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RESEARCH ARTICLE

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Climate change attribution of Typhoon Haiyan with the Imperial College Storm Model

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Abstract

It is difficult to model changes in the likelihood of tropical cyclones under climate change to date. We do this, for the first time, by a applying a stochastic tropical cyclone event set generated by the Imperial College Storm Model to attribute the contribution of climate change to the case of Typhoon Haiyan in 2013. Compared to a pre-industrial baseline, we estimate that a typhoon with a landfall maximum wind speed like Haiyan was larger by +3.5 m/s. This is in good agreement with previous full physics numerical model estimates. A Haiyan type of event has a current return period of 850 years, and the fractional attributable risk due to climate change is 98%. Without climate change, this event was very unlikely. The type of information available from the IRIS model could inform subsidizing of catastrophe bond yield in the context of the loss and damage fund.

KEYWORDS

change and impacts, climate, climate variability, geographic/climatic zone, physical phenomenon, scale, severe weather, tropic, weather/climate extremes

1 | INTRODUCTION

The Philippines is one of the nations most affected by tropical cyclones (TCs) in the world and regularly ranks amongst the nations most vulnerable to climate change (Eckstein et al., 2021). On average, it experiences more TCs than any other nation, with approximately 19 TCs in the Philippines' area of responsibility and nine landfalls per year (Santos, 2021). The influence of climate change on TCs varies by basin, as does the level of scientific evidence on these changes (Knutson et al., 2020). On a global scale, recent decades have seen an increase in more intense TCs (categories 3–5 on the Saffir–Simpson scale) making landfall (Wang & Toumi, 2022a).

Ultimately 'natural' hazards such as TCs only become disasters due to the exposure and vulnerability of people and property to these hazards. The Philippines has a rapidly growing population of nearly 120 million people in 2024, which is increasingly urbanized. The growth of urban populations and relatively high rates of poverty has led to the growth of informal settlements that are unable to withstand extreme weather conditions, as well as other sources of pervasive housing-based vulnerability (Healey et al., 2022).

Typhoon Haiyan (local name Yolanda) is the joint second-strongest landfalling TC on record and has been the most catastrophic tropical cyclone ever to land in the western North Pacific Ocean, struck the Philippines on 8 November 2013. Typhoon Haiyan killed 6000 people and injured almost 30,000. Haiyan led to the widespread destruction of infrastructure and housing in coastal areas, displacing 4 million people, destroying or damaging over a million homes, and disrupting crucial services for months (Lagmay et al., 2015).

While not necessarily representative of the impact of climate change on tropical cyclones in general, the human and economic loss caused by Haiyan has already made it a focus of several modelling studies including attempts at climate change attribution. Baldwin et al., 2023 applied a stochastic event set based on the Columbia HAZard model (CHAZ) model to the Philippines only for the current climate conditions. Their model included vulnerability function and underestimated the economic loss due to Haiyan and pointed to the important role of rain and flood that are not modelled explicitly (Lagmay et al., 2015). To determine the intensification due to climate change Typhoon Haiyan has been studied using a 'pseudo-global warming' approach. It made landfall as a strong Category 5 (defined as a minimum wind speed threshold of 70 m/s) with a maximum wind speed of 85 m/s. Takayabu et al. (2015) modelled wind and surge effects. They estimated an increase in the maximum wind speed of 3 m/s compared to pre-industrial conditions. Delfino et al. (2023) showed that the maximum wind during the lifetime of Haiyan increased by 2 m/s, relative to preindustrial times for the highest resolution model. Increases in sea surface temperature provide more energy input to tropical cyclones leading to intensification. However, attribution can depend on the specifics of assumed anthropogenic change, the storm and the model used. This can lead to ambiguous results in many cases (Patricola & Wehner, 2018).

While these studies have quantified the intensity change, to date it has not been possible to attribute the change in probability of an event to climate change from pre-industrial to now. Here we provide such an attribution for the first time. The Imperial College Storm Model (IRIS, Sparks & Toumi, 2024) is a new global tropical cyclone wind hazard model with some key innovations. Firstly, it recognises that the key step for estimating landfall wind speed is identifying the location and value of the lifetime maximum intensity (LMI) (Wang & Toumi, 2022a). Then, the problem is one of decay only. Secondly, the LMI is assumed to be physically constrained by the thermodynamic state as defined by the potential intensity (PI). PI theory was first proposed by Emanuel (1986) and provides a theoretical upper limit on the intensity of a TC developing in a given thermodynamic environment.

Here we use IRIS to perform a climate change attribution on the Typhoon Haiyan landfall event by comparing stochastic TC event sets produced using estimates of pre-industrial and 2013 PI. This permits an estimate of the effect of climate change on not only the intensity but also, for the first time, the frequency of events like Haiyan.

2 | METHOD

Assessing tropical cyclone risk given the infrequency of landfalling TCs and the short period of reliable observations remains a challenge. Synthetic tropical cyclone models can help overcome these problems. We explore this method here using a new global tropical cyclone wind model, IRIS. In IRIS, tropical cyclone intensities are linked to PI. Potential intensity is a well-established concept in tropical cyclone theory that seeks to define an upper limit of the maximum wind speed (Emanuel, 1986). This upper limit can be diagnosed from the sea surface temperature and the humidity and temperature vertical profile. Observations show that the relative intensity, defined as the observed maximum intensity divided by the potential intensity, follows a robust uniform distribution. This drives the stochastic model lifetime maximum intensity (LMI). The landfall intensity, LI, then depends on the LMI, the time to landfall, t, and the decay rate, κ (Wang & Toumi, 2022b),

$$\mathrm{LI} = \frac{1}{\frac{1}{\mathrm{LMI}} + \kappa t} \qquad (1)$$

Tracks are based on International Best Track Archive for Climate Stewardship (IBTrACS) observations. IRIS calculates basin and landfall wind speed intensity distributions from the location of LMI and the corresponding potential intensity at that location, based on observed tracks between 1980 and 2023.

To simulate the climate of the pre-industrial era, and 2013 with IRIS, we require appropriate PI fields. Regional and local modelling of absolute PI by climate models is problematic as they are known to have biases (Zhang et al., 2023). Regional observed changes are difficult to distinguish from decadal variability or regional forcing and may not be sustainable into the future (Lee et al., 2022). There are also theoretical grounds, supported by most climate model projections, to expect that the tropical zonal temperature gradient will weaken with greenhouse gas forcing (Knutson & Manabe, 1995). We therefore make the assumption that the anthropogenic trend in PI is the global zonal mean PI trend and use the observed PI trend since 1979. We use the sum of the mean PI over the period 1979–2023 and an appropriately scaled PI trend over the same period to estimate the pre-industrial and 2013 PI climates. This approach avoids the selection of any climate model. The method is simple

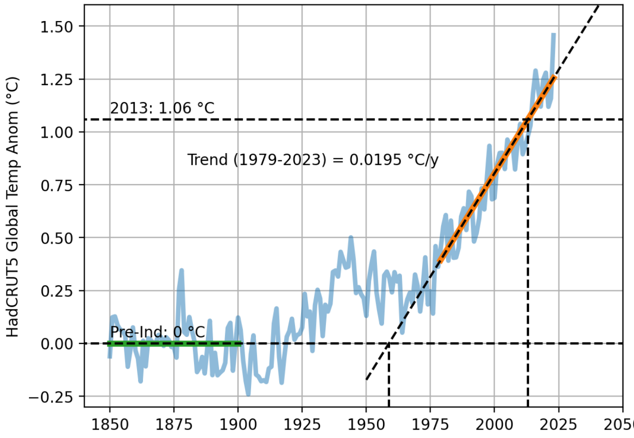

FIGURE 1 Global mean surface temperature showing scaling method. The 2013 warming is +1.06 above pre-industrial, which is defined as the period 1850–1900. The warming trend between 1979 and 2023 (the ERA5 period) is +0.0195°C/year.

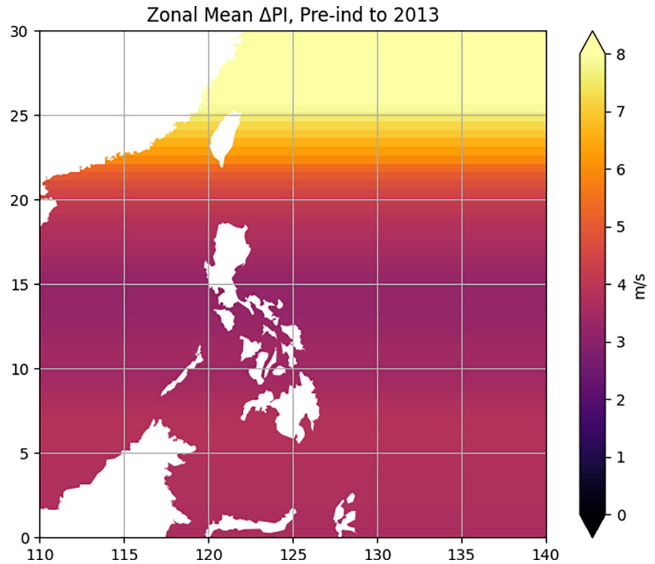

FIGURE 2 Zonally averaged potential intensity change from the pre-industrial baseline to 2013 over the western Pacific region in November.

and robust. We will also examine the impact of regional PI trends.

To determine the scaling of the PI trend, we use the global mean surface temperature anomaly record (HadCRUT5) (Morice et al., 2021). This is shown, relative to the pre-industrial, 1850–1900 mean, baseline in Figure 1. During the period of widespread satellite observations and ERA5, 1979–2023, the global mean rise in temperature has been approximately linear. There has been a recently observed global warming to about 1.2°C in 2023 and about 1.06°C above pre-industrial temperature at the time of Haiyan in 2013.

We calculate the monthly mean PI in terms of maximum sustained wind speed (Vmax, m/s) from ERA5 reanalysis data over the period 1979–2023 using the algorithm developed by Gilford (2021) and Bister and Emanuel (2002) based on the Emanuel (1986) model. From this, we create a climatological monthly mean PI field and calculate the trend in PI (m/s/year) at every grid for each month using linear regression.

The PI for the pre-industrial and 2013 simulations was calculated by adding a scaled PI trend to the mean PI, as follows:

$$\mathrm{PI}_{\mathrm{pre-ind}} = \mathrm{PI}_{\mathrm{mean}} + \Delta Y_{\mathrm{pre-ind}} \mathrm{PI}_{\mathrm{trend}} \tag{2}$$

$$\mathrm{PI}_{2013} = \mathrm{PI}_{\mathrm{mean}} + \Delta Y_{2013} \mathrm{PI}_{\mathrm{trend}} \tag{3}$$

where $\mathrm{PI}_{\mathrm{mean}}$ is the mean PI evaluated over the period 1979–2023 and $\mathrm{PI}_{\mathrm{trend}}$ is the zonal mean regressed linear trend over the same period at the grid point. The scaling parameters, $\Delta Y_{\mathrm{pre-ind}}$ and ΔY_{2013}, were evaluated using the following:

$$\Delta Y_{\mathrm{pre-ind}} = \frac{T_{\mathrm{pre-ind}} - T_{\mathrm{mean}}}{T_{\mathrm{trend}}} \tag{4}$$

$$\Delta Y_{2013} = \frac{T_{2013} - T_{\mathrm{mean}}}{T_{\mathrm{trend}}} \tag{5}$$

where T_{trend} is the regressed linear trend in global mean surface temperature anomaly over the period 1979–2023, T_{mean} is the mean surface temperature anomaly over the same period, $T_{\mathrm{pre-ind}}$ is defined as 0°C, and T_{2013} is the regressed temperature anomaly evaluated in the year 2013. This results in a monthly PI difference between pre-industrial and 2013 simulations equivalent to 65 years of the observed 1979–2023 zonally averaged PI trend. Figure 2 shows the global zonal mean PI change for the region near the Philippines. The observed regional change in PI can also be scaled in the same way and used to drive the model. In this case, the regional warming is more La Nina-like and there are larger changes in PI in the Philippine Sea compared to the zonal mean (Figure S1).

We use IRIS to simulate 100,000 years of stochastic TCs for both the pre-industrial and 2013 climate (PI) states. We select the TCs which make landfall in the Philippines and diagnose their intensity (maximum wind speed, V_{max}) at landfall. We split the Philippines into two zones based on the landfall climatology: north (N) and south (S). Haiyan made landfall in the South (Figure 3). The numbers of landfalling events and their intensities at landfall are tallied, enabling the construction of return curves (Figure 4). From this, the likelihood of a landfalling event at the intensity of Haiyan (or, e.g. Category 5) can be estimated in both current and pre-industrial conditions. This in turn enables estimation of the fractional attributable risk (FAR), given by,

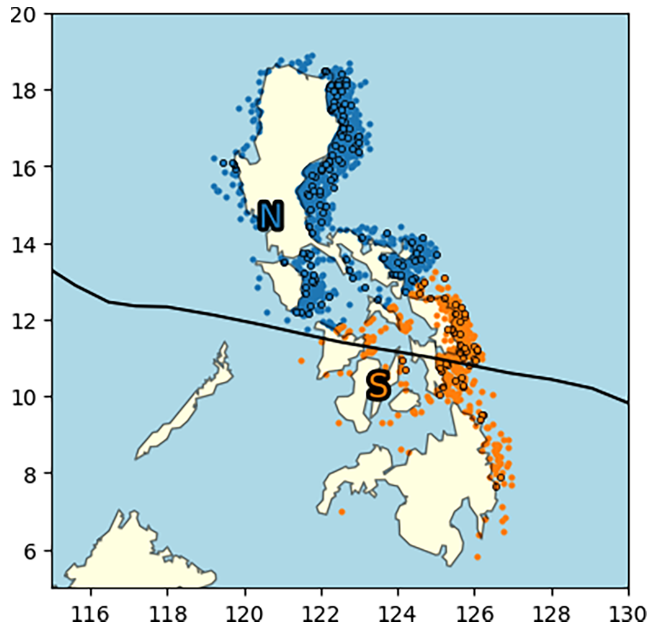

FIGURE 3 Observed (black circles) and IRIS (coloured dots) landfall events in the Philippines. Observations are IBTrACS (1980–2023). IRIS are from a sample of 440 years. Landfall events are categorized by location into North (blue) and South (orange). Black line shows the path of Haiyan.

$$\mathrm{FAR} = 1 - \frac{P_0}{P_1} \tag{6}$$

where P_1 and P_0 are the probabilities of event occurrence in the current (2013) and preindustrial climates, respectively.

3 | RESULTS

Figure 4 shows the all-Philippines return period for the observations and the simulations for a pre-industrial and 2013 potential intensity environment. The model and observations are in close agreement. For the all-Philippine landfall for a maximum wind speed of at least 85 m/s, IRIS estimates a return period of 130 years in the year of Haiyan, 2013, compared to a pre-industrial value of 9300 years (Figure 4). This corresponds to a fractional attributable risk of about 0.99 (equation 6). Another interpretation is that the wind speed of an equivalent pre-industrial era typhoon has increased by about +4 m/s. This wind speed increase is close to the uncertainty of measurements and would not be detectable through observational analysis alone. Figure 4 shows that the fractional attributable risk decreases substantially with a lower wind threshold. In the case of typhoons above Category 5 or a maximum wind speed greater than 70 m/s, the all-Philippines FAR is about 36% and for category 3+ the FAR is only 12%.

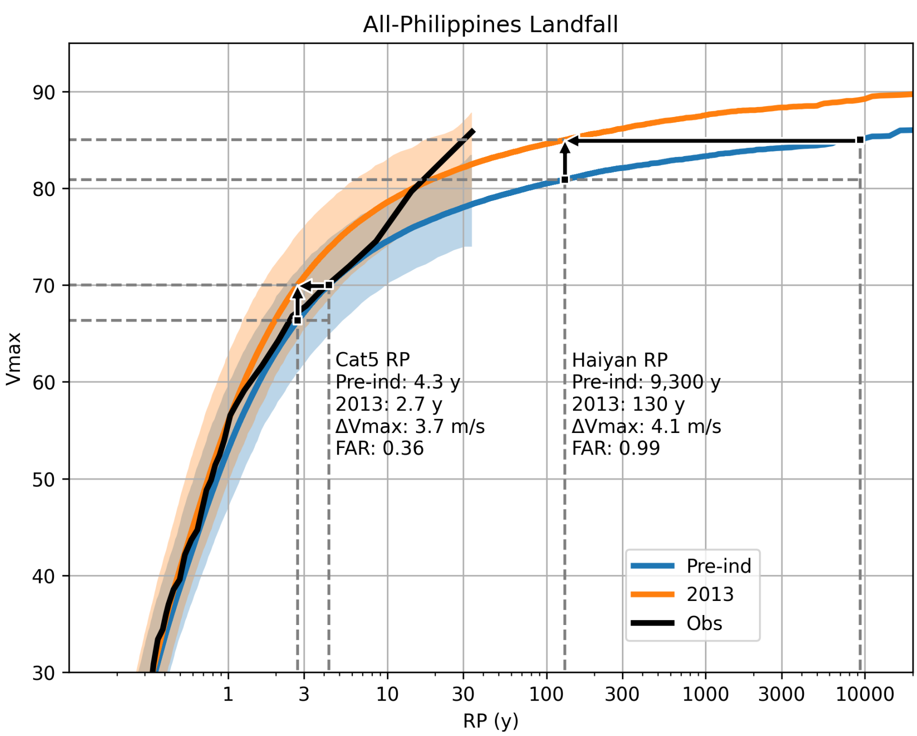

FIGURE 4 Return curves for Philippines landfall events. IBTrACS 1980–2013 observations (black) and 100,000-year IRIS simulations in pre-industrial (blue) and 2013 (orange) climate conditions. Shading shows 2.5%–97.5% range of ensembles of 34-year samples of IRIS output. The dotted lines show the return periods of Category 5 events in IRIS simulations.

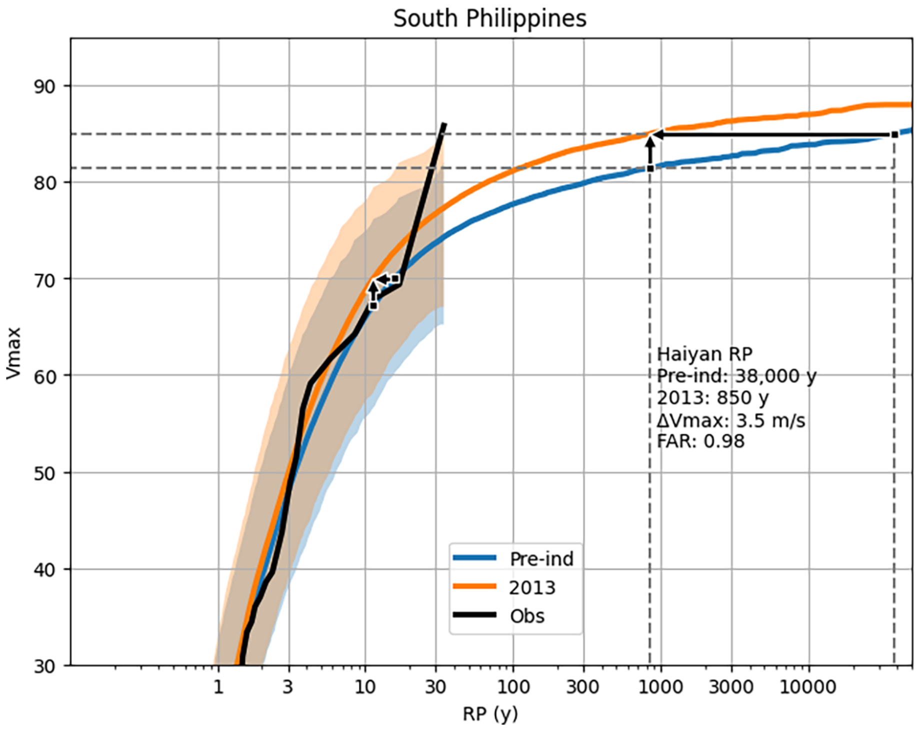

FIGURE 5 As in Figure 4 but for South Philippines shown in Figure 3.

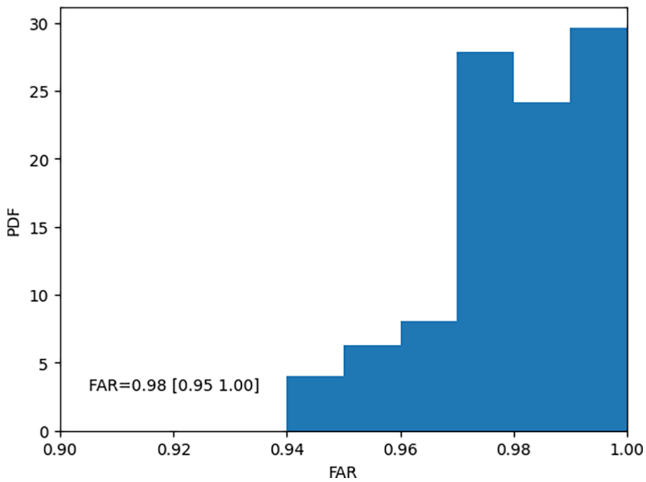

FIGURE 6 Probability distribution of 10,000-year samples of the fractional attributable risk in the 100,000-year simulation, including the 95% confidence intervals on the best estimate FAR value.

The return periods vary with regions. If we consider the return periods of the hypothetical landfall of a Haiyan-type event in the south region, then the fractional attributable risk is 0.98 (Figure 5) and 0.99 in the north (Figure S2). The increased risk with increased latitude can be understood by the similar latitude pattern of PI change (Figure 2). For the more specific location at Haiyan's actual landfall location (south zone), The model's current return period is 850 years and 38,000 years for the pre-industrial climate. Therefore, IRIS suggests that a fractional attributable risk of 0.98 may be reasonably considered for the Haiyan event. The increase of the maximum wind speed is +3.5 m/s compared to pre-industrial climate for this region. Given the limited observed data set used here of 34 years, Haiyan is the maximum or 34-year event. This observational estimate of the return period is therefore a lower limit and observations on their own cannot be used to estimate the return period. For the 100,000-year simulation, we can sample independent 10,000-year samples to determine the probability distribution of fractional attributable risk (Figure 6). This gives a 95% confidence interval of 0.95 and 1.00. The standard error of the best estimate mean, 0.98, is 0.015, or <4%.

If we drive the model with regional rather than zonal mean PI changes, the results are very similar (Figure S3) but the pre-industrial RP is even greater and beyond the simulation time scale (>100,000 years) and the FAR is therefore also larger (>0.99). The increased zonal mean PI simulation provides a conservative FAR with the same qualitative result that Haiyan-type events are very unlikely without climate change.

4 | DISCUSSION AND CONCLUSION

The IRIS model has been applied to the problem of attribution to climate change. The model predicts that the Haiyan maximum wind speed was enhanced by +3.5 m/s compared to the pre-industrial base case. This is remarkably close to previous studies of +2–3 m/s that have used full physics ensemble and physical downscaling model simulations with a pseudo-global warming approaches (Delfino et al., 2023; Takayabu et al., 2015). The similarity in results between IRIS and full physics models is encouraging. Unlike the full physics models, we can readily calculate changes in probability and FAR for this and other events. IRIS can be used for rapid climate change attribution assessments.

The Haiyan landfall intensity enhancement is similar to the average zonal-mean PI change from pre-industrial to 2013 in the Philippines region (Figure 3) of 3.6 m/s. The landfall intensity change can be anticipated from the PI change. However, we also need to know the probability of this intensity. When a TC makes landfall, its intensity at landfall is governed by the PI at the location of LMI, its relative intensity at LMI, the decay rate and duration from LMI to landfall. Crucially, the landfall probability distribution for a given location (i.e. Southern Philippines) is thus due to many TCs. IRIS provides a means by which to link PIs to the landfall intensity probability distributions. Without such a model the PI theory itself does not tell us what influence a changing PI will have on the wind speed probability at landfall.

Defining a Haiyan-like event as a TCs which makes landfall in the Southern Philippines with an intensity of least 85 m/s, the IRIS model suggests that Haiyan was an 850-year event in the 2013 climate. Such a large return period cannot be estimated from the observations alone. Using the CHAZ model, Baldwin et al. (2023) estimated a Haiyan return period of several thousand years. They used a different baseline and applied a landfall bias correction. The synthetic track set also allows us to estimate for the first time the change in probability or frequency of this type of event in 2013 compared to pre-industrial conditions. We estimate that the fractional attributable risk (FAR) due to climate change is about 98% for a strong Category 5 Haiyan-type event in 2013. The significance of such a large FAR is that such a Haiyan-type disaster is very unlikely to have occurred without the increase in potential intensity driven by global warming.

The ability to calculate the probabilistic FAR may be useful in applications to parametric insurance and the proposed loss and damage fund (UNFCC, 2024) set up to enhance resilience to climate change. Parametric insurance or a catastrophe bond could play an important role in the toolkit for this fund. The IRIS simulations suggest that the FAR for all-Philippine landfalls due to climate change for storms of at least Category 5 was about 37% in 2013. This opens the interesting proposition that the loss and damage fund or a development bank could subsidise a fraction of the parametric insurance premium or the yield of a typhoon bond. There are many factors determining the premium or bond yield, but the amount of subsidy could be based on the FAR or about 37% in this case. This subsidy would account for the enhanced climate risk incurred by the historic anthropogenic emissions of the developed world. Global warming has continued since 2013, so this subsidy for Category 5+ events would be much larger now and increase going forward.

Another approach could be to use the FAR to distinguish between the fair needs of different countries/regions within a multinational or multi-regional insurance pool. The demand for premium or yield subsidy by countries/regions typically exceeds the supply. Those countries or regions with a larger FAR could be given preference in the loss and damage fund allocation (Paul Wilson, private communication). A model such as IRIS could play an important role in informing parametric insurance and the allocation of the loss and damage fund.

AUTHOR CONTRIBUTIONS

Nathan Sparks: Conceptualization; methodology; software; data curation; investigation; validation; formal analysis; visualization; writing – review and editing. **Ralf Toumi:** Conceptualization; methodology; investigation; validation; formal analysis; supervision; funding acquisition; project administration; resources; writing – review and editing; writing – original draft.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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