Combining hazard, exposure and vulnerability data to predict historical United States hurricane losses

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Abstract. Hurricanes are among the most destructive natural hazards globally. The widely used Saffir–Simpson scale is an effective public-communication tool, but it is based on a single hazard quantity (wind speed) and has low skill in representing historical economic losses. Accurate risk assessment requires hazard, exposure, and vulnerability information. We present a statistical model to predict losses from North Atlantic hurricanes making landfall in the United States using optimally weighted, normalised-rank quantities describing hazard, exposure, and vulnerability. The model significantly outperforms single-parameter predictions, including landfall wind-speed maxima and central-pressure minima. Root-mean-square error between observed losses and losses predicted from landfall wind speed alone is U.S.$ 35.6 bn, which our model reduces to U.S.$ 7.0 bn. To improve the characterisation of risk, we introduce a loss-based 'Hurricane Predictive Loss Scale' to more directly link hurricane characteristics and landfall to financial impacts. These results demonstrate that integrating exposure and vulnerability data with hazard observations yields skilful estimates of historical hurricane losses, and our approach may help assess how loss from a forecast landfall may rank among historical events. This work is applicable to other cyclone-prone regions and highlights the critical need for open-source exposure and vulnerability data to advance climate risk understanding.

Significance statement. Hurricanes are a destructive natural hazard. Historically, however, their Saffir–Simpson categories and losses are not well correlated. We combined hazard, exposure, and vulnerability data to predict losses from landfalling hurricanes for the United States. Our model significantly reduces errors between predicted and observed losses and is more skilful than hazard-only predictions. Additionally, we developed a novel loss-based hurricane classification scheme to aid risk management.

1 Introduction

Intense tropical cyclones are the most impactful meteorological hazard worldwide ((Aon, 2025; World Meteorological Organization, 2021). Between 1980 and 2024, global economic losses due to tropical cyclone landfalls totals U.S.$ 2.9 tn (National Oceanographic and Atmospheric Administration, 2024), through extreme wind, storm surge and rainfall. Generally, extreme wind induces building damage (Ibrahim et al., 2024) and storm surge and intense rainfall cause fatalities (Rappaport, 2014). Improving our understanding of hurricane risk is essential to mitigating impacts through long-term policies, such as strengthened building codes, and short-term preparedness measures, such as early-warning systems.

Skilful hurricane damage assessments are challenging and uncertain, as the impacted area may be large and building damage highly site-specific. Nonetheless, damage assessment reports over the last century agree that the most financially impactful U.S. hurricanes include the Great Miami Hurricane (1926), Katrina (2005), and Harvey (2017) (Delforge et al., 2025; Grinsted et al., 2019; Muller et al., 2025; National Centers for Environmental Information, 2025; Weinkle et al., 2018). Hurricane-related economic losses have increased over time (Grinsted et al., 2019; Klotzbach et al., 2022b), which will likely continue with increasing development in exposed regions in the U.S. (Iglesias et al., 2021). These trends highlight the urgency of understanding impacts and losses to enhance disaster preparedness and support mitigation. However, uncertainties in studies of high-impact landfalling events are high compared with basin-wide metrics of cyclone activity (Emanuel, 2011). Additionally, significant uncertainty remains over how hurricane-related impacts will evolve in a warming climate (Knutson et al., 2020; Meiler et al., 2025), including U.S. landfalls (Jewson, 2023), so understanding the key factors responsible for, and which therefore help predict, losses regionally is critical.

Recent work has demonstrated skilful multi-year predictions of North Atlantic hurricane activity and U.S. hurricane damage, but individual high-damage events, particularly those occurring during periods of generally low activity, are not well predicted (Lockwood et al., 2023). Each hurricane-related loss is the result of a unique combination of meteorological and socioeconomic factors, and quantifying hurricane risk requires an understanding of hazard, exposure and vulnerability (Ward et al., 2020). Hazard quantities describe a hurricane's physical characteristics, including intensity, duration, size, and associated perils such as storm surge and rainfall-induced flooding. Exposure variables capture the location and value of affected assets, including residential, commercial, and industrial buildings within the storm's footprint. Vulnerability metrics reflect assets' susceptibility to damage, influenced by construction materials, design and age. To account for these factors, open-source catastrophe models, such as CLIMADA (Aznar-Siguan and Bresch, 2019), HAZUS (Federal Emergency Management Agency, 2024a) and OASIS LMF (Oasis Loss Modelling Framework, 2025), simulate a hurricane's track and estimate damage based on exposure and vulnerability at the landfall location. However, case-study evidence suggests such models significantly underestimate historical loss estimates for hurricanes (König, 2017) and other storm types, such as European windstorms (Welker et al., 2021). For hurricanes, this lack of skill may be due to the representation of hazard footprints (e.g., wind, precipitation and storm surge), resulting from the insufficient resolution of forecast model data or reliance on a parametric wind field (e.g., Holland et al., 2010). More complex, proprietary catastrophe models are typically used by (re-)insurers.

North Atlantic hurricanes are categorised using the Saffir–Simpson Hurricane Wind Scale, which indicates damage potential based on 1-minute near-surface wind speed (Kelman, 2013). This scale is a key tool for public communication of hurricane risk (Cass et al., 2023). However, as it is based on a single hazard quantity, it does not predict damage sufficiently skilfully (Bloemendaal et al., 2021). At landfall, central sea-level pressure minima are more strongly correlated with normalised historical hurricane damage than wind-speed maxima (Klotzbach et al., 2020; Klotzbach et al., 2022a), likely due to central pressure being physically related to both hurricane maximum wind speed and size (Chavas et al., 2025). There have been recent calls to modify the Saffir–Simpson scale (Wehner and Kossin, 2024) and develop multi-hazard and multidisciplinary (i.e., including exposure and vulnerability) equivalents (Tripathy et al., 2024) to help understand hurricane impacts and how risk may evolve in a warming climate (Camelo and Mayo, 2021; Gori et al., 2025; Ward et al., 2020).

To develop a hurricane classification more closely aligned with observed damage, Bloemendaal et al. (2021) devised a 'Tropical Cyclone Severity Scale', which categorises hurricanes by incorporating wind speed, storm surge and accumulated rainfall. Hurricanes ranked by this scale corresponded better with historical losses compared with the Saffir–Simpson scale, but several events were still mis-represented and assigned a low category despite causing significant damage. For example, Hurricane Sandy (2012) resulted in an estimated U.S.$ 70 bn in normalised economic losses, but its classification was only changed from category 1 in the Saffir–Simpson scale to category 2 in the 'Tropical Cyclone Severity Scale' (Bloemendaal et al., 2021). Other studies have attempted to develop skilful multidisciplinary scales (i.e., not only hazard information). Pilkington and Mahmoud (2016) used an artificial neural network model to forecast the economic impact from hurricanes using hazard and exposure data, including landfall location, population affected, wind speed, central pressure, precipitation and storm surge. Baldwin et al. (2023) showed the importance of differences in vulnerability between conurbations and rural areas for accurately modelling hurricane risk across the Philippines, stressing the importance of including a vulnerability layer to link a given wind speed to a percentage of exposed assets destroyed. These studies highlight the importance of accounting for multiple risk factors.

Focussing on historical U.S. landfalling hurricanes, this study examines numerous hurricane hazard, exposure and vulnerability quantities to determine whether the inclusion of socioeconomic data into a statistical loss-prediction model improves our ability to predict losses. Additionally, we developed a novel, loss-based hurricane classification scheme, which, if applied prior to forecast landfall, may communicate potential losses more accurately than Saffir–Simpson, thereby providing a usable preparedness tool for governments, disaster management agencies, and the financial sector. Here, 'usable' means skilfully communicating where the expected loss would rank in the context of historical events and revising this estimation as hurricane forecasts evolve (i.e., with shorter lead times). This information could support effective preparedness by response agencies and adequate capital mobilisation by financial institutions and stakeholders. We address the following research questions:

- Which single hazard, exposure and vulnerability variable(s) exhibit the highest correlation(s) to historical U.S. hurricane losses?
- How skilful is a combination of hazard, exposure and vulnerability data in predicting historical U.S. losses compared with hazard-only predictions?
- How skilfully does a loss-based hurricane classification scale represent historical U.S. losses?

This paper is structured as follows: datasets and methods are described in section 2, results presented in sections 3–5, with a novel loss-based hurricane scale evaluated in section 6, and discussion and conclusions presented in section 7.

2 Data and methodology

2.1 Data

In this section, we describe the datasets used to provide loss, hazard, exposure and vulnerability information for historical hurricanes affecting the U.S. Fig. 1 provides a summary of these datasets and the temporal coverage spanned by each.

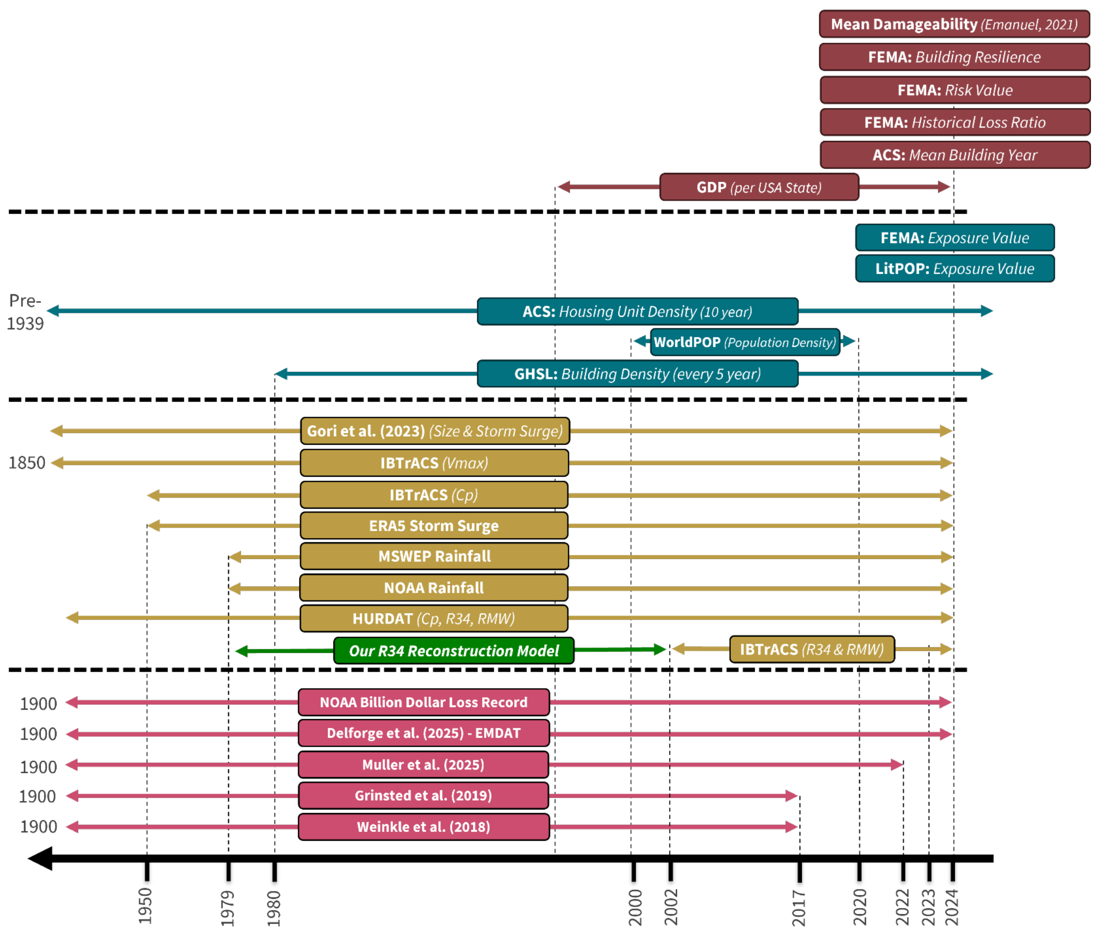

Figure 1. Schematic overview of datasets used in this study. Hazard, exposure and vulnerability predictors were combined, with loss estimates being the predictand. Time-invariant exposure and vulnerability datasets are shown with no arrows. Note that the x-axis timeline is not linear. Table S1 provides additional information and references for these datasets.

2.1.1. Normalised historical hurricane losses

Various sources of historical hurricane loss information exist, but no consensus reference dataset. We collated the following published sources: Grinsted et al. (2019), Muller et al. (2025), National Centers for Environmental Information (2025), Weinkle et al. (2018), and the Emergency Events Database (EM-DAT; Delforge et al., 2025). These datasets differ in temporal coverage, reporting methodology, treatment of damage components, and inclusion of historical hurricane events (Fig. 1; Table 1). To maximise sample size, we combined these datasets and, for events with multiple loss estimates, these were averaged to avoid treating any dataset preferentially and help capture uncertainty. For hurricanes which made multiple landfalls, losses were averaged from the two sources—Grinsted et al. (2019) and Muller et al. (2025)—that provide per-landfall losses. Collating data in this way yielded 134 loss estimates for landfalling (including multiple landfalls) hurricanes for the period 1979–2024, of which all variables are available for 106 events (Table 1).

Table 1. Summary of hurricane loss datasets, the number of U.S. hurricane landfalls (including multiple landfalls) during 1979–2024 for which a loss estimate is available, and the subset of these landfalls for which all predictors (hazard, exposure and vulnerability) are available.

Dataset reference	**Dataset coverage**	**Landfalling hurricanes (1979–2024) with a loss estimate**	**Landfalling hurricanes (1979–2024) with all hazard, exposure, vulnerability and loss data**
National Centers for Environmental Information (2025) (≥ bn loss)	1850–present	58	21
EM-DAT (Delforge *et al.,* 2025)	1900–present	74	57

Muller *et al*. (2025)	1979–2022	33	33
Weinkle *et al*. (2018)	1900–2018	59	57
Grinsted *et al*. (2019)	1900–2018	102	76
All data sources	1979–2024	134	106

Economic loss estimates must be calibrated to present-day levels of damage, including adjustment factors to account for temporal changes in inflation, wealth and building density (Weinkle et al., 2018). Typically, normalisation is based on country-level adjustments and assumes building density may be represented by residential housing changes. Regional variations in these factors, temporal changes in building vulnerability or commercial building density, and the impacts of climate change may not be accounted for (Muller et al., 2025). Each dataset we used (Table 1) provides un-normalised and normalised hurricane loss estimates. However, uncertainty arises due to the differing normalisation methodologies and reference years between datasets. To ensure consistency, we used un-normalised data and applied a unified normalisation approach, based on Weinkle et al. (2018) and Muller et al. (2025), where loss estimates were adjusted using country-level inflation and real-wealth-per-housing-unit factors (both as of 2024), and a county-level housing unit density factor (Eq. 1).

$$\boldsymbol{L_{2024} = L_y \cdot I_{\frac{2024}{y}} \cdot \frac{W}{Hn_{1+\frac{(2024-y)}{y}}} \cdot Hn_{1+\frac{(2024-y)}{y}}} \qquad \text{(Eq. 1)}$$

where L is loss per hurricane (and year), y, I is inflation, W is real national wealth per housing unit, and Hn is housing unit density. I was determined using the annual implicit price deflator for gross domestic product (GDP) for the period 1979–2024 (U.S. Bureau of Economic Analysis, 2023). Hn density was determined within R34 using U.S. housing unit data (U.S. Census

Bureau, 2024). *W* was quantified using an estimate of current-cost net stock of fixed assets and consumer durable goods (U.S. Bureau of Economic Analysis, 2025).

2.1.2. Hazards

Hurricane track location, intensity and size information was obtained from the International Best Track Archive for Climate Stewardship (IBTrACS) v04r01 (Gahtan et al., 2024), provided by the National Hurricane Center. For each historical hurricane, we obtained 1-minute sustained maximum wind speed, v_{max}, minimum central sea-level pressure, c_p, translation speed, radius of maximum wind (from the storm centre), RMW, and the outermost radii of 34-, 50- and 64-knot wind speeds from the storm centre), respectively, R34, R50 and R64. Each quantity was determined at the timestep before the storm centre crosses over land, so atmospheric fields are minimally impacted by land-surface interactions. However, IBTrACS data are incomplete (i.e., not all hazard variables are available at every timestep for every hurricane). Therefore, we supplemented IBTrACS with data from NOAA's HURDAT2 reanalysis (Landsea and Franklin, 2013)—specifically, the 'U.S. Hurricane Impacts / Landfalls' table of landfall information collected by NOAA reconnaissance aircraft (Hurricane Research Division, 2025) and from Gori et al. (2023). Where data are missing in IBTrACS, HURDAT2 data were substituted, if available. Where data are available in IBTrACS and HURDAT2 at a given timestep, HURDAT2 data were prioritised.

Storm surge and rainfall cause damage through coastal and inland flooding. In this study, historical hurricane storm tide (maximum storm surge and tidal height) data were taken from the storm surge residual product (Copernicus Climate Change Service, 2022), derived using the Global Tide and Surge Model version 3.0 (Kernkamp et al., 2011; Wang et al., 2021) forced by European Centre for Medium-Range Weather Forecasts' fifth-generation reanalysis (ERA5; Hersbach et al., 2020). This provides hourly reconstructed historical storm tide height from 1950–present. Storm tide residual is calculated as the difference between the total water level and simulated storm-tide elevation, including the influence of storm surge and tide. Storm tide may be larger in the hours before or after a hurricane makes landfall, depending on antecedent tidal height. To account for this, we defined the maximum storm tide residual as the maximum along the U.S. coastline within a 1,000 km radius of the hurricane's central coordinate and 24 hours before and after a hurricane makes landfall. An example maximum storm tide residual for Hurricane Katrina (2005) is shown in Fig. S1.

Historical hurricane-related rainfall footprints were derived from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset (Beck et al., 2019), which assimilates gauge observations and satellite data to reconstruct 3-hourly rainfall 1979–present. For each hurricane, we determined total accumulated rainfall, maximum 3-hourly rain rate, and maximum total rain accumulation per grid-point along the track, each within a 500-km radius of the hurricane centre (location taken from

IBTrACS) at each timestep. An example rainfall accumulation footprint for Hurricane Katrina is shown in Fig. S2. This chosen radius is based on previous research (e.g., Stansfield and Reed, 2023), although a fixed radius may lead to some overestimation of cyclone-related precipitation (Stansfield et al., 2020). To complement MSWEP, the maximum rainfall accumulation along each hurricane track was collated from National Oceanographic and Atmospheric Administration (2025), providing single maximum rainfall accumulation values, although not allowing differentiation between multiple landfalls with this dataset.

This study considers only landfalling hurricanes, excluding bypassing hurricanes. It is difficult to obtain a comparable measure of hurricane intensity for a bypassing event because its intensity, measured close to the system centre, is over ocean and may therefore be relatively high compared with a directly landfalling event. It is necessary to avoid introducing such an artifact into our statistical model.

2.1.3. Exposure

We took county-level building value information across the U.S. from the National Risk Index (Federal Emergency Management Agency, 2024b), derived from Hazus 6.1 (Federal Emergency Management Agency, 2024a), providing 2022-relative valuations per county based on the 2020 U.S. Census. Building values are time-invariant. Near present-day (2019) building value was quantified using the LitPOP dataset (Eberenz et al., 2020), providing global aggregated building value estimates at a 1-km spatial resolution. Building value estimates vary between the two datasets; hence, we used two building value datasets.

We also used decadal, county-level housing unit density data (U.S. Census Bureau, 2024), available 1950–present, as well as semi-decadal building density estimates from the Global Human Settlement Layer (GHSL), providing built-up surface area data derived from Sentinel-2 composite and Landsat satellite imagery from 1975–present at 1-km spatial resolution (Pesaresi and Politis, 2023). Annual gridded population density data between 2000 and 2020 at 1-km spatial resolution were obtained from WorldPop (2018). For hurricane landfalls outside the temporal coverage of GHSL and WorldPop, we used data for the closest available year. Therefore, a limitation to highlight is that we overestimate population density for pre-2000 events.

2.1.4. Vulnerability

Structural vulnerability—the susceptibility of buildings to damage—is influenced by building age, often used as a proxy for building condition and resilience, and related to changes in building codes (regulated construction standards that include a minimal resistance to extreme weather). We used county-level average building age data (U.S. Census Bureau, 2024) and a county-level indicator of building resistance to extreme weather (Federal Emergency Management Agency, 2025). We also used county-level Hurricane Risk Score and Hurricane Historical Loss Ratio data from Federal Emergency Management Agency (2024b) and Zuzak et al. (2021). Hurricane Risk Score is defined as the average social vulnerability (i.e., extent to which specific social groups are disproportionately susceptible to hurricane impacts) and community resilience (i.e., capacity to prepare for, withstand, and recover from hurricane hazards), and is given as a percentage. Hurricane Historical Loss Ratio is defined as the percentage of a location's exposed value damaged by past hurricanes. We quantified the mean Hurricane Risk Score and Hurricane Historical Loss Ratio across all counties within several hurricane radii (R34, R50 and R64—see section 2.2.). GDP data for each affected U.S. state per year, indicating a state's resilience resources, for the period 1998–2024 (U.S. Bureau of Economic Analysis, 2025) were used, and 1998 GDP values were applied to pre-1998 events.

Hurricane wind vulnerability may also be expressed as a logistic–cubic wind–damage function, relating wind speed to the fractional value of assets lost. This study uses a simple quantification of this (Eq. 2 and Eq. 3), which was deduced by Emanuel (2011).

$$\boldsymbol{f = \frac{v_n^3}{1+v_n^3}}, \qquad \text{(Eq. 2)}$$

where f is the fraction of the property value lost and v_n is defined as:

$$\boldsymbol{v_n = \frac{[(v-v_{thresh}),0]}{v_{half}-v_{thresh}}}, \qquad \text{(Eq. 3)}$$

where v is maximum wind speed, and v_{thresh} and v_{half} are the thresholds at which no asset damage and half asset damage occur, respectively. Building characteristics (e.g., construction type and age) influence vulnerability curves, and Vickery et al. (2006) and Federal Emergency Management Agency (2024a) suggest v_{half} values in the range 120–160 kts. In this study, damage estimates were computed for historical hurricanes using this single vulnerability function for all buildings, with v_{thresh} = 40 kts and v_{half} = 140 kts. However, weaker systems may be damaging, such as tropical depression Allison (2001), modelling suggests v_{half} may be as low as ~50 kts (Federal Emergency Management Agency, 2024a). Multiple vulnerability functions for different building types cannot be applied due to incomplete localised building characteristic data. Instead, asset damage potential was applied to 1-dimensional LitPOP exposure and GHSL building density data within each hurricane footprint to estimate the exposure value and number of buildings damaged. At each timestep, v_{max} was used with Eq. 2 and Eq. 3 (Emanuel, 2011) and the extracted exposure and building density, allowing v_{max} to vary with time.

2.2. Methods

2.2.1. Statistical estimation of hurricane size

Hurricane size (i.e., R34, R50 and R64) data are only available in IBTrACS from 2002 onwards. This is a significant constraint for studies of impact, as size information is needed to determine the region impacted by an event—i.e., its footprint. The exposure and vulnerability impact footprints derived in this study require hurricane size estimates. To estimate size prior to 2002 and extend the sample of landfalling hurricanes for this study, we developed a skilful random-forest statistical model to estimate R34, R50 and R64 for each hurricane and at each timestep, based on v_{max}, RMW, c_p and latitude (Fig. 2), with RMW found to be the most influential predictor. When R34 estimates from this model are compared with R34 observations from 2002 onwards, a Spearman's correlation coefficient, ρ, of 0.85 and a mean absolute error (MAE) of 24.5 nm were found (Fig. 2). This evaluation used a leave-one-out approach (i.e., the prediction model was trained on all observations except one, and skill evaluated on the left-out observation) across 3,984 timesteps (for which R34, v_{max}, RMW, c_p and latitude within IBTrACS are not missing). There is a slight underestimation of R34 at lower values and slight overestimation at higher values, but the model overall performs well. This statistical modelling is a skilful supplement to missing IBTrACS data (Fig. 2 and Fig. S3) and allows storm size estimation back to 1979, which more than doubles our historical hurricane event sample size. Prediction models were also developed to estimate R50 and R64 for historical storms, where observations are available, with evaluation shown in Fig. S3.

From 1979 to 2002, however, there are instances where RMW data are missing from IBTrACS (v_{max}, RMW, c_p and latitude are less often missing). So, for these timesteps, we either substituted the missing RMW value from the corresponding value from HURDAT2 or obtained the RMW value from reconstructions of Gori et al. (2023). Reconstructed RMW from Gori et al. (2023) is based on the hurricane wind model of Chavas et al. (2025) and ERA5 data. Of all 3-hourly timesteps where a hurricane is over land between 1979 and 2002 (approximately 10,000 timesteps), approximately 25% timesteps have a missing RMW estimate from each of these three datasets. In these instances, we replaced the missing value with the RMW from the previous timestep. Although this introduces uncertainty, R34, R50 and R64 estimates from the random-forest model using RMW estimates from previous timesteps are also a function of c_p, v_{max} and latitude, quantities that are much less frequently missing in IBTrACS, and these constrain our R34 statistical model even when using substituted RMW values.

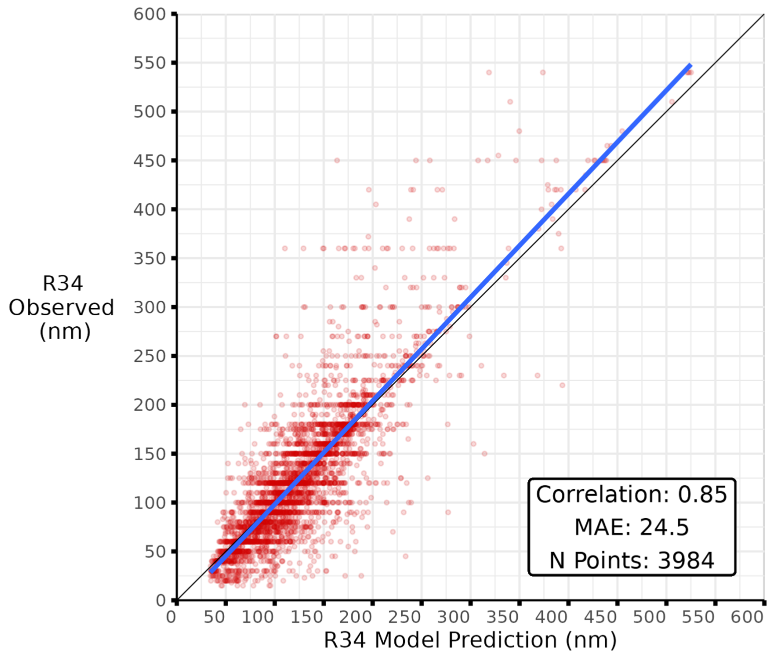

Figure 2. Comparison of estimated and observed hurricane R34 (unit is nautical miles, nm) for the period 2002–2023. Our random-forest statistical model uses hurricane v_{max}, RMW, c_p and latitude as R34 predictors.

2.2.2. Extracting hurricane-centred exposure and vulnerability footprints

For each hurricane, exposure and vulnerability data were extracted within the R34, R50 and R64 radii at each timestep, and accumulated to create two impact footprints: i) along the full hurricane track where v_{max} > 34 kts (Fig. 3) and ii) from the immediate landfall location (i.e., up to 12 hours after landfall). Hurricanes weaken over land, so obtaining two impact footprints captures the immediate landfall, where intensity influences impacts most strongly, and the full hurricane track.

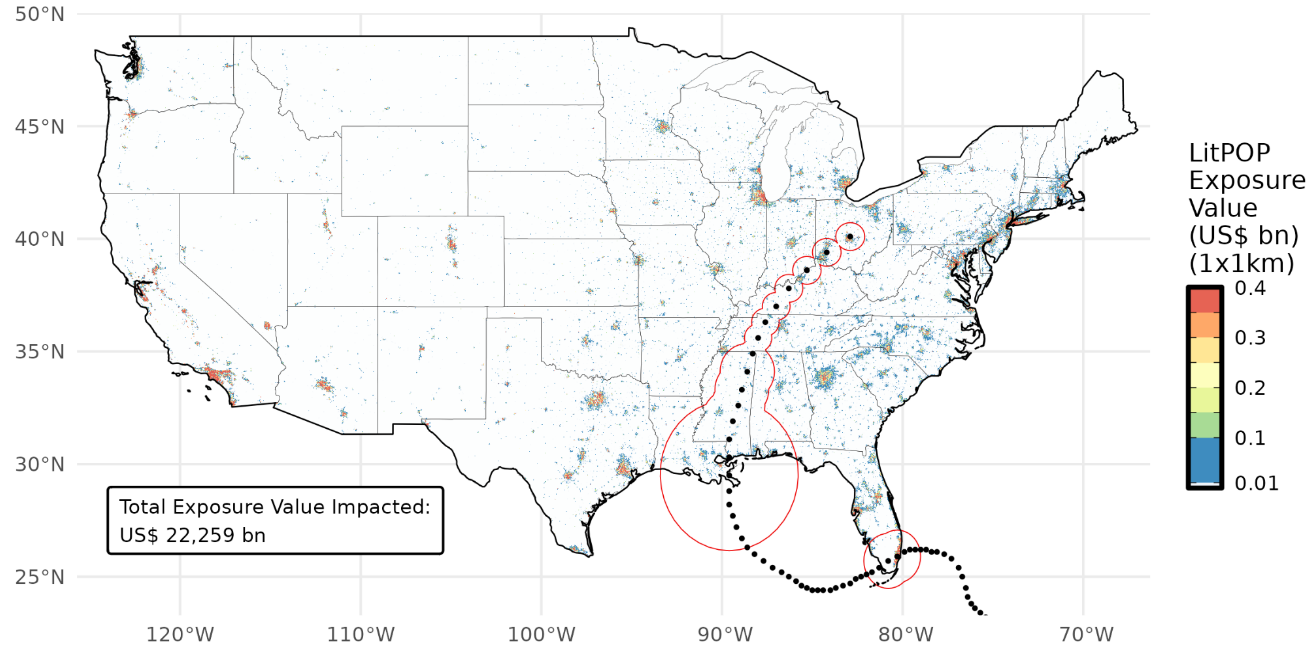

Figure 3. Example LitPOP exposure value impact footprint of Hurricane Katrina (2005). Hurricane locations from IBTrACS every three hours are shown as black dots, with the R34 radius around the hurricane centre indicated by the red lines. Harvey made landfall in southern Florida, traversed the Gulf of Mexico, and made a second landfall in Louisiana.

2.2.3. Predictive statistical approaches

We assessed the skill of three independent statistical approaches to predict hurricane loss, each based on the same set of inputs. These are: (i) a weighted combined-rank framework, (ii) a linear-regression framework, and (iii) a random-forest decision-tree framework. Our target predictand is average loss per hurricane, derived from multiple datasets (see section 2.1.1.). Overall, 106 hurricanes, for which all risk variables could be quantified (Table 1), were used to train our predictive model. To evaluate the skill of the linear regression and random-forest predictive models, leave-one-out cross-validation was used, where each input case was treated once as the test case and the model trained on the remaining cases. The leave-one-out approach is better suited to evaluating the skill of single predictions than, for example, k-fold cross-validation, where input data are split into training subsets. For the weighted combined-rank framework, which determines the combined loss rank from various hazard, exposure and vulnerability ranks, such validation is inappropriate, as the combined-rank approach does not require training data. Instead, optimal combinations of weights between -10 and 10 were determined for each combination of input variables, to minimise a cost function, which in this case was the model root-mean-square error (RMSE) between predicted and observed hurricane loss rank.

Two approaches were considered for representing input variables: raw values and ranked values. As input variables span disparate ranges (e.g., c_p spans 900–1000 hPa; LitPOP exposure spans U.S.$ 10 M to 1 tn), raw values were normalised to the same scale as ranked values 1–*n* (i.e., 1–106). In this normalisation, each variable was linearly rescaled to assign the maximum value a score of 1 and minimum a score of 106, with intermediate values mapped proportionally between these bounds. Linear and normalised input predictor ranks were derived, with rank 1 corresponding to the costliest event and rank 106 to the least costly. To predict each hurricane's loss, the equivalent predicted loss rank and observed loss rank were identified, with the loss from that observed hurricane being attributed to that predicted loss rank.

We quantified model performance with the Spearman correlation coefficient, ρ, testing the ordering of prediction according to correlation between ranked values (i.e., whether one event is more damaging than another), Pearson correlation coefficients, *r*, testing non-ranked correlation, and RMSE. Spearman's ρ and RMSE were used as ρ is a good indicator of the capability of accurately predicting loss rank, but not suitable for identifying cases where large differences occur in the loss prediction of a single hurricane.

3 Historical relationship between hurricane wind speed and loss

Hurricane-related losses across the U.S. have generally increased over time and exhibit large interannual variability (Fig. 4). The most destructive year for losses was 2005, with U.S.$ 153 bn in un-normalised (and approximately U.S.$ 350 bn in normalised) loss. The most damaging event was Hurricane Katrina (Fig. 5), although uncertainty is evident across available loss datasets (Table 1). If Katrina occurred today, loss may be in the range of U.S.$ 190–290 bn (Fig. 5). Katrina, however, is one of numerous high-impact hurricanes whose v_{max}-based Saffir–Simpson category at landfall is at odds with the magnitude of associated loss (Bloemendaal et al., 2021). Katrina was a category-3 landfall, despite causing unprecedented, record-breaking damage (Fig. 5). Other cases whose damage is mismatched with their Saffir–Simpson category include category-1 Hurricane Sandy (2012) and category-2 Hurricane Ike (2008), which each caused substantial losses (Fig. 5). Additionally, Hurricane Harvey (2017) was a category-4 landfall and the second-most damaging hurricane, but its loss is uncertain, with estimates between U.S.$ 90–190 bn. The historical record reveals the limitation of an event's Saffir–Simpson category in conveying its loss.

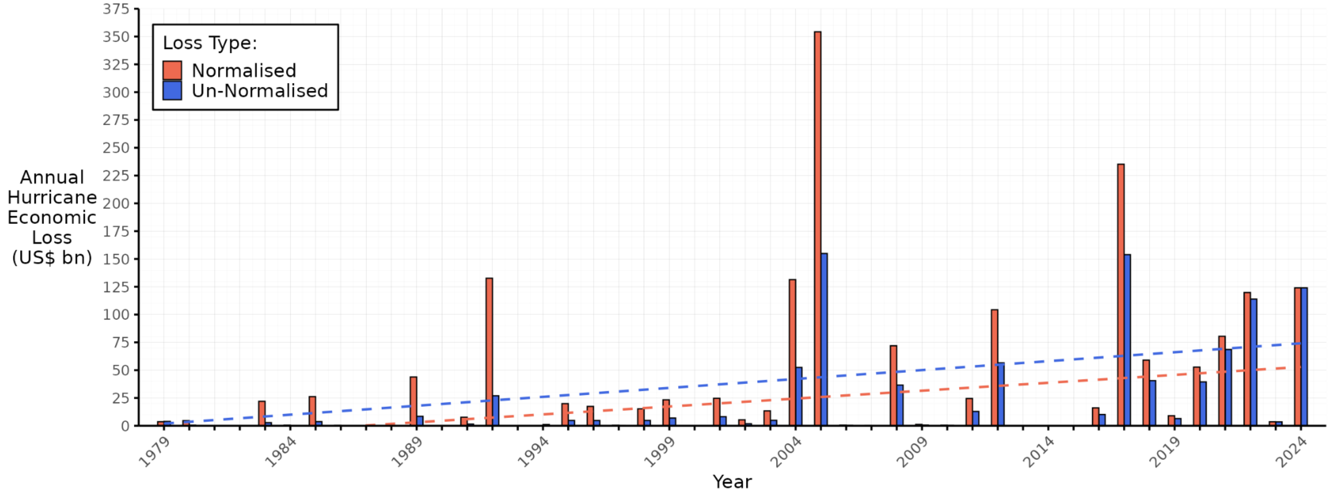

Figure 4. Average historical U.S. hurricane-related losses, (red) normalised to 2024 and (blue) un-normalised by inflation, wealth and housing unit density (blue). Dashed lines indicate upward linear trends.

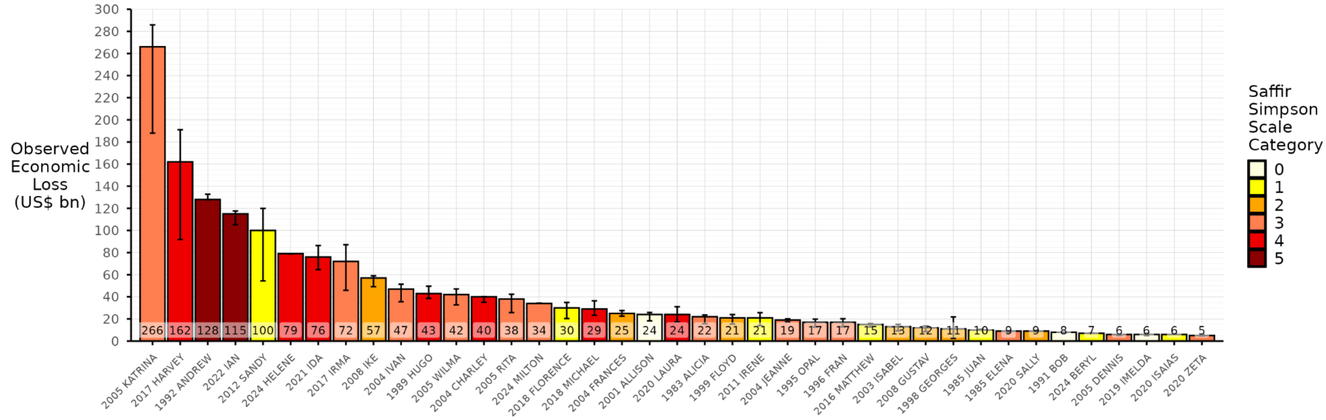

Figure 5. Average loss per hurricane, normalised to 2024, for loss events exceeding U.S.$ 5 bn. Error bars indicate the range in loss estimates across datasets (Fig. 1 and Table 1) and colour indicates landfall Saffir–Simpson category.

Although loss generally increases with the Saffir–Simpson landfall category and therefore wind speed (Fig. 5), the Saffir–Simpson scale has limited skill in predicting loss (Fig. 6a), with a correlation of $\rho = 0.53$ across 106 events (RMSE = U.S.$ 17.1 bn when using Saffir–Simpson category to predict loss rank and associated loss using a linear model). Using v_{max} to predict normalised hurricane loss yields a correlation of $\rho = 0.52$ (RMSE = U.S.$ 17.6 bn), which is slightly lower (Fig. 6b) and consistent with Klotzbach et al. (2020). Notably, landfall v_{max} is significantly less skilful at predicting loss for more extreme storms, with generally higher error at more extreme v_{max} values (Fig. 6b), which is particularly problematic as an inaccurate forecast for these more intense storms would produce larger errors in loss. The relationship between v_{max} and loss is potentially nonlinear but spread, and therefore error, in loss generally increases with v_{max}. Performing a rank correlation between observed loss and loss predicted from v_{max} reveals significant spread (and heteroscedasticity) across the observed range (Fig. 7a), and this is found for all events as well as those where loss exceeds U.S.$ 1 bn (Fig. S4).

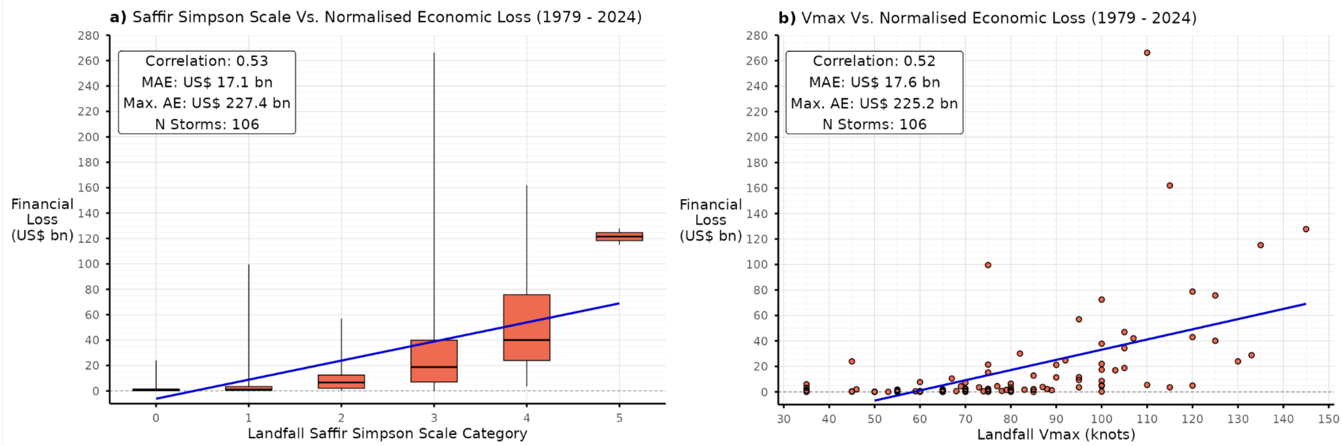

Figure 6. Average economic hurricane financial loss (normalised to 2024) versus a) Saffir–Simpson category and b) landfall v_{max} of U.S. landfalls over the period 1979–2023. Blue lines indicate linear fits and an indication of goodness of fit is given in each legend: mean absolute error (MAE), absolute error (AE), and sample size, N.

4 Historical relationships between multiple hazard, exposure and vulnerability variables and loss

We next analysed linear correlations between single predictors and historical hurricane loss over the period 1979–2024, using both raw (Fig. 7a) and rank (Fig. 7b) values. This analysis demonstrates that high prediction skill may be obtained across numerous hazard, exposure and vulnerability hurricane quantities, with landfall c_p rank yielding the highest correlation (r = -0.78), followed by GHSL building density damage percentage (r = 0.77) and LitPOP exposure value damage percentage (r = 0.74) (Fig. 7a). Overall, using the value rank per storm yields higher correlations than using raw values (Fig. 7c), particularly for exposure predictors, because using ranks normalises to a linear scale, suggesting that landfall attribute ranks may provide more skilful loss predictions. This complements the analysis of Klotzbach et al. (2022b), who showed that landfall c_p better correlates with loss rank than v_{max} or accumulated cyclone energy. Here, we further show that landfall c_p outperforms other hazard variables and that landfall exposure and vulnerability variables yield higher correlations with loss rank than landfall v_{max}.

In this study, several hazard variables at landfall (v_{max}, c_p, storm tide, R34, translation speed, and RMW) remain unchanged, but variables quantified within a hurricane footprint depend on chosen hurricane size metric (i.e., R34, R50 or R64), and those quantified along-track depend on timeframe (i.e., full track or 12 hours post landfall). For landfall variables with significant correlations to loss (i.e., ≥0.3), a 12-hour post-landfall track yields similar (or somewhat higher) correlation compared with using the full track where winds exceed 34 kts (Fig. S5a). This indicates that including the full track, where winds weaken over land, reduces correlation. (Studies of inland impacts using full-track analysis may need to cope with lower skill than landfall-focussed studies.) A notable exception is the percentage of damaged GHSL building density, which has a strong correlation using the full track ($\rho = 0.78$ using R34 and $\rho = 0.79$ using R50). Correlations are generally higher when considering normalised rather than un-normalised loss (Fig. S5b). Additionally, rank correlations are similar when using R34 and R50 to define impact radius, but correlations using R64 are lower (Fig. S5c). R64 is typically less than 100 nm, which may be too small to capture hurricane impacts, especially for lower-resolution data (e.g., county-level housing unit data).

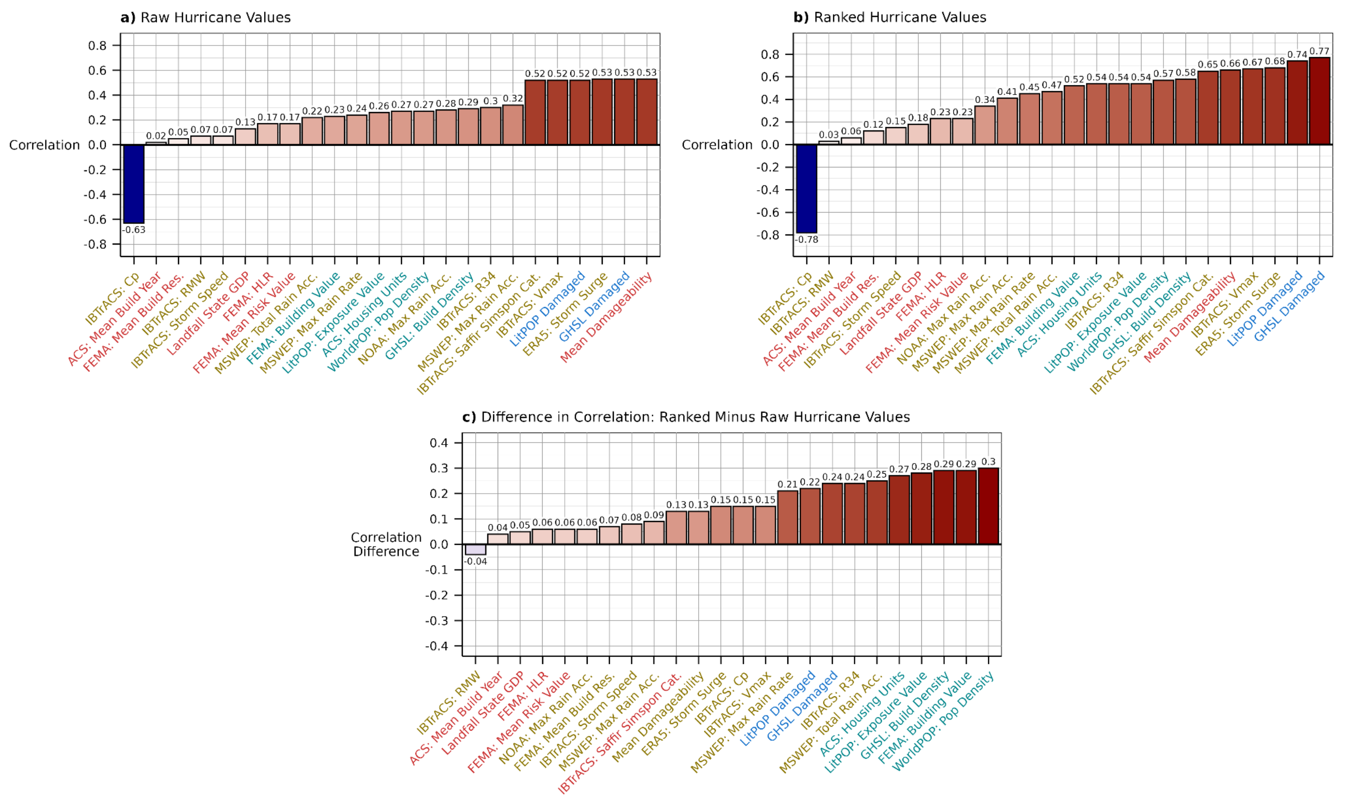

Figure 7. Pearson's correlation coefficients between historical hurricane landfall predictors, quantified at landfall and within 12 hours of landfall, and averaged loss for the period 1979–2024. Shown are (a) raw values versus loss, (b) predictor rank values versus loss, and (c) the coefficient difference between using raw versus ranked values (i.e., ranked minus raw correlations). Note that the x-axes differ between the panels due to correlation ordering. Colours indicate whether the variable is a hazard (yellow), exposure (blue) or vulnerability (red) variable (refer to Fig. 1). Note that c_p is inversely related to hurricane intensity and therefore negatively correlated with damage.

5 Statistical prediction of historical hurricane loss

Using landfall v_{max} rank to predict storm loss, by assigning the loss from the equivalent loss rank, yields $\rho = 0.54$ and RMSE = U.S.$ 35.6 bn (Fig. 8), so v_{max} has limited skill predicting historical loss. Hurricanes Katrina (2005) and Harvey (2017), which were category-3 and category-4 landfalls, respectively (Fig. 4), are among the most underestimated losses despite being the two most damaging events since 1979 (Fig. 9a). Furthermore, using v_{max} alone leads to loss predictions exceeding U.S.$ 30 bn for several less-damaging (≤ U.S.$ 10 bn) events (Fig. 9a), including Michael (2018), Laura (2020), Dennis (2005), Andrew (1992; second landfall) and Idalia (2023). Our analysis (Fig. 7) and recent work (Klotzbach et al., 2020; Klotzbach et al., 2022a) show landfall c_p to be the most skilful single hazard predictor for historical loss, and using landfall c_p rank to predict loss rank improves this correlation (ρ = 0.78 and RMSE = U.S.$ 26.4 bn) (Fig. 8). However, several events, across a range of observed losses, remain poorly predicted: Andrew (1992), Michael (2018), Rita (2005), Hugo (1989), Dennis (2005), Allen (1980) and Idalia (2023) are all overestimated (Fig. 9b). This greater predictive skill of c_p over v_{max} is likely due to the physical pressure–wind balance intrinsic to hurricanes (Chavas et al., 2017), but intensity metrics alone cannot accurately model loss.

We now combine landfall hazard, exposure and vulnerability quantities to derive more skilful models to predict historical hurricane loss, using three statistical approaches: multiple linear repression, random-forest, and weighted combined rank (Fig. 8). Using a random-forest model based on the optimal combination of hazard, exposure and vulnerability predictors is significantly skilful (ρ = 0.85; RMSE = U.S.$ 18.7 bn), with a slight improvement obtained from using a linear-regression model (ρ = 0.87: RMSE = U.S.$ 17.1 bn) (Fig. 8). Further skill is obtained when using a weighted combined-sum approach (ρ = 0.89; RMSE = U.S.$ 7.0 bn), representing a large decrease in RMSE when compared to using c_p and v_{max} (Fig. 8). Overall, effectively combining hazard, exposure and vulnerability predictors is found to significantly reduce RMSE by 67% compared with using landfall v_{max} rank alone, and by 55% when using landfall c_p rank alone (Fig. 8).

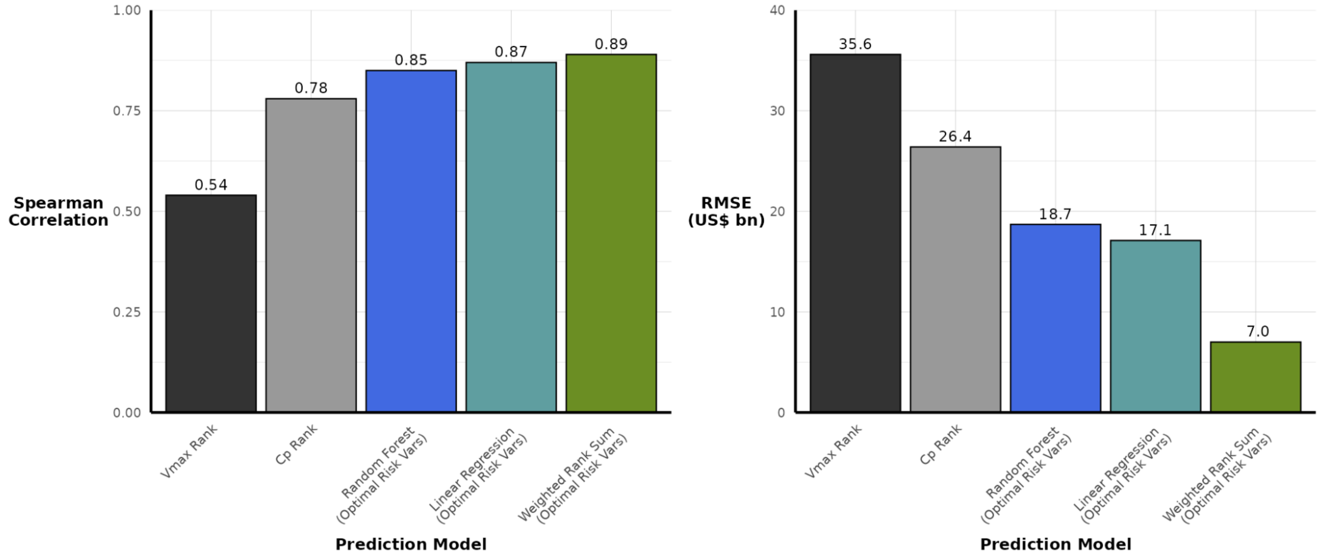

Figure 8. The a) Spearman's correlation coefficient, ρ, *and b) root mean squared error (RMSE) of each tested historical hurricane loss-prediction model.*

This optimal model uses the combined normalised ranks of landfall c_p, maximum rainfall accumulation, and the percentage of total GHSL building density loss within R64 of the hurricane centre and within 12 hours of landfall (Fig 8; Fig. 9c). This model includes two hazard quantities representing hurricane wind and inland flooding intensity (c_p and rainfall), with hurricane radius implicitly included in the percentage of total GHSL building density damage (with storms with larger R64 having higher impacted building density values). This also includes exposure values of impacted building density and applies a vulnerability function, by determining the percentage of damaged buildings proportional to v_{max} (at each timestep). The inclusion of building density within R64 indicates some prediction skill from capturing the inner region of a hurricane, where wind-induced damage to buildings may be highest, but only in combination with other factors. Overall, this model demonstrates the extent to which loss prediction skill can be improved when accounting for hazard, exposure and vulnerability.

Across our sample of 106 historical hurricanes, this prediction model has the lowest RMSE (U.S.$ 7.0 bn) when hazard, exposure and vulnerability predictors are ranked and summed, while also applying optimal weights (Fig. 8c). Moreover, for highly damaging historical hurricanes (≥ U.S.$ 20 bn), $\rho = 0.9$, which is significantly higher than using only landfall v_{max} ($\rho = 0.45$) or c_p ($\rho = 0.66$) (Fig. 9). Our optimal model results in the five most-damaging hurricanes (Katrina, Harvey, Andrew, Ian, and Sandy) being ordered according to observed losses and thus well captured, and higher-loss events (≥ U.S.$ 20–80 bn) overall are skilfully predicted. However, some discrepancies remain. The largest errors include hurricanes Michael (2018), Opal (1995) and Allen (1980), all of which have a high landfall c_p rank (i.e., high intensity) but relatively low loss. Overall, this model is markedly more skilful than using intensity metrics (landfall v_{max} and c_p) to predict historical losses (Fig. 8 and Fig. 9).

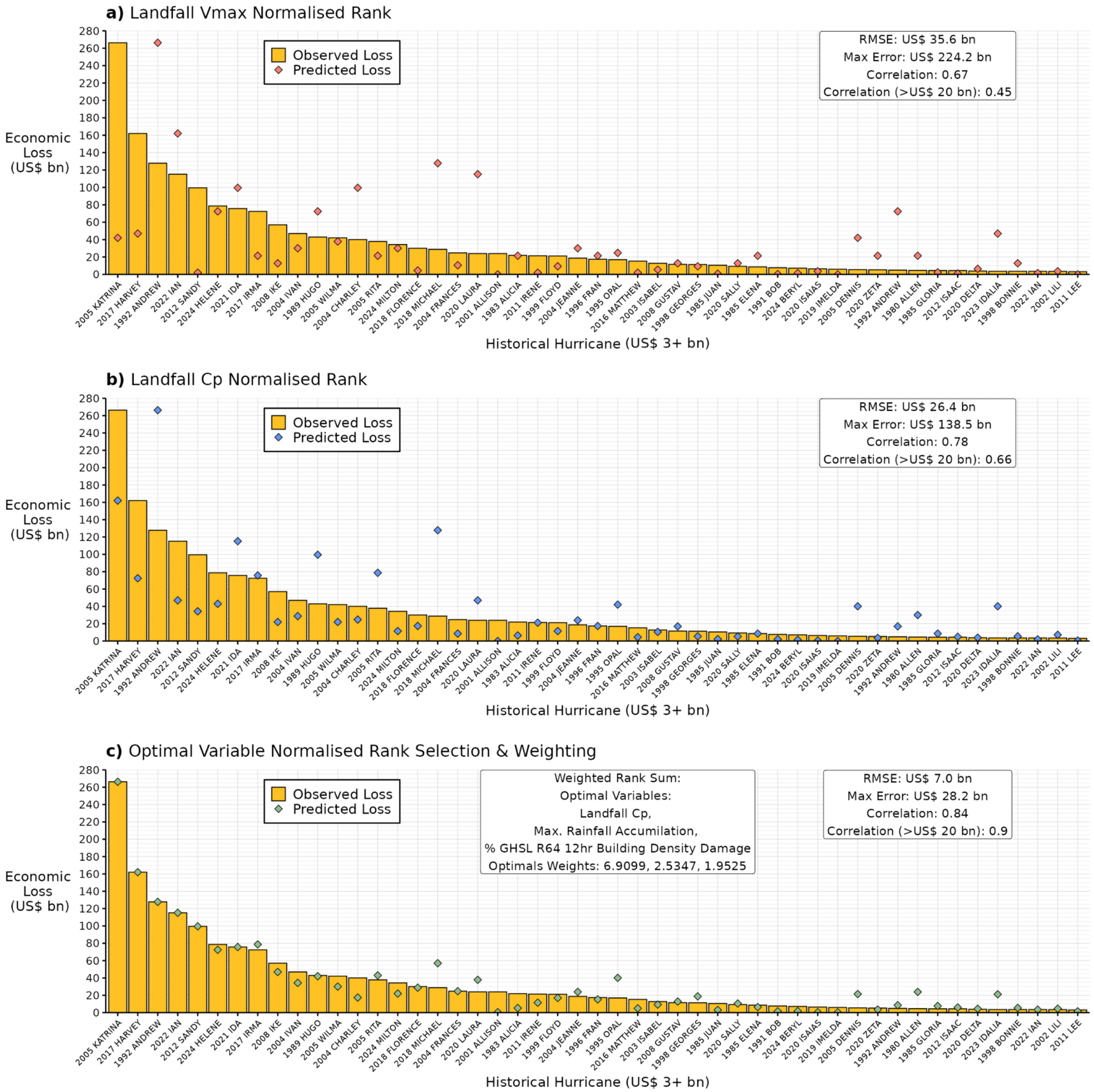

Figure 9. Comparisons of landfall predictor rank with loss rank to predict past hurricane loss given past loss observations, using (a) landfall v_{max} rank, (b) landfall c_p rank, and (c) optimally selected and weighted (refer to Fig. 7) hazard, exposure and vulnerability linear rank variables at landfall. Yellow bars indicate observed historical hurricane loss, and the coloured diamonds indicate predicted historical hurricane loss. Note that the optimal risk predictors and their optimal weights are given in panel (c).

6 A loss-based hurricane classification

The Saffir–Simpson scale is an effective communication tool and a key component of early-warning dissemination (Camelo and Mayo, 2021; Oliver-Smith, 2020; Wehner and Kossin, 2024), but, being based on v_{max} alone, does not correspond adequately with historical loss ranking (Fig. 4, Fig. 5). Based on our analyses, we devised a loss-based hurricane categorisation, termed the 'Hurricane Predictive Loss Scale' (HPLS). We intend this scale to complement the Saffir–Simpson scale, as well as published work (Bloemendaal et al., 2021; Pilkington and Mahmoud, 2016), and be a classification scheme that may be used by stakeholders, particularly (re-)insurance, to predict loss.

Since 1900, 39% of landfalling hurricanes have been category 1, with 12% and 3% being category 4 and 5, respectively (Table S2). We applied the observed relative proportions in each Saffir–Simpson category to averaged historical loss data since 1979 (Table 1) to derive historical loss categories (Table 2) for the HPLS. As examples, a hurricane with loss less than U.S.$ 1.3 bn is a 'loss category 1' event and an event causing loss greater than U.S.$ 119.5 bn is a 'loss category 5' event.

Table 2. Percentage of landfalling historical storms within each Saffir–Simpson category since 1900 (Hurricane Research Division, 2025). Loss category thresholds used to define the proposed HPLS.

Saffir–Simpson category	**Frequency**	**% of all hurricanes**	**v_{max} threshold (kts)**	**HPLS loss category threshold (U.S.$ bn)**
1	84	38.9	64-83	0-1.3

2	54	25.0	83-96	1.3-5.3
3	46	21.3	96-113	5.3-29.5
4	26	12.0	113-136	29.5-119.5
5	6	2.8	136+	119.5+

Using our skilful hurricane loss-prediction model, we determined the HPLS loss category derived from the predicted losses for each historical hurricane (Fig. 9c and Fig. 10). The ranks of the most damaging hurricanes (Katrina, Harvey, and Andrew) are correctly predicted as being 'loss category 5', and the next most damaging storms (Ian to Wilma) are 'loss category 4' events, with losses between U.S.$ 115-42 bn (Fig. 10). Hurricane Sandy (2012), which is under-categorised by the Saffir–Simpson scale (category 1) and the 'Tropical Cyclone Severity Scale' (Bloemendaal et al., 2021) (category 2), is a 'loss category 4' event in our scheme. Combining hazard, exposure and vulnerability quantities and loss-based categorisation is more skilful for many cases than is possible based only on hazard information.

The most damaging hurricane that is misrepresented by the HPLS scheme is Hurricane Charley (2004), whose observed loss (U.S.$ 40.1 bn) is underpredicted by our model (Fig. 10). Charley should be 'loss category 4' (Fig. 4 and Table 2), but its predicted loss (~U.S.$ 20 bn) falls in 'loss category 3'. Additionally, tropical storm Allison (2001) is assigned to 'loss category 1', which stands out as a poor model prediction (Fig. 10). Overall, we found 74 events (70%) are correctly classified by the HPLS (Table 3). However, 28 events (26%) are misrepresented by ±1 'loss category' and 4 (4%) are misrepresented by ±2 'loss categories' (Table 3). By comparison, Saffir–Simpson categories represent just over half (55%) of events correctly, and 31%, 12% and 2% are misrepresented by ±1, ±2 and ±3 'loss categories', respectively (Table 3).

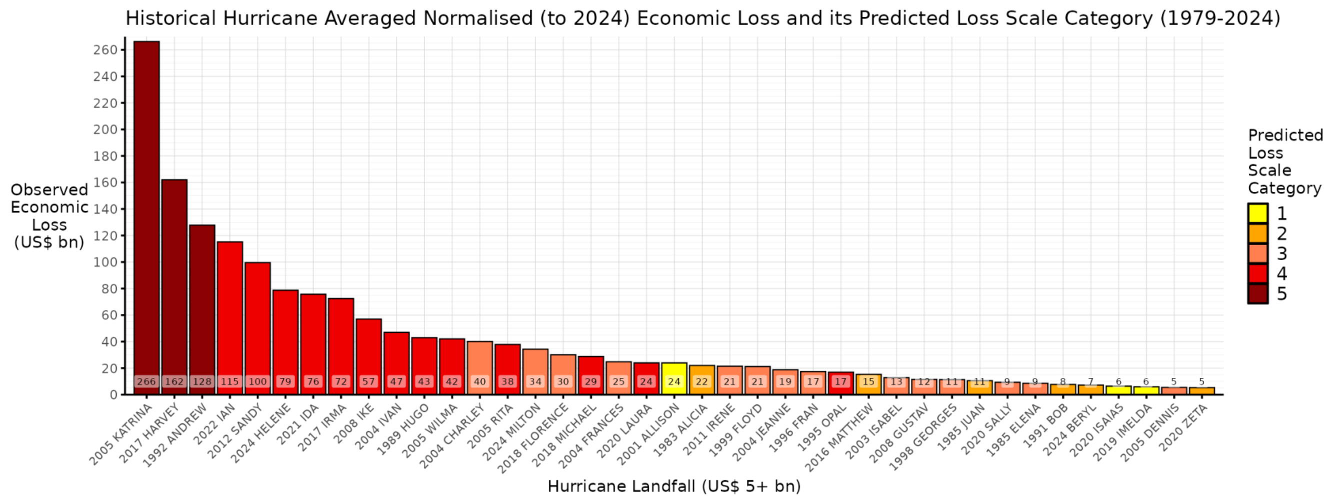

Figure 10. Predicted 'loss category' of each historical landfalling hurricane, using the optimal prediction model (Fig. 9c) and the HPLS (Table 2).

Table 3. Quantified differences between Saffir–Simpson category or predicted 'loss category' using our model (Fig. 9c) and the observed 'loss category' from the HPLS (i.e., derived from observed loss).

Difference from observed 'loss category'	**Saffir–Simpson category**	**Predicted 'loss category'**
0 (i.e., correct prediction)	58 (55%)	74 (70%)
±1	33 (31%)	28 (26%)
±2	15 (12%)	4 (4%)
±3	5 (2%)	0 (0%)

7 Summary and discussion

This study explored statistical relationships between historical U.S. hurricane-related losses and quantities describing hazard, exposure and vulnerability, and makes two contributions. First, we determined whether the inclusion of socioeconomic information into a predictive model for loss from U.S. landfalls yields significant additional skill compared with using only hazard information. For historical hurricanes, we derived storm-centred hazard, exposure and vulnerability quantities, and limited our analysis to cases for which observed loss estimates are available and hurricane radius is either observed or could be skilfully estimated statistically from other observed size information. Second, we devised a loss-based hurricane classification scheme to allow rapid, skilful assessment of the loss potential of forecast events, which is intended for use by stakeholders in hurricane risk, including governmental agencies and the (re-)insurance sector, and complements existing classification schemes.

7.1 Key results and limitations

7.1.1 Integrated hazard, exposure, and vulnerability data predict historical hurricane losses more skilfully than hazard data alone

Although historical losses generally increase with landfall wind speed (and Saffir–Simpson category), hazard information alone has insufficient skill in predicting historical losses, with a large RMSE across all events, a finding which substantiates previous research (Klotzbach et al., 2020; Klotzbach et al., 2022a). We find various hurricane-centred hazard, exposure and vulnerability quantities correlate significantly with losses (i.e., $r > 0.5$), but using a weighted-rank-sum approach to optimally combine these predictors yields markedly more skilful loss predictions ($\rho = 0.89$ for all storms). This high correlation between loss observations and predictions, with a significantly reduced RMSE of U.S.$ 7.0 bn, improves the predicted loss rank of the most impactful historical cases. This optimal prediction model was derived by determining the weighted sum of normalised ranks of landfall c_p, maximum rainfall accumulation, and the percentage of total GHSL building density damage within R64 and within 12 hours of landfall. This model includes two hazard attributes representing hurricane intensity (c_p and rainfall), building density impacted, and applies a vulnerability function (percentage of building damage proportional to v_{max}). For this model, important limitations are related to the observational uncertainties within the input predictor data, as well as in the target variable. There is significant variance among loss estimates for historical events. Additional uncertainty stems from the lack of complete cyclone size information prior to 2002, which is not completely mitigated by our statistical estimation approach and could impact skill for pre-2002 landfalls. A key data gap is the availability of vulnerability information and its temporal granularity. Lastly, historical loss uncertainty necessitated consideration of multiple datasets and averaging losses where required.

Studies based on physical climate model outputs provide evidence of significant interannual to decadal variability in damage (Lavender et al., 2022) and substantial inter-model uncertainty (Meiler et al., 2023). Projected increases in vulnerable assets, assuming no adaptation, may worsen damage to a greater extent than physical hazard changes (Gettelman et al., 2018). Regional vulnerability, particularly building characteristics, is important, and regional factors are accounted for in high-resolution catastrophe models (e.g., Eberenz et al., 2021) and synthetic tropical cyclone models (e.g., Meiler et al., 2022), although results exhibit sensitivity to model setup (Meiler et al., 2025). Open-source catastrophe models may underestimate historical losses (König, 2017; Welker et al., 2021), so a comprehensive intercomparison of such models across historical hurricanes is warranted. While our statistical model may not predict hurricane losses events outside our sample (i.e., loss significantly exceeding that of Hurricane Katrina), it ranks losses in historical context and complements other catastrophe modelling approaches.

7.1.2 A loss-based hurricane scale effectively communicates economic impacts

We devised a 'Hurricane Predictive Loss Scale' in which hurricanes are assigned a 'loss category'. This characterises hurricanes according to economic losses, complementing the Saffir–Simpson scale and prior work (Bloemendaal et al., 2021; Pilkington and Mahmoud, 2016). Our model-predicted 'loss categories' matched observed categories (determined from loss data) in 70% of cases, comparing favourably with the Saffir–Simpson scale. An illustrative example is Hurricane Sandy (2012), a lower-intensity, larger-size storm that is assigned 'loss category 4', a more appropriate characterisation of the actual loss. The HPLS offers a simple method to embed information about potential losses for forecast landfalls to support decision-making. In (re-)insurance, pooling risk across a diversified portfolio reduces capital costs and increases loss predictability (Ciullo et al., 2023). For hurricanes, however, recent basin-wide (Klotzbach et al., 2022b) and near-coast (Qi et al., 2025; Wang and Toumi, 2021; Zhong et al., 2026) trends in hazards will increasingly challenge risk stakeholders. We therefore anticipate that our scheme will be a useful risk-management tool.

7.2. Outlook

Our study highlights clear data needs. First, vulnerability data of higher spatial and temporal granularity are needed. Using open-source datasets here necessitated a combination of time-varying and time-invariant predictors, which is an area for improvement. The development of such datasets using emerging technologies offers potential—for example, combining machine learning and satellite imagery to describe building attributes and structural vulnerability, and their changes, with higher fidelity. Vulnerability may be economic or social and characterised by economic or demographic data, respectively (Wilson et al., 2022). Second, there is a need for hurricane size information for historical events. This key physical quantity directly determines impacted areas (Wang and Toumi, 2016), and future work to develop reconstructions of wind radii (e.g., Xu et al., 2024) would be considerably beneficial. It is somewhat unclear how climate change may impact the horizontal structure of a hurricane's wind field. Expansion rates increase with sea-surface warming (Wang et al., 2025), supported by observed size trends (Balaguru et al., 2026). Climate models, however, do not project changes outer size over this century

(Schenkel et al., 2023), although studies of high-resolution climate models, which adequately capture intensification and horizontal structure (Baker et al., 2024), are needed to help substantiate such projections and evaluate their risk implications.

There is potential to refine our approach for application to a variety of sectors and stakeholders (Beven et al., 2018). We developed a loss-based classification, but different schemes could be developed for specific sectors. For example, governments, disaster-relief organisations and public-health services may employ classification based on expected fatalities, requiring an understanding of human factors, such as risk perception (Wong-Parodi and Garfin, 2022) and the ability of communities to respond to warnings (Black et al., 2013). Predictions of human impacts could be made following our statistical framework, given adequate historical mortality-burden data for model training. Additionally, our methodology may be applied to other cyclone-prone regions, where necessary data are available. Finally, our predictive model may help quantify risk changes in a warming climate by its application to simulated future cyclones, which may be more intense and induce heavier precipitation (Knutson et al., 2020), to quantify how losses may respond to hazard changes and the expected losses due to unprecedented landfalls in regions of significant exposure or vulnerability.

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9 Author contributions

AFV and AJB conceived the study. AFV performed data analysis and figure preparation, supported by AJB, VMH and JM. AFV and AJB wrote the manuscript. All authors interpreted results and approved the final draft.

10 Competing interests

The authors declare no competing interests.

11 Code / data availability

IBTrACS data are available from ncei.noaa.gov/products/international-best-track-archive. All other datasets are available from the cited sources. Data analysis and visualisation code is available at github.com/ncas-metoffice-hrcm/hurricane_loss.

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