

Typhoon Dujuan: in a warming climate even well-prepared nations remain vulnerable to worsening climate extremes

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Main findings

- Typhoon Dujuan brought heavy rainfall, flooding and landslides to Chiba and surrounding areas in Japan, disrupting transport, electricity and essential services. Older adults and those reliant on care were particularly at risk. Repeated flooding and infrastructure damage further worsened existing problems, highlighting how location, land use and social inequalities shape the impact of disasters.
- The rainfall associated with Typhoon Dujuan in the Kantō region is a common event in today's climate, with similar rainfall totals expected approximately every three years, although local return periods were much higher with the rainfall on e.g. Oshima island having a return time of about 20 years, Funabashi and Abiko in Chiba prefecture about 60 years and Miura in the Kanagawa prefecture about 150 years.
- To estimate if human-induced climate change influenced the heavy rainfall, we first determine if there is a trend in the observations. Observation-based datasets suggested that over the historical record, such rainfall extremes have become more likely and intense as the world has warmed, the uncertainties are however very high, making quantification difficult.
- To determine the role of climate change in the rainfall, we combine observations with climate models. The models exhibit substantial uncertainty, with some projecting pronounced increases in heavy precipitation and others indicating little or no change. This large uncertainty, together with the spatial resolution limitations of both climate models and gridded observational datasets, constrains our ability to quantify the influence of climate change on the rainfall event using the probabilistic attribution method.
- Repeating the same analysis for precipitable water - the amount of water available in the atmosphere that could potentially fall as rain - we find strong and consistent trends in both observations and climate models, suggesting an increase in the amount of water vapour of 9% attributable to human-induced climate change, consistent with what we would expect from the Clausius Clapeyron relation.
- In addition to rainfall and water vapour, we analyse the very warm sea surface temperatures (SSTs) over which Dujuan passed before reaching peak intensity were around 2-3°C hotter than in a preindustrial climate.
- In these analyses we also tested whether El Niño affected the event, using different ways of defining the phenomenon. In all cases we found that El Niño did not intensify the rainfall or increased sea surface temperatures.
- Using a separate analysis of Typhoon Dujuan-like events selected based on the spatial distribution of precipitable water in climate model simulations, we find a 20-40% increase in rainfall in the locations that received the highest rainfall in this event under present-day compared to pre-industrial climate conditions. [An analysis](#) by a Japanese government research team using a different methodology and event definition also found a rainfall increase of over 20% attributable to global warming.

- By selecting Typhoon Dujuan-like events from climate model simulations based on their tracks and comparing them under present-day and pre-industrial climates, we find a slight increase in wind intensity but no statistically significant change in frequency.
- Synthesising evidence from these different approaches, we find that anthropogenic global warming has had a relatively limited influence on the frequency and intensity of the typhoon itself, while its contribution to the rainfall associated with the combined effects of the typhoon and the autumn rain front appears more pronounced. However, attribution in small, topographically complex regions remains challenging due to limitations in observational data and climate model resolution, highlighting the importance of combining multiple lines of evidence to draw robust conclusions.
- Japan has extensive forecasting capabilities, early warning systems, flood protection infrastructure, established disaster response mechanisms, and a multi-layered social protection system to respond to shocks. However, Dujuan highlights the limits of preparedness, such as when rainfall exceeds design values for infrastructure. It is important to strengthen structural and physical adaptation planning along with social adaptation measures to the increasingly heavy rainfall resulting from typhoons in this region.

1 Introduction

Typhoon Dujuan, the 25th typhoon of the 2026 typhoon season in Japan, developed over the Western Pacific Ocean in September 2026, evolving from a tropical depression into a tropical storm before strengthening into a typhoon, with sustained winds exceeding 120 km/h and powerful gusts ([RainViewer](#); [WeatherUSA](#)). On 13 September 2026, it originated as a stationary tropical depression, with winds of 28 km/h and a central pressure of 1005 mb, before gradually tracking west and northwest towards Japan. As the system became more organised, it strengthened into a tropical storm by 16 September with sustained winds of 65 km/h, gusts of 75 km/h and a central pressure of 994 mb. On 17 September, Dujuan intensified into a typhoon, reaching sustained winds of 120 km/h, gusts of 138 km/h and a central pressure of 981 mb. On 21 September, Dujuan reached its strongest recorded intensity, with sustained winds of 130 km/h, gusts of 150 km/h and a central pressure of 971 mb. Its centre was at 33.7°N, 139.8°E, approximately 63 km from Japan, moving northeast at 24 km/h ([RainViewer](#); [WeatherUSA](#)).

On 21 September 2026, Typhoon Dujuan made landfall on the Boso Peninsula in Chiba Prefecture, just east of Tokyo, before tracking north along Japan's Pacific coast. The storm brought torrential rainfall, flooding and landslides to the Kantō region, particularly affecting Chiba and Kanagawa prefectures ([BBC, 2026](#); [The Japan Times, 2026](#), [ClimaMeter, 2026](#)). The Japan Meteorological Agency issued its highest-level landslide alerts for parts of the Izu Islands and surrounding prefectures, warning residents of the dangers associated with the exceptionally heavy rainfall ([Independent, 2026](#)). By 22 September, Dujuan had weakened into a tropical storm, with sustained winds of 111 km/h, gusts of 128 km/h and a central pressure of 975 mb. Its centre was located at 39.0°N, 150.2°E, moving northeast at 48 km/h as it continued away from Japan ([RainViewer](#); [WeatherUSA](#)).

1.1 Impacts

Typhoon Dujuan caused significant human, infrastructure and socio-economic impacts across the affected prefectures, with 17 reported deaths in the region as per the latest FDMA reports ([FDMA, 2026](#)). It triggered 470 landslides ([MLIT, 2026](#)), causing river flooding and levee breaches in several regions and disrupting essential services, including electricity, air, railway and road transport networks. Typhoon Dujuan, the succeeding Typhoon Surigae, and subsequent frontal rainfall reportedly affected over 2,400 residential buildings ([FDMA, 2026](#); [Cabinet Office, 2026](#)). Typhoon Dujuan's devastating impacts further compounded damage from earlier flooding events in Chiba prefecture in August and September 2026, placing additional pressure on local infrastructure, livelihoods and community coping capacities ([Lee et al., 2025](#)). Older adults, foreign residents and people dependent on long-term care services were some of the most vulnerable groups who faced heightened risks due to mobility restrictions, language and information barriers, and disruptions to essential services.

1.2 Typhoons in Japan and the western Pacific

The Western North Pacific basin (WNP) is the most active tropical cyclone (TC) region globally, with approximately 26 named storms annually on average, exposing nations across east and southeast Asia to dangerous weather conditions ([Wang & Wang, 2023](#)). 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](#)).

In the WNP, there may have been a slowdown in translation speed, leading to potentially longer exposures to typhoon conditions ([Lai et al., 2019](#); [Yamaguchi and Maeda, 2020a](#)), as well as a poleward (northward) shift in storm tracks resulting in a greater number of typhoons approaching Japan ([Yamaguchi and Maeda, 2020b](#); [Kossin et al., 2016](#)). In Chapter 11 of its sixth assessment report (AR6), the Intergovernmental Panel on Climate Change (IPCC) reported on and projected a further rise in exposure to tropical cyclones towards the northern side of the basin with global warming, affecting Japan and mainland East Asia ([Seneviratne et al., 2021](#)). In Southeast (East) Asia, there is evidence of a decreasing (increasing) trend in TC passages during the boreal autumn (around September-October), also suggestive of a northward shift in storm tracks, 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](#)), and an intensification of landfalling storms across the basin by around 12-15%, resulting in a substantial rise in the fraction of the most intense categories ([Mei & Xie, 2016](#)). Finally, in Japan, statistical analysis of recent typhoon characteristics suggests an increase in wind speeds and extreme rainfall over the past few decades ([Nayak & Takemi, 2023](#); [Shen et al., 2024](#)).

Recent attribution studies help to further elucidate the emerging influence of warming on TCs in the basin. In the Philippines, the wind speeds from landfalling Typhoons Bopha, Mangkhut and Haiyan

were found to have increased by 10 m/s, 2 m/s and 2 m/s, respectively, relative to preindustrial times according to 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 ([Takayabu et al., 2015](#)). 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 total rainfall ([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](#)).

In Japan, several studies have assessed the influence of climate change on Typhoon Hagibis. Using a probabilistic approach, one study found that the extreme amount of rainfall associated with Typhoon Hagibis in 2019 was 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](#)), with a separate pseudo-global warming analysis finding a similar result of a 6-7% increase in rainfall averaged over the Kantō and Tōhoku regions ([Fujiwara et al., 2025](#)).

Attribution studies have also been conducted for other heavy rainfall events in Japan, consistently finding attributable increases except for one TC event in 1993 ([Kawase et al., 2019](#); [Imada et al., 2020](#); [Watanabe et al., 2024](#); [Hatsuzuka et al., 2025](#)). Finally, several studies analyse future characteristics of historical typhoons, again finding consistent increases in extreme rainfall with further warming, alongside increases in intensity, intensification rate, and compound flooding risk ([Tsuboki et al., 2014](#); [Hatsuzuka et al., 2020](#); [Miyasaka et al., 2020](#); [Nayak & Takemi 2020](#); [Toyoda et al., 2025](#); [Tanaka et al., 2023](#)).

1.3 Scope of this report

In this study, we characterise the event in several ways in order to examine all links in the causal chain from human-caused warming to the extreme rainfall that led to the floods. In Section 2, we apply World Weather Attribution's probabilistic attribution protocol to examine changes in extreme rainfall, atmospheric water vapour (precipitable water) and sea surface temperatures across and around the affected region. In Section 3, we present additional analysis using several complementary methods; using a combination of different approaches in this way increases our confidence in the final attribution statement. In Section 4, we evaluate other factors that led to the severe impacts from the typhoon, and in Section 5, we provide a short summary bringing together all of these strands of evidence.

2. Probabilistic attribution

In this section we apply the World Weather Attribution probabilistic attribution protocol to examine trends in extreme rainfall, atmospheric water vapour (precipitable water, PrW) and sea surface temperatures (SSTs). Full details of the methods and datasets used in this section can be found in [Appendix A1](#).

For all indices, we focus on the active typhoon season from August to October each year. The event definitions studied in this section are as follows:

- **Extreme rainfall:** Peak August-October 2-day rainfall accumulation, averaged over the Kantō region (Fig. 2.1.1).
- **Precipitable water:** Peak August-October 2-day running mean of precipitable water vapour, averaged over the region from 33°N-37.2°N, 138.3°E-143°E, containing the Kantō region and surrounding waters to the south and east (Fig. 2.2.1).
- **Sea surface temperatures:** Mean August-October SSTs over the region from 30°N-41°N, 129°E-148°E (Fig. 2.3.1).

For each event definition, we study the influence of anthropogenic climate change by comparing the likelihood and intensity of similar events in the current climate with those in a 1.4°C cooler climate without human-caused warming (based on [Forster et al., 2026](#)). For rainfall and precipitable water we also extend this analysis into the future by assessing the influence of a further 1.4°C of global warming from the present. This is in line with the latest Emissions Gap Report from the United Nations Environment Programme, which shows that, given currently implemented policies, the world is on track for at least a 2.8°C temperature rise by the end of the century ([UNEP, 2025](#)).

2.1 Extreme rainfall

In this section we evaluate trends in 2-day peak rainfall over the Kantō region during the typhoon season (August-October). Precipitable water over the study region is modelled using a generalised extreme value (GEV) distribution that is assumed to scale exponentially with global mean surface temperature (see [Appendix A1](#) for full details of data and methods used).

Three gridded datasets and observed data from 140 stations within the study region (Kantō) were used as candidate observations for studying this event. Figure 2.1.1 shows the 2-day rainfall during September 20-21 associated with Typhoon Dujuan, and the time series for the seasonal (August-October) maxima of 2-day accumulated rainfall (hereafter, ASO-rx2day), area-averaged over the Kantō region (red highlight in Fig. 2.1.1 (a-d)). Despite differences in the resolution of the individual datasets, there is good agreement between the gridded products and the stations in terms of the spatial distribution of the rainfall associated with the event, with the heaviest rainfall recorded over the coast, and becoming less pronounced inland. In the time series of rainfall averaged over the study region, there is good agreement between the gridded datasets and the station observations in terms of interannual variability, although the JRA reanalysis generally exhibits higher magnitudes with slightly more pronounced peaks.

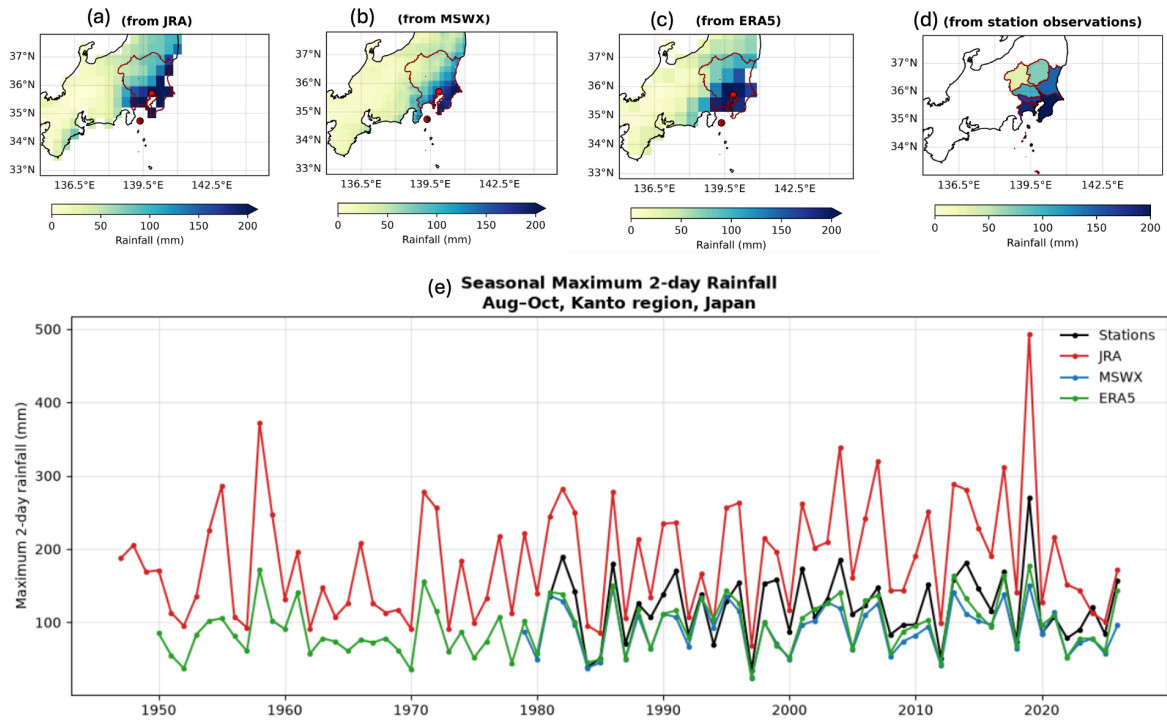


Figure 2.1.1: Maps of rainfall accumulation over the study region from September 20-21, 2026 in (a) JRA3Q reanalysis, (b) ERA5 reanalysis, (c) MSWX and (d) stations (averaged over each of the seven prefectures that constitute the study region). The study region (hereafter, Kantō region) is outlined in dark red. The red dots highlight Oshima Island and Edogawa, Tokyo, where the rainfall associated with the typhoon was record-breaking. (e) Annual time series of the seasonal (Aug-Oct) maxima of 2-day accumulated rainfall over the study region in the respective datasets. The last value in the time series corresponds to the rainfall during Typhoon Dujuan on Sept 20-21, 2026.

2.1.1 Observed trends

As seen in Figure 2.1.1 (e), ASO-rx2day in the Kantō region has high year-to-year variability. Therefore, we test the sensitivity of rainfall to the major modes of variability that may influence rainfall extremes in the region - namely, El-Nino Southern Oscillation - in addition to global mean surface temperature (GMST), to understand the role of long-term warming in influencing trends in rainfall (see [Appendix A1.4](#) for details of the statistical model used).

Figure 2.1.2 shows the fitted model in which ASO-rx2day depends on both smoothed GMST and the concurrent (September) value of the detrended Niño3.4 index, for each dataset. While the fitted trend (black line) is able to capture the long-term trend (dashed green lines) associated with GMST, the year-to-year variability in the rainfall is not effectively explained by the September Niño3.4 index. With the exception of MSWX, which suggests a decrease, all datasets exhibit an increase in extreme 2-day rainfall associated with global warming. Under concurrent El Niño conditions (positive values of the September Niño3.4 index) there is a slight tendency towards increased rainfall in the ERA5, MSWX and station-aggregated data, while the JRA-3Q reanalysis suggests a decrease in rainfall. Since the interannual variability is not effectively captured by the concurrent Niño3.4 state, the remainder of the analysis is therefore carried out using a statistical model in which the ASO-rx2day depends only on the smoothed GMST time series, and the effect of ENSO is not considered further.

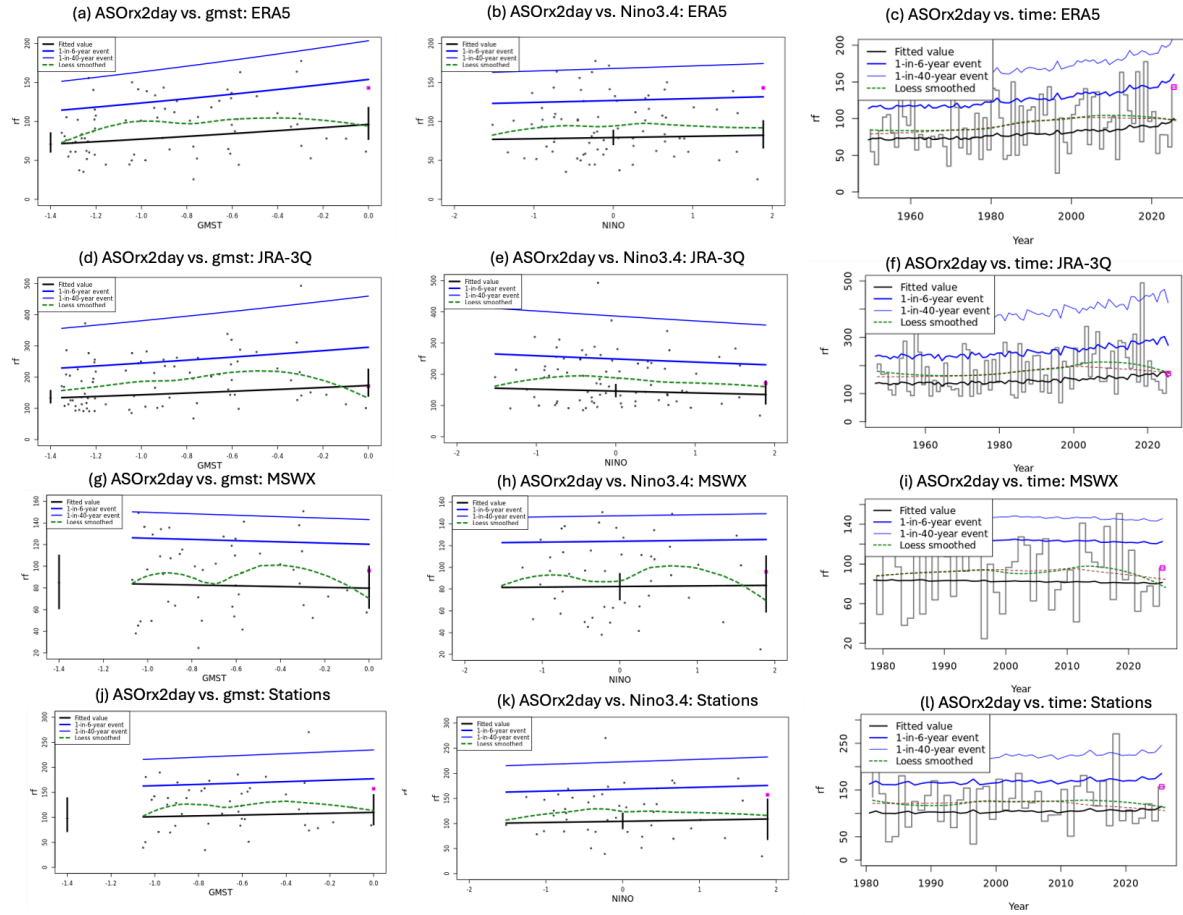


Figure 2.1.2: Fitted model overlaid on observed seasonal (Aug-Oct) maxima of 2-day accumulated rainfall (ASO-rx2day) during the typhoon season from ERA5 (top), JRA-3Q (top middle), MSWX (bottom middle) and the station mean (bottom). In all panels, the solid black line denotes expected rx2day in the season each year, given the observed values of the covariates. Blue lines indicate the expected magnitude each year of a 1-in-6-year (thick line) and 1-in-40-year event (thin line). The green dashed line is a nonparametric Loess smoother. 2026 value is highlighted with a magenta box. **(a, d, g, j)** ASO-rx2day as a function of GMST, with Niño3.4 index held constant; **(b, e, h, k)** ASO-rx2day as a function of September Niño3.4 index, with GMST held constant; **(c, f, i, l)** ASO-rx2day as a function of both GMST and September Niño3.4 index in each year.

Table 2.1.1 summarises the magnitude of the 2 days of heavy rainfall associated with Typhoon Dujuan in the Kantō region in each of the datasets and the return period in today's climate, along with the changes in the likelihood and intensity of similar events in today's climate compared to the pre-industrial climate, which would have been 1.4°C cooler. When averaged over the whole Kantō region, the rainfall event associated with the storm is not exceptional, with best estimates of the return period ranging between 2 and 4 years. For the attribution analysis with climate models, we use a rounded-off value of 3 years to define the event. It is important to note that this return period, which is based on the rainfall averaged over the wider region, does not reflect the locally very extreme nature of the rain spell in the most impacted prefectures, which range from 20 years in Izu Oshima to 150 years in Miura ([Appendix A3](#)). Table A3.1 summarises the estimated return periods in today's climate at stations in Chiba, Kanagawa, Ibaraki and Tokyo prefectures where rainfall records were reportedly

broken ([BBC, 21 September 2026](#)). This is also illustrated in the gridded datasets - Figure A3.1 shows the return period associated with the event in today's climate calculated at each grid. Return periods are higher by at least an order of magnitude in the southeastern part of the wider Kanto region, where most of the rainfall associated with the storm fell.

While ERA5 and JRA-3Q show increasing trends in extreme rainfall associated with GMST, consistent with the station-averaged data, MSWX shows a decreasing trend. However, the estimated changes encompass zero in all datasets (Table 2.1.1), indicating that the change is not statistically significant. To understand whether this difference in the direction of change between MSWX and the other datasets is an artefact of the datasets themselves or the length of the time series, we also model the changes per grid cell for the full series and from 1979 onwards, to discern any differences in the spatial patterns (Figure A3.2). Since 1979 there has been a slight drying in the mountainous northern prefectures of Gunma, Tochigi and Saitama, which is more pronounced in MSWX than the other gridded products; however, the longer-term trend is toward increased rainfall. We additionally investigate the sensitivity of the nature of changes to the choice of the spatial extent for the event definition (Table A3.2), by repeating the trend analysis considering only Chiba, Tokyo, Ibaraki, Saitama and Kanagawa prefectures that received the heavy rainfall during Typhoon Dujuan, which excludes the mountainous northern part of the study region. The results are very similar in terms of the trends, albeit with a less pronounced decrease in MSWX compared to the average over the Kantō region, and once again all datasets encompass no change. This suggests that the choice of the larger Kantō region is not expected to affect the results of the analysis, with the added advantage of being able to carry out the attribution analysis with climate models on a wider homogeneous region.

Table 2.1.1: Return period and observed/derived magnitude for the 2026 observed ASO-rx2day, as well as probability ratio and change in magnitude for the event due to 1.4°C of human-caused global warming.

Dataset	Magnitude (mm/2day)	Return period (years)	% change in intensity	Probability ratio
ERA5	143	4.36 (2.32 to 13.1)	35.8 (-1.21 to 82.9)	6.07 (0.92 to 16914)
JRA	171	1.56 (1.20 to 2.45)	30.2 (-3.55 to 75.7)	1.67 (0.94 to 2.70)
MSWX	96.0	2.28 (1.50 to 8.93)	-6.18 (-40.9 to 42.9)	0.86 (0.16 to 3.41)
Stations	157	3.67 (1.71 to 110)	12.0 (-31.4 to 104.5)	1.59 (0.03 to 36.3)

2.1.2 Multi-model attribution of trends

Next, we evaluate the influence of anthropogenic climate change on ASO-rx2day by fitting the same GEV model with GMST as a covariate to three families of climate models (CORDEX, HighResMIP and the highresolution, single model ensemble- d4PDF) (see [Appendix A1.3](#) for details). For the d4PDF ensemble, for which 100 realisations were available, we first synthesised these results into a single result for the ensemble, then treated that synthesised estimate as a single model in order to combine it with results from reanalysis and the HighResMIP and CORDEX climate models.

Figure 2.1.3 shows synthesised changes in intensity of ASO-rx2day based on the observation-based datasets (blue) and climate models (red) between today's climate and a pre-industrial climate, which would have been 1.4°C cooler than 2026 (Figure 2.1.3a), and between today's climate and a future 1.4°C warmer climate (Figure 2.1.3b). All observed datasets, with the exception of MSWX, suggest an increase in rainfall intensity associated with the 1.4°C warming since pre-industrial times (as already discussed in Section 2.1.1). However, this increase is not consistent in these datasets, with ERA5 and JRA showing stronger increases of ~35% increase in the intensity of rainfall associated with GMST, while the station-average demonstrates a 12% increase, all with uncertainties encompassing no change and very high changes. The high resolution climate models- CORDEX and d4pdf also show increases consistent with observed trends and uncertainties from internal variability. However, the three HighResMIP models that passed model evaluation show no change or a small decreasing trend as the best estimate, but with very narrow confidence intervals implying low variability. (See Figure A6.1 for the full synthesis figures including all the individual observed datasets and climate model simulations.) This may in part be due to resolution of the models from this family that are used in the attribution analysis (e.g., CNRM-CM6-1-HR and EC-Earth-3P with resolutions ~50km and ~70km) not being fine enough to resolve the variability in rainfall that is characteristic of these regions (e.g., [Mizuta et al., 2022](#)), as captured by the four observed datasets and the CORDEX and d4PDF models. Due to the sensitivity of the overall synthesised estimates to HighResMIP, and the need for further research to determine why HighResMIP results show unrealistically low variability, we exclude HighResMIP in the attribution analysis. The synthesised results suggest an increase of 15% in two-day rainfall over the region (95% confidence interval: -23.4% to 74.1%), and a further increase of around 8% (95% confidence interval: -3.25% to 18.8%) as the world continues to warm. The nature of these results is characteristic of rainfall trends in island domains, which are influenced by processes which may not be fully resolved in the climate models (e.g., [Kew et al., 2025](#); [Zachariah et al., 2024](#)) unless tailored for the region. Note that the d4PDF runs are not available for future warming levels, and therefore the projected changes do not include this model family. Taking together the observations, models, and the expectation from Clausius-Clapyeron, despite the noisy nature of rainfall in this region, we conclude that climate change is a driver of increasing heavy 2-day rainfall trends in the region, although we cannot quantify this change due to the large uncertainties in the observations and models.

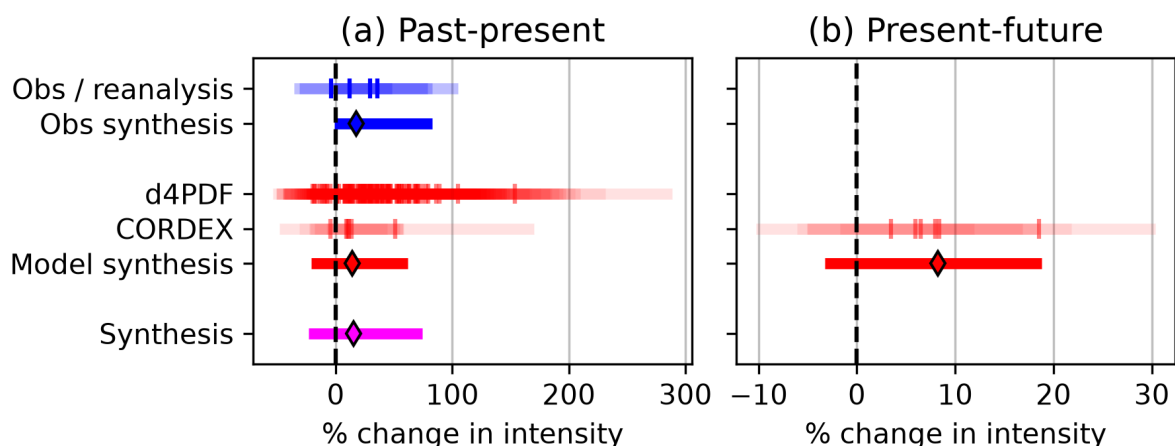


Figure 2.1.3: Synthesised estimates of relative change in intensity of ASO-rx2day associated with (a) 1.4°C from the preindustrial climate to 2026 (past-present) and with a further 1.4°C of warming (present-future, using

climate models only). Shaded bars represent bootstrapped uncertainties in each dataset; vertical ticks indicate results for individual datasets; coloured diamonds represent synthesised results for each group.

		Intensity change (%)	Probability ratio
Observations	Past - present	17.3 (-27.5 to 96.1)	1.95 (0.16 to 72.3)
Models		14 (-20.7 to 61.9)	1.39 (0.524 to 9.94)
Synthesis		15.1 (-23.4 to 74.1)	1.48 (0.367 to 15.8)
Future	Present - future	8.22 (-3.25 to 18.8)	1.38 (0.551 to 8.59)

Table 2.1.2: Summary of results for rx2day during the typhoon season, also presented in Fig. 2.1.3: percentage change in intensity and change in the likelihood of similarly extreme ASO-rx2day associated with 1.4°C of warming from the preindustrial climate to 2026 (past-present) and with a further 1.4°C of warming (present-future, using climate models only). Numbers in brackets indicate 95% confidence intervals. Results are presented for what is currently a 1-in-3-year event.

2.2 Precipitable water

In this section we evaluate trends in precipitable water vapour (PrW) during the typhoon season (August-October). PrW represents the amount of water vapour available in the atmosphere that could potentially fall as rain, so represents the moist atmospheric conditions that enable extreme rainfall. For consistency with the rainfall analysis presented above, we examine two-day peak precipitable water during the season (denoted PrW2x), but we also tested longer durations and found similar trends ([Appendix A4](#)).

This variable is not available in the higher-resolution CORDEX and HighResMIP climate models, so to ensure that the study region is large enough to be identifiable in CMIP6 model output, we extend the study region to a box from 33N-37.2N and 138.3E-143E, of which the Kantō region forms roughly the upper left quarter (Figure 2.2.1). In a further sensitivity analysis ([Appendix A4](#)) we also compared trends over this larger region with trends over Kantō in both JRA3Q and ERA5 reanalysis, and found very similar trends in both regions, so we do not expect the results to be sensitive to this choice.

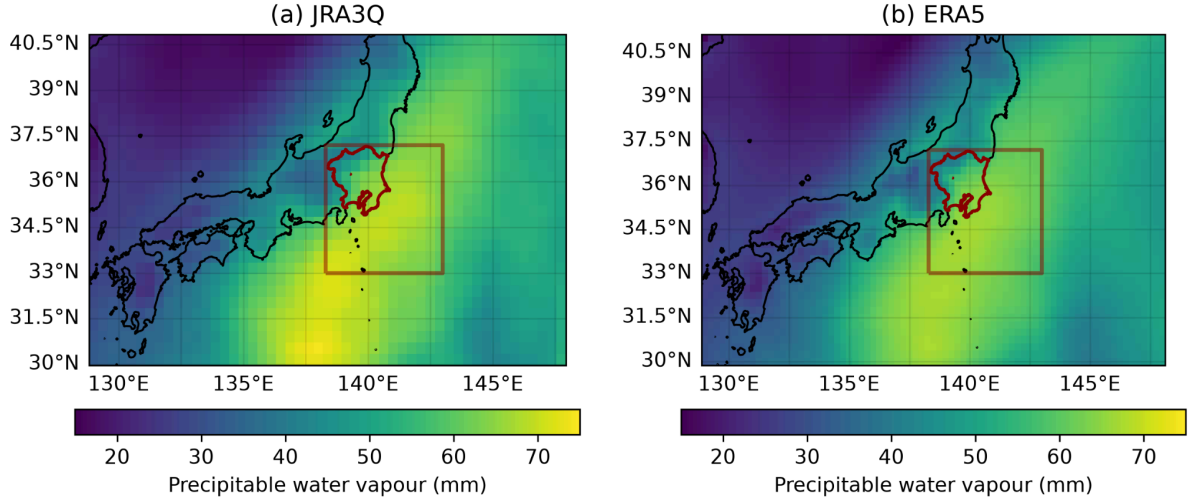


Figure 2.2.1: Mean precipitable water over the study region from September 20-21, 2026 in (a) JRA3Q reanalysis and (b) ERA5 reanalysis. The Kantō region studied in Section 2.1 is outlined in dark red; the box denotes the wider study region considered in this section.

Precipitable water over the study region is modelled using a Gaussian distribution that is assumed to scale exponentially with global mean surface temperature (see [Appendix A1](#) for full details of data and methods used). In line with the protocol described in [Philip et al. \(2020\)](#), climate models are evaluated in their representation of both the seasonal cycle, spatial pattern and statistical distribution of atmospheric moisture over the study region (see [Appendix A5.2](#)) before being included in the attribution analysis. We also investigate the effect of including the concurrent ENSO conditions as a covariate in the model, although this was not found to improve the fit of the statistical model or to contribute to the expected intensity of the event, and so is not included in the full attribution analysis.

2.2.1 Observed trends

Figure 2.2.2 shows the fitted model in which precipitable water (PrW) depends on both smoothed GMST and the September value of the detrended Niño3.4 index, based on the JRA3Q reanalysis dataset. Results using ERA5 reanalysis were very similar (see [Appendix A4](#), Figure A4.2). The fitted trend (black line) does a good job of capturing the long-term trends as a function of both GMST and the September Niño3.4 index (dashed green lines), with increasing GMST generally associated with higher values of PrW and strongly positive values of the September Niño3.4 index typically associated with lower values of PrW than would be expected in a neutral ENSO state (panels a and b). However, very little of the interannual variability is captured by the Niño3.4 state, suggesting that this is unlikely to be playing an important part in determining peak precipitable water during the typhoon season; a comparison of the Akaike information criterion (AIC), a standard statistical measure of goodness of fit, confirms that including the ENSO covariate in the model does not improve the fit enough to justify the inclusion of the additional parameter in the model. The remainder of the analysis is therefore carried out using a statistical model in which PrW_{2x} depends only on the smoothed GMST time series, and the effect of ENSO is not considered further.

The fitted statistical model allows us to estimate how unusual it is to observe similarly high levels of precipitable water in the atmosphere in the current climate; in both the JRA3Q and ERA5 reanalysis

datasets, similar conditions are expected to occur roughly once every ten years, or (equivalently) in about 10% of years (Table 2.2.1). In response to 1.4°C of global warming, the amount of precipitable water in the atmosphere over Kantō and the surrounding oceans has increased by around 7%, slightly below what we would expect from the Clausius Clapeyron relationship between temperature and water vapour but still consistent with the effect. Similarly moist atmospheric conditions are now around twenty times more likely to occur than they would have been in a world without human-caused warming.

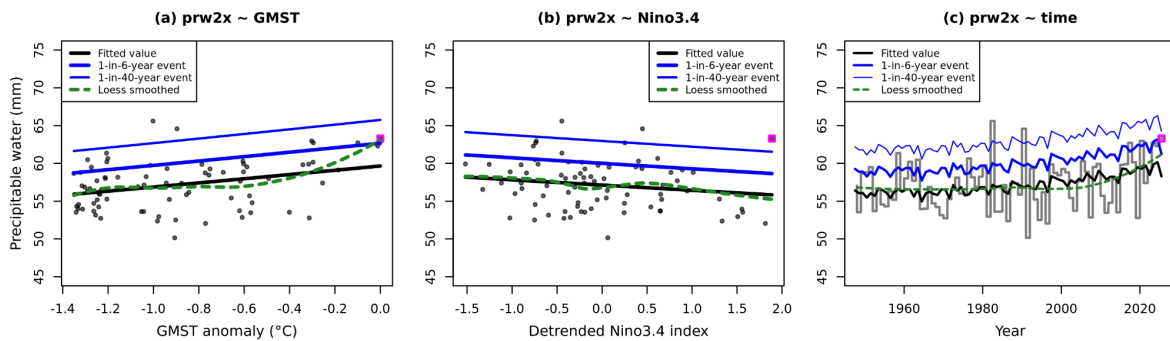


Figure 2.2.2: Fitted model overlaid on observed peak 2-day precipitable water (*PrW2x*) during the typhoon season from the JMA dataset. In all panels, the solid black line denotes an expected 2-day peak precipitable water each year, given the observed values of the covariates. Blue lines indicate the expected magnitude each year of a 1-in-6-year (thick line) and 1-in-40-year event (thin line). The green dashed line is a nonparametric Loess smoother. 2026 value is highlighted with a magenta box. **(a)** Precipitable water as a function of GMST, with Niño3.4 index held constant; **(b)** precipitable water as a function of September Niño3.4 index, with GMST held constant; **(c)** precipitable water as a function of both GMST and September Niño3.4 index in each year.

Dataset	Event magnitude (mm)	Return period (years)	% change in intensity	Probability ratio
JR3Q	63.3	7.8 (3.9 to 27)	7.0 (2.0 to 11)	17 (2.2 to 180)
ERA5	63.9	10 (4.6 to 50)	6.3 (1.4 to 10)	20 (1.8 to 350)

Table 2.2.1: Observed event magnitude of *PrW2x* in each dataset, along with estimated return period, probability ratio and change in magnitude associated with 1.4°C of global warming. Numbers given in parentheses represent a 95% confidence interval obtained via bootstrapping.

2.2.2 Multi-model attribution of trends

We evaluate the influence of anthropogenic climate change on precipitable water by repeating this statistical modelling process for two reanalysis datasets and a multi-model ensemble of runs from the CMIP6 experiment, consisting of 50 realisations from MPI-ESM1-2-LR, 5 from UKESM1-0-LL, 2 from CESM2-WACCM, and one realisation each from six other distinct models (see [Appendix A5.2](#) for details). Where multiple realisations were available for a single model, we first synthesised these results into a single result for each ensemble, then treated each synthesised estimate as a single model in order to combine them with results from reanalysis and the other climate models. All results were combined using the algorithm described in [Otto et al., \(2024\)](#). As discussed above, the possible

contribution of the current El Niño conditions to the intensity or likelihood of the event is not considered in this attribution analysis.

Figure 2.2.3 shows the changes in intensity of PrW2x for the reanalyses (blue) and models (red). JRA3Q and ERA5 exhibit similar increases, with PrW2x now an estimated 7% higher than it would have been in a preindustrial climate (Table 2.2.2). Changes in the climate models are consistently higher than this, leading to a synthesised estimate of 9.6% more precipitable water now than in a 1.4°C cooler climate (95% confidence interval: 5.4% to 13.5%), a change consistent with what we would expect from the Clausius Clapeyron relationship between air temperature and moisture content. This trend is projected to continue into the future at a similar rate.

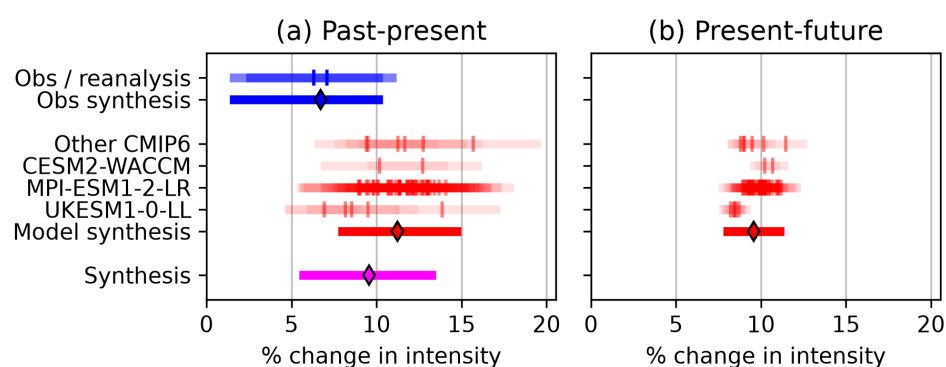


Figure 2.2.3: Synthesised estimates of relative change in intensity of PrW2x associated with (a) 1.4°C from the preindustrial climate to 2026 (past-present) and with a further 1.4°C of warming (present-future, using climate models only). Shaded bars represent bootstrapped uncertainties in each dataset; vertical ticks indicate results for individual datasets; coloured diamonds represent synthesised results for each group.

		% change in intensity	Probability Ratio
Reanalysis	Past - present	6.7 (1.7 to 10.9)	24.4 (1.8 to 833)
Models		11.2 (7.7 to 15)	758 (14 to 83792)
Synthesis		9.6 (5.4 to 13.5)	75.9 (3.4 to 3975)
Models	Present - future	9.6 (7.8 to 11.4)	7.8 (6.5 to 9.3)*

Table 2.2.2: Summary of results for PrW2x during the typhoon season, also presented in Fig. 2.2.3: percentage change in intensity and change in the likelihood of PrW2x associated with 1.4°C of warming from the preindustrial climate to 2026 (past-present) and with a further 1.4°C of warming (present-future, using climate models only). Numbers in brackets indicate 95% confidence intervals. *Results are presented for what is currently a 1-in-10-year event, meaning that the future probability ratio is capped at 10 (annual events cannot have a return period of less than 1 year).

2.3 Sea surface temperatures

In this section, we analyse August-October mean sea surface temperatures (SSTs) within the region from 129E-148E and 30N-41N (Figure 2.3.1) using three observational datasets (see [Appendix A1.1](#) for details). Understanding how SSTs change as a result of GMST and ENSO is important because higher SSTs lead to increased humidity, and thus stronger intensification of cyclones passing over the area. This in turn can increase wind speeds and precipitation levels, leading to increased risk of both flooding and wind damage upon landfall.

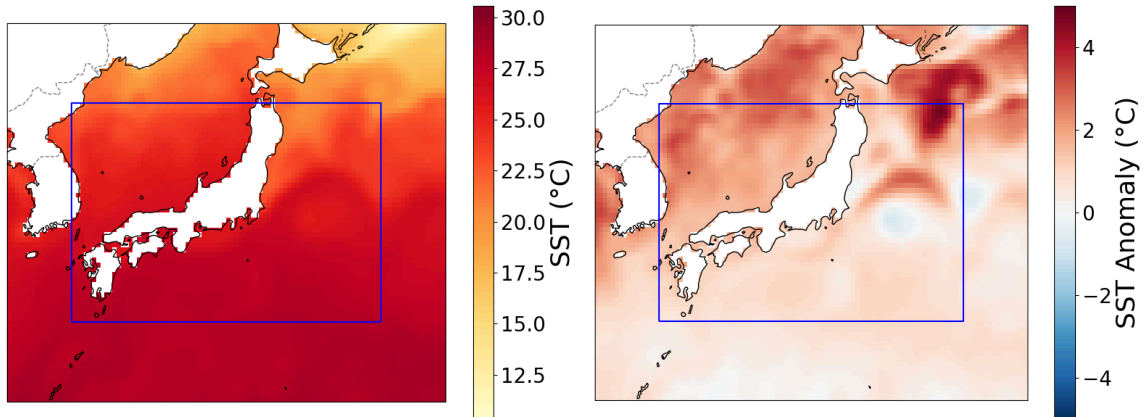


Figure 2.3.1: August-Sept 2026 SSTs (left) and SST anomalies compared to the 1991-2020 average over the full typhoon season (August-October) (right). Made using OISST data.

The 3-month SSTs are modelled using a normal distribution that is assumed to shift with global mean surface temperature. The addition of ENSO as a covariate does improve the fit, according to the Akaike information criterion (AIC), with respect to a statistical model using GMST as the sole covariate. Therefore, we consider ENSO's influence when examining the observational datasets, to quantify the extent to which it may have influenced SSTs relative to the influence of warming in the historical record.

2.3.1 Observed trends

Observed SSTs for October were not available at the time of writing, so we compare the August-September mean with the seasonal mean from previous years to understand how unusual the conditions prior to Typhoon Dujuan were compared to previous seasons. In two of the three datasets, the return period estimates suggest that the SST from August-September 2026 was not particularly unusual for the season in today's climate, although in the ERSST dataset the 2026 value is around 0.7°C higher than in either OISST or OSTIA, reaching extremely unusual temperatures (Table 2.3.1).

In all three datasets, the fitted model follows the nonparametric Loess smoothed trend closely (Figure 2.3.2), and the normal distribution seems to fit the data well (Figure 2.3.3). All datasets show a clear increase in SSTs as the world warms (Figure 2.3.4a); while the addition of the ENSO covariate does improve the fit of the model by capturing more of the variability in the time series, the strongly positive ENSO phase during September 2026 would usually be associated with lower SSTs than in a

neutral phase (Figure 2.3.4b), suggesting that it may be offsetting the effect of human-caused warming to some extent.

All datasets indicate that climate change has caused such events to be significantly more likely and between 1.6°C and 3°C warmer. Uncertainties in temperature change for SSTs are small, indicating a high confidence that climate change has warmed the seas around where Tropical Cyclone Dujuan was formed and travelled. In contrast, the strong El Niño conditions during September 2026 are expected to decrease the likelihood of similarly warm SSTs occurring in the study region.

Dataset	Event		Influence of 1.4°C GMST increase		Influence of El Niño	
	Magnitude (°C)	Return period	Probability ratio	Change in SST (°C)	Probability ratio	Change in SST (°C)
ERSST	26.7	1780 (90.7 to 614000)	>1m (>1m to >1m)	1.64 (1.28 to 1.96)	0.08 (0.01 to 0.52)	-0.38 (-0.59 to -0.13)
OISST	26.0	5.54 (2.13 to 254)	>1m (>1m to >1m)	2.77 (1.94 to 3.42)	0.39 (0.03 to 0.83)	-0.39 (-0.66 to -0.13)
OSTIA	26.0	3.07 (1.54 to 108)	>1m (19700 to >1m)	3.05 (2.08 to 4.01)	0.59 (0.04 to 0.98)	-0.36 (-0.65 to -0.02)

Table 2.3.1: Return period and observed/derived magnitude for the 2026 event, as well as probability ratio and change in magnitude for the August-October average SST due to both GMST and ENSO.

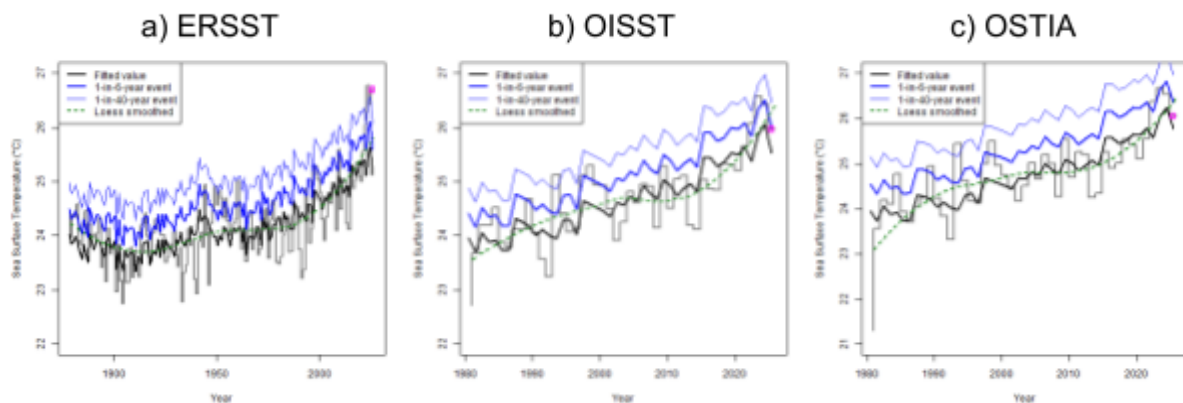


Figure 2.3.2: Fitted model overlaid on time series of August to October SSTs for three observation-based datasets. In all panels, the solid black line denotes an expected August to October SST each year, given the observed values of the covariates. Blue lines indicate the expected magnitude each year of a 1-in-6-year (thick line) and 1-in-40-year event (thin line). The green dashed line is a nonparametric Loess smoother. 2026 value is highlighted with a magenta box.

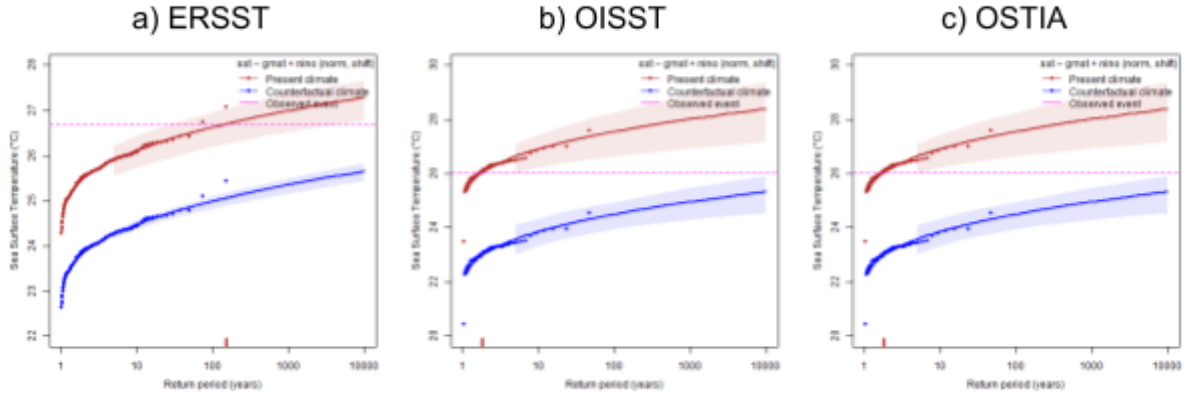


Figure 2.3.3: Return curves for August to October SSTs for three observation-based datasets. The event magnitude is shown with the dashed pink line. The red line shows the best fit curve to the data scaled to the present climate, while the blue curve shows the data scaled to the preindustrial climate for a model including both GMST and ENSO, assuming the ENSO value of 2026. Shaded areas show the 95% confidence interval obtained through bootstrapping.

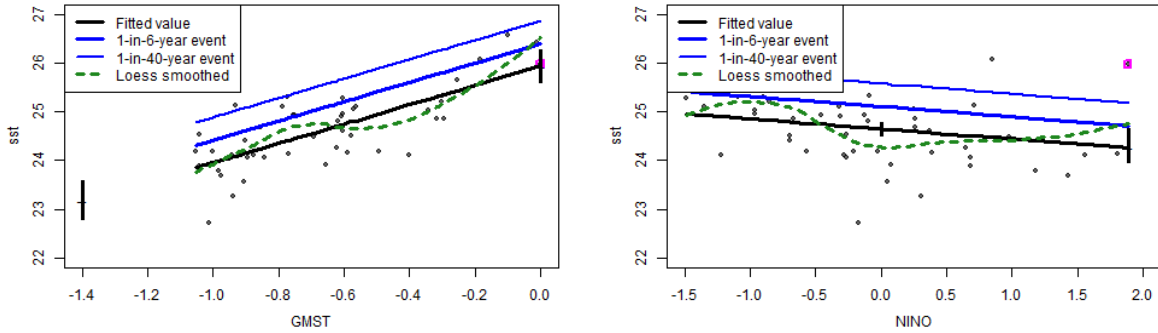


Figure 2.3.4: Fitted model overlaid on August to October SSTs, plotted against GMST (left) and ENSO (right) in the OISST dataset (similar results were obtained for the other datasets). In all panels, the solid black line denotes an expected August to October SST each year, given the observed values of the covariates. Blue lines indicate the expected magnitude each year of a 1-in-6-year (thick line) and 1-in-40-year event (thin line). The green dashed line is a nonparametric Loess smoother. 2026 value is highlighted with a magenta box.

3 Model-based attribution

3.1 Precipitable water vapour analogues

In this section we examine changes in rainfall associated with days with similar spatial patterns of precipitable water vapour (PrW) to those observed during Typhoon Dujuan, using large ensembles of global and regional climate simulations (Tamura and Sato, 2024). By representing the atmospheric moisture state in this way, the selected days (known as analogues) are characterised by both the presence of precipitable water and circulation patterns associated with tropical cyclones and fronts.

For each of September 20 and 21, we identified 100 analogue days with similar patterns of precipitable water vapour (PrW) around Japan from each of the all-forcings (ALL, representing a world with climate change, selected from the period 2011-2016) and natural-forcings (NAT, representing a world without human-caused climate change) experiments in d4PDF, yielding 200

analogues per experiment. Given the continued warming that has occurred since 2016, the impact of anthropogenic warming on the target event is likely to be greater than estimated in this assessment. More details of the method can be found in [Appendix A2.1](#).

3.1.1 Attribution Analysis

The selected precipitable water vapour (PrW)-based analogues produce spatial patterns of precipitation similar to that observed during the Typhoon Dujuan event. The 95th-percentile precipitation among the 200 analogues exceeds 200 mm over parts of the Kantō region, particularly in southern Kantō and the northern mountainous areas. However, the simulated precipitation amounts are lower than observed, possibly due to limitations of the cumulus parameterization scheme and the relatively coarse horizontal resolution (20 km) of the model.

A comparison between the ALL (Fig. 3.1.1a) and NAT experiments (Fig 3.1.1b) reveals a statistically significant increase in the 95th-percentile precipitation at some grid points over the Kantō region due to anthropogenic warming (Fig. 3.1.1c; hatching indicates $p < 0.05$). The 95th-percentile precipitation in the ALL experiment is estimated to be 1.2 – 1.4 times that in the NAT experiment over parts of southern and eastern Kantō region (Tokyo, Kanagawa, Saitama, Chiba, and Ibaraki prefectures). However, the spatial extent and robustness of this increase remain uncertain, as the differences are not statistically significant at many grid points. More robust signals tend to occur in orographically fixed locations associated with topography and coastlines. These results suggest that extreme precipitation under meteorological conditions similar to those observed during Typhoon Dujuan has been intensified by anthropogenic warming, although the precise locations and magnitudes of the enhancement within the Kantō region remain uncertain. Further high-resolution numerical simulations are therefore needed to better quantify these effects.

The probability distributions of the regional maximum 48-hour accumulated precipitation over the southern and eastern Kantō region indicate a higher probability of exceeding 200 mm in the ALL experiment than in the NAT experiment (Fig. 3.1.1d). This finding is consistent with the anthropogenic intensification of extreme precipitation suggested by the 95th-percentile analysis.

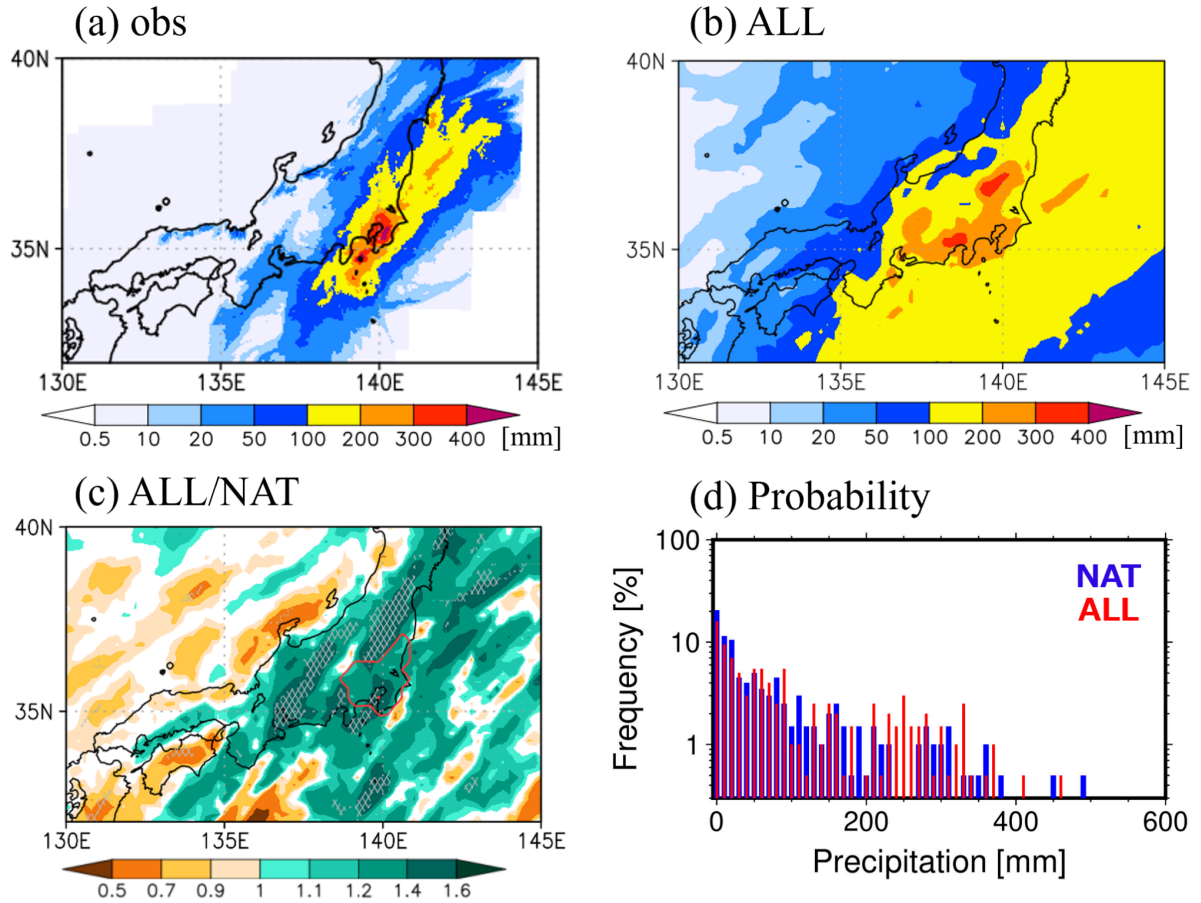


Figure 3.1.1: (a) Spatial distribution of the observed 48-hour precipitation (mm). (b) Spatial distribution of the 95th-percentile 48-hour accumulated precipitation (mm) in a composite of 200 PrW-based analogues in the ALL experiment. (c) Ratio of the 95th-percentile precipitation in the ALL experiment to that in the NAT experiment. Hatching indicates grid cells where the 95% bootstrap confidence interval of the ALL–NAT difference excludes zero. (d) Frequency distributions of the regional maximum 48-hour accumulated precipitation within the Kantō region excluding Gunma and Tochigi prefectures, calculated separately for each analogue in the ALL (red) and NAT (blue) experiments. [Observed data source: [Radar/Raingauge-Analyzed Precipitation \(RAP\)](#)]

3.1.2 Interpretation of results

PrW-based analogues reasonably reproduce the observed precipitation pattern associated with Typhoon Dujuan, although the most intense precipitation amounts are underestimated, likely due in part to the model's relatively coarse 20-km resolution and limitations of the cumulus parameterization.

Anthropogenic warming likely intensified extreme precipitation over the Kantō region, with the 95th-percentile precipitation increasing by approximately 20–40% in parts of the southern and eastern Kantō region. However, the spatial extent and magnitude of the enhancement remain uncertain, highlighting the need for higher-resolution simulations.

3.2 Typhoon tracks and intensity

In this section we evaluate changes in intensity the wind speeds and atmospheric pressures associated with typhoon tracks in the region, based on 100 members (6,000 years of data) using both all-forcings (ALL) and natural-forcings (NAT) simulations from the d4PDF Large-Scale Ensemble Climate Prediction Database. We extracted all typhoons that passed within a radius of 100 km centered on Chiba (Typhoon Dujuan’s landfall point) and grouped similar tracks into clusters. Results are presented for the wider group of typhoons that made landfall or approached the target coastal area, and also for the subset with trajectories similar to that of Typhoon Dujuan. Furthermore, based on the central pressure of the target typhoon at the time of its passage through the circle, the data were divided into three groups—“all typhoons,” “typhoons with central pressures equal to or lower than the target typhoon,” and “typhoons with central pressures within 2% above or below the target typhoon’s central pressure”—to analyze and compare their intensities. More details of the method can be found in [Appendix A2.2](#); the approach is currently in press at the Journal of the Japan Society of Civil Engineers (Saito, R., T. Shimura, N. Mori (2026) *Event attribution of global warming impacts on past extreme typhoons approaching Japan using d4PDF*).

3.2.1 Attribution Analysis

The total number of TCs for analysis by distance within 100 km is 512 in NAT-forced simulations and 535 under the present climate conditions. In the analysis by track cluster, we find 169 TCs under NAT forcings and 151 under present climate conditions with similar trajectories to Typhoon Dujuan. The right-hand panel of Fig. 3.2.1 shows the distribution of the central pressure at the time each simulated track crosses 30°N, in each of the scenarios, with lower pressure representing a stronger typhoon system. The left-hand side of the distribution doesn’t move, but with increasing warming the distribution becomes wider, with the peak of the distribution shifting slightly to the right and the rightmost tail extending to include the possibility of lower pressures / higher intensities. The right-hand panel of Fig. 3.2.1 shows the return period for TC Dujuan-like TC intensity and tracks; this is around 36 years in NAT simulations and 40 years under present climate conditions. There is no statistically significant difference between the likelihood of similar events between NAT and present or future climate conditions.

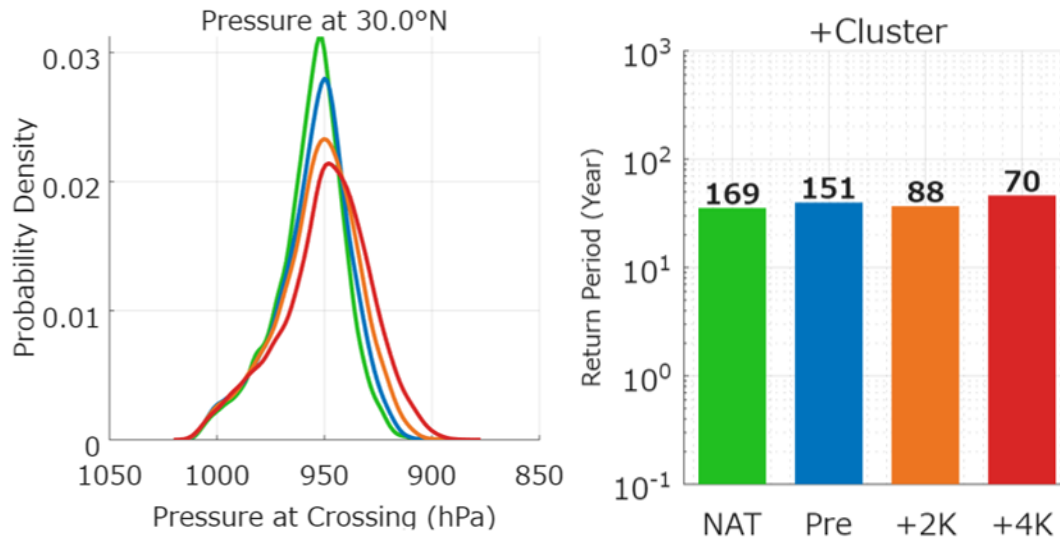


Figure 3.2.1: (left) distribution of central pressure when track crosses 30°N in each of the four climate scenarios; (right) return periods of tracks with TC Dujuan-like intensity; numbers above bars indicate total number of Dujuan-like tracks in each scenario. Both panels: green = NAT (natural forcings without human-caused warming); blue = Pre (present-day conditions using ALL forcings); orange = +2K (2°C of warming since preindustrial, using ALL forcings); red = +4K (4°C of warming since preindustrial, using ALL forcings).

Table 3.2.1 summarizes the change in intensity of TC Dujuan-like tracks between the counterfactual preindustrial climate without human-caused warming (NAT) and present climate conditions. The Lifetime Maximum Intensity (LMI) is shifted northward by 0.5-1.2°N under present climate conditions, a statistically significant change in almost all groups. No significant change is detected in the maximum wind speed along the track, but in Dujuan-like typhoons that passed within 100km of Chiba a statistically significant increase of 3.7m/s was detected, along with a decrease of 2.1hPa in central pressure at landfall.

Table 3.2.1: Summary of statistics for two types of TC samples: (a) those passing within 100km of Chiba, and (b) those with similar trajectories to Typhoon Dujuan. Results are presented for all tracks, for those with central pressures within 2% Typhoon Dujuan's central pressure (DUJUAN-class), and for those with central pressure equal to or lower than Typhoon Dujuan (DUJUAN-class and above). **Bold text** indicates statistically significant results at the 5% confidence level.

	(a) Within 100 km of Chiba		(b) Similar trajectory	
	NAT	Present	NAT	Present
Latitude of LMI [°N]				
All typhoons	33.2	34.2 (p<0.05)	34.55	35.5 (p<0.05)
DUJUAN-class(±2%)	33.9	35.1 (p<0.05)	35.67	36.2 (p=0.23)

DUJUAN-class and above	28.6	29.6 (p<0.05)	30.21	30.8 (p<0.05)
Maximum wind speed [m/s]				
All typhoons	33.60	33.5 (p=0.73)	35.37	34.7 (p=0.33)
DUJUAN-class(±2%)	38.2	38.0 (p=0.47)	38.72	38.0 (p=0.23)
DUJUAN-class and above	48.7	48.9 (p=0.68)	48.21	48.3 (p=0.60)
Wind speed at landfall [m/s]				
All typhoons	27.7	28.2 (p=0.17)	30.79	30.1 (p=0.14)
DUJUAN-class(±2%)	31.8	32.2 (p=0.27)	34.69	33.5 (p=0.06)
DUJUAN-class and above	36.9	40.6 (p<0.05)	40.59	40.9 (p=0.37)
Central pressure at landfall [hPa]				
All typhoons	984.5	984.0 (p=0.35)	979.1	980.3 (p=0.13)
DUJUAN-class(±2%)	978.2	977.9 (p=0.49)	973.3	975.1 (p=0.52)
DUJUAN-class and above	968.2	966.1 (p<0.05)	961.2	959.9 (p=0.25)

3.2.2 Interpretation of results

There is a clear increase in intensity (decrease in central pressure when crossing latitude 30°N) from NAT to present and future climate conditions. There is also a northward shift of LMI from the NAT to the present climate conditions. For Dujuan-class or stronger typhoons, we also find a statistically significant increase in wind speed at landfall and decrease in central pressure at landfall between NAT and present climate simulations

3.3. Other event attribution results by Japanese governmental research teams

The Ministry of Education, Culture, Sports, Science and Technology, and the Meteorological Research Institute, Japan Meteorological Agency have evaluated the impacts of global warming on heavy rainfall caused by Typhoon Dujuan using a storyline event attribution method, called quantitative event attribution ([Kawase et al. 2021](#); [MRI-JMA, 2026](#)). They conducted a hindcast simulation using a high-resolution weather model with 1km grid spacing, which was forced by realistic atmospheric conditions matching those during Typhoon Dujuan. Then, a non-warming experiment was conducted using realistic atmospheric conditions without the historical global warming component. The warming component was derived from the differences between historical and non-warming experiments during 2016-2025 in d4PDF and averaged over the target region at each pressure level.

The 36-hour accumulated precipitation during the period of most intense rainfall, from 03Z on 20 September to 15Z on 21 September, was increased by 22.8% due to global warming. An analysis of the number of grid points in the red box shown in Fig. 3.3.1 experiencing extreme 36-hour accumulated precipitation found that global warming increased the number of grid points with particularly heavy rainfall amounts.

These results suggest that global warming has contributed to the heavy rainfall associated with Typhoon Dujuan. In the simulation without global warming, the typhoon intensity was also found to be slightly weaker; however, further analysis is needed to clarify the significance of this difference.

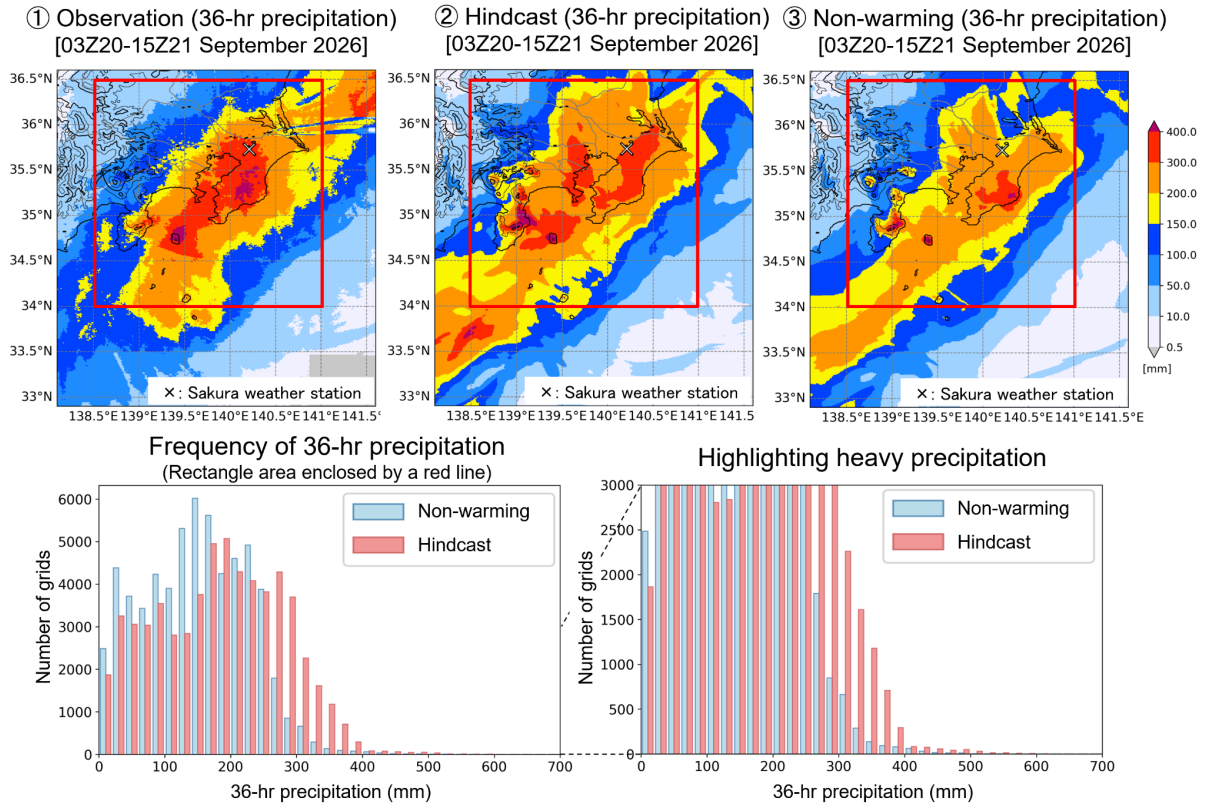


Figure 3.3.1: Simulation of heavy rainfall associated with Typhoon Dujuan. Thirty-six-hour accumulated precipitation from 03Z on 20 to 15Z on 21 September 2026. The top row shows (1) the observed precipitation, (2) precipitation simulated under actual conditions (including the effects of global warming), and (3) precipitation simulated under a hypothetical condition without global warming. For panels (2) and (3), the results are averaged over simulations initialized from nine different initial times (every three hours from 00:00 JST on 19 September to 09:00 JST on 20 September) in order to reduce simulation variability. The bottom row shows the number of grid points within the red box classified by 36-hour accumulated precipitation. In the right panel, the upper limit of the vertical axis has been adjusted to highlight changes in the larger precipitation categories. The light blue bars represent the simulation assuming no global warming, while the light red bars represent the simulation under actual conditions (including the effects of global warming). Translated from the [press release of MEXT and the Meteorological Research Institute](#), dated 23 October 2026.

4 Vulnerability and exposure

Disaster risk is shaped by the interaction between hazards and the social, economic and institutional conditions that shape the exposure, coping capacities and vulnerabilities of populations and systems ([UNDRR, 2017](#); [Rod, Aall & Selseng, 2025](#); [IPCC, 2022](#)). The impacts of a hazardous event depend on the socio-demographic characteristics of affected populations, susceptibility of people and assets to harm and the resources, legal frameworks and institutional capacities available to anticipate, manage and recover from its consequences. These interconnected dimensions highlight why events of comparable magnitude can lead to different outcomes across communities and geographical settings. Typhoon Dujuan, the 25th typhoon of the season in Japan, formed on 16 September and approached the Izu Islands and Kanto-Koshin region on 21 September illustrates this interaction. It led to torrential rainfall between 19th to 21st September, exceeding 800mm at some locations in the Izu Islands and 500mm in Chiba and Shizouka. The storm system evolved from a tropical depression into a tropical storm before strengthening into a category 1 typhoon, with sustained winds exceeding 120 km/h and gusts reaching approximately 162 km/h. Rather than making direct landfall, the system tracked along Japan's eastern coast, bringing heavy rainfall to the affected prefectures ([BBC, 2026](#); [The Japan Times, 2026](#)) particularly on the Boso Peninsula in Chiba Prefecture, Japan, on 21 September 2026, just east of Tokyo ([ClimaMeter, 2026](#)).

The Japan Meteorological Agency (JMA) had issued a highest level (5) landslide alert for parts of the Izu Islands, including Oshima, Chiba, Kanagawa and Shizouka prefectures ([Independent, 2026](#)). The typhoon brought torrential rainfall, resulting in flooding in low-lying areas and triggering landslides due to water accumulation in the soil, at multiple locations in Kanagawa and Chiba prefectures ([EOS, 2026](#)). According to the Ministry of Land, Infrastructure and Tourism's 5th October report, 470 landslides were caused by Dujuan, including 273 in Chiba alone, 175 in Kanagawa and reported flooding along 14 prefecture managed rivers in Chiba and four levee breaches at three locations ([MLIT, 2026](#)). According to Japan's Fire and Disaster Management Agency's (FDMA) 5th October report, the total death toll associated with Typhoon Dujuan rose to 17 across the affected regions, including 10 deaths in Chiba Prefecture alone majorly as a result of landslide ([BBC, 2026](#)), 5 deaths in Kanagawa and 1 casualty in Miyazaki and 1 in Kumamoto ([FDMA, 2026](#)). In Chiba Prefecture, the Koito River overflowed in Kimitsu, a road collapsed in Midori Ward, Chiba City, and flooding, overflowing manholes, or inundated roads were reported in at least 28 municipalities. Flooding was further exacerbated by breaches in the embankments surrounding Lake Inbanuma in northern Chiba, which failed at three locations and inundated surrounding areas. The breaches were reportedly the first since the lake came under management by the prefectural government and other authorities in fiscal year 1968 ([Japannews, 2026](#)). According to FDMA's 5th October report, 2,412 residential buildings have been affected, including 2,297 in Chiba. However, these totals also include Typhoon Surigae (No. 26) and subsequent frontal rainfall and cannot be attributed solely to Dujuan ([FDMA, 2026](#); [Cabinet Office, 2026](#)).

The vulnerability of communities in Chiba Prefecture has been further exacerbated by successive flooding events that affected the region in August and September 2026. Typhoon Dujuan compounded the existing damage caused by the prior flood episodes, placing additional strain on local infrastructure, livelihoods, and communities' coping capacity. A study on urban flood risk management in the Chiba region highlights how its low-lying terrain, high population density,

exposure to typhoons and heavy rainfall increase the region's vulnerability to flooding and other related hazards ([Lee et al., 2025](#)). These recurring floods also inundated 17 houses in Ichihara in July 2024, underscoring the persistent nature of flood risk in the region and its associated socioeconomic impacts. While traditional flood mitigation has focused on structural defences, integrating socio-hydrological approaches with resilience-building measures, sustainable land-use planning, and community participation could support more adaptive flood risk management and strengthen long-term community resilience (*ibid*).

The impact of Dujuan also disrupted essential infrastructure, leaving nearly 45,000 customer accounts across the Tokyo Electric Power Company's service area without electricity by early evening ([Watchers, 2026](#)). Further cascading disruptions affected transport services, with 384 flights cancelled and railway services operated by eight companies suspended. In addition, six expressway routes were closed across 32 sections due to heavy rainfall or wave overtopping, while surface flooding forced the closure of nine sections of prefectural roads in Chiba (*ibid*).

4.1 Sociodemographics, health, and economic capacity and livelihoods

The Kanto region in Eastern Japan is home to 43.6 million people, with a high population density of roughly 1,346 people per km² ([Statistics Bureau of Japan, 2021](#)). It has high overall adaptive capacity. Southern Kanto, which includes Tokyo, Chiba and Kanagawa, recorded the highest subnational HDI in Japan in 2023 at 0.951, above the national value of 0.925 ([Global Data Lab, n.d.](#)). This score reflects strong performance across all three HDI dimensions: high per-capita income, high educational attainment, and long life expectancy. The wider Kanto economic area generates around 45% of Japan's prefectural income. Its economy is dominated by services, which make up about three-quarters of regional output, alongside manufacturing, logistics, agriculture, and advanced research and development ([Ministry of Finance, 2025](#)). Typhoon Dujuan's impacts therefore show how vulnerability is unevenly distributed within an affluent region, rather than a general lack of capacity.

Older adults and foreign residents are the most vulnerable groups in the affected region. Both groups face barriers to receiving warnings or acting on them in time. For older adults, the barrier is largely physical. When Typhoon Hagibis hit Eastern Japan in 2019, 65 of 99 fatalities were aged 65 or over, and 18 of the 20 people who drowned indoors lived in high-risk flood areas and were found on the first floor of their homes ([Yoshida et al., 2021](#)). This indicates limited mobility and delayed evacuation depending on their health status, structure of their residence, and the depth of floodwaters. Typhoon Dujuan followed a similar pattern; at least six of seventeen victims were in their 70s or 80s ([Bernama, 2026](#); [Kyodo News, 2026a](#); [Kyodo News, 2026b](#)). For foreign residents, whose numbers are growing through labour migration, the barrier is primarily informational and about language ability. Research identifies them as among Japan's most vulnerable groups at risk to disasters in the country ([Gyamfi and Shaw, 2021](#)). During Typhoon Hagibis, poor access to official risk information and procedural evacuation or alert actions led many to rely on home-country news or social media for evacuation information ([Sakurai and Gyamfi, 2020](#)).

People who depend on electricity and long-term care services are disproportionately impacted by typhoons. After Typhoon Faxai (2019) caused widespread power, water, and telecommunications

outages in Chiba, interrupted medical and long-term care services undermined older adults' ability to continue living at home ([Otsuka and Nagamatsu, 2024](#)). Furthermore, long-term psychosocial consequences are likely. After Japan's 2018 floods, antidepressant prescriptions among victims peaked 2-3 months after the disaster and persisted up to 1 year after ([Hattori et al., 2025](#)). Among survivors of the same floods, those with lower cognitive social capital tended to have higher odds of post-traumatic stress disorder (PTSD) ([Miyaji et al., 2022](#)).

4.2 Spatial planning, critical systems, and exposure

Typhoon Dujuan's exposure was shaped by decades of post-war land-use decisions. Lake Inbanuma, whose levee breached during the storm, was largely reclaimed between 1963 and 1969 for flood control, rice field improvement and water resource development ([ILEC, n.d.](#)). The reclaimed low-land remains prone to waterlogging; during heavy rain in October 2019, drainage pumps stopped for 31 hours, and roads and farmland around the central reclaimed area were flooded ([Tani et al., 2025](#)).

Spatial planning has unintentionally increased exposure. The number of buildings in Kanto region's flood-prone areas rose significantly between 2008 and 2022. Low-rise housing is increasing even in districts where the entire area faces potential inundation of three metres or more ([Sakahashi and Matsuyuki, 2024](#)). Inherently flood-prone areas are often developed for economic gain where land is scarce. Since hazard maps were upgraded in 2015, however, flood risk has been increasingly reflected in lower land prices, signalling growing risk awareness ([Nagami et al., 2025](#)). Future spatial plans also signal a shift. Japan's River Basin Disaster Resilience and Sustainability by All Policy (2020-2021) moves flood management beyond embankments and levees towards exposure and risk reduction through land-use planning, housing and building measures ([Koike, 2021](#)). In the Inbanuma basin, using paddy fields as temporary storage, known as "paddy-field dams", was shown to be effective in reducing flood discharge and inundation along the Kashima and Takasaki rivers ([Yoshimura et al., 2023](#)).

Critical infrastructure was not designed for the intensity of recent typhoons. During Typhoon Faxai (2019), gusts reached 57.5m/s in Chiba ([Yamamoto et al., 2020](#)), well above the 40m/s design wind load for transmission towers and utility poles. Two towers and 1,996 poles were damaged, cutting power to about 930,000 households in Chiba and neighboring prefectures for up to two weeks, with knock-on disruption to telecommunications and water supply ([Nagata et al., 2022](#)). In response, tower design must now use the higher of 40m/s or the regional basic wind speed ([Ministry of Economy, Trade, and Industry, 2020](#)). Typhoon Faxai's damage to roof tiles also prompted the Japanese government to revise its wind-resistance guidelines for tiled roofs in 2021 as a supplement to the Building Standards Act ([Kikitsu et al., 2022](#)). Nevertheless, Typhoon Dujuan cut power to about 58,000 households in Chiba Prefecture ([Bernama, 2026](#)) and closed part of the JR Uchibo rail line for an expected three months ([Kyodo News, 2026c](#)).

4.3 Storm Risk Management

4.3.1 Governance, policies and plans

In the Kanto region storm and typhoon risk management is executed through a tiered national framework, which relies on several core agencies ([Ogata et al., 2016](#)). The Cabinet Office sets national plans, the Ministry of Land, Infrastructure, Transport and Tourism oversees the major rivers, the Japan Meteorological Agency issues risk warnings, the Fire and Disaster Management Agency coordinates large-scale disaster responses and local mayors order evacuations ([IFRC, 2012](#)). In July 2026, the government announced a new Disaster Management Agency to begin work in November and strengthen central leadership ([ANN, 2026](#)). It is designed to improve the country's centralized command, pre-disaster planning, and cross-ministry coordination for natural disasters. Until now, the country's disaster management system has been described as prioritizing immediate responses to frequent disasters, leaving limited capacity to plan for long-term preparedness ([WEF, 2026](#)). The DMA was established to improve this system by developing national strategies that account for long-term risk analyses and inter-agency coordination.

A 2024 survey of 350 Japanese municipalities found that local flood early warning systems face challenges of limited technical staff, difficulties in data acquisition, and a lack of funds for river monitoring ([Cao et al., 2024](#)). Additionally, limited knowledge of how the public perceives warnings and evacuates were found to limit the effectiveness of early warning systems. Reaching vulnerable groups such as the elderly and people with disabilities during heavy rain was also found to be a particular problem for local agencies.

There are several storm risk management plans and policies in the Kanto region. In 2022 the Tokyo Metropolitan Government launched the Tokyo Resilience Project, an integrated multi-year infrastructure and preparedness program including flood and storm measures like regulating reservoirs on small and medium rivers, sewer flood control, flood information for evacuation, and storm surge risk information ([Tokyo Metropolitan Government, n.d.](#)). Outside Tokyo, Kanto's storm and typhoon policy is built mainly on river-basin plans led by the national government, with councils linking national agencies, prefectures and municipalities.

4.3.2 Early warning and early action

The Automated Meteorological Data Acquisition System (AMeDAS) is the primary measurement network for the storm and typhoon early warning system in the area ([JMA, n.d.](#)). It consists of a dense grid of 1300 automated stations operated by the Japan Meteorological Agency. Typhoon Dujuan was forecasted by the JMA on the 14th of September with initial tracking and warnings providing a 6-7 day lead time before it impacted eastern Japan ([Weather News, 2026](#)). Dujuan rainfall proved to be more intense than expected with as much as 832 mm of rain recorded over a 48-hour period on Izu Oshima Island, well above the predicted 300 mm ([The Japan Times, 2026](#)). Windspeeds were generally in line with the forecast with sustained winds around 130 km/h and peak gusts getting to 194 km/h ([BBC, 2026](#)).

The Kanto area, as well as the rest of Japan recently updated its weather disaster warning system for public risk communication ([JMA, 2026](#)). Through channels like smartphones, weather and media outlets report on the use of a five-level evacuation scale. Weather threats are grouped into four categories, heavy rain, river flooding, landslides and storm tides, which are all assigned an alert level. From Dujuan's initial forecast there were numerous public warnings, including level 4 and 5

emergency warnings through mass media outlets and cellphones. However, the storm did cause power outages for 50000 people causing communication disruptions ([BBC, 2026](#))

4.3.3 Emergency response

Currently, limited information is available on the emergency response of relevant actors. After the initial warning on the 14th of September, the Ministry of Internal Affairs and local government bodies issued non-mandatory evacuation advisories to more than 1.9 million people across Japan. Relief NGOs reported conducting needs assessments on the ground and distributing meals ([PBV, 2026](#)). Self-Defence Forces, local fire departments and prefectural police conducted searches in Chiba and Kanagawa to find survivors of the landslides. The Ministry of Land, Infrastructure and Transport dispatched technical emergency control forces to support emergency embankment restorations after breaches along the Nagato river ([Watchers, 2026](#)). Power outages due to the storm affected 50000 people, possibly impacting the ability of responsible actors to respond. The Japanese Red Cross Society (JRCS) plays an important role in Japan's disaster preparedness and emergency response through community preparedness initiatives, volunteer mobilisation, pre-positioned relief supplies, emergency medical assistance and longer-term recovery support. Its response to previous disasters in Chiba illustrates the capacity and resources that may have been instrumental to support operations following Typhoon Dujuan. During the August floods in Chiba, Narita Red Cross Hospital deployed two Disaster Medical Assistance Teams (DMATs) to Sanno Hospital on 14 and 15 August. The Chiba Chapter also deployed four staff members to the prefectural disaster response headquarters, two of whom supported DMAT coordination. Japanese Red Cross Society (JRCS) volunteers assisted municipal disaster volunteer centres by promoting safety and hygiene, removing mud and providing first aid to volunteers who became unwell. Relief supplies pre-positioned at local JRCS district and subdistrict offices were used to meet immediate needs. These established response capacities, including medical teams, trained volunteers and strategically positioned relief stocks, may have been valuable in supporting the response to Typhoon Dujuan ([JRCS, 2026](#)).

4.3.4 Insurance and social protection

Japan has a well-established social protection system that supports households affected by disasters through public assistance, cash transfers and employment programmes. The Japan National Council of Social Welfare (JNCSSW), together with prefectural and municipal councils complement government-led social protection delivery during disasters and under normal circumstances ([World Bank, 2019](#)). Following the 1995 Great Hanshin-Awaji Earthquake, Japan strengthened financial assistance for disaster-affected households and the Act on Support for Reconstructing the Livelihoods of Disaster Victims was soon enacted in 1999, introducing cash assistance of up to JPY 1million. In 2024 this scheme was revised to allow JPY 2 million for housing reconstruction and recovery. Japan's Geinkin or cash relief donations mobilises public donations to support disaster affected households with the help of the Japanese Red Cross Society. Japan further strengthened its cash for work programme following the 2011 Great East Japan Earthquake (ibid). The Japanese government's wresponse to hazards also includes an efficient employment insurance system guided by legal frameworks and legislations like the Employment Insurance Act, Severe Disaster Act and Disaster Relief Act. This serves as the first line of support within the country's multi-layered social protection

framework to provide unemployment benefits, relaxing benefit restrictions and providing payouts for temporary closure of workplaces ([Kawasoe et al., 2026](#)).

Following Typhoon Hagibis in 2019 which further compounded the damage caused by Typhoon Faxai just a month earlier, the Japanese government announced JPY 710 million (~USD 6.5 million) in emergency assistance- the financial assistance that was drawn from the country's JPY 500million emergency fund. Subsidies were fast-tracked for disbursement to more than 300 affected municipalities to support recovery efforts ([Arab News, 2019](#); [Relief Web, 2019](#)). While the specific financial assistance and social protection coverage for Typhoon Dujuan remains unclear, Japan plans to draft a supplementary budget for relief and reconstruction in November this year, with approval targeted during the regular parliamentary session early next year ([The Japan Times, 2026](#)). Other than government relief, humanitarian assistance from independent organisations and international aid agencies have further supported the condition. For instance, the Japanese Red Cross Society's Kanagawa Chapter provided relief supplies to Yokosuka and Miura immediately after the disaster. JRCS also launched a domestic disaster donation appeal on 5 October for affected people in Chiba and Kanagawa. All donations are being transferred to prefectural allocation committees for distribution to affected people ([JRCS, 2026b](#); [JRCS, 2026c](#)). Other independent institutions like Nippon Foundation have integrated its Typhoon No. 25 (Dujuan) Emergency Relief Fund with its existing fund, donations aimed at supporting regional recovery and reconstruction ([Nippon Foundation, 2026](#)). Along similar lines, Peace Boat Disaster Relief has been actively distributing relief support like meals in collaboration with local communities ([PBV, 2026](#)).

5 Conclusions

In Section 2, we apply World Weather Attribution's probabilistic attribution protocol to examine changes in extreme rainfall, atmospheric water vapour (precipitable water) and sea surface temperatures across and around the affected region. Across both observations and models we find an increase of around 15% in peak two-day rainfall during the typhoon season, along with consistent trends in precipitable water - the amount of water available in the atmosphere that could potentially fall as rain - which has increased by around 9%, broadly consistent with what we would expect from the Clausius Clapeyron relation. We also find that sea surface temperatures around Japan are 2-3°C warmer now than in a preindustrial climate, a change that would be expected to increase the intensity of typhoons passing over the area as well as humidity and therefore the availability of precipitable water. El Niño conditions like those observed in September 2026, at the time of the typhoon, were not found to intensify any of these factors.

In Section 3, analysis of events similar to Typhoon Dujuan in terms of the spatial pattern of precipitable water in the atmosphere found a 20-40% increase in the most intense rainfall under present-day compared to pre-industrial climate conditions in climate model simulations. In events selected on the basis of similarity of typhoon tracks, we find a slight decrease in central pressure (indicating more intense typhoons) and an increase in wind speeds in typhoons of similar or greater intensity than Typhoon Dujuan. We find no change in the frequency of typhoons, although tracks have shifted northwards, meaning that they are more likely to impact Japan. A separate analysis by a Japanese government research team using a different methodology and event definition also found an increase of over 20% in rainfall attributable to global warming.

Taking all of these lines of evidence together, we conclude that human-caused warming has had a relatively limited influence on the likelihood and intensity of the typhoon itself, while human-caused climate change did increase the rainfall intensity associated with typhoons. Due to the small size of the region, many models struggle to resolve the rainfall though, making quantification difficult, but the increase could locally be as high as 40% as suggested by the track-based methodology. In addition, anthropogenic climate change increased the conditions that fueled the typhoon. These factors are summarised in the causal network diagram in Figure 5.1.

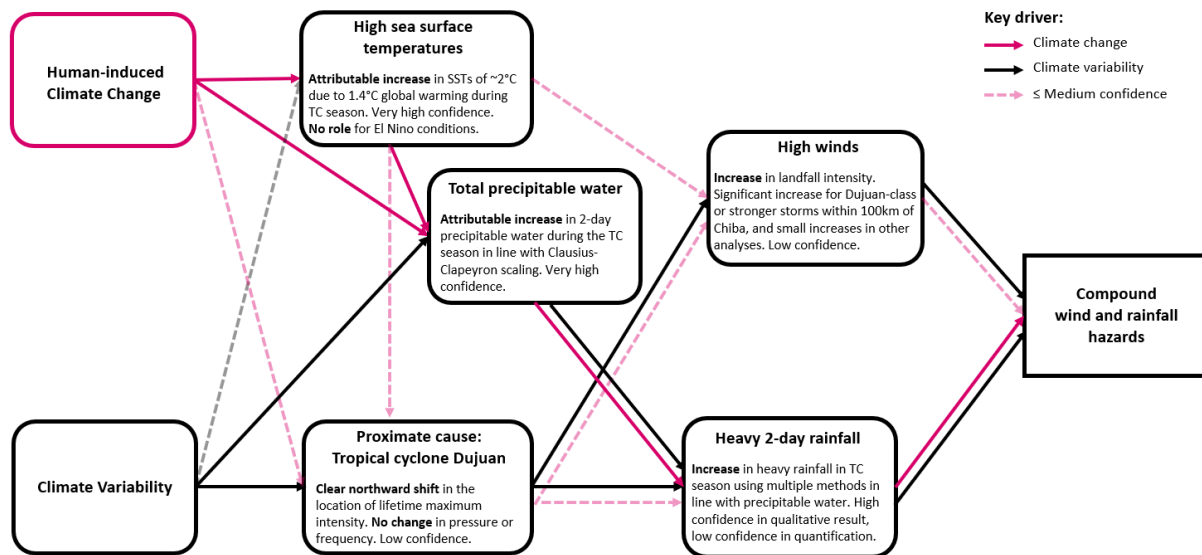


Figure 5.1: Causal network illustrating potential factors influencing the high winds and heavy rainfall from Typhoon Dujuan based on the analysis in sections 2 & 3 of this report. Arrows indicate links to climate change (pink) and climate variability (black). Solid arrows indicate at least high confidence of this link, while dashed arrows indicate medium or lower confidence in the link. A short description of key evidence is given within each box.

While Japan has extensive forecasting capabilities, early warning systems, flood protection infrastructure and established disaster response mechanisms, some gaps remain in robust spatial planning and critical infrastructure, especially for regions impacted by repeated typhoons and subsequent flooding. Japan has a well-established multi-layered social protection system with shock-responsive mechanisms, including government financial assistance, cash transfers, employment insurance and livelihood recovery programmes. As one of the most hazard-prone countries, reforms following major disasters have strengthened support for affected households over the years. While information on the extent of the government's social protection support in the aftermath of Typhoon Dujuan remains limited, independent organisations and humanitarian aid agencies, including the Japanese Red Cross Society, have initiated recovery efforts by providing in-kind assistance and mobilising donations to support affected communities.

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AI tools were used during the initial scoping phase of the vulnerability and exposure analysis to identify relevant white and grey literature. They were also used to assist with translating government documents and bulletins relevant to the study. All AI-generated translations were then reviewed and verified by native-language technical experts to ensure accuracy and contextual relevance.

This work used data obtained from JASMIN, the UK's collaborative data analysis environment (<https://www.jasmin.ac.uk>) and from the data repository of the Deutsches Klimarechenzentrum (DKRZ), granted by its Scientific Steering Committee (WLA) under project ID bk1088 and datasets provided by ESGF/Copernicus via the DKRZ data pool. Analysis was carried out using Imperial College Research Computing Service, DOI: 10.14469/hpc/2232.

Data availability

Key data and notebooks used in this analysis are available via Zenodo (<https://zenodo.org/records/23079873>).

Time series used in the probabilistic attribution analysis are available via [KNMI's Climate Explorer](#).

References

All references are given as hyperlinks in the text.

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A1 Probabilistic attribution - Data and Methods

A1.1 Observational datasets

We first use observational and reanalysis data to estimate the return period of a similar event in the present day and to assess the historical trends with increasing GMST. The datasets used for analysis of trends in rainfall and atmospheric moisture are as follows:

- **JRA3Q** - JRA-3Q (Japanese Reanalysis for Three Quarters of a Century) is the 3rd-generation global atmospheric reanalysis dataset produced by the Japan Meteorological Agency (JMA; [Kosaka et al., 2024](#)). It reconstructs past global atmospheric conditions seamlessly across space and time by assimilating historical weather observations with modern numerical weather prediction models and data assimilation systems.
- **ERA5** - The European Centre for Medium-Range Weather Forecasts's 5th generation reanalysis product, ERA5, is a gridded dataset that combines historical observations into global estimates from the years 1950 to present, using advanced modelling and data assimilation systems ([Hersbach et al., 2020](#)). From this product, we obtain total precipitation (tp) and total column water vapour (tcwv), both at a resolution of $0.25^{\circ} \times 0.25^{\circ}$.
- **MSWX** - The Multi-Source Weather dataset ([Beck et al., 2022](#)), which combines various observational and reanalysis-based data (including ERA5) for reliable bias-corrected weather variable estimates, at 3-hourly intervals from 1979 to near real-time. From this product, we obtain daily precipitation totals at 0.1° spatial resolution.

- **AMeDAS** - The Automated Meteorological Data Acquisition System (**AMeDAS**) is a collection of Automatic Weather Stations (AWSs) run by JMA for automatic observation of precipitation, wind direction/speed, temperature and humidity to support real-time monitoring of weather conditions with high temporal and spatial resolution. The AMeDAS system currently includes as many as 1,300 rain gauges at average intervals of 17 km nationwide.

Gridded reconstructions of observed sea surface temperatures were obtained from the following products:

- **ERSST** - NOAA's Extended Reconstructed Sea Surface Temperature (ERSST), combining data from multiple sources into a reanalysis of SSTs from 1850 to the present at $2^\circ \times 2^\circ$ spatial resolution ([Huang et al., 2025a](#) and [2025b](#)). Last available date at time of writing: September 2026.
- **OISST** - The NOAA Optimum Interpolation Sea Surface Temperature, OISST v2, is a high-resolution ($0.25^\circ \times 0.25^\circ$) blended analysis of monthly SSTs and sea ice based on data from multi-satellite sensors, ships, buoys and Argo floats ([Huang et al., 2021](#)). Last available date at time of writing: 7th October 2026.
- **OSTIA** - The Operational SST and Ice Analysis is a satellite and in-situ foundation SST analysis created using reprocessed ESA SST CCI, C3S, EUMETSAT and REMSS satellite data and in situ data from the HadIOD dataset. The product is available from 1st October 1981 on a global regular grid at 0.05° resolution ([Worsfold et al., 2024](#)). Last available date at time of writing: 7th October 2026.

A1.2 Covariate time series

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](#)). To remove the effect of the El Niño - Southern Oscillation on global mean temperatures, we use a four-year running mean of the GMST, centred on the third year.

As a measure of the El Niño - Southern Oscillation cycle (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 Nino3.4 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.

A1.3 Climate model and experiment descriptions

In the probabilistic attribution of rainfall and precipitable water, we use four ensembles of climate models from climate modelling experiments using very different framings ([Philip et al., 2020](#)):

d4PDF

The Database for Policy Decision-making for Future climate change (d4PDF, [Mizuta et al. 2017](#)) is a large ensemble of nested global and regional climate model simulations. The global climate simulations were conducted using the atmospheric general circulation model (MRI-AGCM3.2) developed by the Meteorological Research Institute, with a grid spacing of approximately 60 km ([Mizuta et al. 2012](#)). The regional climate simulations were conducted using the nonhydrostatic regional climate model (NHRCM) with a 20 km grid spacing ([Sasaki et al. 2008](#)). The regional climate simulation covered the East Asian region. The historical simulations were forced by the historical sea surface temperature and sea ice thickness/concentration based on COBE-SST2 ([Hirahara et al. 2014](#)) and historical anthropogenic and natural forcing agents such as greenhouse gases and solar irradiance; the RCP4.5 emission scenario was used for the period after 2006, comprising a 100-member ensemble with different initial conditions and SST perturbations from 1951 to 2010. The database is a key part of promoting climate and risk assessment studies and for devising climate adaptation policies ([Ishii and Mori. 2022](#))

CORDEX

1. Coordinated Regional Climate Downscaling Experiment (CORDEX)- East Asia domain with 0.22° resolution (EAS-22) and 0.44 resolution (EAS-44) ([Kim et al., 2020](#)). The EAS-22 ensemble consists of six simulations resulting from pairings of four GCMs and two RCMs, and the EAS-44 ensemble consists of five simulations from pairings of four GCMs and two RCMs. These simulations are composed of historical simulations up to 2005, and extended to the year 2100 using the RCP8.5 scenario.

HighResMIP

From the HighResMIP experiments we use the SST-forced model ensemble ([Haarsma et al. 2016](#)), the simulations for which span from 1950 to 2050. The SST and sea ice forcings for the period 1950-2014 are obtained from the 0.25° x 0.25° Hadley Centre Global Sea Ice and Sea Surface Temperature dataset that have undergone area-weighted regridding to match the climate model resolution. For the ‘future’ time period (2015-2050), SST/sea-ice data are derived from RCP8.5 (CMIP5) data, and combined with greenhouse gas forcings from SSP5-8.5 (CMIP6) simulations (see Section 3.3 of [Haarsma et al. \(2016\)](#) for further details).

CMIP6

In [Section 2.2.2](#) we analyse trends in precipitable water vapour (prw) in a multi-model ensemble of CMIP6 models. This consists of simulations from twelve participating models with varying resolutions, with three of those providing multiple realisations (see [Appendix A5.2](#) for details of the models used). For more details on CMIP6, see [Eyring et al., \(2016\)](#). For all simulations, the period 1850 to 2014 is based on historical simulations, while the SSP5-8.5 scenario is used for the remainder of the 21st century.

A1.4 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., \(2021\)](#), [Otto et al., \(2024\)](#) and [here](#). The key steps, presented in sections 3-6, are: (3) trend estimation from observations; (4)

model validation; (5) multi-method multi-model attribution; and (6) synthesis of the attribution statement.

Short-term precipitation is modelled using a generalised extreme value distribution (GEV), while precipitable water and sea surface temperatures are better represented by a normal distribution. For both precipitation and precipitable water, 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; for sea surface temperatures, the distribution is assumed to shift linearly with the covariates, while the variance remains constant.

In order to examine the effect of the concurrent ENSO phase on the event alongside that of increasing GMST, we extend the nonstationary model to accommodate an additional covariate. The variable of interest, X , is assumed to follow a distribution in which the location and scale parameters vary with both GMST and ENSO, so that for rainfall,

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

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.

For each time series, we calculate the return period and intensity of the event under study for the 2026 GMST and for 1.4°C cooler GMST: this allows us to compare the climate of now and of the preindustrial past without human-caused warming (based on [Forster et al., 2026](#)), by calculating the probability ratio (PR; the factor-change in the event's probability) and change in intensity of the event.

A2 Model-based attribution - Methods

A2.1 Analogues

We employed a weather analogue method using large ensembles of global and regional climate simulations, as described in [Tamura and Sato \(2024\)](#). In the present analysis, we used precipitable water vapour (PrW) instead of sea level pressure to identify analogues based on spatial pattern similarity. As a variable representing the atmospheric moisture state, PrW characterizes moisture distributions associated with tropical cyclones and fronts, while also indirectly reflecting their circulation patterns. For each of September 20 and 21, we identified 100 analogue days with similar patterns of PrW around Japan from each of the ALL and NAT experiments in d4PDF, yielding 200 analogues per experiment. Precipitation in the selected days was analyzed using regional climate simulations at a 20-km horizontal resolution. Due to data availability, the analogues were selected from the period corresponding to 2011–2016, comprising 600 simulation years (6 years $\times$ 100 ensemble members) per experiment. Thus, the sampling rate was approximately one analogue per three simulation years (200 analogues per 600 simulation years). The estimated anthropogenic influence therefore reflects the warming level reached during 2011–2016. Given the continued warming that has occurred since 2016, the impact of anthropogenic warming on the target event is likely to be greater than estimated in this assessment.

A2.2 Typhoons

We determined typhoon intensity characteristics based on typhoon tracks from the Large-Scale Ensemble Climate Prediction Database (d4PDF). The d4PDF dataset used for the analysis consisted of 100 members (covering 6,000 years) from present experiments and non-warming experiments (NAT), from which the effects of global warming had been removed. For maximum intensity, we performed bias correction using quantile mapping based on the observed typhoon dataset (IBTrACS).

Fig. 3.2.1 indicates TC intensity north of 30°N in all d4PDF data.

For each target region (e.g., Chiba), we extracted all typhoons that passed within a radius of 100 km centered on the typhoon's landfall point. Next, we grouped similar track clusters using K-means cluster analysis. We used latitude and longitude data from a total of four days—two days before and two days after the closest approach—as classification features, and classified all typhoons that passed through the circle into a total of six clusters based on Euclidean distance in the feature space (**Fig. A2.2.1**). Although the composition ratio and specific number of typhoons extracted for each cluster vary depending on the target typhoon, in every case, a sufficient sample size was extracted to allow for comparisons by intensity level.

Through this two-step extraction process, we analyzed both a broad dataset of typhoons that made landfall or approached the target coastal area and a subset of that dataset further restricted to typhoons with trajectories similar to those of the target typhoon. Furthermore, based on the central pressure of the target typhoon at the time of its passage through the circle, the data were divided into three groups—"all typhoons," "typhoons with central pressures equal to or lower than the target typhoon," and "typhoons with central pressures within 2% above or below the target typhoon's central pressure"—to analyze and compare their intensities.

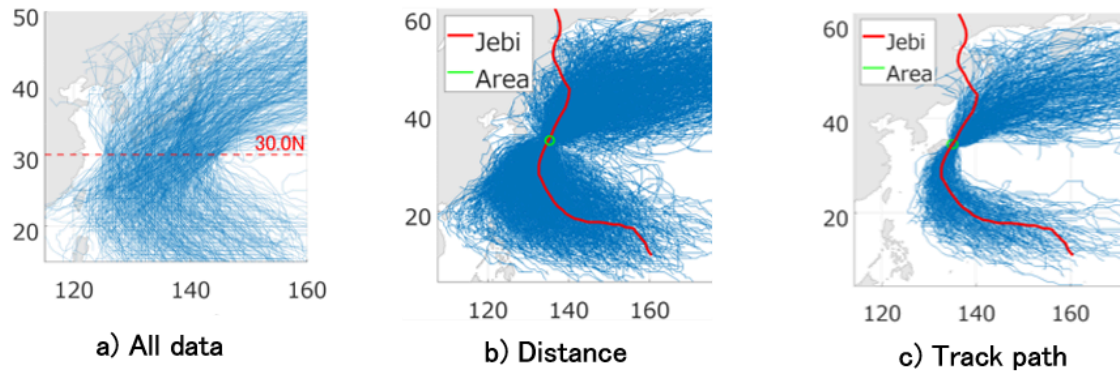


Figure A2.2.1: A sample of TC tracks by d4PDF in the present climate condition. a) TC tracks across higher than 30N, b) distance from landfall within 100 km, c) similar tracks by cluster analysis.

A3 Sensitivity of trends in rainfall to event definitions and datasets

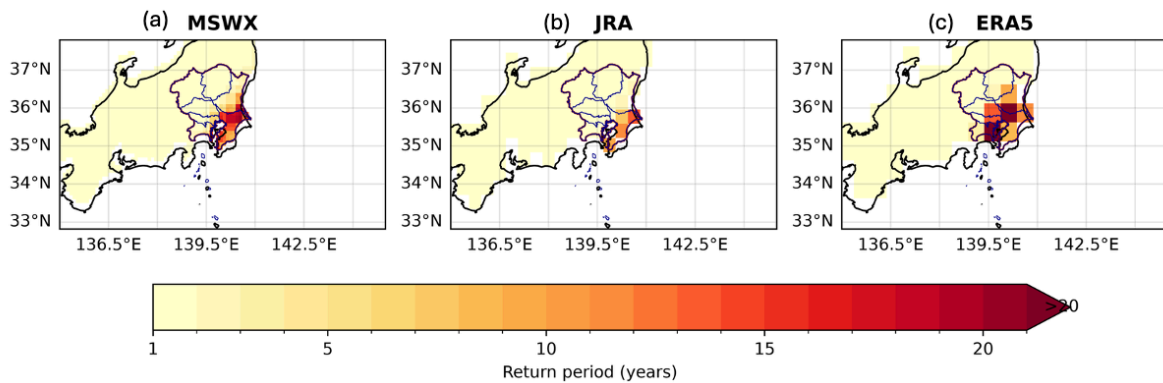


Figure A3.1: Gridded return period estimates of Rx2day during Sep 20-21, 2026 associated with Typhoon Dujuan in (a) MSWX, (b) JRA-3Q and (c) ERA5 datasets. The red highlight indicates the study region (Kanto region), and the blue outlines highlight the prefectures.

Table A3.1: Estimated return periods of 2-day rainfall associated with Typhoon Dujuan in today's climate, at a subset of locations where the rainfall reportedly broke records ([BBC, 21 Sep 2026](#)), and where station data is available covering the event.

Prefecture	Station	Magnitude (mm/2day)	Return period (years)
Ibaraki	Ryugasaki	297	36.93
Kanagawa	Miura	365.5	149.06
Tokyo	Edogawa	325	79.49
Tokyo	Oshima	413	23.46
Chiba	Sakura	377.5	46.89

Chiba	Funabashi	393.5	61.41
Chiba	Abiko	327.5	58.72

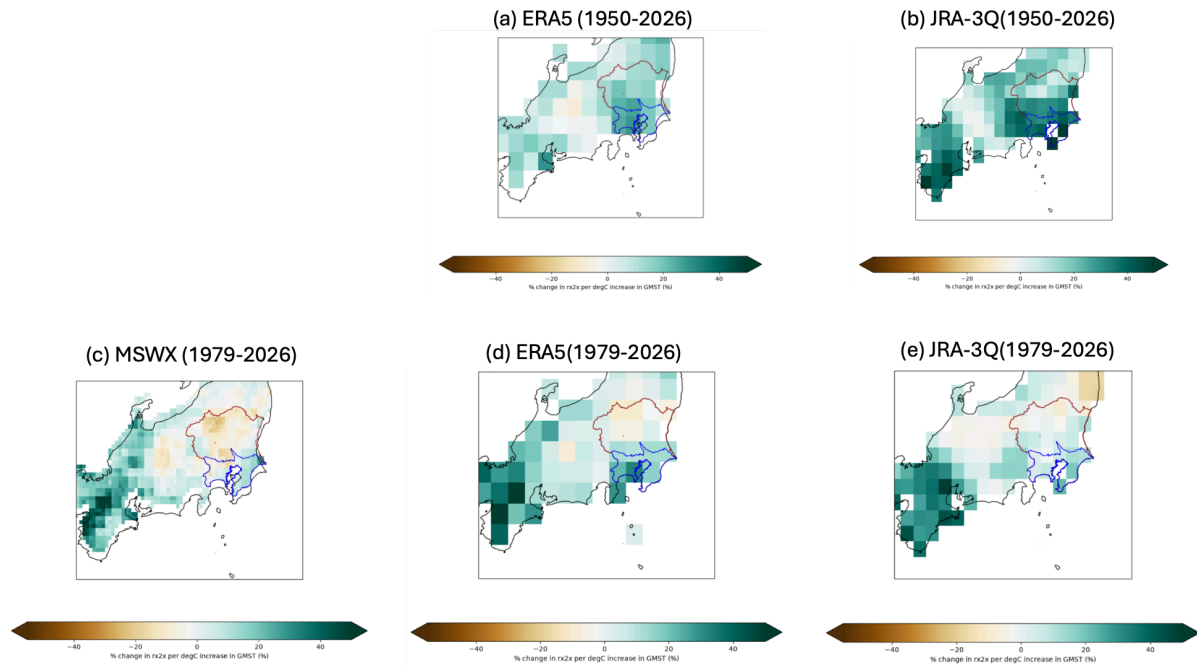


Figure A3.2: Percentage intensity change with respect to pre-industrial climate for seasonal (Aug-Oct) maxima of 2-day rainfall at each grid cell, associated with global warming. The brown shades suggest decreasing rainfall tendencies with respect to warming while the green shades suggest increasing trends.

Table A3.2: Return period and observed/derived magnitude for the 2026 event, as well as probability ratio and change in magnitude for the 2-day rainfall associated with Typhoon Dujuan due to GMST. The values are based on rainfall over a revised region excluding the mountainous prefectures, which incidentally is also where it rained the most during the storms. Statistically significant results at the 95% level (if any) are highlighted in **bold text**.

Dataset	Magnitude (mm/2day)	Return period (years)	Probability Ratio	Change in magnitude (%)
ERA5	173	9.1 (3.8 to 52)	12.6 (0.73 to Inf)	35.0 (-4.1 to 78.0)
JRA	234	2.3 (1.5 to 4.1)	2.6 (0.91 to 5.2)	32.0 (-2.8 to 81.0)
MSWX	129	5.8 (2.6 to 52)	0.85 (0.06 to 13.89)	-2.7 (-35.3 to 49.9)
Stations	199	6.5 (2.2 to Inf)	4.0 (0.00 to Inf)	20.6 (-23.4 to 101.2)

A4 Sensitivity of trends in precipitable water to event definition & dataset

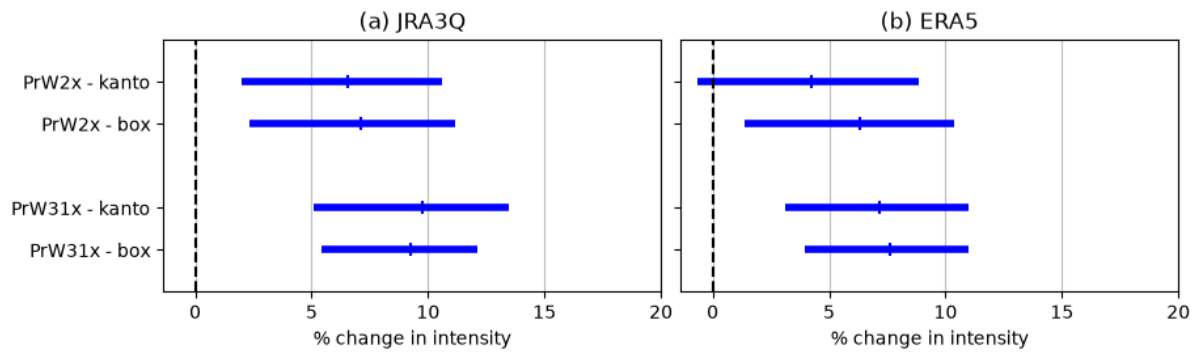


Figure A4.1: Sensitivity of trends in precipitable water to domain & duration: relative change in peak PrW associated with 1.4°C of warming under different event definitions: for peak 2-day and 31-day PrW during the typhoon season, and averaged over the Kanto study region and the wider box shown in Figure 2.2.1.

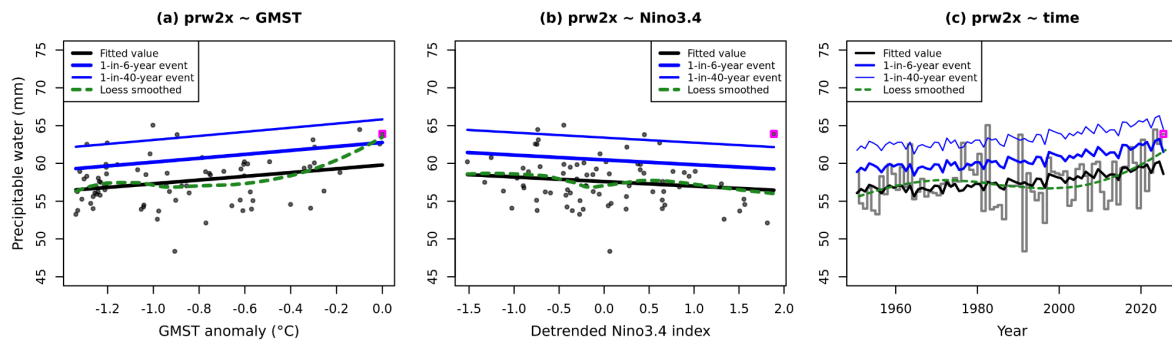


Figure A4.2: As Figure 2.2.2, but using the ERA5 reanalysis dataset.

A5 Model evaluation tables

In the subsections below we show the results of the model evaluation for ASO-rx2day and PrW2x. For each framing or model setup we aim to use only ‘good’ models, but if five or fewer models for a given ensemble reach that standard, we also include ‘reasonable’ models.. The tables show the model evaluation results. 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 spatial distribution of precipitation or precipitable water are excluded.

3. Parameters of the fitted statistical models. We discard the model if the model and observation parameter ranges do not overlap.

The models are labelled as ‘good’, ‘reasonable’ or ‘bad’ based on their performance 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’.

A5.1 Model evaluation - extreme rainfall

Of the 22 models from the CORDEX and HighResMIP ensembles, 13 were rated ‘bad’ and discarded from the attribution analysis. Given that neither set of models had 5 or more models rated ‘good’, both ‘good’ and ‘reasonable’ models were used. In total 9 models were retained - 6 from CORDEX and 3 from HighResMIP - alongside the 100 members of the d4PDF ensemble.

Observations/Model	Seasonal cycle	Spatial pattern	Dispersion	Shape parameter	Event magnitude 2026/Magnitude of 3-year event (mm/2day)	Overall evaluation	Include ?
ERA5			0.403 (0.337 ... 0.452)	-0.16 (-0.39 ... 0.035)	143		
JRA			0.390 (0.319 ... 0.436)	0.075 (-0.27 ... 0.44)	171.40		
MSWX			0.412 (0.323 ... 0.487)	-0.42 (-0.72 ... -0.15)	95.98		
Stations			0.413 (0.309 ... 0.492)	-0.16 (-0.75 ... -0.013)	157.1		
CORDEX			(...)	(...)			
EAS-22_HadGEM2-ES_r1i1p1_RegCM4-4 ()	good	good	0.296 (0.240 ... 0.345)	-0.050 (-0.44 ... 0.13)	135.55	bad	n
EAS-22_HadGEM2-ES_r1i1p1_REMO2015 ()	bad	good	0.376 (0.297 ... 0.441)	-0.13 (-0.34 ... 0.054)	186.77	bad	n
EAS-22_MPI-ESM-LR_r1i1p1_REMO2015 ()	reasonable	good	0.342 (0.277 ... 0.391)	-0.081 (-0.38 ... 0.18)	163.68	reasonable	y
EAS-22_MPI-ESM-MR_r1i1p1_RegCM4-4 ()	good	good	0.427 (0.322 ... 0.496)	0.062 (-0.26 ... 0.25)	114.67	good	y
EAS-22_NorESM1-M_r1i1p1_RegCM4-4 ()	reasonable	bad	0.384 (0.292 ... 0.453)	0.021 (-0.22 ... 0.37)	100.65	bad	n

1p1_RegCM4-4 ()							
EAS-22_NorESM1-M_r1i1p1_REMO2015 ()	reasonable	good	0.334 (0.276 ... 0.378)	-0.033 (-0.31 ... 0.17)	134.55	reasonable	y
EAS-44_CNRM-CM5_r1i1p1_CCLM5-0-2 ()	good	good	0.444 (0.371 ... 0.497)	0.015 (-0.28 ... 0.30)	142.10	good	y
EAS-44_EC-EARTH_r12i1p1_CCLM5-0-2 ()	good	good	0.348 (0.276 ... 0.394)	0.012 (-0.14 ... 0.17)	126.05	good	y
EAS-44_EC-EARTH_r3i1p1_HIRHAM5 ()	bad	bad	0.400 (0.330 ... 0.453)	0.018 (-0.17 ... 0.17)	100.87	bad	n
EAS-44_HadGEM2-ES_r1i1p1_CCLM5-0-2 ()	bad	good	0.426 (0.348 ... 0.489)	-0.16 (-0.38 ... -0.026)	146.21	bad	n
EAS-44_MPI-ESM-LR_r1i1p1_CCLM5-0-2 ()	good	good	0.351 (0.291 ... 0.404)	-0.12 (-0.33 ... 0.077)	133.69	good	y
HighResMIP			(...)	(...)			
CMCC-CM2-HR4_r1i1p1f1 ()	reasonable	bad	0.499 (0.420 ... 0.561)	0.14 (-0.014 ... 0.29)	76.75	bad	n
CMCC-CM2-VHR4_r1i1p1f1 ()	good	bad	0.444 (0.380 ... 0.496)	-0.034 (-0.20 ... 0.098)	118.09	bad	n
CNRM-CM6-1_r1i1p1f2 ()	reasonable	bad	0.380 (0.305 ... 0.447)	-0.34 (-0.46 ... -0.19)	130.84	bad	n
CNRM-CM6-1-HR_r1i1p1f2 ()	good	reasonable	0.414 (0.335 ... 0.480)	-0.40 (-0.56 ... -0.27)	139.87	reasonable	y
EC-Earth3P_r1i1p1f1 ()	good	good	0.457 (0.391 ... 0.513)	0.15 (-0.026 ... 0.35)	90.47	good	y
EC-Earth3P-HR_r1i1p1f1 ()	good	good	0.414 (0.336 ... 0.484)	-0.013 (-0.16 ... 0.11)	89.84	good	y
HadGEM3-GC31-HM_r1i1p1f1 ()	bad	bad	0.451 (0.382 ... 0.507)	0.094 (-0.11 ... 0.28)	163.32	bad	n
HadGEM3-GC31-LM_r1i1p1f1 ()	good	bad	0.467 (0.389 ... 0.520)	0.20 (-0.0011 ... 0.41)	116.63	bad	n
HadGEM3-GC31-MM_r1i1p1f1 ()	bad	reasonable	0.497 (0.430 ... 0.558)	0.063 (-0.14 ... 0.24)	186.76	bad	n

MPI-ESM1-2 -HR_r1i1p1f1 ()	bad	bad	0.405 (0.342 ... 0.467)	-0.012 (-0.20 ... 0.20)	50.31	bad	n
MPI-ESM1-2 -XR_r1i1p1f1 ()	bad	good	0.377 (0.317 ... 0.423)	-0.024 (-0.20 ... 0.15)	50.57	bad	n

Table A5.1: Evaluation results of the climate models considered for attribution analysis of ASO-rx2day. For each model, the qualitative assessments of the seasonal cycle and spatial pattern are recorded, along with the best estimates of the dispersion and shape parameters and the event magnitude in 2026 associated with the event (for observations), and the magnitudes corresponding to 3-year return period in the 2026 climate in the climate models. Figures in parentheses indicate 95% confidence intervals. The overall conclusion is recorded in the last column.

A5.2 Model evaluation - precipitable water

Availability of the PrW variable is limited compared to many surface weather variables, so the pool of candidate models - all from the CMIP6 experiments - is relatively small, consisting of nine single realisations and three ensembles, contributing two, fifty and five realisations. We evaluate the seasonal cycle, spatial pattern and parameter estimates for each realisation separately but only present summarised results for each ensemble here, including the mean of the best estimates and the range of upper and lower bounds. Due to the small number of distinct models available, we only discard models that were found to perform badly in some respect, or where a better-performing or higher-resolution variant of the same model was also available; this is noted in the ‘overall evaluation’ column. Most models were found to represent observed patterns of precipitable water well, and we retained six of the nine individual realisations, and all three of the ensembles.

Observations / Models	Seasonal cycle	Spatial pattern	Dispersion parameter	Overall evaluation	Include?
JRA3Q			0.053 (0.043 - 0.061)		
ERA5			0.052 (0.043 - 0.061)		
AWI-ESM-1-REcoM r1i1p1f1	reasonable	good	0.046 (0.039 - 0.051)	reasonable	Y
CMCC-CM2-SR5 r1i1p1f1	bad	bad	0.200 (0.160 - 0.240)	bad wrong units	N
CNRM-CM6-1 r1i1p1f2	reasonable	good	0.043 (0.036 - 0.049)	reasonable	Y
CNRM-CM6-1-HR r1i1p1f2	reasonable	good	0.046 (0.038 - 0.053)	less good duplicate	N
CNRM-ESM2-1 r1i1p1f2	good	good	0.038 (0.032 - 0.043)	reasonable	Y
GFDL-CM4 r1i1p1f1	reasonable	good	0.052 (0.044 - 0.058)	reasonable	Y
HadGEM3-GC31-LL	good	good	0.046	good	Y

r1i1p1f3			(0.039 - 0.052)		
NorESM2-LM r1i1p1f1	reasonable	good	0.057 (0.048 - 0.064)	Lower-res duplicate	N
NorESM2-MM r1i1p1f1	reasonable	good	0.056 (0.045 - 0.064)	reasonable	Y
CESM2-WACCM (2)	reasonable	good	0.068 (0.055 - 0.080)	reasonable	Y
MPI-ESM1-2-LR (50)	good	good	0.054 (0.039 - 0.073)	good	Y
UKESM1-0-LL (5)	good	good	0.049 (0.039 - 0.061)	good	Y

Table A5.2: Evaluation results of the climate models considered for attribution analysis of 2-day. For each model, the qualitative assessments of the seasonal cycle and spatial pattern are recorded, along with the best estimates of the dispersion and shape parameters. Dispersion estimates in parentheses indicate 95% confidence intervals. The overall conclusion is recorded in the last column.

A6 Synthesis figures - Rx2day

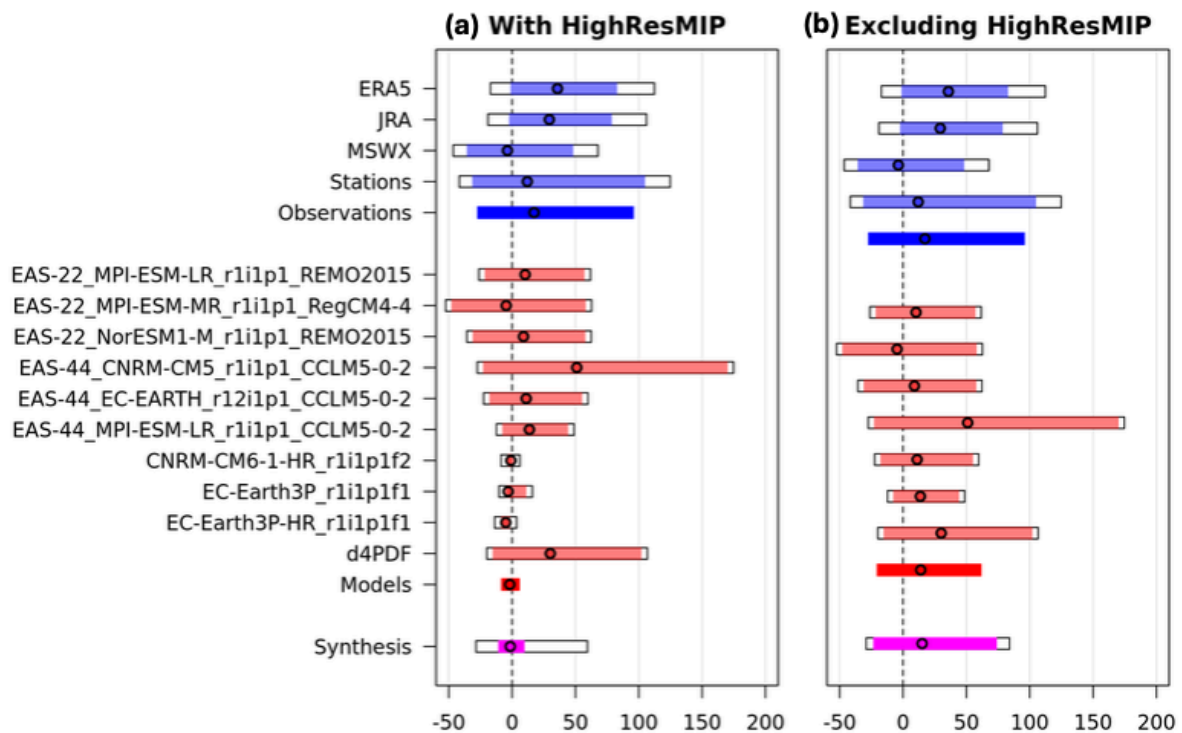


Figure A6.1: Synthesised estimates of relative change in intensity of ASO-rx2day associated with 1.4°C from the preindustrial climate to 2026 (past-present), (a) including the three HighResMIP models that passed model evaluation (Table A5.1) and (b) excluding them.