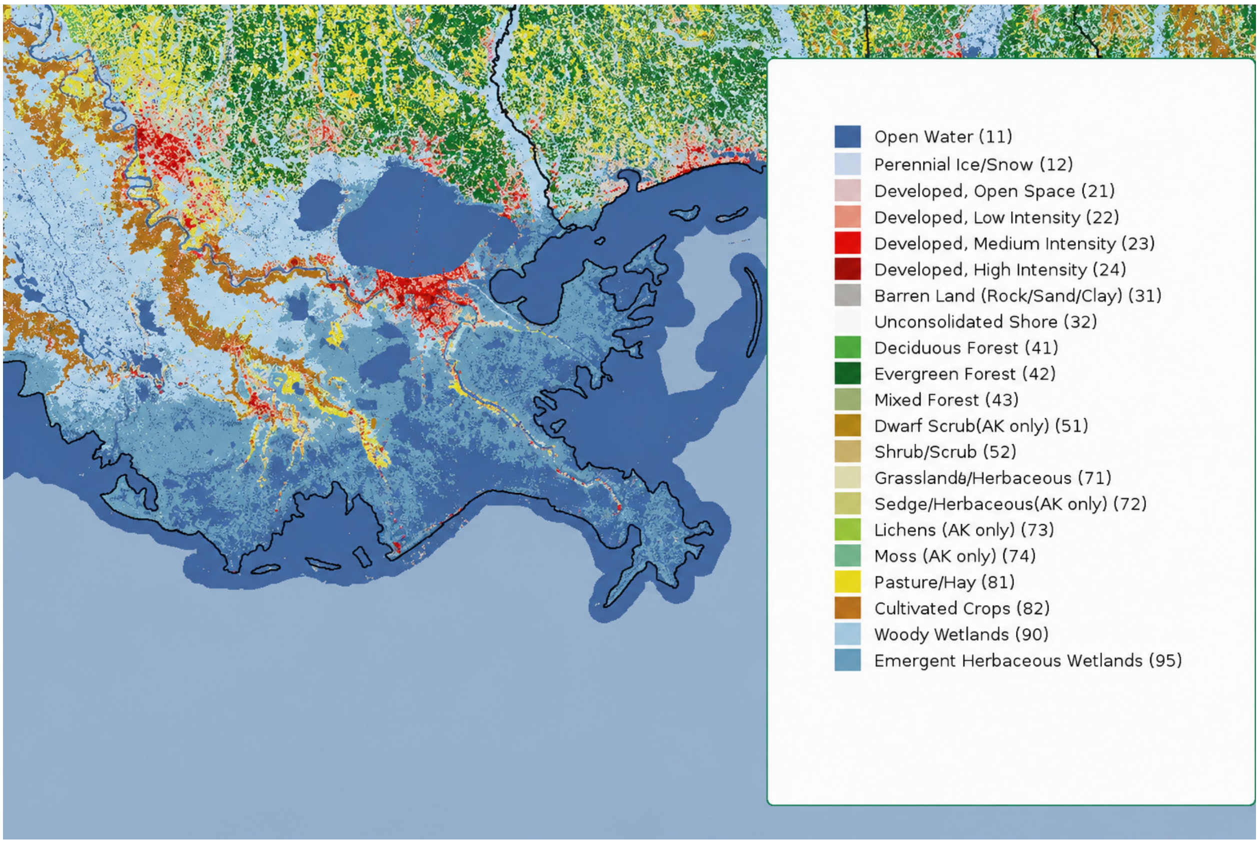

Figure 1A: *Land use categories as available from the US National Land Cover Database (NLCD) at 30m resolution.*

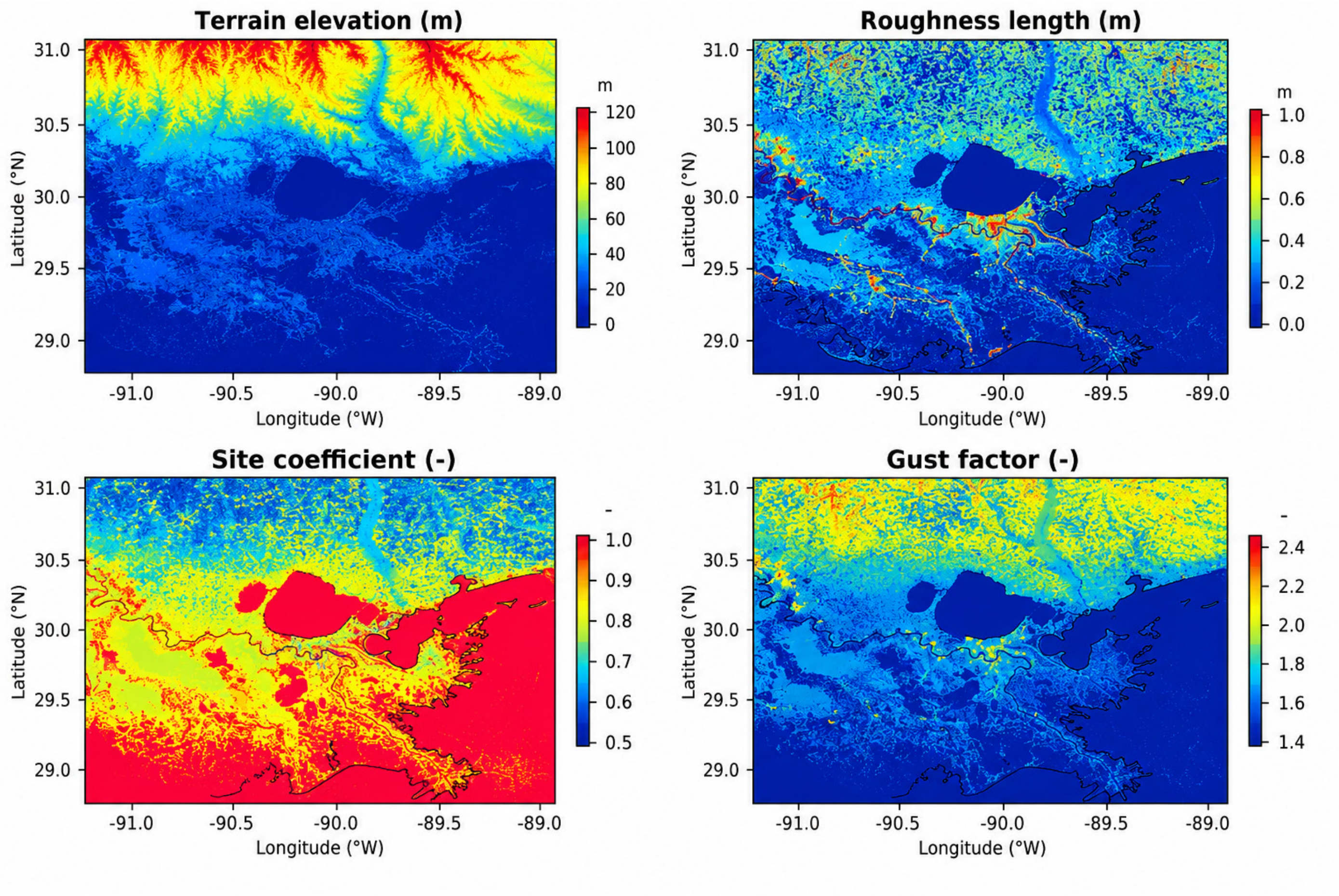

Figure 2A: *1km resolution grids of terrain elevation, roughness length, site coefficients and gust factors.*

Appendix 2: Wind gust observations

Observational sources

This section summaries the observational sources used in our analysis. Each source is summarised in Table A2 along with the storms, region, type of wind observation and the reference. Additionally, the section below introduces each source.

- Weather Underground provides historical weather from various airport stations around the world.
- For most of the U.S. storms analysed, NOAA has published a National Hurricane Center Tropical Cyclone Report which includes station observations during the storms lifetime.
- The Global Historical Climatology Network daily (GHCNd) is an integrated database of daily climate summaries from land surface stations across the globe. GHCNd is made up of daily climate records from numerous sources that have been integrated and subjected to a common suite of quality assurance reviews.
- Global Surface Summary of the Day (GSOD) is derived from The Integrated Surface Hourly (ISH) dataset. The ISH dataset includes global data obtained from the USAF Climatology Center, located in the Federal Climate Complex with NCDC.
- The Automated Meteorological Data Acquisition System (AMeDAS) is a collection of Automatic Weather Stations run by JMA (Japan Meteorological Agency) for automatic observation of weather conditions. Around 840 stations observe wind direction/speed.

Conditions applied to observational sources

We have chosen a simple selection criteria for removing observations data that are plausibly erroneous due to instrument failure or non-TC winds:

1. Buddy check: A station showing extremely low winds (<20 m/s) compared to nearby stations (within 25 km) is removed from validation.
2. Non-TC winds: Stations located outside of twice the lifetime maximum radius of maximum winds (2 × Rm, max) are not considered.

Note that we considered daily maximum recorded winds for observations that are sub-daily or hourly and mapped stations with day of storm arrival within the radial distance of twice the lifetime maximum radius of maximum winds (2 × Rm,max). For stations with overlapping days, we considered the maximum recorded winds for validation.

Table A2: Summary of observations used. Note all winds have been converted to gust. Gusts are in m/s.

Source	Storms	Region	Observation used	Data access
Wunderground (labelled as 'Other' in figures)	Hagibis 2019, Jebi 2018, Debbie 2017	Global	Gust	https://www.wunderground.com/
NOAA NHC pdf	Laura 2020, Ida 2021, Michael 2018, Harvey 2017, Sally 2020, Zeta 2020, Delta 2020, Florence 2018	U.S.	Gust	E.g., for Laura 2020 Pasch *et al*. (2021)
NOAA GHNC	Ian 2022 , Laura 2020, Ida 2021, Michael 2018, Harvey 2017, Idalia 2023	Global	WSF2: = Fastest 2-minute wind speed	https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily
NOAA GSOD	Ian 2022, Idalia 2023, Ida 2021, Michael 2018, Harvey 2017, Ilsa 2023, Debbie 2017	Global	Gust	https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00516
AMeDAS	Jebi 2018, Hagibis 2019, Faxai 2019, Trami 2018, Nanmadol 2022, Cimaron 2018, Jongdari 2018, Lan 201', Noru 2017, Malakas 2016	Japan	maximum moment windspeed (m/s)	https://www.data.jma.go.jp/stats/etrn/select/prefecture.php?prec_no=84&block_no=&year=&month=&day=&view=
BoM	Debbie 2017	Australia	3sec gust (km/h)	http://www.bom.gov.au/qld/flood/fld_reports/Tropical-Cyclone-Debbie-Technical-Report-Final.pdf

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Declarations

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