

Climate change increased Typhoon Gaemi's wind speeds and rainfall, with devastating impacts across the western Pacific region

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Main findings

- Typhoon Gaemi brought destructive winds and rainfall to large regions of southeast Asia, including the northern Philippines, Taiwan, and Hunan . At least 90 people were killed, thousands were injured and hundreds of thousands had to leave their homes. The extreme rainfall and high winds triggered landslides, widespread power outages and severe damage to infrastructure and agriculture.
- In today's climate, that has already been warmed by 1.2°C due to the burning of fossil fuels, weather observations indicate that rainfall events as severe as those brought by Typhoon Gaemi now occur about once every 20 (5 - 30) years in the northern Philippines, about once every 5 (1.5 - 20) years in Taiwan, and about once every 100 (90 - 160) years in Hunan province.
- To determine the role of climate change we combine observations with climate models. In Taiwan and Hunan, the rainfall was about 14% and 9% heavier respectively due to climate change, and in both regions, the rainfall total was made about 60% more likely by climate change. If the world continues to burn fossil fuels, causing global warming to reach 2°C above pre industrial levels, devastating Typhoon rainfall events in both regions will become 30-50% more likely.
- In the northern Philippines, the analysis did not identify a significant trend up to today. Observations indicate that 3-day rainfall events have increased by about 12%, however, there is large uncertainty in these data sets. Climate models suggest both increases and decreases in rainfall in the current climate, but an increase in a future climate with 2°C of warming.
- The IRIS model was used to investigate Gaemi's strong winds by analysing category 4-equivalent storms in the Western North Pacific basin, a region that includes the South China and Philippine seas.
- By statistically modelling storms in a 1.2°C cooler climate, this model showed that climate change was responsible for an increase of about 30% in the number of such storms (now 6-7 times per year, up from 5 times), and equivalently that the maximum wind speeds of similar storms are now 3.9 m/s (around 7%) more intense.
- The conditions that formed and fueled Typhoon Gaemi were studied for links to climate change, using potential intensity and sea surface temperatures surrounding the storm track in

July 2024. These conditions occur about every second year for potential intensity and about once every 15 years for sea surface temperatures.

- The influence of climate change on potential intensity is highly uncertain, as observations show a very large increase with warming (about a factor of 100 and a potential intensity increase of 6 m/s) that climate models do not capture. Sea surface temperatures as hot as those observed in July 2024 were almost impossible without climate change and have become about 1 degree warmer. If global warming reaches 2°C, sea surface temperatures are projected to be another 0.6°C warmer, and the conditions associated with Typhoon Gaemi will continue to increase in likelihood by a further factor of about 10.
- Together, these findings indicate that climate change is enhancing conditions conducive to Typhoons, and when they occur the resulting rainfall totals and wind speeds are more intense. This is in line with other scientific findings that tropical cyclones are becoming more intense and wetter under climate change.
- Rural communities with climate sensitive livelihoods (e.g. agriculture), the urban poor residing in the lowest lying land, and those living on exposed hillsides susceptible to landslides were the most affected by the multitude of hazards stemming from the typhoon.
- The regions affected by Typhoon Gaemi have early warning systems and comprehensive emergency response systems in place for tropical cyclones that help manage impacts. Flood risk associated with extreme rainfall is well-assessed in the affected regions, but existing urban plans and flood control infrastructure are not able to withstand the more extreme floods that are driven by climate change. Unplanned urban development, including in Metro Manila where the population has rapidly increased, is increasing the number of people at risk, especially in lower lying informal areas.

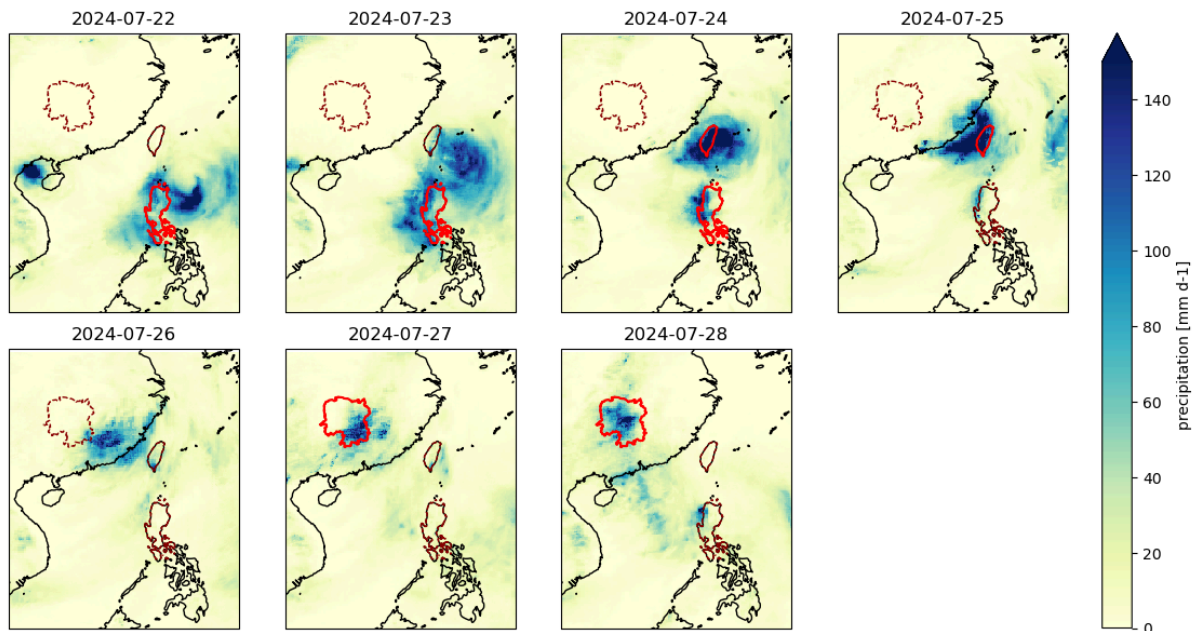


Figure 1.1: Daily rainfall totals from July 22nd-28th over the regions affected by Typhoon Gaemi (MSWEP). The three regions (Hunan, Taiwan and the Northern Philippines) studied in the rainfall analysis in this report are highlighted in red: bright on the days affected, dashed/dark otherwise.

1 Introduction

Typhoon Gaemi (known locally in the Philippines as Super Typhoon Carina) began as a tropical depression in the western North Pacific around July 19th 2024. It strengthened into a tropical storm by the 20th while moving northwest towards the Philippines under the influence of a sub-tropical ridge. Gaemi did not make landfall in the Philippines but interacted with the ongoing southwest monsoon (known locally as Habagat), leading to advection of moisture over the archipelago. On the 22nd, 23rd and 24th July heavy winds and torrential rainfall affected the northern part of the country, including the western side of the large northern island of Luzon on which Manila is situated. The [PAGASA Science Garden Synoptic Station](#) received around 324 mm of rainfall in 24 hours and around 600 mm over the 3 days. In total, 48 people were killed across the affected areas, and around 6.5 million were exposed to severe conditions. 45 landslides were triggered across the northern islands, power was disrupted in over 100 cities and municipalities, and around 400 sections of road and 30 bridges were damaged ([NDRRMC, 2024](#)).

The storm intensified as it continued northwards towards the island of Taiwan, becoming a very strong Typhoon (equivalent to a category 4 storm) on the 24th, with maximum (10-minute) sustained winds of 185 km/h (51.4 m/s). It weakened slightly before making landfall in northeast Taiwan on the 24th, bringing both heavy rain and high winds (see Figure 1.3 for the track). 10 people were killed by the storm and another 900 were injured, while the agricultural sector reported damages of roughly US\$ 50 million ([FocusTaiwan, 2024a](#), [FocusTaiwan, 2024b](#)). Gaemi emerged 6 hours later into the Taiwan strait before making landfall as a tropical storm in east China. Heavy rainfall affected coastal regions before moving further inland, reaching Hunan as it weakened to a tropical depression that brought severe rainfall. Typhoon-associated rainfall is uncommon so far inland and the widespread, heavy and rapid nature of the precipitation led to flooding and a mudslide that killed 15 people. In total 30 people were killed in China due to Gaemi, many of whom were in Hunan, while another 35 remained missing a week after the disaster, and 290,000 people were evacuated ([CNN, 2024](#)).

1.1 Typhoons in the Western North Pacific basin and climate change

The Western North Pacific basin (WNP) is the most active TC region globally ([Wang & Wang, 2023](#)), exposing nations across east and southeast Asia to extreme weather conditions. The majority of TCs occur during the most active months of June-November, with a less active season from December-March, though events have historically occurred at all times of the year ([Basconcillo & Moon, 2021](#); [Basconcillo et al., 2024](#)).

The Philippines is one of the nations most affected by tropical cyclones (TCs) in the world, with approximately 19 TCs in the Philippines area of responsibility and 9 landfalls per year ([Santos, 2020](#); [Cinco et al., 2016](#)). Taiwan and southeast China, directly to the northeast of the Philippines, also experience around 9 landfalls per year combined ([Hsu et al., 2021](#)). Clearly, understanding potential ongoing and future changes in the characteristics of TCs are crucial.

Globally, the overall frequency of tropical cyclones is not significantly changing in time, but there is evidence that the most intense TCs (categories 3-5 on the Saffir-Simpson hurricane wind scale) are

increasing in number. This is in part due to the rise in sea surface temperatures (SSTs). Additionally, rainfall from TCs is becoming more intense in part due to the Clausius-Clapeyron relation, which states that warmer air holds more moisture at a rate of 6-7% / °C.

On the scale of individual basins, more complex changes are emerging. In the WNP, there may have been a slowdown in translation speed ([Lai et al., 2019](#); [Yamaguchi and Maeda, 2020a](#)), as well as a poleward (northward) shift in storm tracks ([Yamaguchi and Maeda, 2020b](#); [Kossin et al., 2016](#)). In the Philippines, no trend in landfalling rate has been found to date ([Cinco et al., 2016](#)). Changes are also occurring at sub-basin scales. For instance, in Southeast (East) Asia, there is evidence of a decreasing (increasing) trend in TC passages during the boreal autumn (around September-October), which is linked to decadal-scale variability ([Basconcillo and Moon, 2023](#)). Coupled to this, analysis of annual mean accumulated cyclone energy (ACE) in the Philippines' area of responsibility has seen an abrupt increase since 2003 ([Basconcillo et al., 2022](#)).

In China, TCs have struck at higher intensities and moved further inland ([Liu et al., 2020](#)), are moving more slowly over land leading to greater rainfall totals ([Lai et al., 2020](#)), are reaching the lifetime maximum intensity closer to the coast ([Li et al., 2022](#)), and are more frequently co-occurring with heatwaves as compound events ([Wang et al., 2023](#)).

Recent attribution studies help to elucidate the emerging influence of warming on TCs in the basin further. In the Philippines, the wind speeds from landfalling Typhoons Bopha, Mangkhut and Haiyan were increased by 10 m/s, 2 m/s and 2 m/s, respectively, relative to preindustrial times in a study using a Pseudo-Global warming approach ([Delfino et al., 2023](#)). Another study found that the storm surge from Haiyan was 20% higher due to human-induced warming. In Japan, the extreme rainfall associated with Typhoon Hagabis in 2019 was found to be 15-150% more likely to occur because of human induced climate change, which in turn was linked with an increase of approximately US\$4 billion in damages ([Li & Otto, 2022](#)). In addition, a storyline approach to extreme attribution found that rainfall from the typhoon was amplified by around 11% due to human-induced warming across the atmosphere and oceans ([Kawase et al., 2021](#)). Similarly, in early August 2009, Typhoon Morakot made landfall and stalled in Taiwan, causing extreme rainfall. The previous 20 years of anthropogenic forcing accounted for an increase of approximately 3.5% in the rainfall total ([Wang et al., 2019](#)). Finally, in 2020, central Vietnam experienced a series of typhoon-induced extreme rainfall events leading to severe impacts, but a study found that anthropogenic climate change had no detectable influence on the rainfall from the consecutive events when they struck Vietnam ([Luu et al., 2021](#)).

Studying the anthropogenic influence on individual tropical cyclones is challenging for several reasons. First, observation records predating the satellite era are very sparse ([Walsh et al., 2016](#)). Second, there are many conditions and physical mechanisms through which climate change may affect the impact-relevant variables of a given storm or storm season, such as sea surface temperatures, sea level, vertical wind shear, genesis location, steering pattern, and intensification rate, among others ([Knutson et al., 2021](#)). Finally, the extreme winds are the result of phenomena at scales on the order of ~10 km or less, meaning that almost all climate models cannot resolve the most extreme events and higher resolution bespoke modelling is required to explicitly simulate them ([Wehner et al., 2019](#)). The timescale of rapid attribution makes this even more challenging, as it is not possible to set up and validate higher resolution models. To date, rapid studies have been conducted only for rainfall totals over relatively large areas that can be reasonably captured by climate models at resolutions of ~25-50 km, including Hurricanes Harvey ([van Oldenborgh et al., 2017](#)) and Imelda ([van](#)

[Oldenborgh et al., 2019](#)), ex-TC Gabrielle in New Zealand ([Harrington et al., 2023](#)), and a series of cyclones affecting Mozambique ([Otto et al., 2022](#)). However, the impacts of Typhoon Gaemi, like many TCs, were the result of both extreme rainfall and wind. Since our aim is always to find an event definition that corresponds with the impacts of an event, this study aims to evaluate the anthropogenic influence on the rainfall, the wind, and the conditions leading to such an event.

1.2 Aims of this study

As set out above, the central aim of this study is to untangle the anthropogenic influence on Typhoon Gaemi. To do so, several aspects of the storm are considered using different methods. As such, this report contains many more event definitions and attribution statements, using several more methods, than would be included in a normal rapid study. This is because it is also a pathfinder study for rapid attribution of tropical cyclones more broadly.

Here, we present the range of tools now available for this purpose that address different facets of these complex events, using the established World Weather Attribution protocol alongside a stochastic storm model. The different types of results and their different interpretations are discussed. Future studies may draw upon any combination of these methods, where appropriate, for rapidly studying any given event. Given its severe impacts across several regions resulting from both extreme rain and winds, Typhoon Gaemi presented both an important and informative case study for thinking about how we address tropical cyclones going forwards. The range of hazard assessments are incorporated in a summary section and alongside the analysis of vulnerability and exposure, which develops the report into an assessment of overall risk.

1.3 Event definitions

There are four key sections for analysis and attribution of the hazard(s) from the typhoon, each featuring 1-3 event definitions, which are used to cover the affected areas and each method. These are set out below.

First, the traditional WWA protocol is applied to rainfall across three key affected regions where impacts were reported. This gives a probabilistic analysis of precipitation using a synthesis of observational and climate model products.

Rainfall:

1. **Northern Philippines:** 3-day accumulated precipitation June-September maximum in the northern Philippines, defined as all land areas above 12.5 ° N, area averaged
2. **Taiwan:** 2-day accumulated precipitation June-September maximum, area averaged over the island
3. **Hunan:** 2-day accumulated precipitation June-September maximum, area averaged over the province

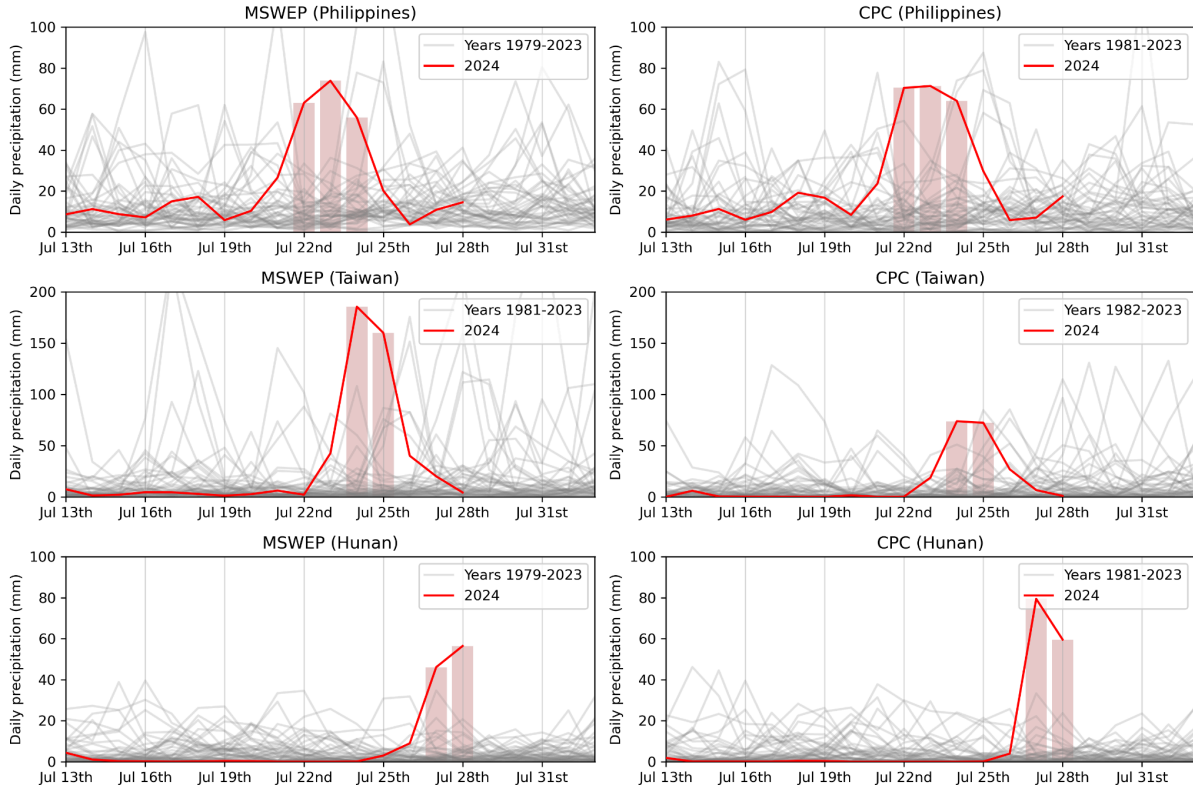


Figure 1.2: Daily rainfall totals in late July each year over the three regions studied in the rainfall analysis, the Northern philippines (top), Taiwan (middle) and Hunan (bottom), in two reanalysis datasets MSWEP (left) and CPC (right). 2024 is highlighted in red and the days in which extreme rainfall was driven by Typhoon Gaemi are highlighted with red bars.

Second, the environmental conditions leading to the event are also studied in the same way. This is quantified using the potential intensity, a metric that predicts maximum typhoon wind speed using sea surface temperatures, sea level pressure, and temperature and humidity vertical profiles (Pérez-Alarcón et al., 2023; Emanuel, 1986). The sea surface temperatures are also studied in isolation. While it would be more informative to study ocean heat content, doing so on a rapid basis was not feasible for this study given data availability, but future studies should strive to do so where possible. While potential intensity and SSTs are related, studying SSTs in isolation helps to disentangle the influence of climate change on the more complex overall potential intensity quantity.

Environmental conditions:

1. **Potential intensity (PI):** June-September maximum of monthly mean PI averaged over an area bounded by 115 - 135 °E, 10 - 30 °N (figure 1.3)
2. **Sea Surface Temperatures (SSTs):** June-September maximum of monthly mean SSTs averaged over an area bounded by 115 - 135 °E, 10 - 30 °N (figure 1.3)

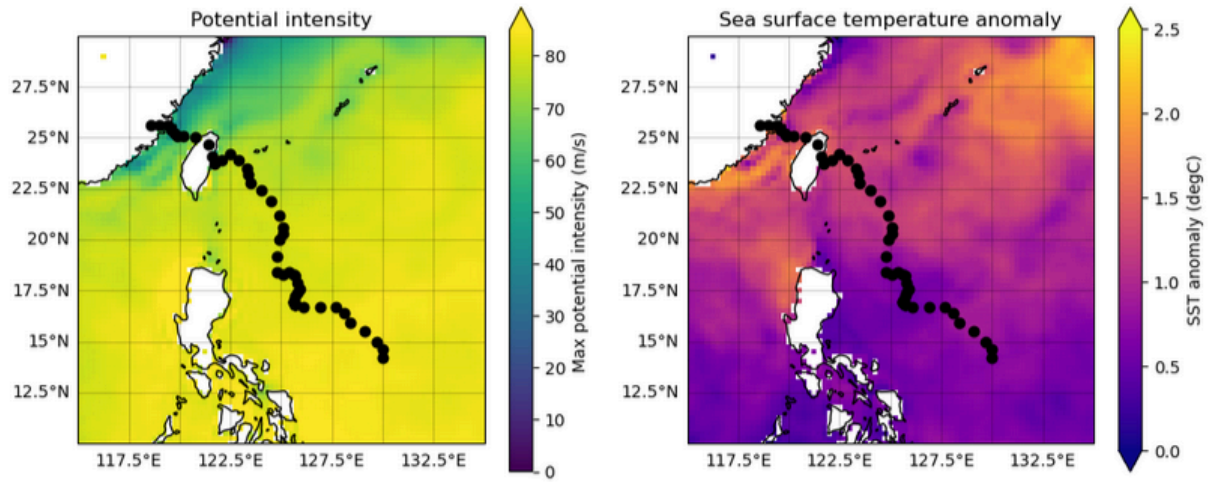


Figure 1.3: Potential intensity (left) and Sea Surface Temperature anomaly (versus the 1990-2020 climatology) (right) in July 2024 over the study region. The track of Typhoon Gaemi is shown in black.

Next, the attributable changes in wind speed intensity are assessed using a stochastic model of storm tracks and intensities.

Wind speeds:

1. **All-basin:** category 4+ Typhoons occurring in the entire Western North Pacific basin (figure 1.4)
2. **Taiwan:** A similar analysis but considering those that come within 2 degrees of the centre of Taiwan at the point of closest approach.

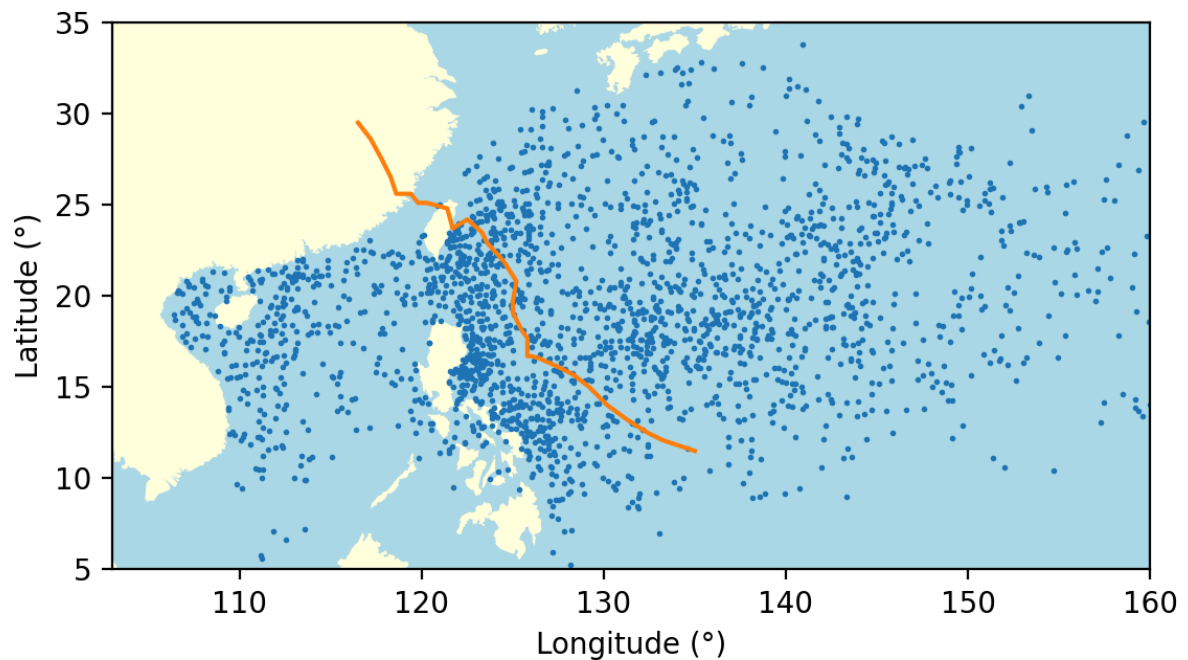


Figure 1.4: *A representative sample (440/10000 years) of points of lifetime maximum intensity (LMI) in the Western North Pacific basin in the IRIS dataset. The track of Typhoon Gaemi is shown in orange.*

2 Extreme rainfall attribution using WWA protocol

The event definitions studied in this section are as follows:

1. **Northern Philippines:** 3-day accumulated precipitation June-September maximum in the northern Philippines, defined as all land areas above 12.5 ° N, area averaged
2. **Taiwan:** 2-day accumulated precipitation June-September maximum, area averaged over the island
3. **Hunan:** 2-day accumulated precipitation June-September maximum, area averaged over the province

2.1 Data and methods

2.1.1 Observational data

Several observational and reanalysis datasets are used to analyse the anthropogenic influence upon Typhoon Gaemi:

- CPC daily precipitation: this is the gridded product from NOAA PSL, Boulder, Colorado, USA known as the CPC Global Unified Daily Gridded data, available at 0.5° x 0.5° resolution, for the period 1979-present. Data are available from [NOAA](#).
- MSWEP: The Multi-Source Weighted-Ensemble Precipitation (MSWEP) v2.8 dataset (updated from [Beck et al., 2019](#)) is fully global, available at 3-hourly intervals and at 0.1° spatial resolution, available from 1979 to ~3 hours from real-time. This product combines gauge-, satellite-, and reanalysis-based data.
- CHIRPS: The rainfall product developed by the UC Santa Barbara Climate Hazards Group called “Climate Hazards Group InfraRed Precipitation with Station data” (CHIRPS; [Funk et al. 2015](#)). Daily data are available at 0.05° resolution, from 1981-30 June 2024. The product incorporates satellite imagery with in-situ station data.
- ERA5: The European Centre for Medium-Range Weather Forecasts, or the ERA5 reanalysis product begins in the year 1950 ([Hersbach et al., 2020](#)). We use precipitation data from this product. It should be noted that the variables from ERA5 are not directly assimilated, but these are generated by atmospheric components of the Integrated Forecast System (IFS) modelling system.
- The [PAGASA Science Garden Synoptic Station](#) is based in Quezon City on the island of Luzon. We use daily precipitation records from this station since the beginning of 1979.

Finally, there are two datasets used as covariates for these analyses. First, as a measure of anthropogenic climate change we use the (low-pass filtered) global mean surface temperature

(GMST), where GMST is taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GISTEMP, [Hansen et al., 2010](#) and [Lenssen et al. 2019](#)). Second, as a measure of the El Niño - Southern Oscillation state (ENSO) we use the detrended Niño3.4 index. This is computed from NOAA's ERSST v.5 sea surface temperatures, by subtracting the mean tropical SST (20S-20N) from the mean SST over the Niño3.4 region (5S-5N, 170W-120W). This index is therefore adjusted to remove the linear trend associated with climate change as proposed in [van Oldenborgh et al., 2021](#), but without rescaling each calendar month.

2.1.2 Model and experiment descriptions

In this study we use a multi-model ensemble from climate modelling experiments using very different framings ([Philip et al., 2020](#)): regional climate models, atmosphere-only climate models, and coupled global circulation models.

We use 2 multi-model ensembles from regional climate modelling experiments:

1. Coordinated Regional Climate Downscaling Experiment (CORDEX). For the Southeast Asia domain (CORDEX-SEA, 0.22° resolution; SEA-22, [Tangang et al., 2020](#)), the ensemble consists of 8 simulations resulting from pairings of 4 Global Climate Models (GCMs) and 3 Regional Climate Models (RCMs). For the East Asia domain (CORDEX-EAS, 0.22° resolution; EAS-22, [Kim et al., 2020](#)) the ensemble consists of 6 simulations resulting from pairings of 3 GCMs and 2 RCMs. These simulations are composed of historical simulations up to 2005, and extended to the year 2100 using the RCP8.5 scenario.
2. AM2.5C360 ([Yang et al. 2021](#), [Chan et al. 2021](#)) and the FLOR ([Vecchi et al. 2014](#)) climate models developed at Geophysical Fluid Dynamics Laboratory (GFDL). The AM2.5C360 is an atmospheric GCM based on that in the FLOR model ([Delworth et al. 2012](#), [Vecchi et al. 2014](#)) with a horizontal resolution of 25 km. Three ensemble simulations of the Atmospheric Model Intercomparison Project (AMIP) experiment (1871-2021) are analysed. These simulations are initialised from three different pre-industrial conditions but forced by the same SSTs from HadISST1 ([Rayner et al. 2003](#)) after groupwise adjustments ([Chan et al. 2021](#)), as well as the same historical radiative forcings. The FLOR model, on the other hand, is an atmosphere-ocean coupled GCM with a resolution of 50 km for land and atmosphere and 1 degree for ocean and ice. Ten ensemble simulations from FLOR are analysed, which cover the period from 1860 to 2100 and include both the historical and RCP4.5 experiments driven by transient radiative forcings from CMIP5 ([Taylor et al. 2012](#)).

2.1.3 Statistical methods

Methods for observational and model analysis and for model evaluation and synthesis are used according to the World Weather Attribution Protocol, described in [Philip et al., \(2020\)](#), with supporting details found in [van Oldenborgh et al., \(2021\)](#), [Ciavarella et al., \(2021\)](#) and [here](#). The key steps, presented in sections 2.2-2.4, are: (3) trend estimation from observations; (4) model validation; (5) multi-method multi-model attribution and synthesis of the attribution statement.

In this section we analyse time series of precipitation over three spatiotemporal domains (shown in figure 1):

1. 3-day accumulated precipitation June-September maximum in land areas in the Philippines above 12.5 °N
2. 2-day accumulated precipitation June-September maximum in Taiwan
3. 2-day accumulated precipitation June-September maximum in Hunan

A nonstationary GEV distribution is used to model each of these indices. For precipitation, the distribution is assumed to scale exponentially with the covariates, with the dispersion (the ratio between the standard deviation and the mean) remaining constant over time; while for temperatures, the distribution is assumed to shift linearly with the covariates, while the variance remains constant. The parameters of the statistical model are estimated using maximum likelihood.

For each time series we calculate the return periods, probability ratio (PR; the factor-change in the event's probability) and change in intensity of the event under study for the 2024 GMST and for 1.2 C cooler GMST: this allows us to compare the climate of now and of the preindustrial past (1850-1900, based on the [Global Warming Index](#)).

In order to examine the effect of the ENSO phase on extreme precipitation in the Northern Philippines alongside that of increasing GMST, we extend the nonstationary model to accommodate an additional covariate. All results quoted for the Northern Philippines are from a statistical model including both covariates, while all results for Taiwan and Hunan include only GMST as a covariate.

The statistical model with multiple covariate is as follows. The variable of interest, X , is assumed to follow a GEV distribution in which the location and scale parameters vary with both GMST and ENSO:

$$X \sim GEV(\mu, \sigma, \xi \mid \mu_0, \sigma_0, \alpha, \beta, T, I),$$

where X denotes the variable of interest, rainy-season precipitation; T is the smoothed GMST; I is the detrended Niño3.4 index; μ_0 , σ_0 and ξ are the location, scale and shape parameters of the nonstationary distribution; and α , β are the trends due to GMST and ENSO, respectively. As a result, the location and scale of the distribution have a different value in each year, determined by both the GMST and Niño3.4 states. Maximum likelihood estimation is used to estimate the model parameters, with

$$\mu = \mu_0 \exp\left(\frac{\alpha T + \beta I}{\mu_0}\right) \quad \text{and} \quad \sigma = \sigma_0 \exp\left(\frac{\alpha T + \beta I}{\mu_0}\right).$$

This formulation reflects the Clausius Clapeyron relation, which implies that precipitation scales exponentially with temperature ([Trenberth et.al., 2003](#), [O’Gorman and Schneider 2009](#)), and so that precipitation will scale exponentially with the strength of the detrended Niño3.4 index. Under this model, the effects of GMST and the detrended Niño3.4 index are assumed to be independent of one another, so that the change in intensity due to GMST is unaffected by the change in intensity due to the ENSO phase. We note that this may not be the case in the real world, as the intensity and frequency of El Niño events may have been influenced by climate change ([Cai et al., 2021](#)); however,

by using a detrended Niño3.4 index (see Section 2.1) we aim to minimise the correlation between the two factors, and so do not expect the qualitative findings of this study to be affected by this simplifying assumption.

2.1.3.1 Estimation of return periods

Extra care must be taken when reporting and interpreting return periods that depend on more than one covariate. Typically, WWA reports estimated return periods for the event of interest under current climatic conditions: that is, with the GMST fixed at the 2024 level. In this study, there are two covariates to consider: the GMST and ENSO. By fixing both the ENSO and the GMST at their 2024 levels, we can estimate the return period of the 2024 event in the current climate and in the current ENSO state. Mathematically, this return period is written as

$$1 / P(X > x_{2024} | T = t_{2024}, D = d_{2024}),$$

where x_{2024} is the 2024 value of observed precipitation; t_{2024} denotes the 2024 GMST; and d_{2024} denotes the 2024 ENSO (given by the relative December-February mean). Altogether, the expression in brackets gives the probability that X will exceed x_{2024} , given that $T = t_{2024}$ and $D = d_{2024}$; inverting this probability gives us an expected return period, in years. It is crucial to note that this return period tells us the probability of experiencing a similar event under current ENSO conditions and current warming levels.

2.1.3.2 Defining the ENSO state in climate models

The multi-method multi-model attribution step of the WWA protocol involves estimating, for each climate model, the effective return level of a 1-in- n -year event under the current climate state, and estimating the expected change in likelihood and intensity of such an event after a specified change in the covariates. Because the smoothed GMST is generally monotonically increasing, the standard WWA approach is simply to take the model's 2024 GMST as a covariate and to estimate the expected magnitude of an n -year event. However, the factual climate in this study is defined by the 2024 GMST and by the mean of the detrended Niño3.4 index preceding the rainy season. During the attribution step, the detrended Niño3.4 index derived from the climate model is standardised so that the subset from 1979-2024 has mean 0 and variance 1; the 'factual' climate is then defined as having the model's 2024 GMST and the 2024 observed value of the detrended Niño3.4 index, standardised in the same way. This removes any potential biases in the results due to differences between the amplitude of the modelled Niño3.4 index and that observed.

2.2 Observational analysis: return period and trend

2.2.1 Analysis of point station data and gridded data

The statistical model described in the previous section is fit to the time series of each extreme index from each observational dataset. This enables estimation of the return periods in the present day for an

event of the magnitude observed during the passage of Typhoon Gaemi (table 2.1). There is very strong variation between regions in how extreme the rainfall was. In the Northern Philippines, 3-day precipitation totals of 128-206 mm (depending on dataset) have return periods of between 5-30 years, with more datasets towards the lower end. This analysis is supplemented by the ‘science garden’ observed time series, which is located in Quezon City (Metro Manila) and which received 604 mm over the three days of interest. Despite the difference in spatial scales between a single station and the wide area studied, this was also a 1 in ~30 year event. As a result, the 20 year event, at the upper end of the range of observational estimates, is studied in this analysis.

In Taiwan, there is variation of more than a factor of 2.5 in the observed magnitudes of the event, between 146 - 384 mm over two days, which also leads to a variation in the return periods between 1.5-20 years. The 5 year event was selected for study to balance these estimates.

In Hunan, this event was extremely rare in three of the four datasets, with return periods of 94-157 years. As a result, the return period studied is 1 in 100 years. This reflects the fact that Hunan does not usually experience rainfall from TCs. Given that the final dataset, CHIRPS, gave a much lower return period, the 100 year event was also selected as it also fell at the lower end of the range of other estimates.

Dataset	Northern Philippines 3-day precipitation		Taiwan 2-day precipitation		Hunan 2-day precipitation	
	Magnitude (mm)	Return period (95% C.I.)	Magnitude (mm)	Return period (95% C.I.)	Magnitude (mm)	Return period (95% C.I.)
CPC	205.57	14.39 (4.4 - inf)	146.08	1.45 (1.14 - 2.85)	138.99	157.39 (31.6 - inf)
MSWEP	192.66	29.15 (6.1 - 3294.6)	345.53	7.27 (4.04 - 97.5)	95.07	125.35 (6.2 - inf)
Science garden time series	604	28.36 (8.53 - inf)				
ERA5	140.95	4.91 (2.20 - 18.37)	383.73	18.40 (6.58 - 297.5)	101.60	94.05 (18.58 - inf)
CHIRPS	128.78	7.93 (2.79 - inf)	148.95	1.71 (1.25 - 2.76)	84.55	6.70 (2.23 - 93.52)
Return periods		20		5		100

Table 2.1: Estimated return periods for each rainfall event considered in the path of Typhoon Gaemi in observational and reanalysis datasets.

Next, the influence of GMST on the observed event was tested by evaluating the likelihood and magnitude of the observed event at covariate values of present and preindustrial warming, given by 0 and -1.2 C (tables 2.2 & 2.3). In the Northern Philippines region, the effect of the preceding (December-February) El Niño is also tested versus a neutral phase (table 2.2). In this region, the effect of GMST is unclear in observations. While CPC gives a statistically significant increase, suggesting that the event could not have occurred without global warming, ERA5 and the science garden time series (not included in the final synthesis) give modest increases from 15-120% in likelihood, and MSWEP and CHIRPS give decreases. However, the CHIRPS estimate of probability ratio varies between 0-infinity, giving essentially no useful information, and is therefore neglected from further analysis. Furthermore, all datasets give a similar effect of El Niño, suggesting that it approximately halved the likelihood of such an event in this part of the Philippines.

Dataset	Northern Philippines 3-day precipitation			
	GMST		Niño 3.4 rel (DJF)	
	Probability Ratio	Change in magnitude (%)	Probability Ratio	Change in magnitude (%)
CPC	Inf (2.5 - inf)	87.02 (20.87 - 173.49)	0.45 (0.008 - 0.97)	-7.82 (-20.88 - -0.22)
MSWEP	0.17 (0.001 - 4.96)	-27.65 (-61.32 - 19.22)	0.54 (0.08 - 1.24)	-9.24 (-22.56 - 2.57)
Science Garden Station time series	2.19 (0.32 - 10 ¹³)	19.99 (-28.98 - 87.27)	0.72 (0.018 - 1.20)	-7.74 (-19.03 - 7.19)
ERA5	1.15 (0.23 - 5.50)	2.44 (-17.66 - 31.52)	0.72 (0.42 - 1.02)	-6.07 (-11.75 - 0.31)
CHIRPS	0.42 (0 - inf)	-14.81 (-43.58 - 25.10)	0.58 (0 - 0.96)	-9.30 (-17.93 - -0.67)

Table 2.2: Change in probability ratio and magnitude for the Typhoon Gaemi rainfall in Northern Philippines in June-September due to GMST and El Niño. Light blue (orange) indicates a wetting (drying) trend that crosses no change, while dark blue (orange) indicates a statistically significant wetting (drying) trend.

The results for Taiwan and Hunan are also mixed, though in both cases the majority of datasets (3/4) give increasing trends in both magnitude and likelihood. In Taiwan, estimates range from 60-1300% increase in likelihood and 10-54% increase in intensity, though CHIRPS suggests a decrease of ~30% in both likelihood and intensity. In Hunan, CPC gives a statistically significant increase in . Interestingly, ERA5 and CHIRPS give very similar probability ratios of 24-35, though the change in intensity varies from 13-49%. Meanwhile, MSWEP suggests a decrease in likelihood by a factor of 5,

though the uncertainty bounds on this estimate also vary from 0-infinity, and it is removed going forwards.

Dataset	Taiwan 2-day precipitation		Hunan 2-day precipitation	
	Probability Ratio	Change in magnitude (%)	Probability Ratio	Change in magnitude (%)
CPC	2.2 (0.65 - 16.29)	53.78 (-17.51 - 145.75)	24.44 (1.60 - inf)	48.71 (7.77 - 210.91)
MSWEP	1.61 (0.042 - 11.26)	9.65 (-45.10 - 45.12)	0.21 (0 - inf)	-17.02 (-48.85 - 125.64)
ERA5	13.79 (0.77 - inf)	33.35 (-2.33 - 79.91)	24.47 (0.13 - inf)	12.72 (-5.61 - 37.04)
CHIRPS	0.69 (0.39 - 1.29)	-26.40 (-56.33 - 17.54)	35.19 (0.16 - inf)	27.12 (-14.66 - 81.50)

Table 2.3: Change in probability ratio and magnitude for the Typhoon Gaemi rainfall in Taiwan and Hunan due to GMST. Light blue (orange) indicates a wetting (drying) trend that crosses no change, while dark blue (orange) indicates a statistically significant wetting (drying) trend.

2.3 Model evaluation

In this section we show the results of the model evaluation for the assessed region (individual figures shown in appendix A.1). The climate models are evaluated against the observations in their ability to capture:

1. Seasonal cycles: For this, we qualitatively compare the seasonal cycles based on model outputs against observations-based cycles. We discard the models that exhibit ill-defined peaks in their seasonal cycles. We also discard the model if the rainy season onset/termination varies significantly from the observations.
2. Spatial patterns: Models that do not match the observations in terms of the large-scale precipitation patterns are excluded.
3. Parameters of the fitted statistical models. We discard the model if the model and observation parameters ranges do not overlap.

The models are labelled as ‘good’, ‘reasonable’, or ‘bad’ based on their performances in terms of the three criteria discussed above. A model is given an overall rating of ‘good’ if it is rated ‘good’ for all three characteristics. If there is at least one ‘reasonable’, then its overall rating will be ‘reasonable’ and ‘bad’ if there is at least one ‘bad’.

Per framing or model setup we also use models that only just pass the validation tests if we only have five models or less for that framing that perform well. The FLOR and AM2 models are single model ensembles. We therefore undertake evaluation on each run individually, removing those that perform badly and ranking the overall model as reasonable or good depending on the majority of those remaining. The tables show the model validation results.

2.3.1 Northern Philippines

For the Northern Philippines region, out of the 27 model runs from the three modelling experiments (CORDEX, FLOR and AM2) used in the model-based evaluation and attribution, only four were evaluated ‘good’. From CORDEX, 3 models were ‘good’, 3 were ‘reasonable’, and the other 8 were ‘bad’. The runs in the FLOR model were mostly ‘reasonable’, with 1 ‘bad’ and 1 ‘good’. All AM2 runs were ‘bad’. We therefore use the 6 reasonable and good models from CORDEX and the 9 out of 10 runs from FLOR for the attribution analysis, which is rated overall as ‘reasonable’.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	ENSO correlation	Conclusion
CPC			0.293 (0.201 ... 0.338)	-0.35 (-0.58 ... -0.072)	
MSWEP			0.306 (0.216 ... 0.356)	-0.23 (-0.49 ... 0.065)	
ERA5			0.271 (0.222 ... 0.309)	-0.21 (-0.42 ... 0.017)	

CORDEX					
EAS-22_HadGEM2-E S_RegCM4-4 (1)	good	good	0.195 (0.121 ... 0.236)	0.16 (-0.047 ... 0.37)	reasonable
EAS-22_HadGEM2-E S_REMO2015 (1)	bad	reasonable	0.191 (0.138 ... 0.221)	-0.033 (-0.23 ... 0.18)	bad
EAS-22_MPI-ESM-LR _REMO2015 (1)	good	good	0.262 (0.155 ... 0.329)	0.45 (0.25 ... 0.64)	bad
EAS-22_MPI-ESM-M R_RegCM4-4 (1)	good	good	0.258 (0.180 ... 0.300)	0.50 (0.22 ... 0.69)	bad
EAS-22_NorESM1-M _RegCM4-4 (1)	good	good	0.257 (0.183 ... 0.301)	0.045 (-0.13 ... 0.24)	good
EAS-22_NorESM1-M _REMO2015 (1)	good	good	0.250 (0.174 ... 0.304)	-0.043 (-0.27 ... 0.19)	good
SEA-22_CNRM-CM5_ RCA4 (1)	reasonable	reasonable	0.433 (0.322 ... 0.514)	0.11 (-0.074 ... 0.28)	reasonable
SEA-22_HadGEM2-E S_RCA4 (1)	reasonable	bad	0.242 (0.180 ... 0.292)	0.11 (-0.081 ... 0.30)	bad
SEA-22_HadGEM2-E S_RegCM4-7 (1)	bad	bad	0.249 (0.159 ... 0.301)	0.10 (-0.10 ... 0.29)	bad
SEA-22_HadGEM2-E S_REMO2015 (1)	bad	bad	0.176 (0.124 ... 0.225)	0.068 (-0.15 ... 0.27)	bad
SEA-22_MPI-ESM-LR _REMO2015 (1)	reasonable	reasonable	0.313 (0.221 ... 0.359)	0.29 (0.097 ... 0.47)	bad
SEA-22_MPI-ESM-M R_RegCM4-7 (1)	reasonable	bad	0.320 (0.231 ... 0.369)	0.18 (0.0094 ... 0.36)	bad
SEA-22_NorESM1-M _RegCM4-7 (1)	good	reasonable	0.281 (0.199 ... 0.325)	-0.012 (-0.22 ... 0.16)	good
SEA-22_NorESM1-M _REMO2015 ()	reasonable	reasonable	0.279 (0.167 ... 0.329)	0.21 (-0.0079 ... 0.43)	reasonable
FLOR ensemble (10)					reasonable
pr3day_1 ()	good	good	0.190 (0.133 ... 0.227)	0.11 (-0.0065 ... 0.22)	reasonable
pr3day_10 ()	good	good	0.234 (0.153 ... 0.286)	0.064 (-0.060 ... 0.18)	good
pr3day_2 ()	good	good	0.207 (0.151 ... 0.245)	0.16 (0.050 ... 0.28)	reasonable
pr3day_3 ()	good	good	0.222 (0.156 ... 0.263)	0.093 (-0.031 ... 0.20)	reasonable
pr3day_4 ()	good	good	0.191 (0.117 ... 0.228)	0.067 (-0.031 ... 0.17)	reasonable
pr3day_5 ()	good	good	0.167 (0.124 ... 0.194)	0.10 (-0.023 ... 0.20)	bad
pr3day_6 ()	good	good	0.171 (0.117 ... 0.217)	0.18 (0.063 ... 0.30)	reasonable
pr3day_7 ()	good	good	0.188 (0.107 ... 0.235)	0.043 (-0.081 ... 0.16)	reasonable
pr3day_8 ()	good	good	0.206 (0.138 ... 0.250)	0.092 (-0.038 ... 0.22)	reasonable
pr3day_9 ()	good	good	0.175 (0.117 ... 0.235)	0.15 (0.023 ... 0.28)	reasonable

			0.213)	0.28)	
AM2 ensemble (3)					bad
pr3day_6 ()	bad	reasonable	0.199 (0.147 ... 0.242)	-0.048 (-0.16 ... 0.073)	bad
pr3day_7 ()	bad	reasonable	0.160 (0.0934 ... 0.195)	-0.10 (-0.23 ... 0.016)	bad
pr3day_8 ()	bad	reasonable	0.234 (0.173 ... 0.269)	-0.12 (-0.24 ... 0.0031)	bad

Table 2.4: Evaluation of the climate models considered for attribution of rainfall over the Northern Philippines region. For each model, the best estimate of the dispersion parameter is shown, along with the correlation between the ENSO index and the extreme precipitation index, and a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

2.3.2 Taiwan

For Taiwan, out of the 27 model runs from the three modelling experiments (CORDEX, FLOR and AM2) used in the model-based evaluation and attribution, only 5 were evaluated ‘bad’, all from CORDEX-SEA. However, 5 models were ‘good’ and 4 were ‘reasonable’. Of the runs in the FLOR model, 6 were ‘good’ and the other 4 were ‘reasonable’. All AM2 runs were ‘reasonable’. We therefore use the 9 reasonable and good models from CORDEX and all runs from FLOR and AM2 for the attribution analysis, rating FLOR and AM2 as ‘good’ and ‘reasonable’, respectively.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Shape	Conclusion
CPC			0.375 (0.255 ... 0.455)	-0.045 (-0.28 ... 0.24)	
MSWEP			0.451 (0.348 ... 0.528)	-0.14 (-0.36 ... 0.058)	
ERA5			0.430 (0.353 ... 0.494)	-0.12 (-0.28 ... 0.027)	
CHIRPS			0.351 (0.265 ... 0.415)	-0.24 (-0.54 ... -0.030)	
CORDEX					
EAS-22_HadGEM2-E S_RegCM4-4 (1)	good	good	0.277 (0.213 ... 0.329)	-0.17 (-0.72 ... 0.056)	good
EAS-22_HadGEM2-E S_REMO2015 (1)	good	reasonable	0.331 (0.228 ... 0.404)	-0.0035 (-0.37 ... 0.26)	reasonable
EAS-22_MPI-ESM-L R_REMO2015 (1)	good	good	0.314 (0.229 ... 0.378)	0.14 (-0.17 ... 0.45)	good
EAS-22_MPI-ESM-M R_RegCM4-4 (1)	good	good	0.355 (0.222 ... 0.439)	0.23 (-0.027 ... 0.63)	good
EAS-22_NorESM1-M _RegCM4-4 (1)	good	good	0.427 (0.294 ... 0.504)	0.22 (0.034 ... 0.58)	good
EAS-22_NorESM1-M _REMO2015 (1)	good	good	0.371 (0.281 ... 0.436)	-0.084 (-0.37 ... 0.10)	good

SEA-22_CNRM-CM5_RCA4 (1)	reasonable	reasonable	0.302 (0.229 ... 0.364)	-0.28 (-0.57 ... -0.084)	reasonable
SEA-22_HadGEM2-ES_RCA4 (1)	reasonable	bad	0.299 (0.233 ... 0.348)	0.024 (-0.55 ... 0.28)	bad
SEA-22_HadGEM2-ES_RegCM4-7 (1)	bad	bad	0.312 (0.238 ... 0.362)	0.17 (-0.12 ... 0.45)	bad
SEA-22_HadGEM2-ES_REMO2015 (1)	reasonable	bad	0.296 (0.214 ... 0.348)	0.13 (-0.32 ... 0.44)	bad
SEA-22_MPI-ESM-LR_REMO2015 (1)	good	reasonable	0.390 (0.287 ... 0.467)	-0.043 (-0.44 ... 0.11)	reasonable
SEA-22_MPI-ESM-MR_RegCM4-7 (1)	reasonable	bad	0.254 (0.172 ... 0.306)	0.16 (-0.10 ... 0.51)	bad
SEA-22_NorESM1-MR_RegCM4-7 (1)	bad	reasonable	0.350 (0.257 ... 0.404)	-0.069 (-0.35 ... 0.30)	bad
SEA-22_NorESM1-MR_REMO2015 (1)	reasonable	reasonable	0.320 (0.242 ... 0.375)	0.043 (-0.21 ... 0.31)	reasonable
FLOR ensemble (10)					good
pr2day_1 ()	reasonable	good	0.321 (0.247 ... 0.376)	-0.039 (-0.75 ... 0.16)	good
pr2day_10 ()	reasonable	good	0.277 (0.205 ... 0.322)	0.12 (-0.094 ... 0.41)	good
pr2day_2 ()	reasonable	good	0.210 (0.134 ... 0.261)	0.20 (-0.31 ... 0.84)	reasonable
pr2day_3 ()	reasonable	good	0.227 (0.138 ... 0.266)	0.23 (-0.17 ... 1.2)	reasonable
pr2day_4 ()	reasonable	good	0.306 (0.215 ... 0.363)	0.042 (-0.41 ... 0.45)	good
pr2day_5 ()	reasonable	good	0.292 (0.218 ... 0.345)	-0.023 (-0.32 ... 0.40)	good
pr2day_6 ()	reasonable	good	0.270 (0.194 ... 0.325)	0.21 (-0.036 ... 0.54)	good
pr2day_7 ()	reasonable	good	0.344 (0.247 ... 0.413)	-0.37 (-0.82 ... 0.24)	good
pr2day_8 ()	reasonable	good	0.287 (0.196 ... 0.353)	0.25 (0.0075 ... 0.59)	reasonable
pr2day_9 ()	reasonable	good	0.219 (0.159 ... 0.256)	0.20 (-0.082 ... 0.63)	reasonable
AM2 ensemble (3)					reasonable
pr2day_6 ()	reasonable	reasonable	0.418 (0.290 ... 0.504)	-0.075 (-0.27 ... 0.075)	reasonable
pr2day_7 ()	reasonable	reasonable	0.330 (0.249 ... 0.392)	-0.10 (-0.63 ... 0.11)	reasonable
pr2day_8 ()	reasonable	reasonable	0.373 (0.290 ... 0.437)	-0.058 (-0.31 ... 0.14)	reasonable

Table 2.5: Evaluation of the climate models considered for attribution of rainfall over Taiwan. For each model, the best estimate of the dispersion parameter is shown, along with the correlation between the ENSO index and the extreme precipitation index, and a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

2.3.3 Hunan

For Hunan, only CORDEX-EAS was available (the CORDEX-SEA domain ends further south). However, out of the 19 model runs from the three modelling experiments (CORDEX, FLOR and AM2) used in the model-based evaluation and attribution, only 3 were evaluated ‘bad’, all from the AM2 model (due to the statistical properties). From CORDEX, 3 models were ‘good’ and 3 were ‘reasonable’. The runs in the FLOR model were all ‘good’ and therefore the overall model is rated ‘good’. We therefore use the 6 reasonable and good models from CORDEX and all 10 runs from the FLOR model for the attribution analysis.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Shape	Conclusion
CPC			0.217 (0.168 ... 0.274)	0.073 (-0.48 ... 0.38)	
ERA5			0.213 (0.138 ... 0.255)	-0.20 (-0.35 ... 0.0031)	
CHIRPS			0.199 (0.143 ... 0.235)	-0.20 (-0.61 ... 0.12)	
CORDEX					
EAS-22_HadGEM2-ES_RegCM4-4 (1)	good	good	0.212 (0.164 ... 0.243)	0.0060 (-0.19 ... 0.27)	good
EAS-22_HadGEM2-ES_REMO2015 (1)	good	reasonable	0.295 (0.207 ... 0.351)	0.011 (-0.18 ... 0.24)	reasonable
EAS-22_MPI-ESM-LR_REMO2015 (1)	good	good	0.269 (0.187 ... 0.319)	0.16 (-0.23 ... 0.58)	good
EAS-22_MPI-ESM-MR_RegCM4-4 (1)	good	good	0.261 (0.188 ... 0.296)	0.047 (-0.29 ... 0.64)	good
EAS-22_NorESM1-M_RegCM4-4 (1)	good	good	0.321 (0.260 ... 0.371)	-0.27 (-0.71 ... -0.056)	reasonable
EAS-22_NorESM1-M_REMO2015 (1)	good	good	0.303 (0.232 ... 0.354)	-0.16 (-0.47 ... 0.10)	reasonable
FLOR ensemble (10)					good
pr2day_1 ()	good	good	0.213 (0.150 ... 0.255)	-0.11 (-0.36 ... 0.25)	good
pr2day_10 ()	good	good	0.182 (0.136 ... 0.215)	-0.14 (-0.34 ... 0.047)	good
pr2day_2 ()	good	good	0.238 (0.163 ... 0.287)	-0.024 (-0.23 ... 0.25)	good
pr2day_3 ()	good	good	0.205 (0.156 ... 0.240)	0.066 (-0.38 ... 0.29)	good
pr2day_4 ()	good	good	0.161 (0.115 ... 0.197)	0.27 (-0.090 ... 0.69)	good
pr2day_5 ()	good	good	0.190 (0.141 ... 0.223)	-0.072 (-0.36 ... 0.24)	good
pr2day_6 ()	good	good	0.230 (0.163 ... 0.274)	0.0091 (-0.26 ... 0.34)	good
pr2day_7 ()	good	good	0.207 (0.129 ... 0.259)	-0.011 (-0.25 ... 0.38)	good

pr2day_8 ()	good	good	0.221 (0.162 ... 0.257)	0.084 (-0.23 ... 0.38)	good
pr2day_9 ()	good	good	0.154 (0.113 ... 0.185)	-0.038 (-0.43 ... 0.28)	good
AM2 ensemble (3)					bad
pr2day_6 ()	reasonable	reasonable	0.463 (0.359 ... 0.517)	0.084 (-0.30 ... 0.37)	bad
pr2day_7 ()	reasonable	reasonable	0.425 (0.341 ... 0.488)	-0.25 (-0.53 ... 0.055)	bad
pr2day_8 ()	reasonable	reasonable	0.418 (0.330 ... 0.470)	-0.18 (-0.55 ... 0.093)	bad

Table 2.6: Evaluation of the climate models considered for attribution of rainfall over Hunan. For each model, the best estimate of the dispersion parameter is shown, along with the correlation between the ENSO index and the extreme precipitation index, and a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

2.4 Multi-method multi-model attribution and synthesis

This section shows Probability Ratios and change in intensity ΔI for models that passed model evaluation and also includes the values calculated from the fits with observations. Then, for the event definitions described above, we evaluate the overall influence of anthropogenic climate change on the events by calculating the probability ratio as well as the change in intensity using observations and climate models. Models which do not pass the evaluation described above are excluded from the analysis. The aim is to synthesise results from models that pass the evaluation along with the observations-based products, to give an overarching attribution statement.

Figures 2.1-2.4 show the changes in probability and intensity for the observations (blue) and models (red). Before combining them into a synthesised assessment, first, a representation error is added (in quadrature) to the observations, to account for the difference between observations-based datasets that cannot be explained by natural variability. This is shown in these figures as white boxes around the light blue bars. The dark blue bar shows the average over the observation-based products. Next, a term to account for intermodel spread is added (in quadrature) to the natural variability of the models. This is shown in the figures as white boxes around the light red bars. The dark red bar shows the model average, consisting of a weighted mean using the (uncorrelated) uncertainties due to natural variability plus the term representing intermodel spread (i.e., the inverse square of the white bars).

Observation-based products and models are combined into a single result in two ways. Firstly, we neglect common model uncertainties beyond the intermodel spread that is depicted by the model average, and compute the weighted average of models (dark red bar) and observations (dark blue bar): this is indicated by the magenta bar. As, due to common model uncertainties, model uncertainty can be larger than the intermodel spread, secondly, we also show the more conservative estimate of an unweighted, direct average of observations (dark red bar) and models (dark blue bar) contributing 50% each, indicated by the white box around the magenta bar in the synthesis figures.

The multiple runs of the FLOR and AM2 models are synthesised into a single attribution statement and then combined with other results. The number in brackets by each model shows the number of runs used in the first synthesis. The final synthesised results are also tabulated in section 6 alongside the other hazard sections for ease of comparison.

2.4.1 Northern Philippines

There is a consensus between observations and models that the influence of GMST at present compared to preindustrial is negligible in rainfall events such as those influenced by Typhoon Gaemi in the Philippines (figure 2.1a & 2.1b). Overall, observations give a slight increase while models give a slight decrease, but none of the results are statistically significant and the synthesised results are close to no change. Notably, in the future at 2 degrees of global warming, the models project a statistically significant increase in likelihood of 40% (10 - 74%), and a (non-significant) increase in intensity of 5% (-3 - 14%), suggesting that the climate change signal is yet to emerge (figure 2.1c & 2.1d; section 6, table 6.1). This may be an underestimate given that models do not give the same increase as observations at present.

Models and observations show strong disagreement over the influence of ENSO on the extreme rainfall event (figure 2.2). While observations give a consensus on an approximate halving in likelihood and decrease in intensity by ~7%, models suggest that ENSO had almost no influence on the event. As a result, the unweighted uncertainty bounds (white bars) are quoted in order to reflect this disagreement (table 6.1).

Model / Observations	Threshold for return period 20 yr	Current warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [%]	Future warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [%]
CPC	205.57 mm	1.2	5.5 (2.5 ... 59)	87 (21 ... 1.7e+2)			
MSWEP	192.66 mm	1.2	0.17 (0.0014 ... 5.0)	-28 (-61 ... 19)			
ERA5	140.95 mm	1.2	1.1 (0.23 ... 5.5)	2.4 (-18 ... 32)			
EAS-22_HadG EM2-ES_RegC M4-4 (1)	2.4e+2 mm	1.2	0.69 (0.34 ... 1.6)	-8.7 (-22 ... 14)	2.0	1.0 (0.79 ... 1.3)	-0.066 (-5.2 ... 5.0)
EAS-22_NorE SM1-M_RegC M4-4 (1)	1.5e+2 mm	1.2	0.57 (0.18 ... 2.1)	-11 (-32 ... 13)	2.0	2.1 (1.1 ... 4.7)	14 (3.5 ... 23)
EAS-22_NorE SM1-M_REMO 2015 (1)	3.0e+2 mm	1.2	0.49 (0.12 ... 3.7)	-14 (-33 ... 15)	2.0	1.1 (0.69 ... 1.9)	1.8 (-6.4 ... 9.1)
SEA-22_CNR M-CM5_RCA4 (1)	3.0e+2 mm	1.2	0.64 (0.16 ... 5.0)	-8.9 (-36 ... 30)	2.0	0.95 (0.36 ... 1.6)	-1.2 (-17 ... 11)
SEA-22_NorE SM1-M_RegC M4-7 (1)	2.1e+2 mm	1.2	0.67 (0.15 ... 9.8)	-8.1 (-35 ... 28)	2.0	2.0 (1.2 ... 4.6)	15 (3.9 ... 25)
SEA-22_NorE SM1-M_REMO 2015 (1)	4.0e+2 mm	1.2	0.53 (0.12 ... 2.4)	-11 (-35 ... 15)	2.0	1.3 (0.67 ... 2.3)	3.5 (-6.0 ... 11)
FLOR ensemble (9)		1.2	1.3 (0.80 ... 2.1)	4.8 (-2.9 ... 13)	2.0	1.2 (0.98 ... 1.6)	4.7 (2.0 ... 7.4)

Table 2.7: Event magnitude, probability ratio and relative change in intensity for a 20-year 3-day JJAS maximum rainfall event over the Northern Philippines for observational datasets and each model that passed evaluation: (a) from the pre-industrial climate to the present and (b) from the present to 2°C above pre-industrial. Where data is not applicable (e.g. observations of the future), cells have been shaded grey.

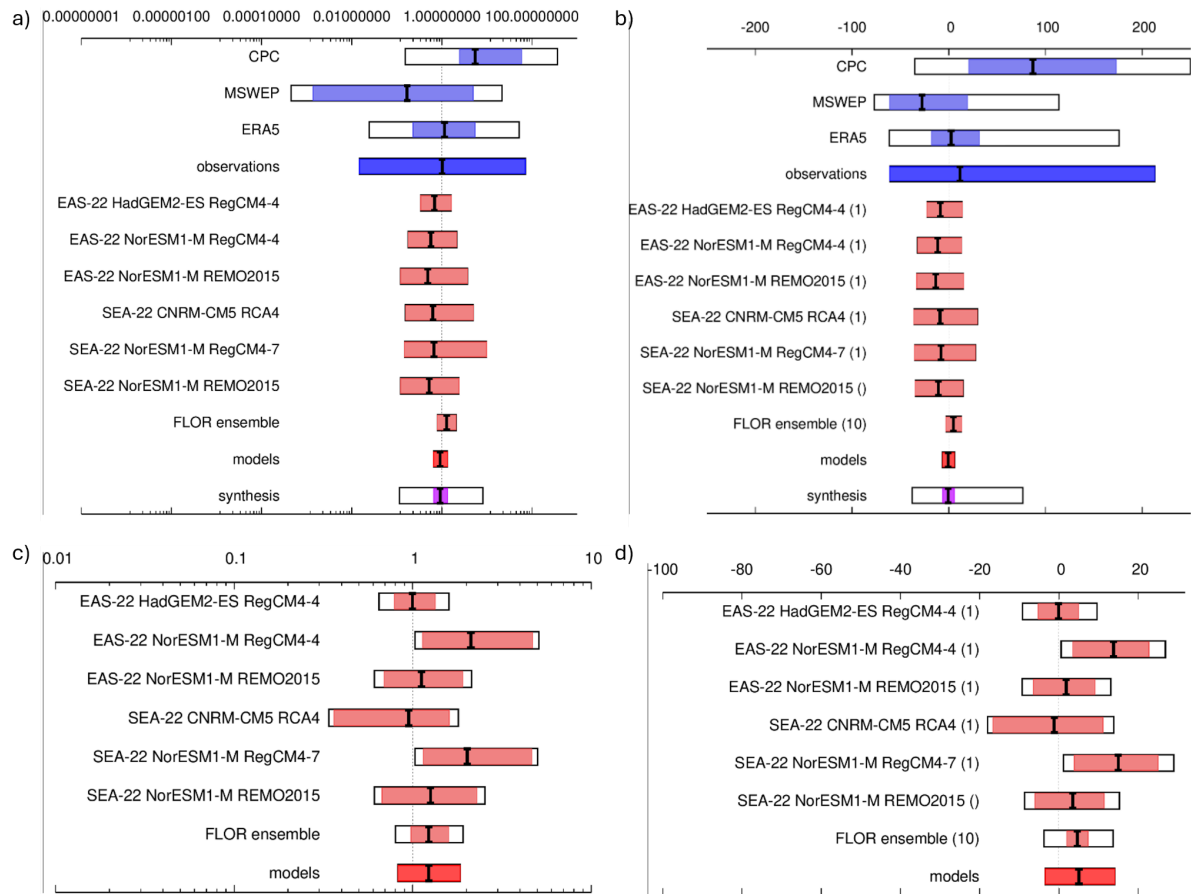


Figure 2.1: Synthesised changes for a 20-year 3-day JJAS maximum rainfall event over the Northern Philippines domain due to GMST. Changes in PR (left) and intensity (right) are shown for a historical period comparing the past 1.2°C cooler climate with the present (top row) and for a future period, based on model projections only, comparing the present and a 2°C warmed climate (bottom row).

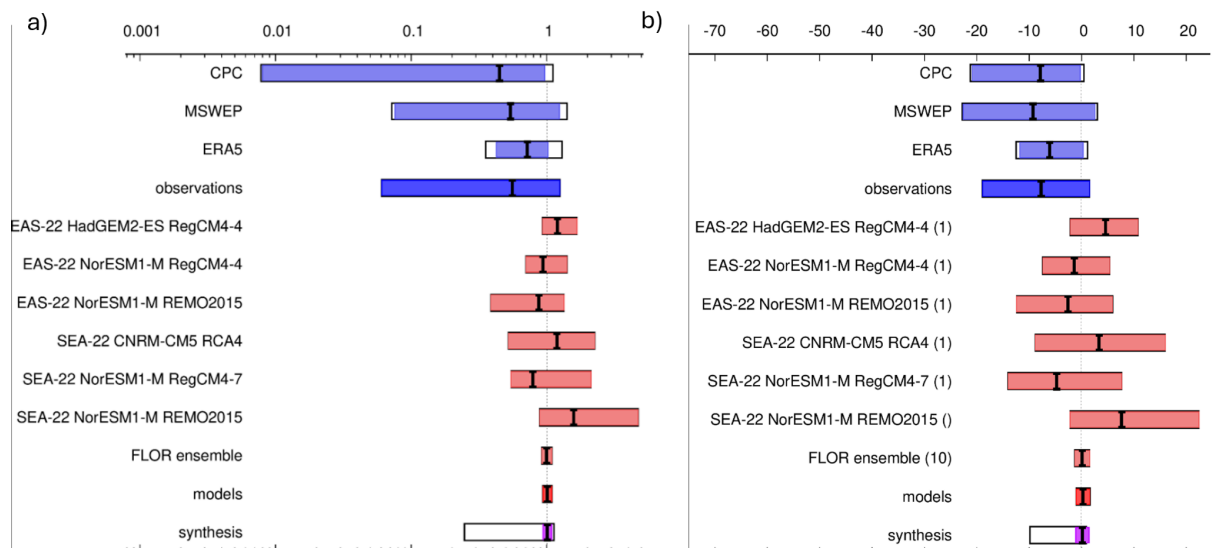


Figure 2.2: Synthesised changes for a 20-year 3-day JJAS maximum rainfall event over the Northern Philippines domain due to ENSO. Changes in PR (left) and intensity (right) are shown comparing the current (at the time of occurrence) phase of ENSO with a neutral phase.

2.4.2 Taiwan

There is a consistent signal across most datasets for the Taiwan rainfall, both in present and future, that GMST is driving increases in the likelihood and intensity of extreme 2-day rainfall in June-September. Though none of the changes are statistically significant, both agreement across models and observations and the underlying physical reasoning based on thermodynamics indicate high confidence in the sign of change for both likelihood and intensity.

Model / Observations	Threshold for return period 10 yr	Current warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [mm]	Future warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [%]
CPC	146.08 mm	1.2	2.7 (0.65 ... 16)	54 (-18 ... 1.5e+2)			
MSWEP	345.53 mm	1.2	1.6 (0.042 ... 11)	9.7 (-45 ... 45)			
ERA5	383.73 mm	1.2	14 (0.77 ... 7.9e+4)	33 (-2.3 ... 80)			
CHIRPS	148.95 mm	1.2	0.69 (0.39 ... 1.3)	-26 (-56 ... 18)			
EAS-22_Had GEM2-ES_Re gCM4-4 (1)	2.0e+2 mm	1.2	0.88 (0.32 ... 2.4)	-2.7 (-26 ... 22)	2.0	1.1 (0.78 ... 1.5)	2.8 (-6.6 ... 10)
EAS-22_Had GEM2-ES_RE MO2015 (1)	3.5e+2 mm	1.2	6.2 (2.2 ... 1.0e+2)	43 (18 ... 76)	2.0	1.5 (1.2 ... 2.0)	12 (4.6 ... 18)
EAS-22_MPI- ESM-MR_Reg CM4-4 (1)	1.8e+2 mm	1.2	0.44 (0.23 ... 1.5)	-27 (-52 ... 13)	2.0	0.93 (0.65 ... 1.4)	-2.5 (-16 ... 9.5)
EAS-22_NorE SM1-M_RegC M4-4 (1)	1.9e+2 mm	1.2	1.8 (0.45 ... 10)	22 (-27 ... 74)	2.0	1.8 (1.3 ... 2.4)	20 (8.4 ... 30)
EAS-22_NorE SM1-M_REM O2015 (1)	2.2e+2 mm	1.2	0.70 (0.30 ... 3.9)	-9.2 (-37 ... 24)	2.0	1.4 (0.98 ... 2.0)	8.4 (-0.34 ... 17)
SEA-22_CNR M-CM5_RCA 4 (1)	4.7e+2 mm	1.2	3.2 (0.92 ... 96)	17 (-1.3 ... 42)	2.0	1.1 (0.78 ... 1.6)	2.3 (-5.5 ... 10)
SEA-22_MPI- ESM-LR_RE MO2015 (1)	4.4e+2 mm	1.2	1.9 (0.70 ... 30)	16 (-9.3 ... 57)	2.0	1.3 (0.84 ... 2.0)	7.0 (-4.4 ... 16)
SEA-22_NorE SM1-M_REM O2015 (1)	4.1e+2 mm	1.2	1.6 (0.49 ... 7.4)	13 (-19 ... 51)	2.0	0.97 (0.50 ... 1.5)	-0.75 (-14 ... 9.1)
FLOR ensemble (10)		1.2	1.5 (1.3 ... 1.8)	10 (5.8 ... 15)	2.0	1.2 (1.1 ... 1.6)	5.8 (4.0 ... 7.5)
AM2 ensemble (3)		1.2	4.1 (2.1 ... 14)	32 (15 ... 50)	2.0	1.7 (1.4 ... 9.8)	15 (9.4 ... 19)

Table 2.8: Event magnitude, probability ratio and relative change in intensity for a 5-year 2-day JJAS maximum rainfall event over Taiwan for observational datasets and each model that passed evaluation: (a) from the pre-industrial climate to the present and (b) from the present to 2°C above

pre-industrial. Where data is not applicable (e.g. observations of the future), cells have been shaded grey.

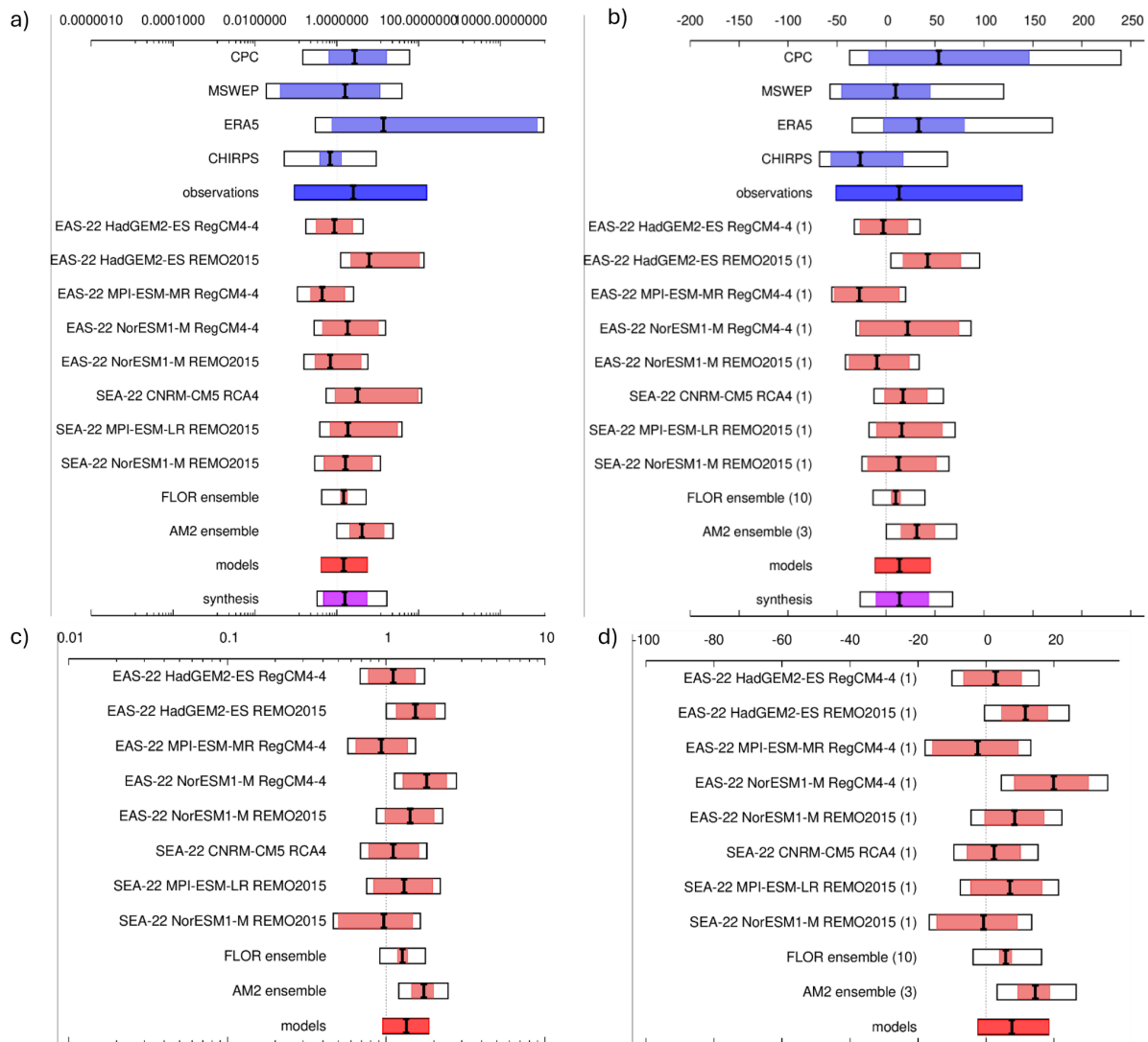


Figure 2.3: Synthesised changes for a 5-year 2-day JJAS maximum rainfall event over Taiwan. Changes in PR (left) and intensity (right) are shown for a historical period comparing the past 1.2°C cooler climate with the present (top row) and for a future period, based on model projections only, comparing the present and a 2°C warmed climate (bottom row).

2.4.3 Hunan

In Hunan, observational changes give an overall increasing trend in 2 day extreme rainfall in June-September. This statement is stronger than the models, which give a mixed signal for the role of warming at present. As a result, the synthesis statement is a slight increasing trend that crosses no change, though the unweighted uncertainty bounds suggest a potentially larger upper bound to the increase. In the future at 2 degrees of warming, the models project a stronger increase than at present,

suggesting that increases are very likely. In particular, this may be an underestimate given that they give a weaker signal than observations at present.

Model / Observations	Threshold for return period 10 yr	Current warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [mm]	Future warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [%]
CPC	138.99 mm	1.2	24 (1.6 ... 8.7e+4)	49 (7.8 ... 2.1e+2)			
ERA5	101.6 mm	1.2	24 (0.13 ... 1.6e+8)	13 (-5.6 ... 37)			
CHIRPS	84.55 mm	1.2	35 (0.16 ... 3.7e+8)	27 (-15 ... 38)			
EAS-22_Had GEM2-ES_Re gCM4-4 (1)	99 mm	1.2	3.3 (0.80 ... 1.9e+2)	13 (-1.7 ... 29)	2.0	1.6 (0.97 ... 3.0)	4.8 (-0.31 ... 9.5)
EAS-22_Had GEM2-ES_RE MO2015 (1)	1.4e+2 mm	1.2	1.1 (0.23 ... 2.4e+3)	1.1 (-20 ... 27)	2.0	1.7 (1.0 ... 3.6)	6.1 (0.27 ... 11)
EAS-22_MPI- ESM-LR_RE MO2015 (1)	1.3e+2 mm	1.2	0.60 (0.19 ... ∞)	-9.0 (-31 ... 32)	2.0	0.97 (0.58 ... 1.8)	-0.52 (-9.8 ... 8.2)
EAS-22_MPI- ESM-MR_Reg CM4-4 (1)	90 mm	1.2	0.29 (0.020 ... 2.3)	-17 (-40 ... 22)	2.0	1.1 (0.41 ... 2.3)	1.9 (-11 ... 13)
EAS-22_NorE SM1-M_RegC M4-4 (1)	1.1e+2 mm	1.2	6.6e+4 (1.7 ... ∞)	41 (3.3 ... 95)	2.0	4.7 (2.2 ... 17)	18 (7.0 ... 26)
EAS-22_NorE SM1-M_REM O2015 (1)	1.3e+2 mm	1.2	24 (0.19 ... ∞)	22 (-15 ... 67)	2.0	1.9 (0.66 ... 5.1)	6.0 (-3.8 ... 14)
FLOR ensemble (10)	mm	1.2	0.95 (0.22 ... 4.3)	1.4 (-8.9 ... 13)	2.0	1.1 (0.78 ... 1.7)	2.8 (1.3 ... 4.2)

Table 2.9: Event magnitude, probability ratio and relative change in intensity for a 150-year 2-day JJAS maximum rainfall event over Hunan for observational datasets and each model that passed evaluation: (a) from the pre-industrial climate to the present and (b) from the present to 2°C above pre-industrial. Where data is not applicable (e.g. observations of the future), cells have been shaded grey.

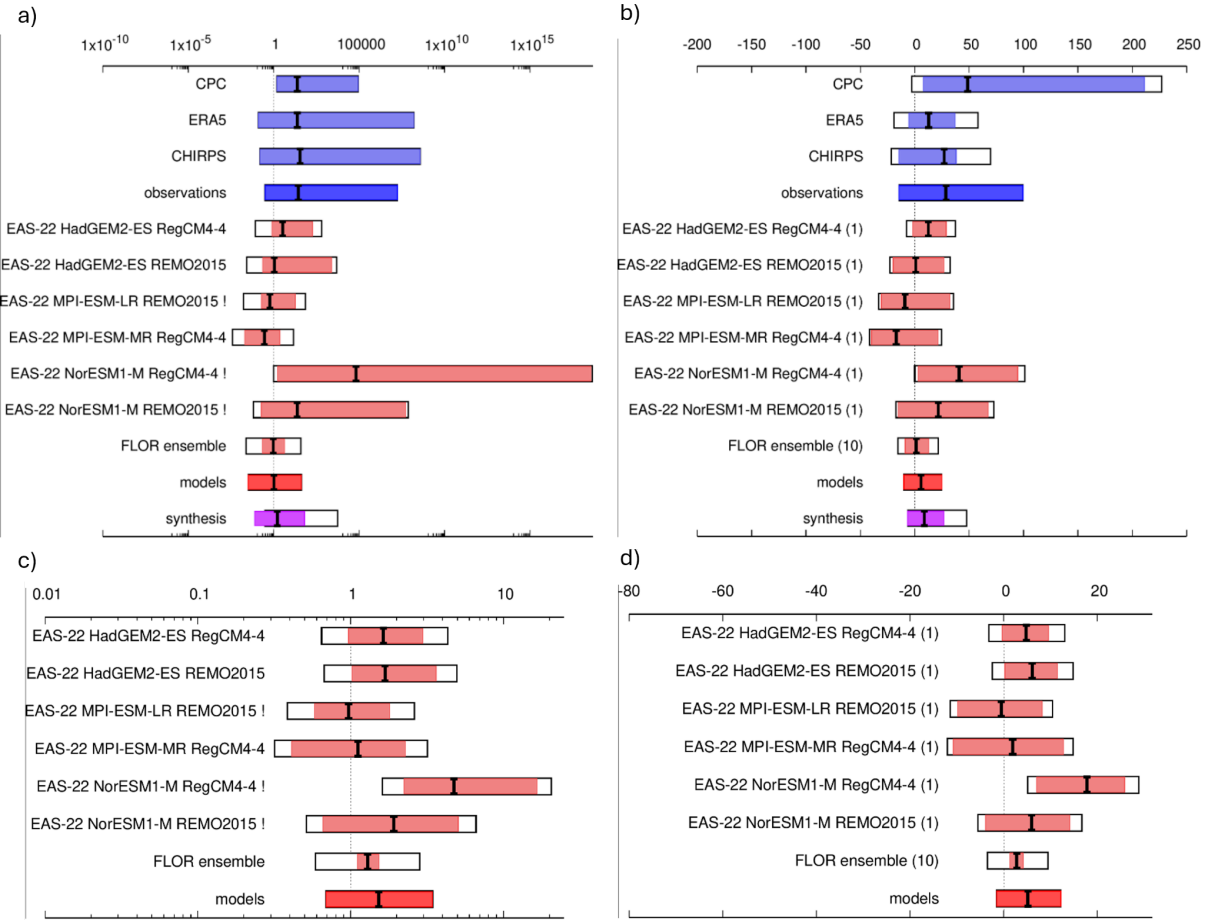


Figure 2.4: Synthesised changes for a 150-year 2-day JJAS maximum rainfall event over Hunan. Changes in PR (left) and intensity (right) are shown for a historical period comparing the past 1.2°C cooler climate with the present (top row) and for a future period, based on model projections only, comparing the present and a 2°C warmed climate (bottom row).

3 Environmental conditions attribution using WWA protocol

The event definitions studied in this section are as follows:

1. **Potential intensity (PI):** June-September maximum of monthly mean PI over an area bounded by 115 - 135 °E, 10 - 30 °N (figure 1.3)
2. **Sea Surface Temperatures (SSTs):** June-September maximum of monthly mean SSTs over an area bounded by 115 - 135 °E, 10 - 30 °N (figure 1.3)

3.1 Data and methods

3.1.1 Observational data

ERA5 ([Hersbach et al., 2020](#)) is used to analyse the anthropogenic influence upon the conditions leading to Typhoon Gaemi. We use sea surface temperatures, sea level pressure, and specific humidity and atmospheric temperatures at all available pressure levels from this product. The Potential Intensity is calculated from these variables using the open-source PyPI package ([Gilford, 2021](#)).

As in the previous section, as a measure of anthropogenic climate change we use the (low-pass filtered) global mean surface temperature (GMST), where GMST is taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GISTEMP, [Hansen et al., 2010](#) and [Lenssen et al. 2019](#)).

3.1.2 Model and experiment descriptions

To estimate the influence of anthropogenic climate change upon the potential intensity and sea surface temperatures in which Gaemi occurred, we use the CMIP6 multi-model ensemble. This consists of simulations from 12 participating models with varying resolutions. For more details on CMIP6, please see [Eyring et al., \(2016\)](#). For all simulations, the period 1850 to 2015 is based on historical simulations, while the SSP5-8.5 scenario is used for the remainder of the 21st century.

3.1.3 Statistical methods

The methods for attribution of the extreme indices detailed above are the same as set out in section 2.1.3 with a few minor changes. A nonstationary Gaussian distribution is used to model each of these indices. For PI and SSTs, the distribution is assumed to shift linearly with the covariate GMST, while the variance remains constant. In addition, the ENSO covariate is not considered in this analysis.

3.2 Observational analysis: return period and trend

3.2.1 Analysis of point station data and gridded data

The statistical model described in sections 2.1.3 and 3.1.3 is fit to the time series (figure 3.1) of each extreme index from the observational dataset ERA5. This enables estimation of the return periods in the present day for an event of the observed magnitude at the time of Typhoon Gaemi (table 3.1). The potential intensity in the region of Typhoon Gaemi is very common in the current climate with a

return period of 2.5 years. The SSTs were more extreme, with a monthly average of 30.23 °C occurring roughly once every 15 years. This suggests that the other factors affecting potential intensity, such as specific humidity and temperature gradient, were far less extreme in July 2024.

Dataset	Potential intensity		Sea Surface Temperatures	
	Magnitude (m/s)	Return period (95% C.I.)	Magnitude (°C)	Return period (95% C.I.)
ERA5	78.20	2.55 (1.59 - 5.35)	30.23	14.80 (5.41 - 184.08)

Table 3.1: Estimated return periods for environmental conditions around the path of Typhoon Gaemi in ERA5, region shown in figure 1.3.

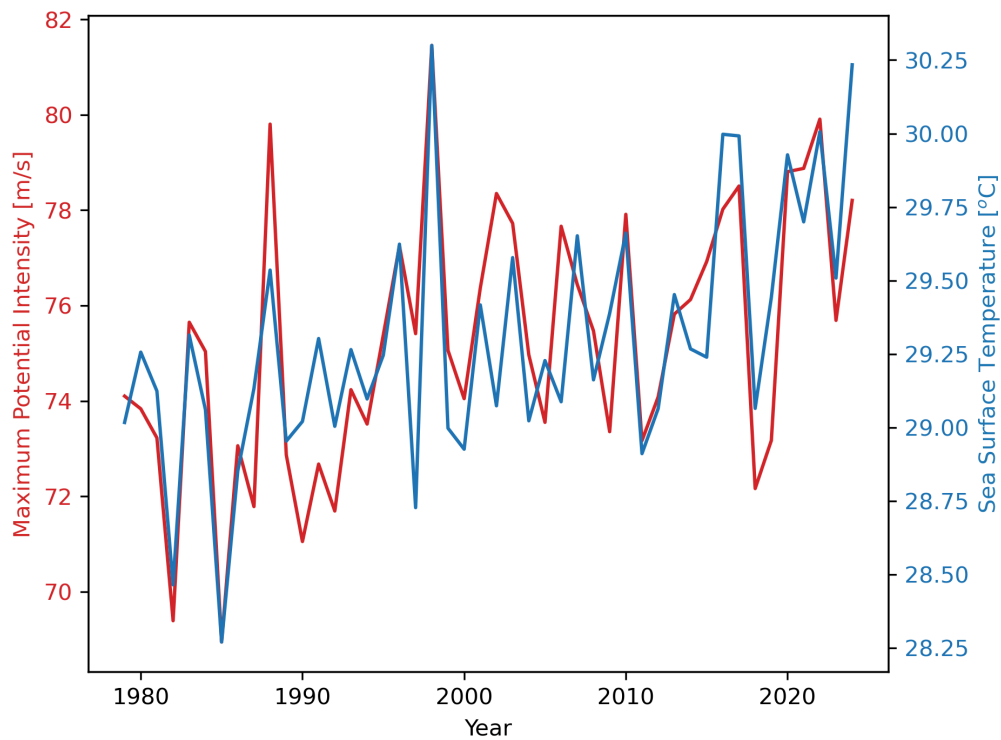


Figure 3.1: Time series of maximum monthly (June-September) potential intensity (red) and sea surface temperature (blue), averaged over an area around the track of Typhoon Gaemi. Data from ERA5.

Figure 3.1 shows the time series of both PI and SSTs in the region as a monthly maximum each June-September since 1979. There is a clear strong trend over time in both variables and the link between them is evident. However, the trend in SSTs is more linear and the 2024 event is one of the strongest on record, while PI exhibits more inter-decadal variability and has a less remarkable, albeit high, magnitude in 2024.

By varying the covariate GMST between its present and pre industrial levels, the probability ratio and change in magnitude of 2024-like events are estimated (table 3.2). As expected from figure 1.3, both

indices exhibit strong and statistically significant increasing trends with warming. The PI in July 2024 has become around 120 times more likely, suggesting that it was previously a 1 in 300 year event. Equivalently, the maximum wind velocity became roughly 6 m/s stronger. Meanwhile, the warm SST event has become tens of thousands of times more likely, meaning they would have been essentially impossible without global warming. This is equivalent to an increase of roughly 1 C over the month.

Dataset	Potential intensity		Sea Surface Temperatures	
	Probability Ratio	Change in magnitude (m/s)	Probability Ratio	Change in magnitude (C)
ERA5	120 (6.03 - 122000)	5.93 (2.52 - 9.11)	45800 (241 - $\sim 10^{10}$)	1.09 (0.61 - 1.53)

Table 3.2: Change in probability ratio and magnitude for the potential intensity and sea surface temperatures in July 2024 in a region around the track of Typhoon Gaemi, due to GMST. Dark blue indicates a statistically significant increasing trend.

3.3 Model evaluation

In the subsections below we show the results of the model evaluation for each location (individual figures shown in appendix A.1). The model evaluation steps are the same as set out in section 2.3. The tables show the model evaluation results.

3.3.1 Potential intensity

Of the 9 CMIP6 models analysed, 3 were rated ‘bad’ and discarded from the attribution analysis. Only 1 model performed well across all criteria, so all 6 remaining models were used.

Model / Observations	Seasonal cycle	Spatial pattern	Sigma	Conclusion
ERA5			2.42 (1.78 ... 2.88)	
CMIP6				
cmip6_CanESM5 (1)	good	reasonable	3.02 (2.35 ... 3.55)	reasonable
cmip6_CMCC-ESM2 (1)	reasonable	good	3.92 (3.00 ... 4.53)	bad
cmip6_EC-Earth3-CC (1)	reasonable	good	2.45 (1.95 ... 2.81)	reasonable
cmip6_EC-Earth3-Veg-LR (1)	reasonable	good	2.78 (2.25 ... 3.13)	reasonable
cmip6_MIROC6 (1)	reasonable	reasonable	3.92 (3.13 ... 4.53)	bad
cmip6_MPI-ESM1-2-HR (1)	reasonable	good	2.84 (2.09 ... 3.50)	reasonable
cmip6_MPI-ESM1-2-LR (1)	bad	bad	3.47 (2.73 ... 4.05)	bad
cmip6_NorESM2-LM (1)	good	reasonable	3.06 (2.34 ... 3.56)	reasonable

cmip6_NorESM2-MM (1)	good	good	2.73 (2.16 ... 3.16)	good
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Table 3.3: Evaluation of the climate models considered for attribution of potential intensity around the track of Gaemi. For each model, the best estimate of the sigma parameter is shown with a 95% confidence interval, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

3.3.2 Sea Surface Temperatures

Of the 8 CMIP6 models analysed, 1 was rated ‘bad’ and discarded from the attribution analysis. Only 1 model performed well across all criteria, so all 7 remaining models were used.

Model / Observations	Seasonal cycle	Spatial pattern	Sigma	Conclusion
ERA5			0.343 (0.261 ... 0.414)	
CMIP6				
cmip6_CanESM5 (1)	good	reasonable	0.244 (0.188 ... 0.290)	reasonable
cmip6_CMCC-ESM2 (1)	good	reasonable	0.408 (0.311 ... 0.478)	reasonable
cmip6_MIROC6 (1)	reasonable	reasonable	0.400 (0.324 ... 0.457)	reasonable
cmip6_MPI-ESM1-2-HR (1)	good	good	0.246 (0.179 ... 0.293)	reasonable
cmip6_MPI-ESM1-2-LR (1)	reasonable	bad	0.326 (0.261 ... 0.371)	bad
cmip6_MRI-ESM2-0 (1)	good	good	0.301 (0.236 ... 0.350)	good
cmip6_NorESM2-LM (1)	reasonable	reasonable	0.383 (0.310 ... 0.439)	reasonable
cmip6_NorESM2-MM (1)	reasonable	reasonable	0.342 (0.276 ... 0.387)	reasonable

Table 3.4: Evaluation of the climate models considered for attribution of SSTs around the track of Gaemi. For each model, the best estimate of the sigma parameter is shown with a 95% confidence interval, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

3.4 Multi-method multi-model attribution

This section shows Probability Ratios and change in intensity ΔI for models that passed model evaluation and also includes the values calculated from the fits with observations. The synthesis process (to produce figures 3.2 & 3.3) is conducted as set out in section 2.4. The synthesised results are also tabulated in section 6 alongside the other hazard sections for ease of comparison.

3.4.1 Potential intensity

There is a stark difference between the observed data and the models in the trend of PI (table 3.5, figure 3.2). The upper bound of all model estimates are below the lower bound of the observational

estimate. Overall, models suggest that there has been a slight decrease (crossing no change) in the likelihood of such events, while ERA5 gives an increase of more than a factor of 100. Notably, the only model ranked ‘good’ does also predict an increase, though it is very minor. As a result of this stark discrepancy, we report both the weighted and unweighted results from this analysis in section 6. With future warming, models project a slightly increasing trend, which may be an underestimate given the potentially significant underestimation at present.

Model / Observations	Threshold for return period 2 yr	Current warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [m/s]	Future warming level [°C]	Probability ratio PR [-]	Change in intensity ΔI [m/s]
ERA5	78.2 m/s	1.2	1.2e+2 (6.0 ... 1.2e+5)	5.9 (2.5 ... 9.1)			
cmip6_CanES M5 (1)	64 m/s	1.2	0.86 (0.64 ... 1.2)	-0.49 (-1.7 ... 0.50)	2.0	1.0 (0.92 ... 1.1)	0.11 (-0.23 ... 0.44)
cmip6_EC-Ea rth3-CC (1)	73 m/s	1.2	0.82 (0.65 ... 1.1)	-0.60 (-1.4 ... 0.23)	2.0	0.99 (0.84 ... 1.1)	-0.037 (-0.44 ... 0.36)
cmip6_EC-Ea rth3-Veg-LR (1)	74 m/s	1.2	1.2 (0.74 ... 2.6)	0.57 (-0.96 ... 2.0)	2.0	1.2 (0.98 ... 1.4)	0.49 (-0.042 ... 0.93)
cmip6_MPI-E SM1-2-HR (1)	71 m/s	1.2	0.76 (0.58 ... 1.2)	-0.92 (-2.3 ... 0.41)	2.0	0.96 (0.74 ... 1.2)	-0.14 (-0.83 ... 0.47)
cmip6_NorES M2-LM (1)	73 m/s	1.2	1.5 (0.73 ... 5.0)	1.2 (-1.1 ... 3.6)	2.0	1.2 (1.0 ... 1.5)	0.78 (0.032 ... 1.6)
cmip6_NorES M2-MM (1)	72 m/s	1.2	1.2 (0.70 ... 2.5)	0.39 (-1.2 ... 1.9)	2.0	1.1 (0.85 ... 1.3)	0.28 (-0.45 ... 0.91)

Table 3.5: Event magnitude, probability ratio and change in intensity for a 2-year monthly average JJAS maximum potential intensity event around the track of Gaemi for observational datasets and each model that passed evaluation: (a) from the pre-industrial climate to the present and (b) from the present to 2°C above pre-industrial. Where data is not applicable (e.g. observations of the future), cells have been shaded grey.

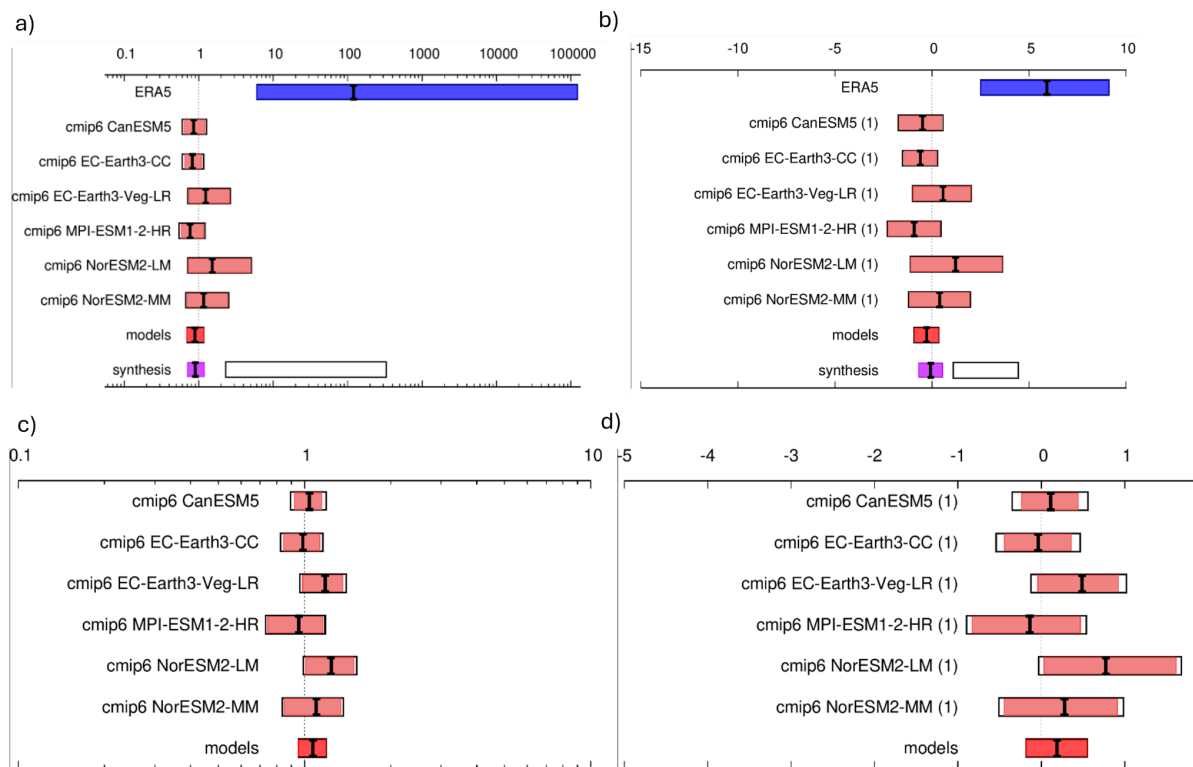


Figure 3.2: Synthesised changes for a 2-year monthly average JJAS maximum potential intensity event around the track of Gaemi. Changes in PR (left) and intensity (right) are shown for a historical period comparing the past 1.2°C cooler climate with the present (top row) and for a future period, based on model projections only, comparing the present and a 2°C warmed climate (bottom row).

3.4.2 Sea Surface Temperatures

The signal for increasing SSTs due to warming is extremely strong across all models and observations. This is expected given the direct link to the temperature of the atmosphere and the attribution statements at present and in future are statistically significant.

Model / Observations	Threshold for return period 15 yr	Current warming level [°C]	Probability ratio PR [-]	Change in intensity Δ [°C]	Future warming level [°C]	Probability ratio PR [-]	Change in intensity Δ [°C]
ERA5	30.23 C	1.2	4.6e+4 (2.4e+2 ... 6.5e+8)	1.1 (0.61 ... 1.5)			
cmip6_CanESM5 (1)	31 C	1.2	4.0e+5 (3.5e+4 ... 9.7e+6)	0.90 (0.81 ... 0.97)	2.0	12 (11 ... 13)	0.59 (0.56 ... 0.62)
cmip6_CMCC-ESM2 (1)	31 C	1.2	1.8e+2 (36 ... 1.6e+3)	0.71 (0.51 ... 0.90)	2.0	7.4 (6.2 ... 8.8)	0.55 (0.49 ... 0.61)
cmip6_MIROC6 (1)	30 C	1.2	2.9e+2 (25 ... 7.0e+3)	0.74 (0.45 ... 1.0)	2.0	7.9 (6.4 ... 9.6)	0.59 (0.50 ... 0.68)
cmip6_MPI-ESM1-2-HR (1)	30 C	1.2	2.1e+3 (2.9e+2 ... 2.9e+4)	0.68 (0.56 ... 0.81)	2.0	9.6 (8.1 ... 11)	0.54 (0.47 ... 0.60)
cmip6_MRI-E	30 C	1.2	1.5e+2 (33 ...)	0.57 (0.43 ...)	2.0	8.3 (7.3 ... 9.7)	0.52 (0.47 ...)

SM2-0 (1)			1.3e+3)	0.72)			0.57)
cmip6_NorES M2-LM (1)	31 C	1.2	9.6e+3 (4.3e+2 ... 6.5e+5)	1.2 (0.87 ... 1.5)	2.0	9.8 (8.0 ... 12)	0.80 (0.69 ... 0.92)
cmip6_NorES M2-MM (1)	31 C	1.2	7.4e+3 (5.6e+2 ... 1.7e+5)	1.0 (0.80 ... 1.3)	2.0	10 (9.0 ... 12)	0.74 (0.66 ... 0.82)

Table 3.6: Event magnitude, probability ratio and change in intensity for a 15-year monthly average JJAS maximum SST event around the track of Gaemi for observational datasets and each model that passed evaluation: (a) from the pre-industrial climate to the present and (b) from the present to 2°C above pre-industrial. Where data is not applicable (e.g. observations of the future), cells have been shaded grey.

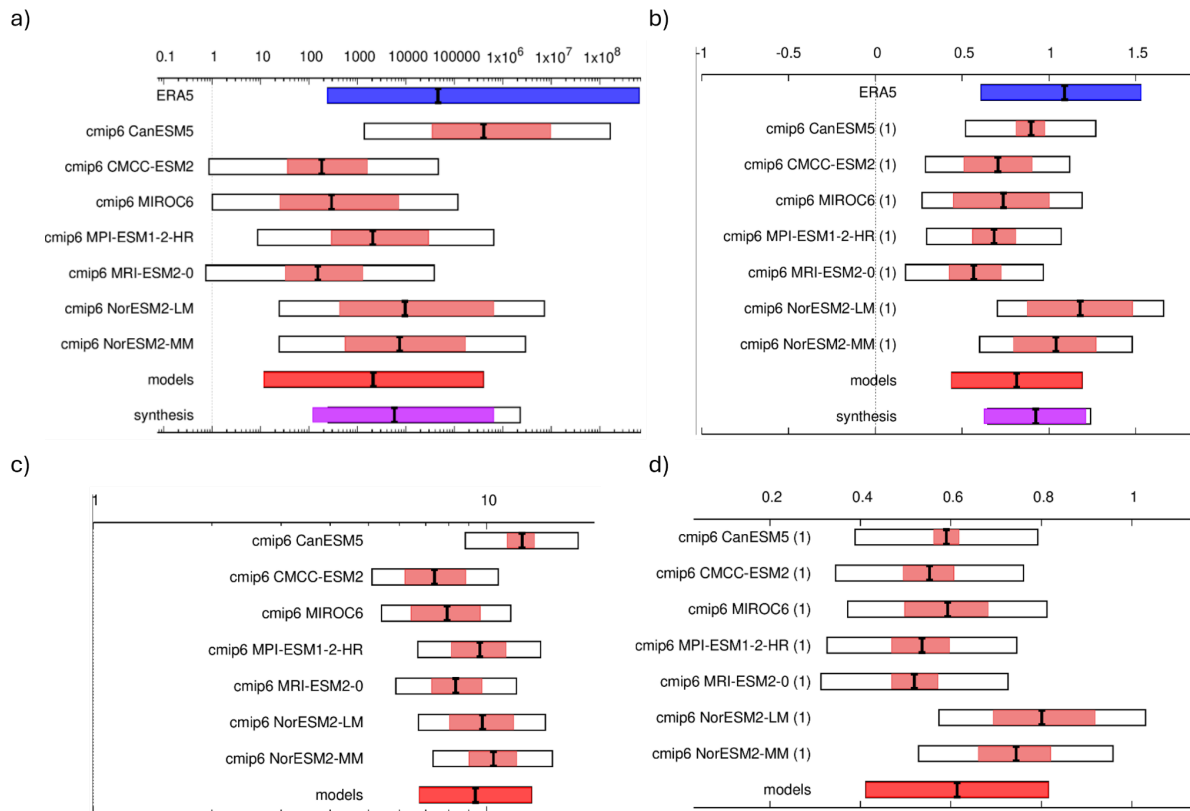


Figure 3.3: Synthesised changes for a 2-year monthly average JJAS maximum SST event around the track of Gaemi. Changes in PR (left) and intensity (right) are shown for a historical period comparing the past 1.2°C cooler climate with the present (top row) and for a future period, based on model projections only, comparing the present and a 2°C warmed climate (bottom row).

4 Wind speed attribution using IRIS

The event definitions studied in this section are as follows:

1. **All-basin:** category 4+ Typhoons occurring in the entire Western North Pacific basin (figure 1.4)
2. **Taiwan:** A similar analysis but considering those that come within 2 degrees of the centre of Taiwan at the point of closest approach. This analysis has already been published online but is referred to here for further comparison.

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. 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 to be physically constrained by the thermodynamic state as defined by the potential intensity (PI).

4.1 Data and methods

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. The original model description paper has been accepted for publication ([Sparks and Toumi, 2024](#)). 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 2024.

There has been a recent observed global warming of about 0.9°C , putting the global mean temperature close to about 1.2°C above pre-industrial temperature at the time of Gaemi. 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.

4.2 Attribution

The change in wind speed for an event like Typhoon Gaemi is clear, both in the wider basin and in the vicinity of Taiwan. Events that reach category 4 in the whole basin, which now occur roughly 6.5 times per year, were previously 3.9 (1.0 - 6.6) m/s slower, or equivalently only occurred around 5 times per year. This represents an increase in likelihood of approximately 30%. Uncertainties calculated through bootstrapping 44-year samples from the wider dataset show that the results for the wider basin are statistically significant. The results referred to for Taiwan do not have these uncertainty bounds ([Grantham Institute, 2024](#)). However, the best estimate results are in line with the wider basin, with an increase in magnitude of 4.2 m/s and in probability of ~50%. Both of these results are also in line with the observed change in PI over the Gaemi track shown in section 3.2.1, which gave a change of +5.9 (2.5 - 9.1) m/s.

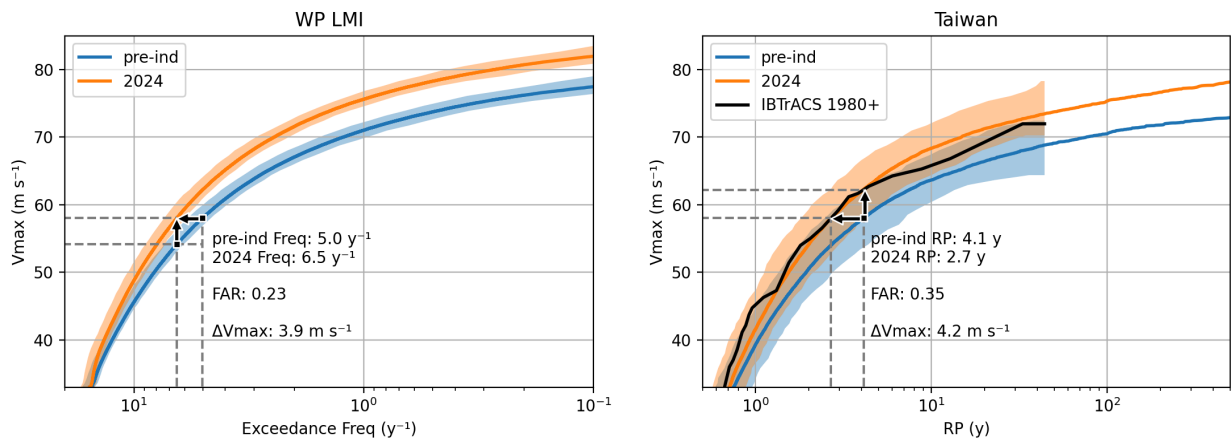


Figure 4.1: Return curves for tropical cyclones across the entire West North Pacific (WNP) basin (left) and around Taiwan (right). The x axis for the WNP is given as an exceedance frequency due to the high probability of storms occurring every year over such a large area, while the Taiwan plot shows return period. The orange curves show the present day climate in 2024, while the blue curves show the pre-industrial climate. The black line shows the distribution of observed storms around Taiwan since 1980.

4.3 Interpretation of results

This is a new approach that sits alongside the usual WWA protocol. First, it is a single model, whereas WWA normally combines multiple models and approaches into a single statement. In general, additional models help to sample a wider range of possibilities to ensure that we are as close to reality as possible. However, this approach is fundamentally different in nature. It is a stochastic model that is not based on climate models, only on observations and well understood physics. This means that it is not subject to the same biases and challenges around simulating phenomena at small scales that climate models struggle with. Furthermore, it is based on a very large number of data points (~10000 years of synthetic data) and the results are tested against observed storm tracks and intensities.

With its basis in fairly simple and robust thermodynamic and physical arguments, this method is complementary to the WWA protocol. In particular, for tropical cyclones, it allows us to make

statements about wind speeds that we cannot do on a rapid basis using the traditional method. This is because climate models (and therefore our method) are fundamentally limited in their ability to resolve the phenomena leading to these intensities. This approach just leverages other knowledge to bypass that challenge. However, overall, the results are still valid for the ‘class of event’ in the same way as our normal results, and thus the interpretation is essentially the same. Similarly, as shown by the study of both whole-basin wind speeds and those storms close to Taiwan, the analysis can be constrained in various ways so that they are as close to the impacts as we can manage.

5 Hazard summary

5.1 Summary of results

This section contains all of the final results for each hazard analysis. First, the results for the extreme rainfall were highly dependent on the region studied (tables 5.1 & 5.2). For the Northern Philippines, observations and models gave a different direction of change but both were very minor in magnitude and included “no change”, suggesting no overall change attributable to human-induced climate change. In addition, El Niño did play a role in the heavy rainfall in the Philippines, but was not relevant for the other regions. However, while El Niño was found to reduce the likelihood of similar events in the observations, the models giving no strong change, a finding in line with other literature (eg. [Seager et al., 2019](#)). Due to the differing sign, we communicate the unweighted uncertainty bounds: due to GMST similar rainfall may have become anywhere from 8 times less to 8 times more likely, and 40% less to 80% more intense; due to the El Niño, it may have been 4 times less to 13% more likely and 10% less to 1% more intense. However, in future, models project that such rainfall will become 20% more likely and 5% more intense.

In Taiwan and Hunan, results were more straightforward as observations and models agreed, showing an increase in likelihood and intensity both at present and in future. Though none of the results were statistically significant, combining overall agreement with physical reasoning we conclude that climate change has amplified the amount of rainfall in both regions. The best estimates are as follows. In Taiwan, such rainfall now occurs roughly every 5 years, compared to 8 years previously, and is 14% more intense. In the future, it will become another 30% more likely and 8% more intense. In Hunan, such rainfall now occurs roughly every 100 years, compared to 160 years previously, and is 9% more intense. In the future, it will become another 50% more likely and 5% more intense.

The conditions forming such a storm are shown in table 5.3. For potential intensity, models and observations strongly disagree on the sign of the change due to GMST. As a result for the present day we quote both the weighted and unweighted results. If we give the weighted estimate, which places more weight on models due to smaller uncertainty bounds, the conclusion is that such conditions have become 30% less to 20% more likely, with a best estimate of 10% less. If, on the other hand, we weigh models and observations equally, recognising that observations are likely closer to the real world, we conclude that such conditions have become significantly more likely at around a factor of 10 (2.3 - 330) and with a change in intensity of 2.9 (1.1-4.5) m/s. In future, models project a small non-significant increase, which is likely an underestimate. However, the picture is much clearer for SSTs. Anomalously warm summer SSTs like July 2024 would have been extremely unlikely without global warming, with a rise of approximately 1 degree in the 1 in 15 year event. In future, such

changes are likely to continue albeit less drastically, with another factor of 9 (making this a 1 in ~2 year event) and become 0.6 degrees hotter again.

Using IRIS, the wind speed of storms like Gaemi across the wider basin and close to Taiwan have increased due to warming (table 5.4). Category 4 storms are about 30% more frequent, and storms of that likelihood are about 4 m/s more intense.

Data	Northern Philippines 3-day precipitation				
	GMST			Niño 3.4 rel (DJF)	
	Time period	Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
Observations	Past - present	1.02 (0.015 - 71.8)	11.5 (-61.0 - 213.0)	0.56 (0.061 - 1.25)	-7.72 (-18.9 - 1.53)
Models		0.92 (0.66 - 1.34)	-0.52 (-6.51 - 6.05)	1.01 (0.94 - 1.09)	0.27 (-1.02 - 1.61)
Synthesis		0.92 (0.12 - 8.18)*	-0.48 (-37.8 - 76.6)*	1.01 (0.25 - 1.13)*	0.16 (-9.86 - 0.94)*
Models only	Present - future	1.23 (0.83 - 1.85)	5.04 (-3.42 - 14.1)		

Table 5.1: Summary of results for extreme precipitation in the Northern Philippines, presented in Figs 2.1&2.2: changes due to GMST include past-present changes and present-future changes for the El Niño state of 2023/24, changes due to ENSO include the El Niño versus a neutral state in the present climate. Statistically significant increases (decreases) in probability and intensity are highlighted in dark blue (orange), while non-significant increases are highlighted in light blue (orange). * shows where the uncertainty bounds are unweighted between observations and models due to their divergence.

Data		Taiwan 2-day precipitation		Hunan 2-day precipitation	
		Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
Observations	Past-Present	2.54 (0.093 - 156.0)	13.4 (-50.8 - 139.0)	27.6 (0.315 - 18000000)	28.7 (-14.5 - 99.4)
Models		1.48 (0.42 - 5.54)	13.7 (-11.0 - 45.2)	1.04 (0.033 - 42.0)	5.93 (-10.1 - 24.9)
Synthesis		1.57 (0.48 - 5.52)	13.7 (-10.1 - 43.5)	1.64 (0.079 - 65.3)	8.67 (-6.64 - 26.8)
Models only	Present-Future	1.34 (0.96 - 1.86)	7.59 (-2.32 - 18.4)	1.53 (0.69 - 3.44)	5.21 (-1.49 - 12.2)

Table 5.2: Summary of results for extreme precipitation in Taiwan and Hunan, presented in Figs 2.3&2.4: changes due to GMST include past-present changes and present-future changes. Statistically significant increases (decreases) in probability and intensity are highlighted in dark blue (orange), while non-significant increases are highlighted in light blue (orange).

Data		Potential intensity		Sea surface temperatures	
		Probability ratio	Change in intensity (m/s)	Probability ratio	Change in intensity (°C)
Observations	Past - present	120 (6.03 - 122000)	5.93 (2.52 - 9.11)	45800 (241 - ~10 ¹⁰)	1.09 (0.61 - 1.53)
Models		0.89 (0.69 - 1.17)	-0.27 (-0.91 - 0.34)	2100 (11.8 - 391000)	0.81 (0.44 - 1.19)
Synthesis (weighted)		0.90 (0.70 - 1.19)	-0.057 (-0.68 - 0.55)	58100 (120 - 649000)	0.92 (0.63 - 1.21)
Synthesis (unweighted)		10.33 (2.30 - 330)	2.94 (1.09 - 4.45)		
Models only	Present - future	1.07 (0.95 - 1.19)	0.19 (-0.18 - 0.55)	9.36 (6.75 - 13.0)	0.61 (0.41 - 0.82)

Table 5.3: Summary of results for potential intensity and sea surface temperatures, presented in figs 3.2 & 3.3: changes due to GMST include past-present changes and present-future changes. Statistically significant increases (decreases) in probability and intensity are highlighted in dark blue (orange), while non-significant increases are highlighted in light blue (orange).

Data	All-basin winds		Taiwan winds	
	Probability ratio (95% C.I.)	Change in intensity (m/s) (95% C.I.)	Probability ratio	Change in intensity (m/s)
IRIS model	1.3 (1.08 - 1.54)	3.9 (1.0 - 6.6)	1.52	+4.2

Table 5.4: Summary of results for wind speeds associated with category 4+ typhoons across the whole basin and in the vicinity of Taiwan, presented in Fig 4.1.

Overall, it is clear that the rainfall, wind speeds and conditions leading to Typhoon Gaemi have all increased by climate change. In particular, winds have become robustly more likely and intense, the Philippines is likely to experience more severe rainfall in future, and the warm sea surface temperature conditions leading to such an event will continue to become more intense. Other aspects remain more uncertain but with an overall increase due to warming.

It is therefore also overwhelmingly likely that the impacts of the typhoon were more severe as a result of climate change. These impacts were complex and occurred over multiple regions in different ways. Additionally, individual variables such as wind may drive impacts in different ways, such as through direct damage and driving storm surge, which may then compound rainfall-based flooding. In particular, while the changes in the magnitude of wind speeds seem small (~2-5 m/s), the damage potential of wind in the region of category 4 storms scales with the cube of intensity. Even small changes can therefore result in substantial increases in damage potential. In terms of this event, the impacts are also directly related to the multiple aspects of vulnerability and exposure of people affected by the storm (see section 7).

5.2 Implications for rapid tropical cyclone attribution

This report has shown that it is now feasible to rapidly study tropical cyclone events in different basins around the world, whether the impacts are driven by extreme winds, rainfall, or a combination of both. This study features several approaches, both new and existing:

1. Probabilistic event attribution of extreme rainfall
2. Probabilistic event attribution of conditions leading to such an event, such as the potential intensity and sea surface temperatures
3. Attribution of wind intensity using a stochastic storm track-intensity model (IRIS)

Approaches (1) and (3) are most useful when the impacts of the storm are related to rainfall or wind, respectively, or a combination of the two. Approach (2), while not providing attribution statements directly concerning the hazard, provides insight into the changing mechanisms underlying these increasingly damaging storms, and provides insight into the ability of models to simulate such extremes. As such, for almost all storms, there are now at least two approaches that can be used to assess the role of GMST and other complimentary lines of evidence on the changing thermodynamic influence over different time periods.

There remain several challenges. In particular, ensuring that the event definitions relate as closely as possible to the impacts when there are compounding rainfall and winds and when many regions are

affected. Standard attribution of compound events is challenging to apply since the approaches for different variables are built on different frameworks. However, given the rapid nature of these studies, the expectation is not to attribute damages directly, and we can make the robust assumption that when there are multiple extreme indices affected by climate change, the damage is likely more than the sum of the damage of each had they occurred in isolation.

Overall, integrating multiple lines of evidence to rapidly attribute these complex, highly destructive events represents a step forward in providing practical information where none would have existed previously, and ultimately towards operational attribution services.

6 Vulnerability and exposure

Typhoon Gaemi, in the Philippines locally known as Typhoon Carina, struck these regions in July 2024, bringing severe flooding and landslides. Typhoon Gaemi was characterised by its timing during the peak of the monsoon season, its widespread impact across multiple countries, and its interaction with pre-existing saturated conditions, particularly in Hunan ([Al Jazeera, 2024](#)). The typhoon caused extensive damage due to its intensity, prolonged rainfall, and the cascading hazards of landslides, particularly in the mountainous regions of Taiwan, where steep slopes generate high-velocity runoff and the limited flat land pushes development into areas prone to flooding ([Broomby, 2024](#)). Across low-lying and coastal areas in particular, significant mortality and morbidity have been reported. The Philippines saw the highest number of fatalities, with at least 39 people dead, most of whom drowned or were buried by landslides ([AA, 2024](#)). Taiwan, while experiencing fewer fatalities, suffered substantial economic losses, especially in agriculture, and widespread power outages affecting hundreds of thousands of households ([Focus Taiwan, 2024](#)). In Hunan, the typhoon led to the displacement of over 128,000 people and the destruction of critical infrastructure ([News AZ, 2024](#)).

The most vulnerable groups during Typhoon Gaemi include those living in informal settlements or low-income areas with poor housing, such as in Metro Manila, where makeshift housing materials failed to withstand floodwaters ([PSA, 2015](#)). Vulnerability in Metro Manila is rooted in historical processes of systemic exclusion, rapid urbanisation, and inadequate infrastructure, resulting in the urban poor residing in informal settlements along waterways, which have left large segments of the population with limited access to critical services such as electricity, water, and healthcare ([Rubio et al., 2020](#); [Pante, 2016](#)). In Taiwan, rural populations in coastal and riparian townships, already exposed due to their location and climate-sensitive livelihoods (such as agriculture), faced heightened risks due to insufficient flood defences and limited adaptive capacity ([Chen et al., 2022](#)).

This analysis focuses on the complex interplay between natural hazards and underlying drivers of vulnerability and exposure in the context of Typhoon Gaemi, with the objective to inform climate-smart recovery, adaptation, and flood risk management strategies.

6.1 Flood risk

Flood risk is a critical concern in the Philippines, Taiwan, and Hunan, all of which face significant exposure to tropical cyclones and their associated hazards. These regions have a long history of vulnerability to flooding due to a combination of geographical, climatic, and socio-economic factors.

In the Philippines, Metro Manila, including Quezon City, with its low elevation and proximity to major water bodies, is particularly flood-prone, due in part to inadequate drainage and rapid urbanisation ([Pante, 2016](#)) (see figure 7.1). Hunan, especially the Dongting Lake region, constitutes a hotspot for flood risk, exacerbated by inadequate flood control projects and socio-economic vulnerabilities ([Wang et al., 2011](#)) (see figure 7.1). Taiwan, regularly exposed to severe tropical storms, experiences the highest flood risks in its northern, northeastern, and southern regions, where coastal and riparian areas are most vulnerable ([Chen et al., 2022](#)) (see figure 7.2).

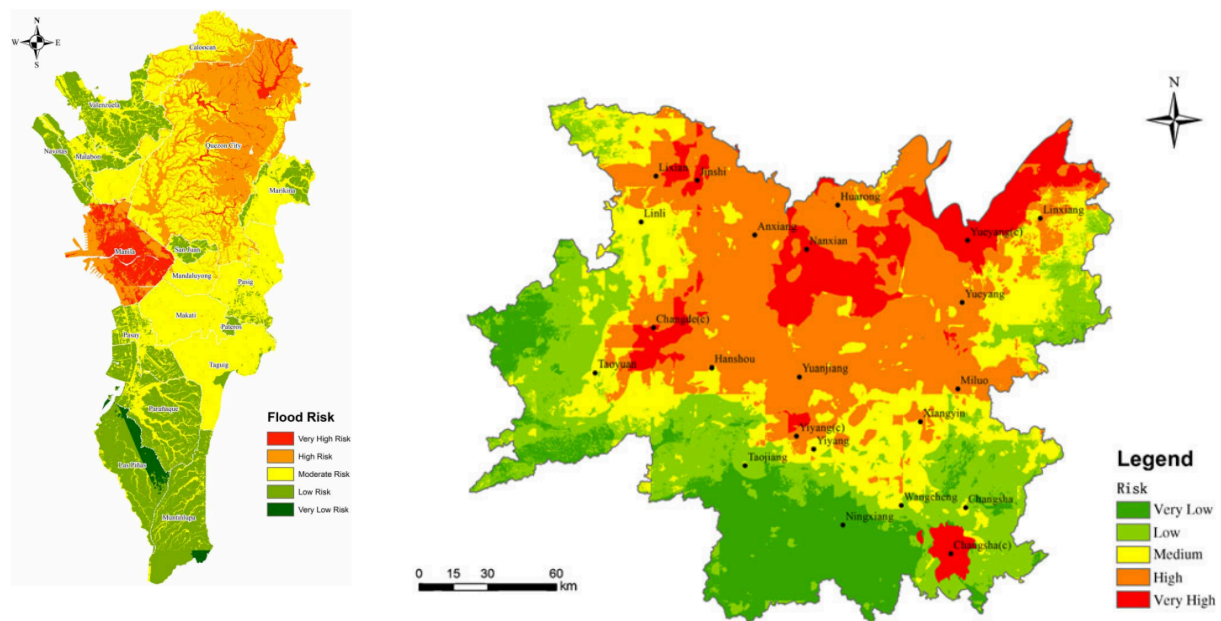


Figure 6.1. Flood risk maps for metro Manila, the Philippines (left), and Hunan province, China (right). Sources: Rubio et al. ([2020](#)), Wang et al. ([2011](#)).

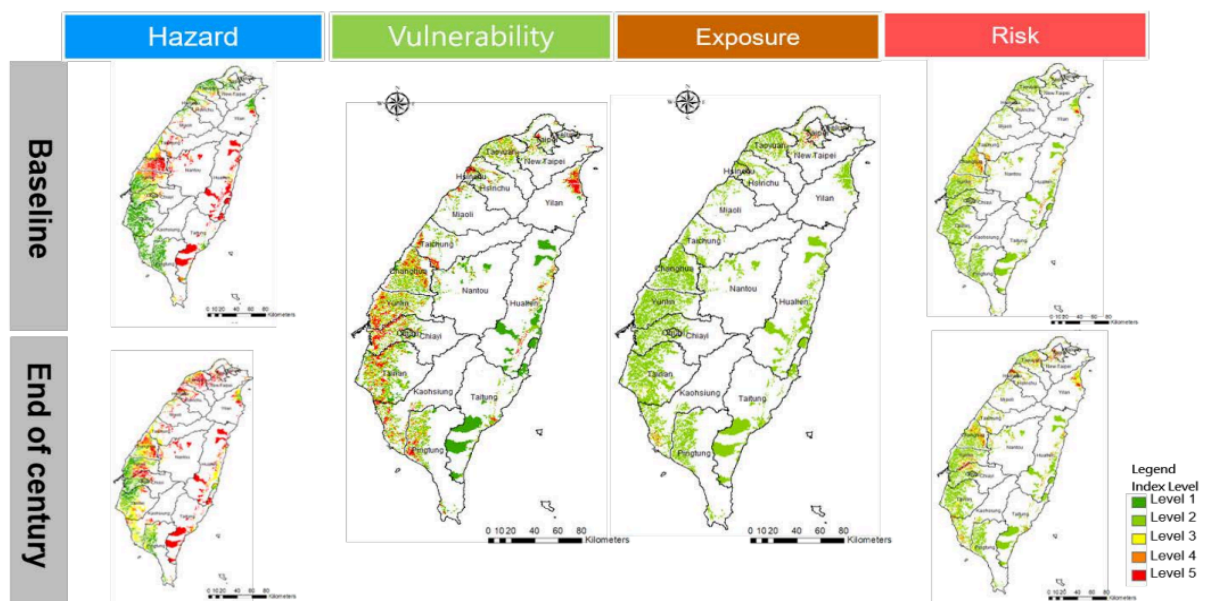


Figure 6.2. Flood risk map on township area scale across Taiwan. Source: Chen et al. ([2022](#)).

6.2 Land use and land cover changes

Since the 1970s, the population of Metro Manila has increased from 4.9 million residents to over 11 million today, resulting in various urban planning challenges and a highly urbanised city with limited green spaces. Densification of buildings, riverbed and canal silting, an increase in asphalt and concrete surfaces, waterways obstruction, and deforestation of the watershed all played a role in rapidly altering the landscape of the metropolis and contributed to the creation of flood-prone areas ([Lagmay et al., 2017](#)). The flood risk is further aggravated by poorly maintained, small or antiquated drains which cannot handle increased water flow during storms.

In the Philippines, laws and policies on Disaster Risk Reduction and Management (DRRM) require the local government to devise comprehensive land use and climate change action plans to help reduce risk and increase preparedness measures to mitigate flood impacts ([HLURB, 2013](#)). Furthermore, the Metro Manila Flood Control Plan, a World-Bank funded PHP 350 billion governmental project, is currently underway, with the bulk of the funding allocated for structural mitigation measures, such as dams and pump stations.

When it comes to Hunan, historically, most land-use changes were caused by deforestation from the expansion of human settlements and activities (see e.g. [Li et al., 2022](#)). Taiwan, on the other hand, has experienced a gradual recovery in forest cover in recent years. Between 2005 and 2015, Taiwan saw 27.33% public farmland and 0.72% private farmland changed into forestland, primarily attributed to afforestation as well as ecotourism strategy ([Tu & Chen, 2020](#)). Additionally, there has been significant investment in watershed improvement, aimed primarily at sediment reduction, forest restoration, and stream conservation ([Lin et al., 2020](#)). Environmentally, the greatest benefits came from improving the quality and the supply of water, the value of which will exceed both the operation and maintenance costs within three decades of the investment ([ADB, 2017](#)). Importantly, forest cover can also significantly reduce the impacts of cyclones by acting as a natural barrier against both wind and flooding, while also enhancing soil stability and absorbing rainfall, which helps mitigate surface runoff and associated flooding.

6.3 Urban planning and flood protection infrastructure

In the Philippines, particularly in Metro Manila, maintaining drainage systems is crucial for reducing flood risk ([Lagmay et al., 2017](#)). The implementation of the PHP 350 billion Metro Manila Flood Management Master Plan, supported by the World Bank Group, aims to reduce flooding from river systems and eliminate long-term flooding in the Laguna de Bay floodplain over a 20-25 year period starting in 2017 ([MMDA, n.d.](#)). Taiwan has also taken steps to address flood risks through various measures. The government has implemented drainage systems in some regions, which has substantially reduced flood risk ([Peng, 2018](#)). Additionally, recent legislation in Taiwan has included amendments for the institutionalisation of outflow control and runoff allocation in new developments, potentially reducing flooding in affected areas by up to 96% ([Wang et al., 2024](#)).

In Metro Manila, Philippines, urban planning has exacerbated some flood risks. The city is highly urbanised with limited green spaces, and most flood control projects have a 25-year design period,

with exceptional cases having a 50-year return period ([JICA, 2002](#)). This design standard is insufficient for extreme events like the July 2024 Typhoon Gaemi enhanced monsoon rains which is estimated to have a 100-year return period. Furthermore, urban plans in Metro Manila, except for Quezon City, rely on deterministic flood hazard maps from the Mines and Geosciences Bureau, which can lead to maladaptation by underestimating potential impacts ([Lagmay et al., 2023](#)). There is a need for probabilistic multi-scenario hazard maps that incorporate climate change scenarios to better inform urban planning decisions ([Lagmay & Racoma, 2019](#)). In Taiwan, there is a mismatch between local flood management plans and general urban plans in regulating land uses ([Wang et al., 2024](#)). The increase in impervious surfaces due to urban sprawl has contributed to increased flood flow ([Su et al., 2021](#)). However, recent amendments to environmental and risk management legislation aim to address climate change and urban development impacts on flooding ([Wang et al., 2024](#)).

In the Philippines, flood protection measures include both structural and non-structural interventions. The "making room for the river" approach has been suggested as an additional intervention to complement flood control projects ([Lagmay, 2010](#)). However, examples of maladaptation exist, such as the DPWH-JICA project for CAMANAVA (Caloocan, Malabon, Navotas, and Valenzuela) that did not consider subsidence, potentially compromising flood control projects since subsidence lowers ground levels, compromising drainage systems and increasing flood risks ([Arcilla, 2015](#)). Taiwan has implemented various flood protection measures, including the construction of drainage systems and the use of regulatory flood maps. However, there is a need for stronger building codes related to flood risks, as current codes do not meet the same standards as those for fire and earthquake disasters, which are considered to hold "world-class" robustness ([Wang et al., 2024](#)).

In the Philippines, most flood control projects in Metro Manila are not designed to handle extreme events, such as the Ketsana floods in 2009, Ulysses in 2020, and Gaemi in 2024 ([Lagmay, 2010](#); [Buan, 2020](#); [Angeles, 2024](#)). This indicates that critical infrastructure may not be built to withstand these types of events. In Taiwan, flood control measures such as levees are designed to a certain level of protection (e.g., 100 years for large rivers), but they can breach or overtop during more extreme events ([Wang et al., 2024](#)). This highlights the concept of residual risk, which is not well addressed in the climate adaptation literature nor explicitly acknowledged in urban planning in Taiwan ([Wang et al., 2024](#)). Importantly, the hazard analysis shows that climate change is driving more intense and frequent storms in the region, further increasing the residual risk.

Urban planning and flood protection infrastructure in the Philippines, Taiwan, and Hunan face significant challenges in addressing increasing flood risks. While efforts are being made to reduce flood risks through various measures, there are still gaps in urban planning, infrastructure design, and the consideration of climate change impacts. Moving forward, there is a need to develop more resilient urban plans, implement nature-based solutions, and design infrastructure that can withstand the more intense extreme events of today and tomorrow in a changing climate.

6.4 Early warning early action

On 21 July 2024, Gaemi intensified into a Severe Tropical Storm and further strengthened into a Typhoon, meandering over the Philippine Sea on 22 July. This led to the issuance of Tropical Cyclone Wind Signal No. 1 in certain areas of Northern Luzon. Some areas in Southwest Luzon experienced

flooding on 23 July as Typhoon Gaemi continued to intensify while moving northward, raising Tropical Wind Signal No. 2 in Batanes ([Crisis24, 2024](#)).

As a consequence of monsoon rains and Typhoon Gaemi, extreme floods in Metro Manila happened on 24 July 2024. The day previous, PAGASA forecasted 50-100mm of rainfall for the metropolis ([PAGASA](#)). The actual record of rain as recorded by rain gauges in Science Garden, and La Mesa dam in Quezon was much higher (see figure 7.3). Forecasting rainfall totals is difficult due, in part, to the complexity of multi-scale phenomenon when forecasting monsoon rains compared to Tropical Cyclones ([Bagtasa, 2021](#)). By the time colour-coded warnings for heavy rainfall were issued in the early morning of 24 July, many areas of Metro Manila were already flooded. The floods of 24 July 2024 had a 100-year rain return period (see figure 7.4). In comparison, Tropical Storm Ondoy which caused widespread flooding and killed more than 400 people in Metro Manila in 2009 was estimated to have a return period of 180 years ([Ybañez, 2013](#)).

Rainfall Data From PAGASA Rain Gauges

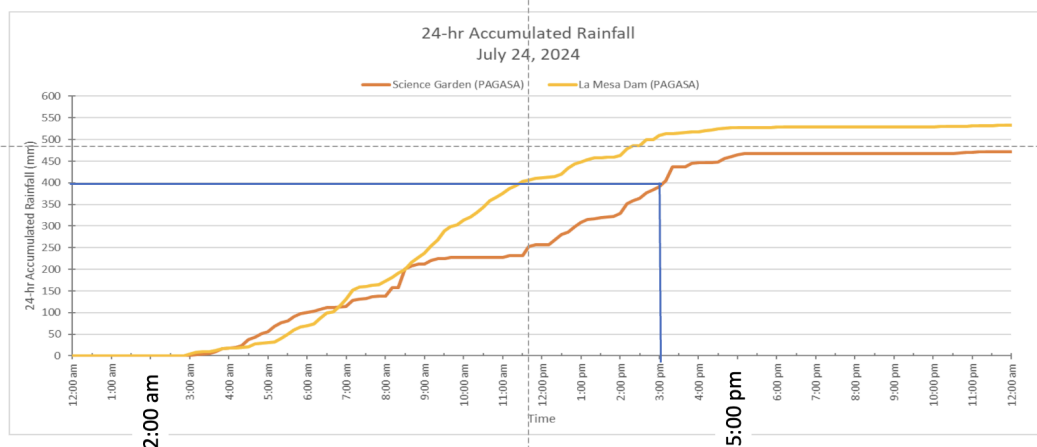


Figure 6.3. Rainfall data from PAGASA Rain Gauges in Science Garden and La Mesa Dam.

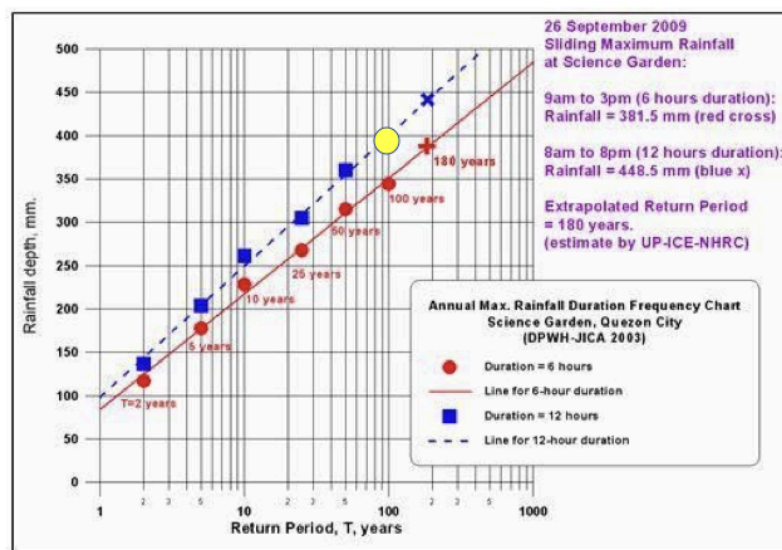


Figure 6.4. Graph of rainfall return period computed for 6 and 12 hours. Science Garden Station (PAGASA) and NHRC.

Passing of Typhoon Gaemi to the north of the Philippines further compounded the problem. Given that its eye was several hundred kilometres north of Metro Manila, no storm signal warning was raised in the Metropolis, even though the Philippines have an early action protocol (EAP) in place. EAPs are structured documents that provide a systemic approach for actions to prepare for and respond to specific types of hazards. Across the Philippines, 14 actors operating in the country have developed 14 early actions for typhoons, and an additional seven for flooding, including, for example, early harvesting of crops and evacuation of livestock ([Anticipation Hub, n.d.](#); [Asia-Pacific TWGAA, 2024](#)). In the Philippines, there is increasing recognition of the need to progress in Integrated Climate and Disaster Risk Governance to prepare and respond to climate hazards, and recently filed its bill for the Declaration of a State of Imminent Disaster, which will institutionalise and operationalize anticipatory action within the government sector. Set to become the first national legislation for anticipatory action worldwide, it will allow for national and local resources to be used to act before a hazard strikes ([Anticipation Hub, 2024](#); [IFRC Disaster Law, 2021](#)).

In 2012, the country launched a responsive programme for disaster prevention and mitigation called the Nationwide Operational Assessment of Hazards (formerly Project NOAH, now UP NOAH). It was specifically designed so that government agencies would be able to warn vulnerable communities against impending floods 6-hrs prior to the event, and use advanced technology to enhance current geo-hazard vulnerability maps ([Lagmay et al., 2017](#)). On 24 July, UP NOAH website saw a spike in activity, with more than 2.65 million search requests from Netizens to check flood hazards in their neighbourhood. Ideally, the probabilistic (multi-scenario) hazard maps of UP NOAH should have been reviewed in the days leading up to the event once detailed forecasts, warnings, and alerts were issued and not on the day of the flooding event. This underscores the necessity of accessing hazard data as a preparatory tool for planning and anticipatory action.

Similarly, though Taiwan has boosted its warning system ([The Albertan, 2024](#)), one of the most effective strategies in Taiwan to raise awareness about floods impacts is to do so through community-based initiatives and citizen science-based early warning systems ([Wang et al., 2024](#)). Even those, however, have had some mixed results in communicating floods risks on the local level, particularly amongst the coastal communities. Interviews have shown that the public retains a preference for transferring flood risk to the authorities rather than acting upon it communally ([Wang et al., 2024](#)).

6.5 Emergency response

In the Philippines, the government and local city authorities faced challenges, with hundreds of rescue calls from flooded neighbourhoods (personal communication with OCD officials). Despite substantial efforts by national and local responders, the scale of the disaster exposed significant gaps, especially in less-prepared Barangays (the smallest administrative unit in the Philippines). The Department of Trade and Industry (DTI) activated Republic Act 7581 (Price Act), providing protection to consumers by stabilising the prices of necessities and prime commodities and by prescribing measures to prevent undue price increases during emergency situations. In light of the severe damage, 118 cities and municipalities were declared under a State of Calamity, enabling local governments to access emergency resources and assistance for recovery efforts. The Department of Social Welfare and Development (DSWD) responded by providing over Php 70 million in humanitarian aid and distributing cash assistance through the Assistance to Individuals in Crisis Situation (AICS) program ([DSWD, 2024](#)). However, despite pre-positioned resources and a robust response strategy, the sheer volume of those needing rescue outstripped capacity, revealing areas where improved coordination and resources were necessary.

As first responders, the Philippine Red Cross (PRC) provided meals and basic needs to 23,000 people, provided water to 1,250 families, rescued 400 people and established 44 first aid stations in the evacuation centres in Manila, Pasig, Pateros, Valenzuela, Marikina, Paranaque, Navotas, Rizal, Ilocos Sur, and Bataan. IFRC released a DREF for 739,170 CHF to cover Shelter, Livelihoods, Health and Basic Needs of 33,000 people during the next 6 months, with ongoing monitoring and adjustments to meet the evolving needs of impacted communities ([IFRC GO, 2024](#)). The United States government, through the U.S. Agency for International Development (USAID), is providing Php55 million (\$1 million) in humanitarian aid to communities affected by widespread flooding triggered by Typhoon Carina ([U.S. Embassy Manila, 2024](#)).

Taiwan's response was marked by swift government action, including the closure of schools, offices, and financial markets, and the evacuation of over 8,000 people from high-risk areas ([Crisis24, 2024](#)). The Ministry of National Defense also mobilised 29,000 soldiers to assist with disaster response ([Al Jazeera, 2024](#)). These actions were largely effective, though the impact on infrastructure, such as halted transportation services, posed challenges to mobility and logistics, potentially delaying some aspects of the response. The Taiwan Red Cross Organization (TRCO), anticipating the impact of Gaemi, deployed disaster relief vehicles into rain battered regions near Zigan and teamed with the Fire Department of Kaohsiung to rescue lives, shelter evacuees, and provide relief supplies ([The Red Cross Society of The Republic of China \(Taiwan\), 2024](#)).

In Hunan, the government's preemptive deployment of 95 professional rescue teams, along with additional resources, exemplified a proactive approach. The Ministry of Emergency Management further supported these efforts by deploying aerial vehicles and allocating disaster relief materials worth 4.41 million yuan ([OCHA, 2024](#)).

V&E conclusions

The impacts of Typhoon Gaemi underscore the existing vulnerabilities and exposures in the Philippines, Taiwan, and Hunan, as well as resilience to typhoons. The Western Pacific region is familiar with intense tropical cyclones experiencing multiple storms each season, and this experience is apparent in the strong existing early warning systems, early actions, and emergency responses carried out around the storm in the affected places. There is also a recognition of flood risks, with projects underway to address the risk such as the Metro Manila Flood Management Master Plan. However, the existing early warning systems and early action protocols do not cover everyone. For example, in the Philippines, there are many existing protocols but the approach is scattered and has gaps, pointing to a need to support risk governance and scale of forecast-based actions by including them in disaster policy to ensure everyone is covered. The impacts from Typhoon Gaemi on people and economic activity also underscores the needs for comprehensive flood risk management, and urban planning especially as the rainfall and winds from storms like Typhoon Gaemi are becoming more intense due to climate change.

Data availability

All time series used in the attribution analysis are available via the Climate Explorer.

References

All references are given as hyperlinks in the text.

Appendix

A.1 Model evaluation figures

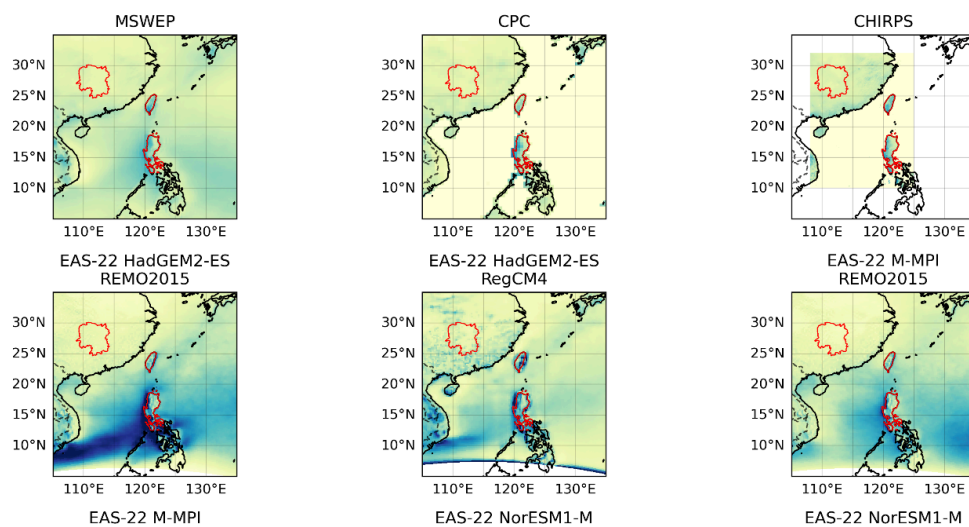


Figure A.1: *Spatial patterns of precipitation in June-September in observations and CORDEX models. The three study regions for the rainfall analysis are highlighted in red.*

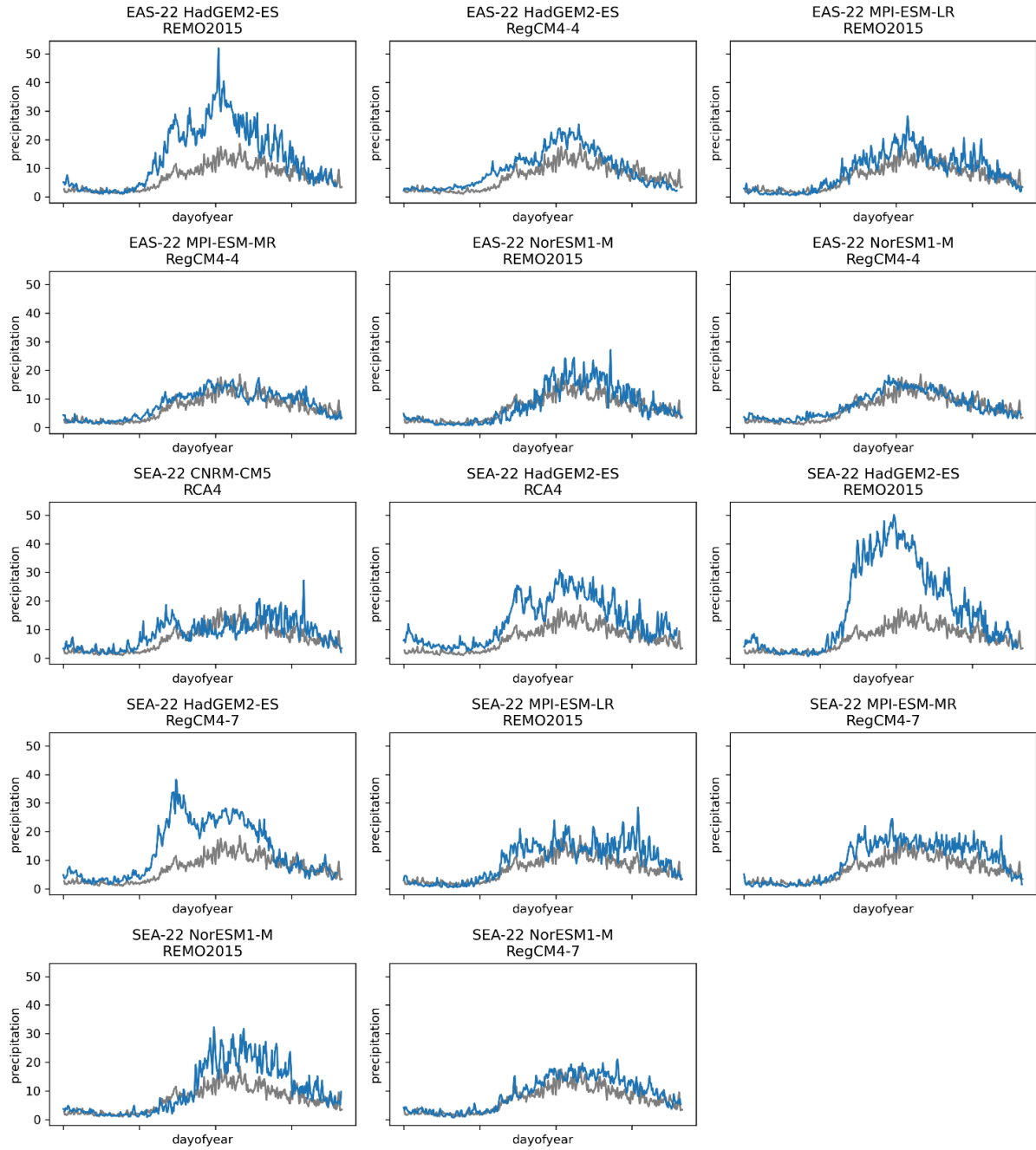


Figure A.2: Seasonal cycles of precipitation in the Northern Philippines in observations and CORDEX models.

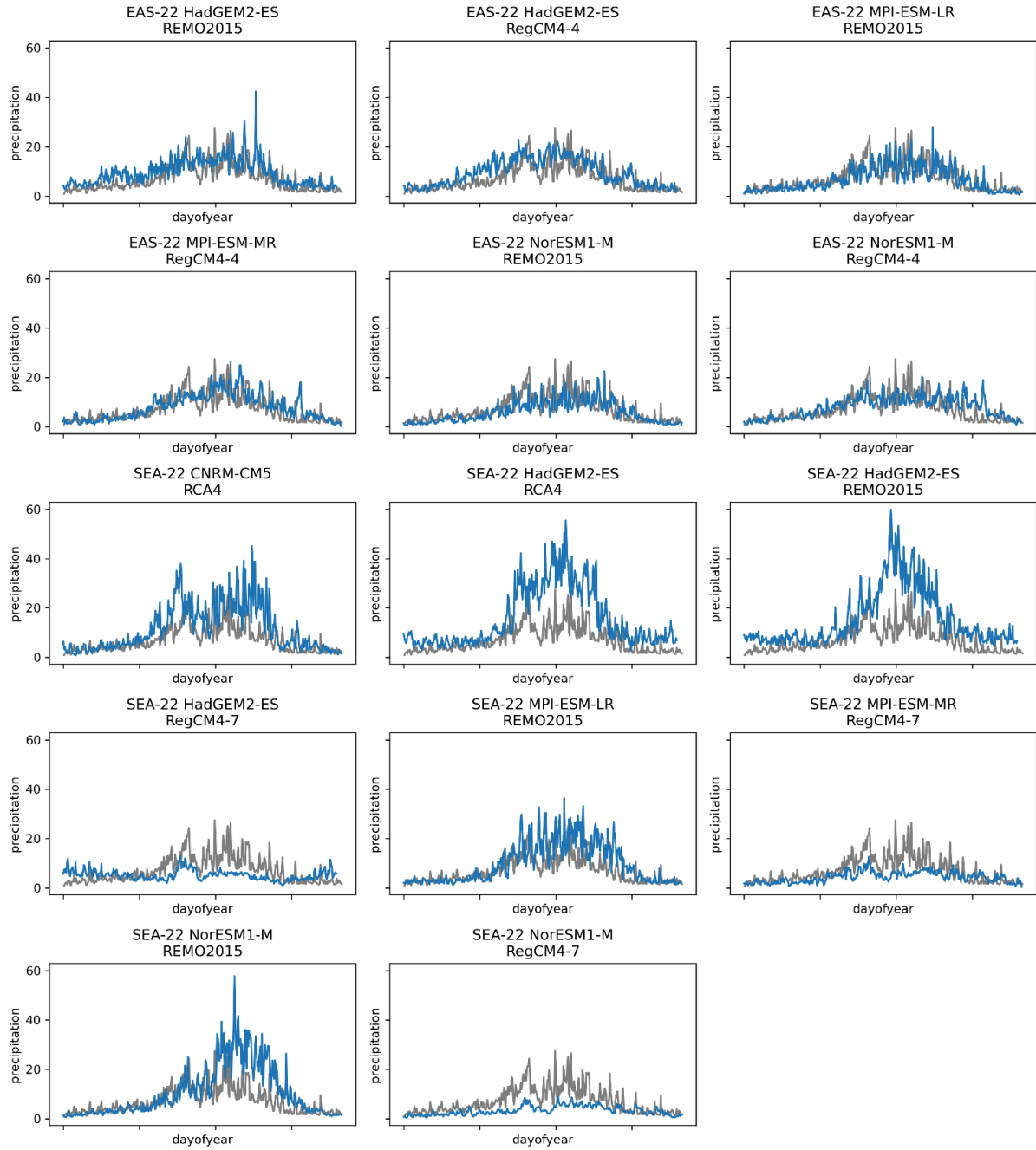


Figure A.3: Seasonal cycles of precipitation in Taiwan in observations and CORDEX models.

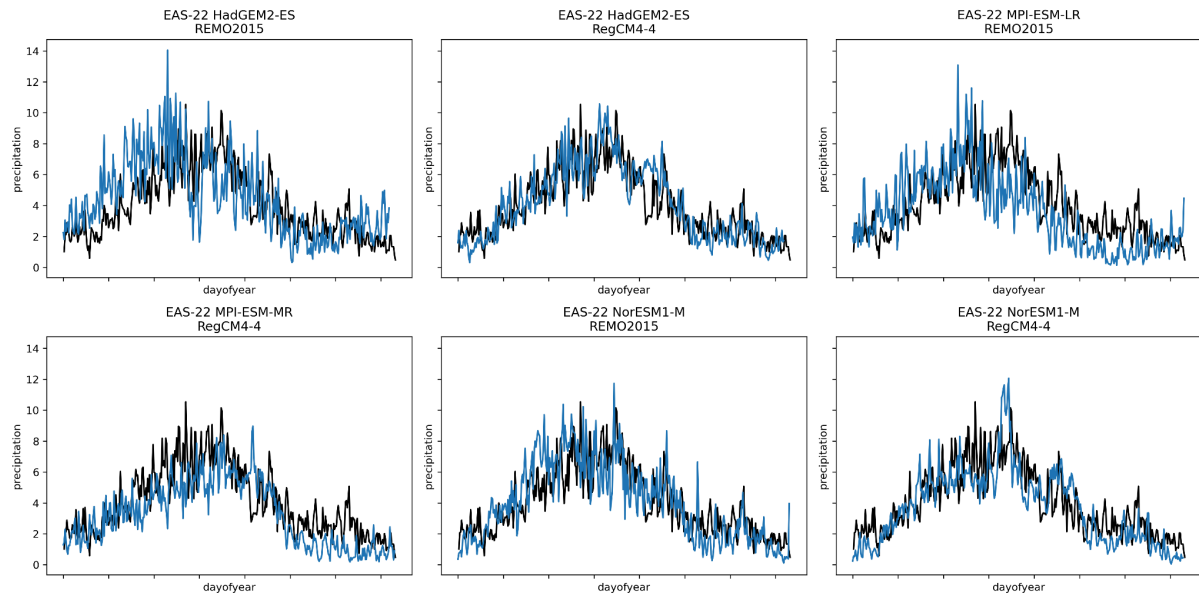


Figure A.4: Seasonal cycles of precipitation in Hunan in observations and CORDEX models.

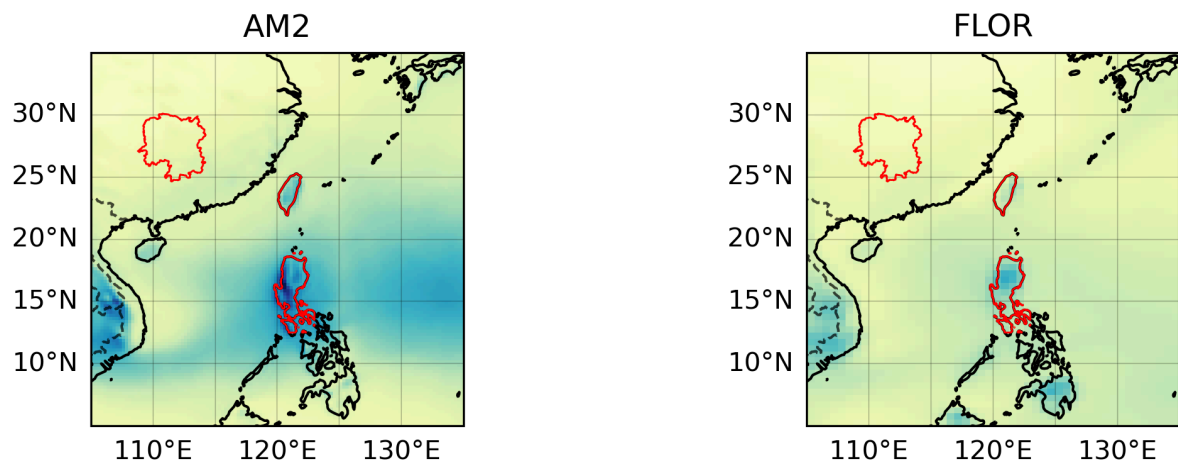


Figure A.5: Spatial patterns of precipitation in June-September in the AM2 and FLOR models. The three study regions for the rainfall analysis are highlighted in red.

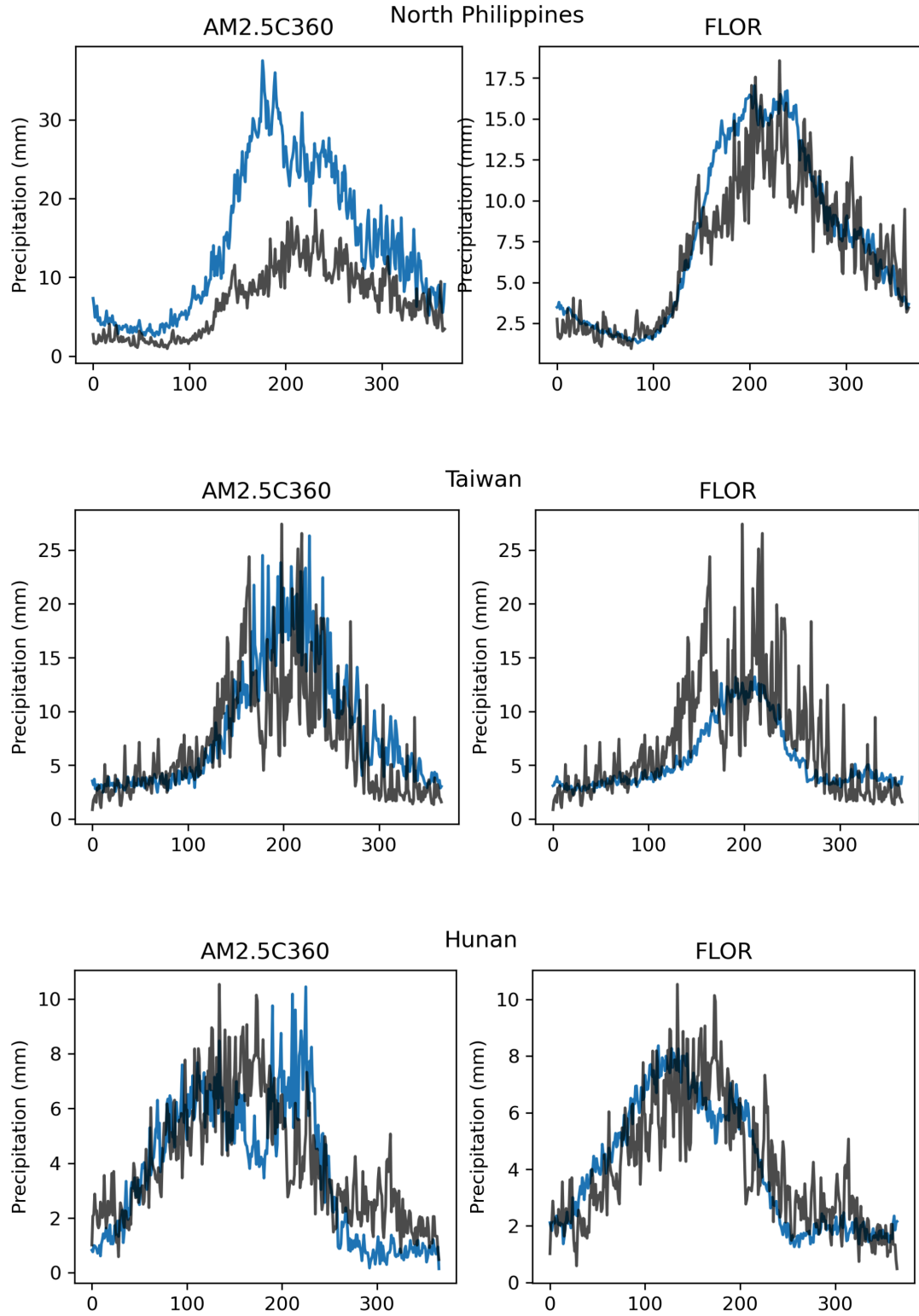


Figure A.6: Seasonal cycles of precipitation in the three study regions in the observational dataset and AM2 and FLOR models.

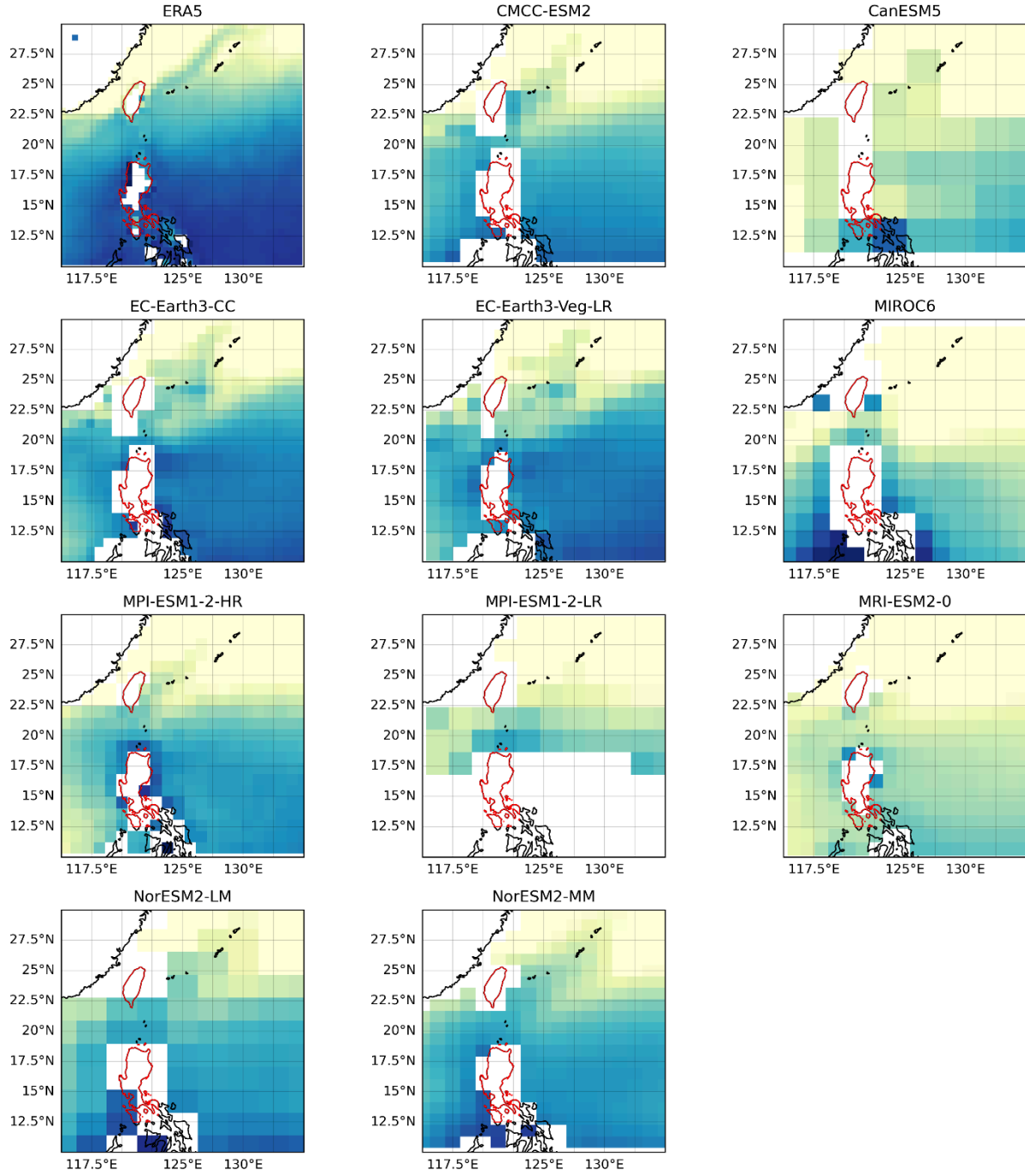


Figure A.7: Spatial patterns of Potential Intensity in June-September in ERA5 and CMIP6 models. The area of the figure is the study region.

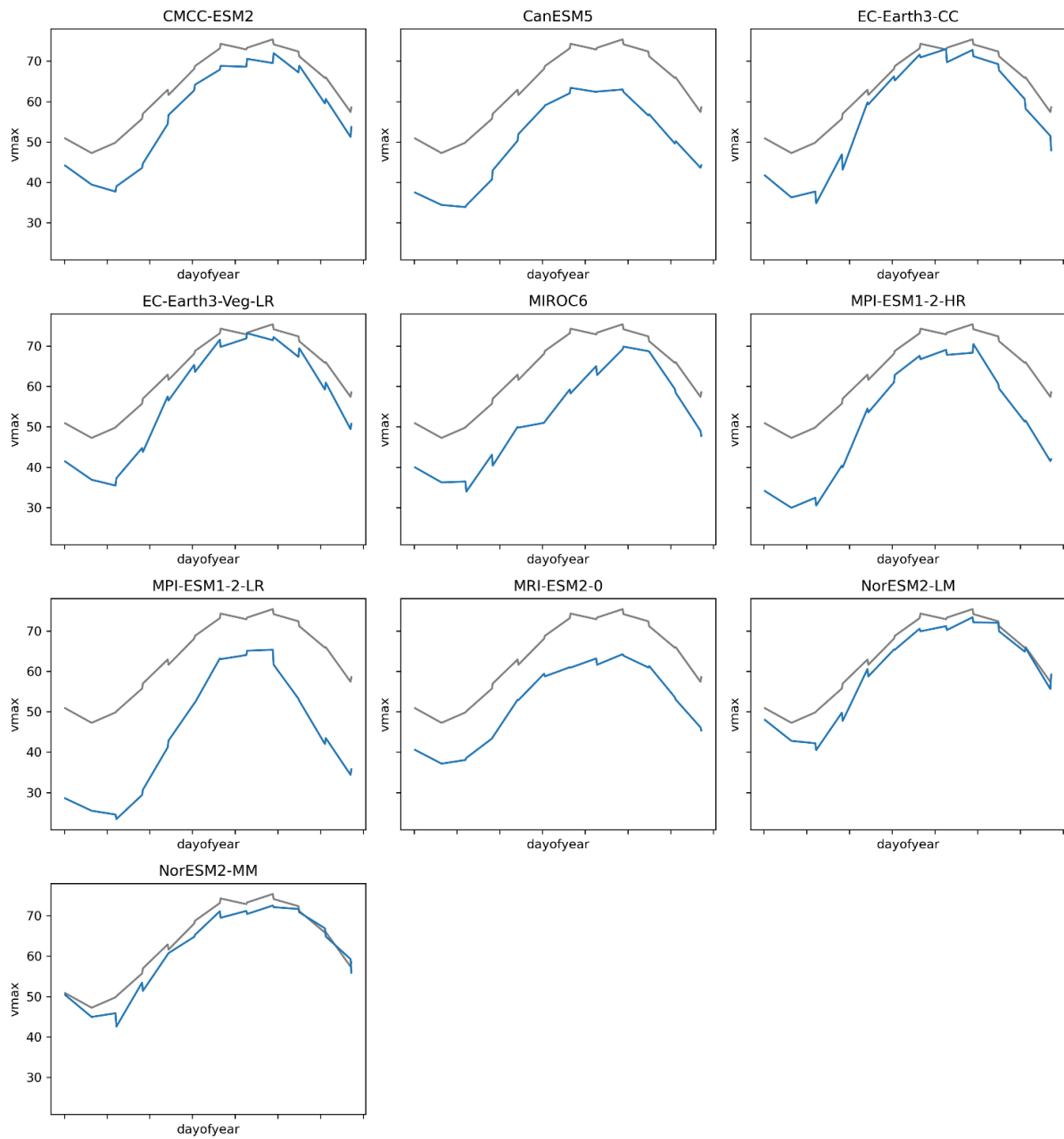


Figure A.8: Seasonal cycles of Potential Intensity in the study region in ERA5 and CMIP6 models.

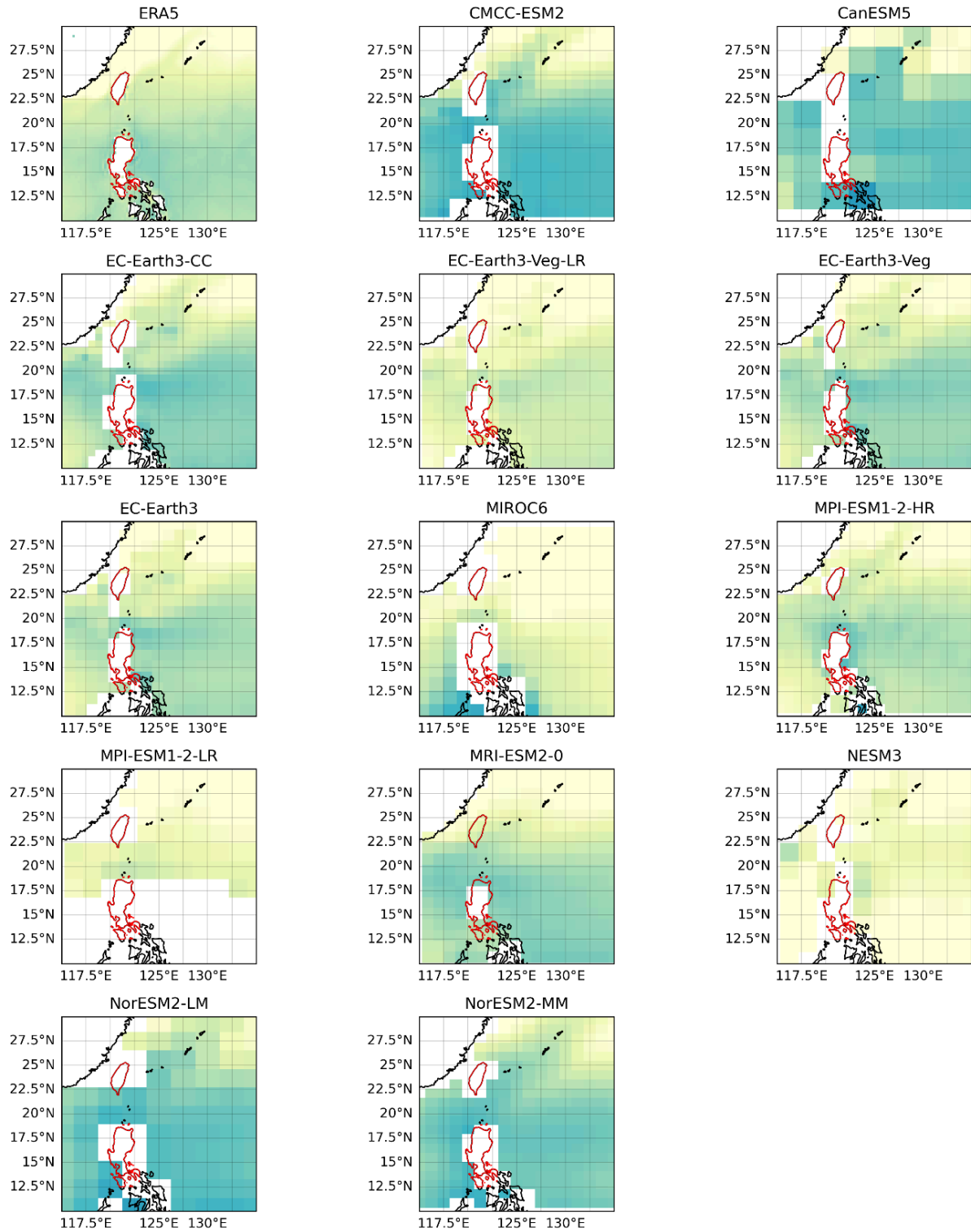


Figure A.9: Spatial patterns of SSTs in June-September in ERA5 and CMIP6 models. The area of the figure is the study region.

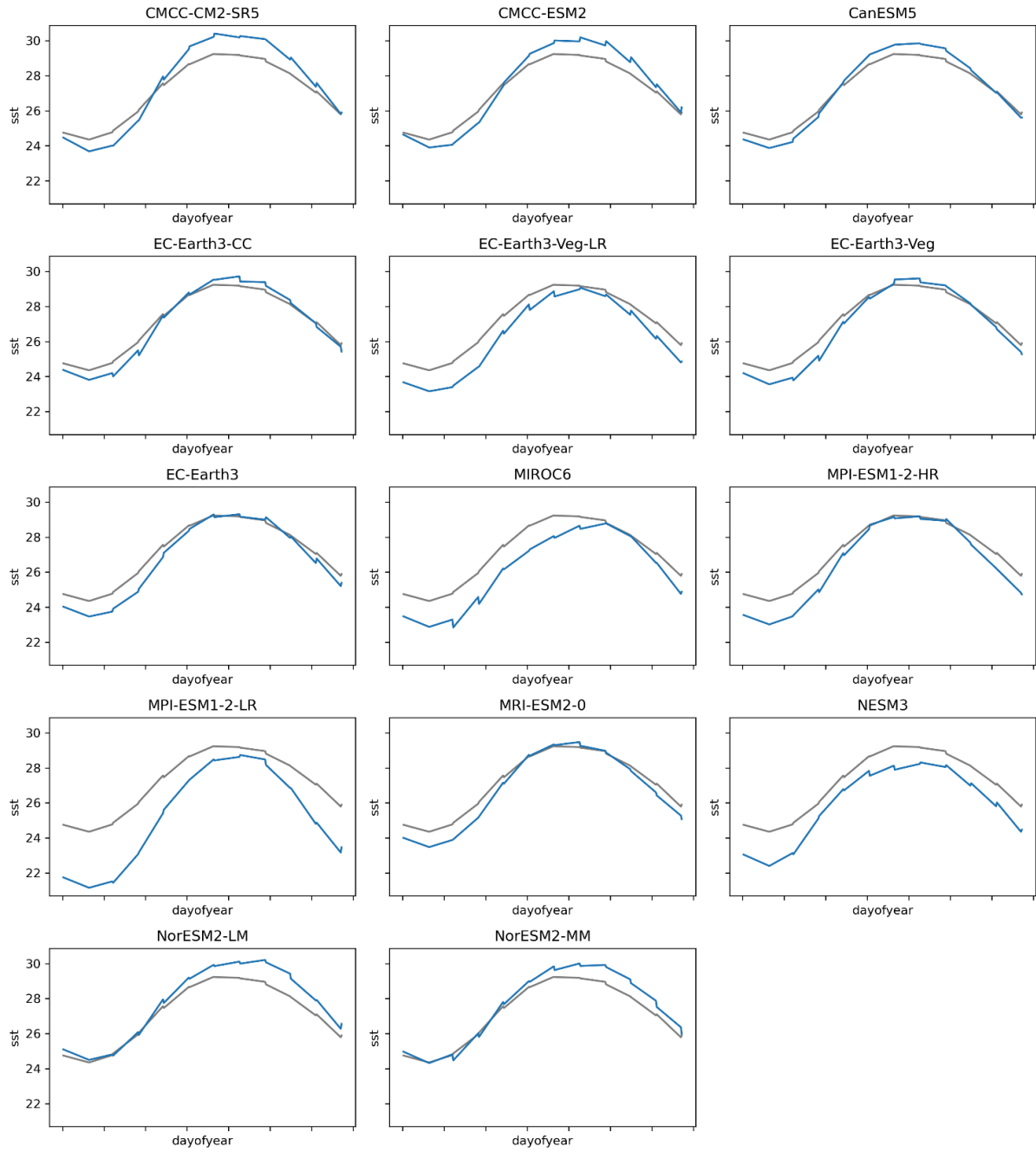


Figure A.10: Seasonal cycles of SSTs in the study region in ERA5 and CMIP6 models.