Climate Change Attribution of Typhoon Haiyan with the IRIS model

Sparks, Nathan and Toumi, Ralf

Department of Physics, Imperial College London

Abstract

A stochastic tropical cyclone event set generated by the IRIS model was applied to attribute the contribution of climate change to the case of Typhoon Haiyan in 2013. Compared to a pre-industrial base line we estimate that a typhoon with a landfall maximum wind speed like Haiyan was larger by about + 3 m/s. This is in good agreement with previous full physics numerical model estimates. For the first time we can also quantify the change in probability given our 100,000-year event set. A Haiyan type of event has a current return period of about 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 subsidising of catastrophe bond yield in the context of the loss and damage fund.

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 9 landfalls per year (Santos, 2020). 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 (category 3-5 on the Saffir-Simpson scale) making landfall (Wang and Toumi, 2022).

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 urbanised. 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) 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 30000. 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). Baldwin et al. , 2023 applied a stochastic event set based on the CHAZ model to the Philippines. Their model included vulnerability function and underestimated the economic loss due to Haiyan and point to important role of rain and flood that are not modelled explicitly (Lagmay et al., 2015). The IRIS model used here is also a wind only model (Sparks and Toumi, 2024).

Typhoon Haiyan has been studied using a ‘pseudo-global warming’ approach. It made a 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 in crease in the maximum wind wind speed of 3 m/s compared to pre-industrial conditions. Delfino et al., 2023 showed that the maximum wind during the life-time 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 and Wehner, 2018).

Method

Assessing tropical cyclone risk given the infrequency of landfalling tropical cyclones (TC) and the short period of reliable observations remains a challenge. Synthetic tropical cyclone datasets can help overcome these problems. We explore this third method here using a new global tropical cyclone wind model, IRIS, with several key innovations (Sparks and Toumi, 2024). It recognises that the key step for estimating landfall wind speed is the location and value of the life-time maximum intensity (LMI). It redefines the problem as one of decay only. The initial intensity, life-time maximum, is assumed physically constrained by the thermodynamic state as defined by the potential intensity (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 observed maximum intensity divided by the potential intensity, follows a robust uniform distribution. This drives the stochastic model lifetime maximum intensity. The landfall intensity is then a fraction of this lifetime maximum depending on the time to landfall. Tracks are based on 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.

There has been a recent 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 (Fig. 1). Regional and local prediction of absolute PI by climate models is problematic as they are known to have biases. Regional observed changes are difficult to distinguish from natural variability. We therefore make the assumption that the anthropogenic trend is the global zonal mean PI trend and use the observed PI trend since 1979 from ERA-5. There is some warming from pre-industrial to 1979 for which we have incomplete potential intensity data. To estimate the pre-industrial potential intensity state, we extrapolate backwards the current observed trends. This approach avoids the selection of any climate model. The method is simple and robust. Figure 1 shows the global mean surface temperature time series we use to scale to the pre-industrial PI. Figure 2 shows the global zonal mean PI change for the region near the Philippines. The model simulates 100,000 years for both the pre-industrial and 2013 climate (PI) state.

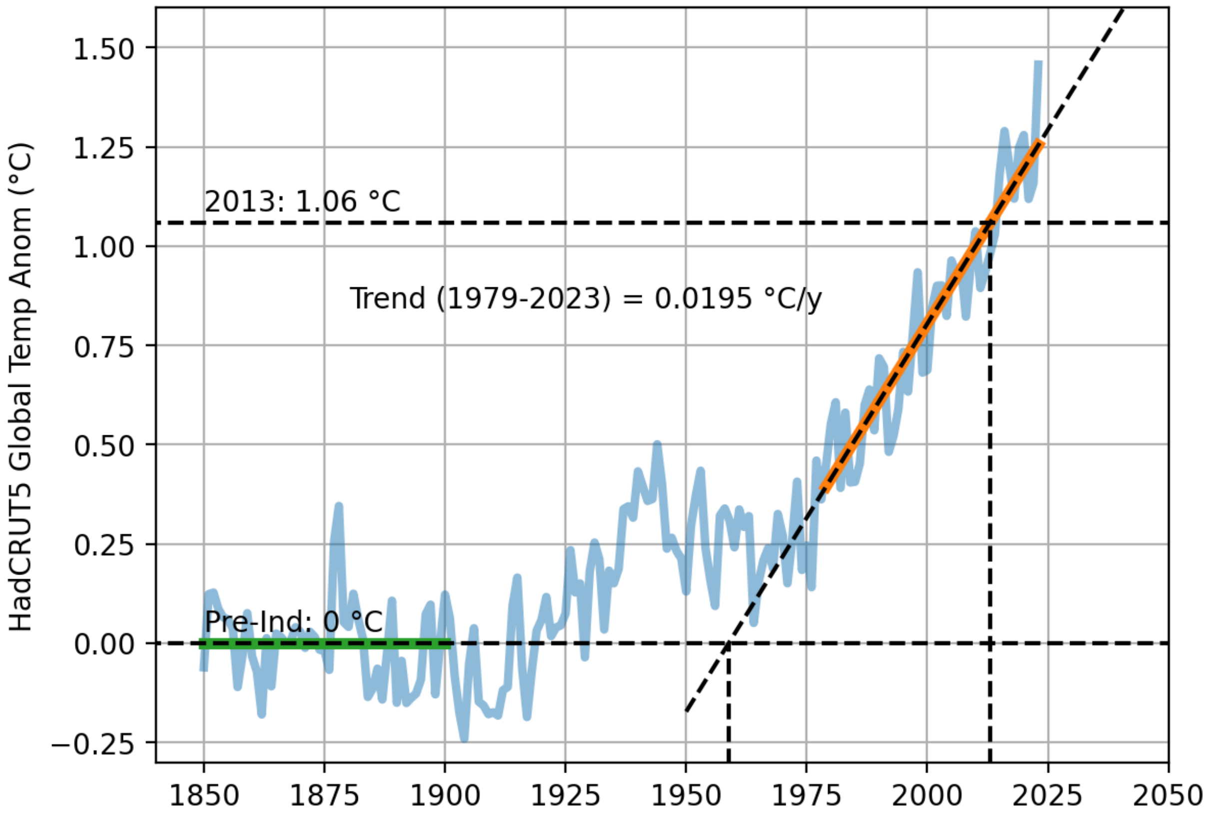

Figure 1: Global mean surface temperature showing scaling method. The 2013 warming is +1.06 above pre-industrial, which is defined as the period 1850-1900. The warming trend between 1979-2023(the ERA5 period) is +0.0195 °C/yr.

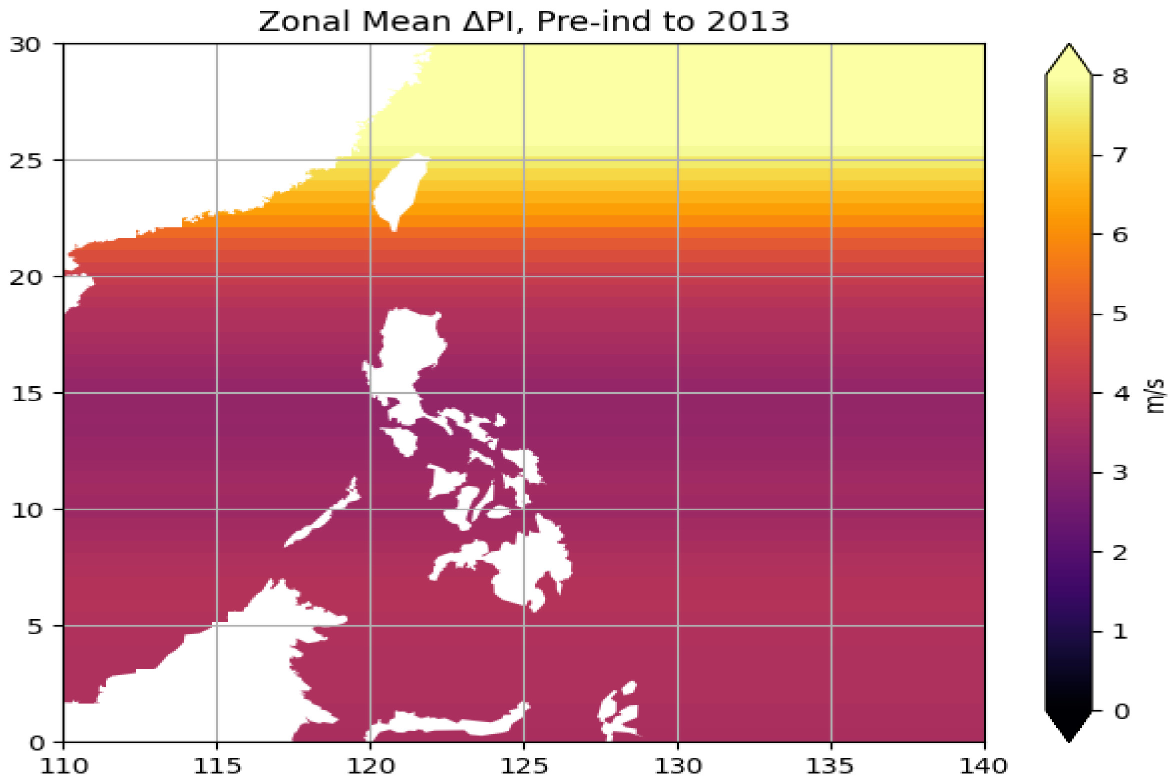

Figure 2.: Zonally averaged potential intensity change from the pre-industrial baseline to 2013 over the western Pacific region in November.

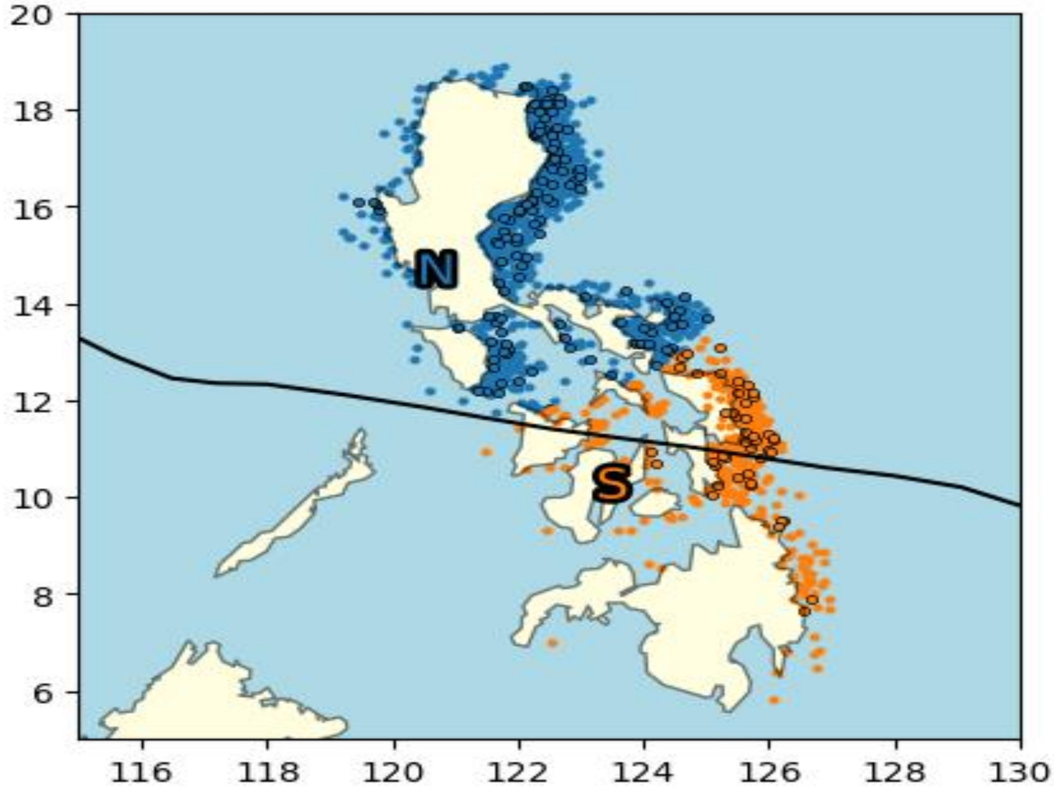

Figure 3.: Observed (black circles) and IRIS (coloured dots) landfall events in the Philippines. Observations are IBTrACS (1980-2023). IRIS are from a sample of 440 years. Landfall events are categorised by location into North (blue), and South (orange). Black line shows the path of Haiyan.

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 (Fig. 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 preindustrial conditions. This in turn enables estimation of the fractional attributable risk (FAR), given by

$$FAR = 1 - \frac{P_0}{P_1}, \quad (1)$$

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

Results

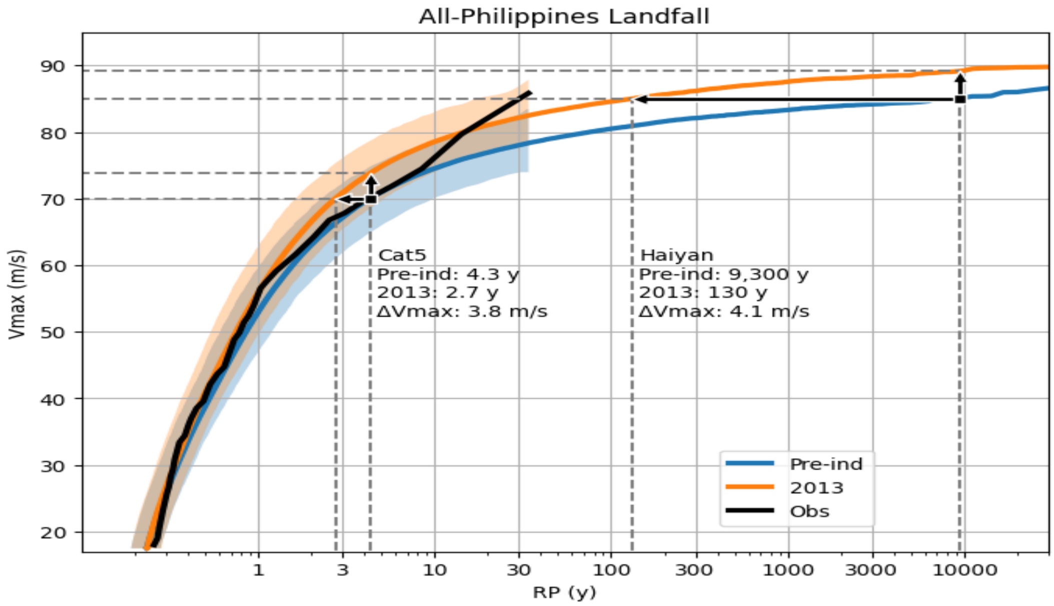

Figure 4: Return curves for Philippines landfall events. IBTrACS 1980-2013 observations (black) and 100,000-year IRIS simulations in pre-industrial (blue) and 2013 (orange) climate conditions. Shading shows 2.5 - 97.5 percentile range of ensembles of 34-year samples of IRIS output. Dotted lines show return periods of Cat 5 events in IRIS simulations.

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 9,300 years (Figure 4). This corresponds to a fractional attributable risk of about 0.99 (equation 1). 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.

The return periods vary with regions. If we consider the return periods of hypothetical landfall of a Haiyan type event in the two regions, North and South, then the fractional attributable risk is 0.99 and 0.98 respectively (Figure 5). The increased risk with increased latitude can be understood by the similar latitude pattern of PI change (Fig. 2). For the more specific location at Haiyan's actual landfall location (South zone), The model current return period is about 850 years and 38,000 years for the pre-industrial climate. Therefore, IRIS suggests that a fractional attributable risk of about 0.98may be reasonably considered for the Haiyan event. The increase of the maximum wind speed is about 3 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 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 (Fig. 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 less than 4%. Figure 4 shows that the fractional attributable risk decreases substantially with lower wind threshold. In the case of typhoons above Category 5 or a maximum wind speed greater than 70 m/s the FAR is about 37% and for Category 3+ the FAR is only 12%.

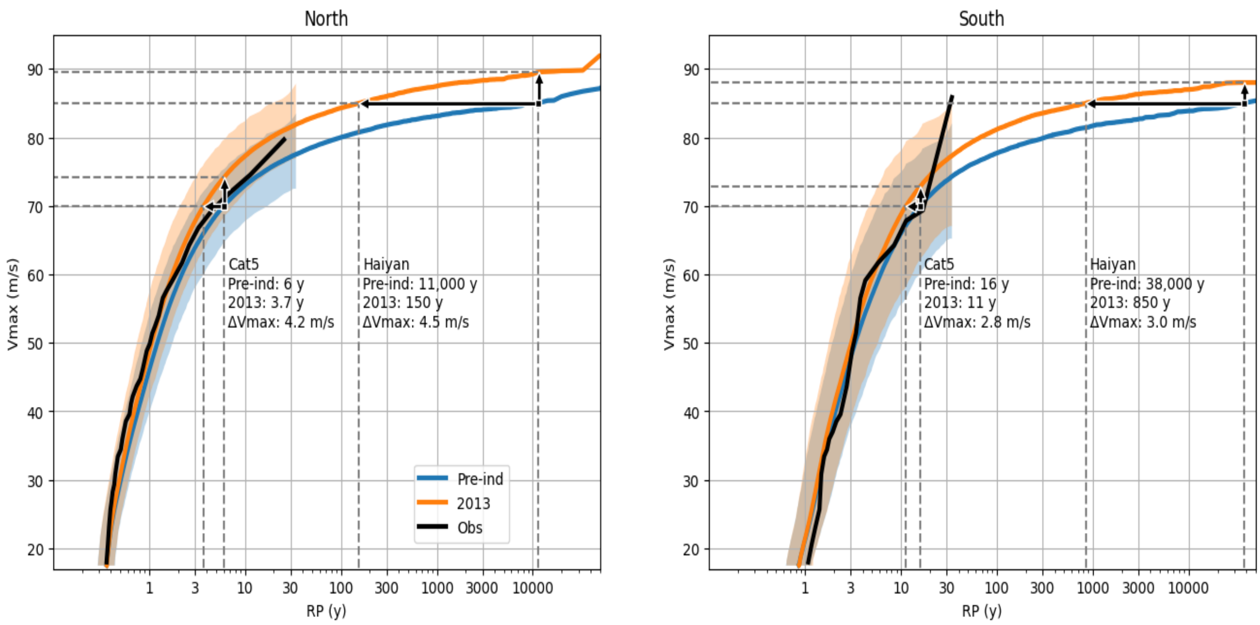

Figure 5: As in Figure 4 but for regions of Philippines shown in Figure 3.

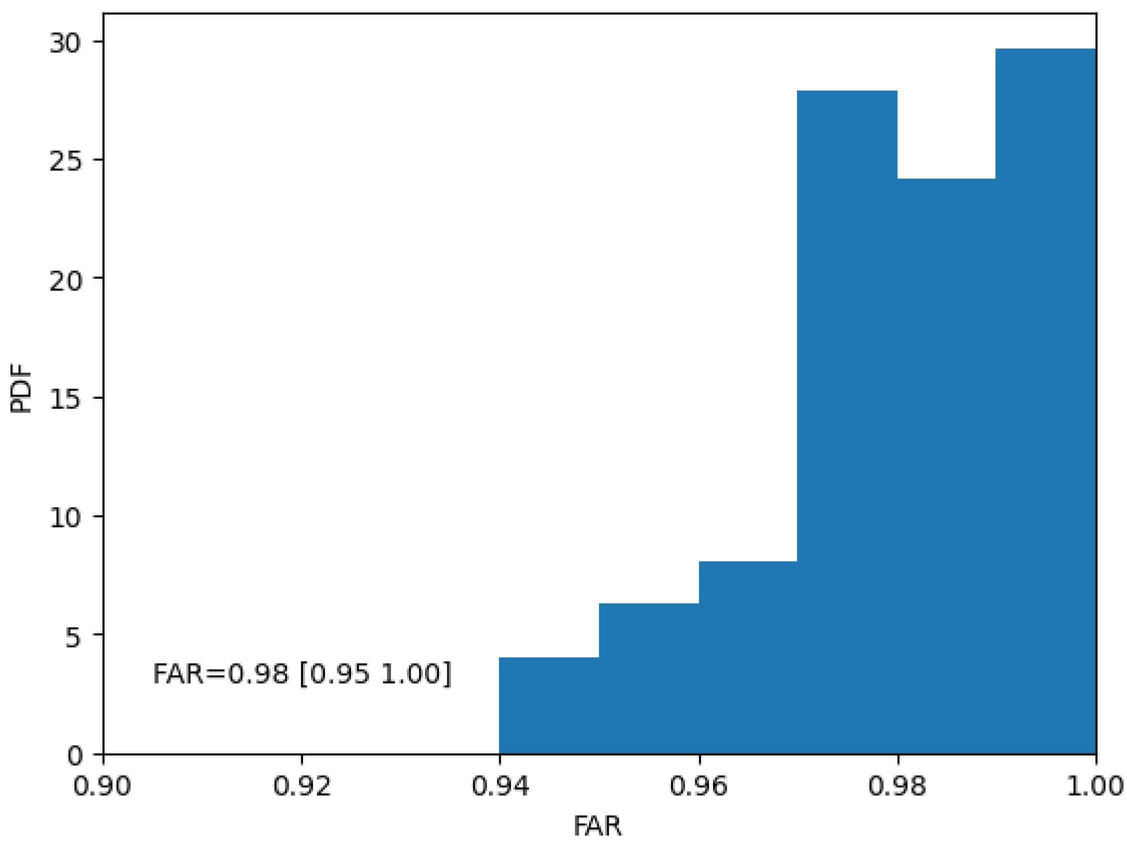

Figure. 6: Probability distribution of 10,000-year samples of the fractional attributable risk in the 100,000 year simulation, including the 95% confidence intervals on the best estimate FAR value.

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 about +3 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 (Takayabu et al., 2015, Delfino et al., 2023). IRIS is a very different model. It is much simpler model by construction and has comparatively negligible computational requirements so 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 could be used for rapid climate change attribution assessments.

The IRIS model suggests that Haiyan was a 850 year event. Such a large return period can not 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 the Haiyan disaster is very unlikely to have occurred without the increase in potential intensity driven by global warming.

The ability to calculate the FAR maybe 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 landfall 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 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.

Acknowledgements

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