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**COASTAL HYDROMETEOROLOGICAL
EXTREMES IN A WARMING CLIMATE**

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PhD

The Hong Kong Polytechnic University

2026

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Department of Land Surveying and Geo-Informatics

**Coastal Hydrometeorological Extremes in a
Warming Climate**

ZHOU Mo

A thesis submitted in partial fulfilment of the requirements for the
degree of doctor of philosophy

November 2025

CERTIFICATE OF ORIGINALITY

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_____ (Signed)

ZHOU Mo (Name of student)

Dedication

This dissertation is dedicated to my family, whose unconditional love, unwavering support, and constant encouragement have carried me through every stage of this journey.

Above all, I dedicate this work to my late maternal grandmother, Yuyin Zhu (1936–2024). Although Alzheimer’s disease prevented her from knowing that I was pursuing a doctoral degree, the strength and resilience she instilled in me have remained a lasting source of inspiration.

My deepest gratitude goes to my parents. My mother, Hongying Chen, has always sheltered me from the storms of life, caring for me through every step of my growth and every worry along the way. She never places pressure on me, yet always understands me with tenderness and patience. My father, Zhi Zhou, has profoundly shaped me through his humor and optimism, which have become an essential part of who I am. Every time I return home, the laughter we share fills me with strength and reminds me that joy can carry me through life’s challenges. Heartfelt thanks also go to all my family members, who have supported me quietly and encouraged me to keep growing.

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Abstract

Global warming is reshaping the climate system by intensifying tropical cyclones, increasing heat extremes, and worsening coastal hazards through sea-level rise. It also affects coastal compound events, such as concurrent heatwaves and extreme sea levels, by altering their frequency, duration, intensity, and lag dependence. These evolving hazards have already caused substantial socio-economic and environmental impacts, highlighting the need for improved prediction, risk assessment, and disaster preparedness.

Although research on coastal extremes and compound events has expanded, understanding of their dynamic evolution and underlying physical mechanisms remains limited. To address this gap, this dissertation investigates the evolution, mechanisms, and interactions of coastal extremes. First, I developed an integrated framework combining a wind-pressure model, a hydrodynamic model, and a depth-damage function to assess tropical cyclone-induced coastal flood hazards in Hong Kong. Building on this, I examined compound heatwaves and extreme sea levels, including both concurrent and consecutive events, and finally analyzed the global lag dependence between heatwaves and tropical cyclones. The main findings are as follows.

(1) The northwestern region of Hong Kong is the most vulnerable to coastal flooding. In the case of Typhoon Hato (2017), the effects of extreme high tide and sea-level rise are comparable in their contribution to coastal flooding. In contrast, for Typhoon Mangkhut (2018) and Typhoon Saola (2023), extreme high tide has a more pronounced impact on exacerbating flooding. The worst-case scenario, combining extreme tides with sea level rise under SSP585, could amplify economic losses by 1.2–1.5, 1.7–1.9, and 2.0–2.3 times for the three typhoons. Residential areas are particularly vulnerable, with economic losses five times higher than commercial buildings and double those of industrial buildings.

(2) Along Europe's coastline, nearly half of the coastal areas have experienced an increase in the frequency of consecutive heatwaves and extreme sea levels in recent years, with an average rate of 0.4 events per decade. Heatwaves followed by extreme sea levels exhibit an average air temperature that is 0.3°C higher than heatwaves not followed by extreme sea levels. By mid-century, under a high-emission scenario, the frequency of such consecutive extreme events is

projected to increase eightfold compared to that during the historical period, primarily due to the rising frequency of heatwaves.

(3) 88% of global coastlines have experienced concurrent heatwaves and extreme sea levels during 1979–2017. There is an average increase of 3.7 days in the occurrence during 1998–2017 compared to 1979–1998. A one-percentile increase in heatwave intensity is associated with a 2% increase in the likelihood of concurrent extremes. Global coastlines are projected to experience 38 days of concurrent extremes each year during 2025–2049 under the highest emission scenario. The weakening of geopotential height associated with a surface low-pressure system may serve as an important indicator for the occurrence of extreme sea levels during heatwaves.

(4) Overall, 31% of tropical cyclones are preceded by heatwaves, with East Asia showing the shortest average time lag of 3.2 days. From 1981 to 2022, the time lag between preceding heatwaves and subsequent tropical cyclones shortened by 16% (approximately 0.8 days). Heatwaves preceding tropical cyclones are generally shorter but more intense, likely fueled by heat and moisture associated with approaching tropical cyclones. In addition, faster tropical cyclone translation speeds may be a key driver of the recent shortening of the time lag, particularly for the shortest-lag events (time lag = 1 day), with an attributable fraction of 10.8% (95% CI: 8.8%–13.0%).

The findings of this dissertation reveal that coastal extremes and coastal compound events have intensified over recent decades, posing serious challenges to the adaptive capacity of both ecosystems and human societies under global warming. The simulation and estimation of coastal flood losses advance existing methodologies in flood risk assessment and highlight the critical importance of addressing flood risks in coastal cities. Investigations into compound heatwaves occurring alongside extreme sea levels and tropical cyclones provide valuable insights for mitigating the cascading impacts of both consecutive and concurrent extreme events. The findings emphasize the importance of adopting integrated and cross-sectoral approaches to manage interrelated vulnerabilities and build resilience, particularly in areas most affected by compound hydrometeorological events.

Keywords: Climate change; Coastal hydrometeorological extremes; Coastal flooding; Heatwave; Extreme sea level; Tropical cyclone

List of Awards

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Chapter 1. Introduction

This chapter provides background information and a comprehensive review of the existing literature on coastal flooding and coastal compound climate extremes (i.e., compound heatwaves and extreme sea levels, as well as compound heatwaves and tropical cyclones). It also identifies key research gaps and discusses their significance. Furthermore, the chapter outlines the aims and objectives of the research and concludes with an overview of the structure of the dissertation.

1.1 Background

Coastal areas are the frontlines of climate change [*Fan and Li, 2022; Seibert et al., 2020; Weymer et al., 2022*]. Hydrometeorological extremes, e.g., tropical cyclones (TCs, also called typhoon in the Northwest Pacific basin), coastal flooding, extreme sea levels, heatwaves, are recurrent natural disasters in globally coastal areas. Many countries have experienced severe hydrometeorological extreme events over the past decades, leading to catastrophic economic losses, widespread ecological damage, food shortages, and millions of deaths. For example, the 2006 California heatwave resulted in over 600 deaths, disproportionately affecting densely populated coastal areas [*Clemesha et al., 2017; Guirguis et al., 2014*]. During tropical cyclones, extreme sea levels can cause coastal flooding when flood defenses are overtopped, threatening life and property in coastal communities [*Grimley et al., 2024; Rasmussen et al., 2018*]. Currently, it is estimated that around 76 million people worldwide are at risk from coastal flooding associated with a 100-year return period extreme sea level event [*Muis et al., 2016*]. The high vulnerability of coastal areas can also exaggerate their dangers, as global population and economic activity tend to concentrate in low-lying coastal areas [*Hinkel et al., 2014; MacManus et al., 2021*]. Thus, understanding the underlying mechanisms of hydrometeorological extremes and performing reliable risk assessments have received increasing attention from all over the world.

Coastal flooding is a combination of multiple drivers, such as storm surges, extreme sea levels, heavy rainfall, and sea level rise, which together can lead to severe inundation in low-lying coastal areas [*Hauer et al., 2021*]. This phenomenon is particularly dangerous for coastal cities, where high population density, concentrated infrastructure, and economic assets amplify the potential impacts [*Becker et al., 2023*]. As climate change intensifies these physical drivers, coastal flooding

poses increasing risks to human safety, urban resilience, and sustainable development in vulnerable regions worldwide. The IPCC AR6 report predicts a significant rise in coastal flooding across nearly all global regions by mid-century, particularly under all but the lowest emission scenarios [Duong *et al.*, 2024]. During tropical cyclone events, the threat of coastal flooding is especially high since landfalling TC systems are typically accompanied by wind-driven storm surge and intense precipitation at the coast [A. Gori *et al.*, 2020a]. Therefore, it is crucial to quantify typhoon-induced flood hazards and losses at the city scale, particularly in the context of climate change.

Extreme sea level is a major consequence of TCs. It can co-occur with, or occur consecutively to, other climate extremes such as heatwaves, giving rise to coastal compound extreme events. Compound events have been widely recognized as an alarming phenomenon because their impacts are often far greater than the sum of individual hazards. This growing concern has been acknowledged in both global assessment frameworks (e.g., IPCC) and regional initiatives (e.g., the European COST Action DAMOCLES). Although such events are relatively rare, their high-impact nature has drawn increasing attention from researchers worldwide [Yang Chen *et al.*, 2022; He and Sheffield, 2020; T Liu *et al.*, 2024b; You *et al.*, 2023; M Zhou and Wang, 2024]. For example, a heatwave preceding a precipitation extreme can increase atmospheric instability and moisture availability, intensifying short-duration rainfall and elevating the risk of flash floods [Yang Chen *et al.*, 2022; You and Wang, 2021; You *et al.*, 2023]. Similarly, an atmospheric heatwave coinciding with a marine heatwave can modify air-sea heat fluxes, intensifying sea-surface warming and prolonging marine heatwaves [Paredes-Fortuny *et al.*, 2025]. As climate change progresses, the frequency and intensity of these compound extremes are projected to increase, creating complex challenges for resilience planning, disaster preparedness, and the development of adaptive strategies to safeguard natural and human systems [Bevacqua *et al.*, 2021; Bevacqua *et al.*, 2023].

1.2 Literature review on typhoon-induced coastal flooding

Recent flood disasters highlight the vulnerability of coastal cities, where populations and assets are concentrated, to coastal flooding [Fang *et al.*, 2020]. Hong Kong, for instance, typically encounters about 5–6 TCs annually [Wong and Choy, 2018]. In recent years, typhoons such as Typhoon Hato (2017), Typhoon Mangkhut (2018), and Typhoon Saola (2023) have generated extensive storm surges in Hong Kong, resulting in maximum inundation depths exceeding 1 m in

low-elevation areas [*Observatory*, 2019; 2021; 2024]. Despite Hong Kong's frequent encounters with storm tide flooding, recent devastating TCs have brought record-breaking winds and rainfall, leaving the city ill-prepared [*Choy et al.*, 2020; *L Li et al.*, 2018]. Since 1988, the economic losses in Hong Kong due to TCs have reached up to 21 billion Hong Kong Dollars (HKD), with damages from Typhoon Mangkhut alone amounting to 9 billion HKD (see <https://www.hko.gov.hk/en/publica/tc/tc2018/annex1.html>). Moreover, coastal flooding is expected to become increasingly frequent and severe due to rapid urbanization, rising sea levels, and the intensification of typhoons in a warming climate [*Dullaart et al.*, 2021; *Kirezci et al.*, 2020; *H Wang et al.*, 2024].

There are usually two steps involved in assessing the risk of coastal flooding: hazard assessment and vulnerability assessment. Flood hazard assessment aims to evaluate the intensity of disasters by using numerical simulations of storm surges, tidal levels, waves, and flooding [*Le Roy et al.*, 2015; *Pasquier et al.*, 2018]. Process-driven hydrodynamic models, such as ADCIRC [*Ayyad et al.*, 2023; *Avantika Gori et al.*, 2020b], Delft3D [*Anderson et al.*, 2021; *Bakhtyar et al.*, 2020b; *S Han and Tahvildari*, 2024], and the FVCOM [*Xiao et al.*, 2021; *Y Zhang and Najafi*, 2020], are widely used to hindcast storm tides and coastal flooding during the passage of typhoons. Among various models, Delft3D allows for the seamless integration of different grid types, such as rectangular and triangular cells, to create computationally efficient grids for typical typhoon modeling domains [*Duong et al.*, 2024; *Q Liu et al.*, 2022]. It can outperform other hydrodynamic models in both computational efficiency and accuracy [*Hemmerling et al.*, 2023; *Muñoz et al.*, 2021]. Delft3D has been used by the Naval Oceanographic Office (US) and the Civil Engineering and Development Department (Hong Kong) to model nearshore ocean dynamics [*Civil Engineering and Development Department*, 2022; *Veeramony et al.*, 2014]. For example, Duong et al. introduced the coupling of flow and wave models to investigate coastal flooding in France [*Duong et al.*, 2024]. Combined with flood hazard assessment, vulnerability curves (depth-damage functions) can be used to conduct vulnerability assessments at both global and regional scales [*Dottori et al.*, 2023; *Hummel et al.*, 2021; *Tiggeloven et al.*, 2020; *M. I. Vousdoukas et al.*, 2018; *Wing et al.*, 2022].

Effective local adaptation necessitates detailed numerical modeling of coastal flooding, focusing on the most destructive events and worst-case scenarios [*Kulp and Strauss*, 2019; *Qiu et*

al., 2022; *Y Shen et al.*, 2019]. The selection of these events can be broadly categorized into two approaches: synthetic TCs and storyline methods. The synthetic TCs approach employs statistical techniques to develop probabilistic track models that incorporate various environmental and oceanic variables crucial to TC development [*Bloemendaal et al.*, 2020; *Dazhi Xi and Lin*, 2021]. This method is commonly used to generate large samples of synthetic TCs for specific locations (e.g., cities) of interest, addressing the need for numerous TC events when evaluating extreme flood hazards caused by low-probability storms [*Avantika Gori et al.*, 2022; *Yin et al.*, 2021]. However, it has limitations, including high computational demands and the introduction of significant uncertainty into flood risk assessments, as synthetic typhoons often assume a symmetric structure [*Grimley et al.*, 2024].

In contrast, storyline methods use historical TCs to create plausible future TC scenarios, which are then designated as worst-case scenarios [*Grimley et al.*, 2024; *Schaller et al.*, 2020]. For example, the Hong Kong government has identified Typhoon Hato as a worst-case scenario and intends to use it as a benchmark for designing new coastal protection measures [*Drainage Services Department*, 2019]. This use of real events is valuable for planning because it leverages extensive observational data to understand the physical processes driving flood hazards and exposure. The model outputs can be validated more convincingly [*J H Wang and Liu*, 2021; *J Yang et al.*, 2019]. Moreover, past typhoons are instrumental in communicating and planning for extreme events, as they remain in the public's collective memory for a long time [*Grimley et al.*, 2024]. When setting future scenarios, two key trends emerge: one incorporates the changing intrinsic properties of typhoons (e.g., intensity, size, and location) [*J Yang et al.*, 2019; *Yu et al.*, 2024], while the other focuses on background environmental factors (e.g., tidal level and sea level rise (SLR)) [*Hsiao et al.*, 2022; *Hsiao et al.*, 2024; *Long and Gao*, 2023]. Given that historical typhoons already represent the most destructive situations, focusing on changes in the ambient environment may provide a more comprehensive understanding of future risks.

However, there remains a lack of understanding of coastal flooding under worst-case scenarios for Hong Kong, a region characterized by significant coastal hydrodynamic interactions [*Choy et al.*, 2020]. The simple nearest neighbor extrapolation method employed in previous studies may not adequately capture the dynamic nature of flood routing [*Leijnse et al.*, 2021], potentially leading to biases in the final inundation maps. Furthermore, given the high density of

buildings in the area, there is an urgent need to investigate the potential monetary losses associated with flooding events.

1.3 Literature review on compound heatwaves and extreme sea levels

Heatwaves followed by extreme sea levels can lead to a new type of compound extreme weather event that is more destructive than coastal flooding caused by extreme sea levels alone. Heatwaves followed by extreme sea levels can cause disproportionate increases in the losses, damages, and emergency response needs like other sequential extremes [*Bevacqua et al.*, 2019; *K Feng et al.*, 2022; *P. Ganguli et al.*, 2020; *W Han et al.*, 2022; *Wahl et al.*, 2015] along coastlines. Higher temperatures can significantly weaken the capacity for effective post-emergency responses during coastal flood events. Civil protection efforts may become less efficient, leading to harsher conditions for affected populations. One example of such compound heatwave and extreme sea level events (CHWESL events) is the high sea levels caused by storms and waves from Storm Agnes in Ireland in September 2023, which followed a heatwave and resulted in significant economic losses and damages from coastal flooding [*Boland*, 2023]. Scorching heat stresses both animals and plants, potentially setting the stage for subsequent widespread stormy weather and flash floods, which can lead to livestock losses, infrastructure damage, and water quality issues [*L Gu et al.*, 2022; *W Zhang and Villarini*, 2020]. In coastal regions, the situation can worsen, as strong winds during storms can also induce storm surges, resulting in further coastal flooding. While the winds associated with extreme sea levels following heatwaves may provide some relief, the abrupt shift from one extreme to another can increase the vulnerability of coastal social and ecological systems due to the limited time available for adaptation.

Worse still, heatwaves and extreme sea levels may even occur on the very same day, further compounding their destructive impacts. Specifically, CHWESL events can pose unexpected flooding and drowning risks, posing a threat to coastal residents and tourists during heatwaves. An example of this phenomenon occurred in August 2021: extreme sea level-induced flooding struck the Mediterranean region while local temperatures reached approximately 50°C [*Knox*, 2021; *Peacock*, 2021]. In addition, acting as different stressors, concurrent heatwaves and extreme sea levels may exceed the coping capacity of an affected system like other compound events [*Seneviratne*, 2021].

Despite the substantial impacts, CHWESL events have received far less attention compared to other types of compound events. There is currently a lack of global picture of CHWESL dynamics and evolution in response to the changing climate. The physical mechanisms behind CHWESL events also remain unclear. Thus, there is an urgent need for a comprehensive assessment of CHWESL events from a global perspective, particularly given the projected increases in both the intensity and frequency of heatwaves and extreme sea levels [IPCC, 2021; Muis *et al.*, 2020; Seneviratne, 2021] as well as the projected growth of coastal population and urbanization [Barragán and de Andrés, 2015; Jones and O'Neill, 2020; Neumann *et al.*, 2015].

1.4 Literature review on compound heatwaves and tropical cyclones

TCs (i.e., Tropical cyclones) are responsible for the highest insured losses of any natural hazard in the world [Choi *et al.*, 2024; S Wang and Toumi, 2021]. They are often accompanied by heavy precipitation, storm surges, waves, and strong winds, leading to extensive damage and casualties in the areas where they make landfall and in adjacent coastal regions due to coastal flooding [Lockwood *et al.*, 2024; Shan *et al.*, 2023; Wei *et al.*, 2024; Yin *et al.*, 2021]. These losses are expected to worsen in population-dense coastal areas, owing to a combination of coastal development [Bloemendaal *et al.*, 2022; Bouwer, 2018], sea level rise [Hermans *et al.*, 2023], and changes in extreme weather patterns [Lange *et al.*, 2020; Michalis I. Vourdoukas *et al.*, 2020]. Coastal flooding from storm surges and extreme precipitation, along with extreme winds, are not the only hazards associated with the passage of TCs. It has been observed that coastal areas may experience higher air temperature and specific humidity prior to the landfall of TCs [T C Chen *et al.*, 2010; Poulomi Ganguli and Merz, 2024; T. Matthews *et al.*, 2019; P Y Wang *et al.*, 2023a; M Zhang *et al.*, 2024]. Extreme heat can pose significant risks to human health by both aggravating pre-existing medical conditions and creating new health hazards. These include life-threatening conditions like heat exhaustion and heat stroke, as well as dehydration and reduced work capacity, all of which contribute to excess mortality [Garcia-Leon *et al.*, 2021; A Hsu *et al.*, 2021; Tom Matthews *et al.*, 2024]. Epidemiological studies have demonstrated associations between heatwave exposure and increased mortality risks across from a diverse range of diseases [J Liu *et al.*, 2025; J D Liu *et al.*, 2024a; D. Xi *et al.*, 2024].

TCs affecting coastal regions with a preceding heatwave are defined as H-TC events. Analysis of TCs and heatwaves worldwide has shown that humid heat peaks just before TC landfall [T. Matthews *et al.*, 2019]. Regional studies reveal that H-TC events may arise from a combination of low cloudiness, clear skies, intense solar radiation, and the adiabatic effects of downdrafts in the outer regions of TCs [Chang *et al.*, 2024; D Zhao *et al.*, 2021a]. Low cloudiness and intense solar radiation create favorable conditions for diabatic heating. Subsequently, the divergent outflow at upper levels of TCs promotes subsidence in their outer regions, causing dry air from the upper troposphere to descend and compress, thereby enhancing adiabatic warming [T J Parker *et al.*, 2013]. This compression induces adiabatic warming, which can further intensify near-surface temperatures and amplify surface solar radiation [Sijia Wu *et al.*, 2023]. For instance, descending motion over Central China occurs when low-pressure systems are situated in the nearby tropical northwest Pacific, accompanied by abnormal ascending motion [P Y Wang *et al.*, 2023a]. As the TCs approach the coastline, the induced heatwaves may gradually intensify. Apart from favorable synoptic conditions, heatwaves can also be induced by local adiabatic warming before the arrival of TCs, such as the foehn wind—a dry and warm downslope wind that occurs on the leeward side of a mountain [T C Chen *et al.*, 2010; D Zhao *et al.*, 2021a]. The arrival of TCs can then trigger extreme winds, heavy rainfall, and coastal flooding [Avantika Gori *et al.*, 2020b; B. Zhang and Wang, 2021] after the heatwave ends. Therefore, the TCs following closely after extreme heat events is likely to be shaped by large-scale thermodynamics, shifts in circulation, and land-sea atmospheric feedbacks. These drivers – and therefore the joint distribution of H-TC events – are very likely to be non-stationary, especially under large-scale climate warming.

The H-TC events may lead to greater impacts than the sum of the individual events to coastal regions. Preceding heatwaves can exacerbate the physical damage associated with TCs or increase the exposure and vulnerability of coastal residents. First, research indicates that risk of flash floods is heightened when heavy rainfall and stormy weather follow heatwaves, resulting in extensive damage to water quality, critical infrastructure, crop fields, and human livelihoods [Yang Chen *et al.*, 2022; Poulomi Ganguli and Merz, 2024; Gao *et al.*, 2023; L Gu *et al.*, 2022; You and Wang, 2021]. Second, coastal communities must manage two distinct hazards within a short timeframe, which may lead to significant increases in vulnerability and exposure. For example, evacuating from a TC during a heatwave can force people away from air conditioning and other cooling measures, increasing the likelihood of heat-related health impacts. Indeed, those in harm's way,

could therefore have the impossible decision of evacuating and facing potentially deadly heat, or remaining and facing the TC. TC Rita in 2005 highlights the dangers. Around 3.7 million people in Texas evacuated during a heatwave that reached temperatures of 38°C [Carpender *et al.*, 2006]. Ultimately, 107 people died during the evacuation (compared to just 6 people who died directly from the following TC), with well over 50 % of these fatalities linked with extreme heat [Baker, 2018; Carpendar *et al.*, 2006]. Furthermore, evacuation orders communicated through social media or television may be missed if high power demand for air conditioning during heatwaves leads to blackouts. The time lag between the end of heatwaves and the following arrival of TCs is evidently crucial. As it decreases, the available period for safely evacuating reduces. Greater congestion and, therefore, travel times, are likely within the shrinking evacuation window. Given that both heatwaves and TCs exhibit markedly changing characteristics under global warming [Jyoteeshkumar reddy *et al.*, 2021; N Li *et al.*, 2021; Xu *et al.*, 2024; Yamaguchi *et al.*, 2020], it is essential to understand how the time lag between them has been evolving.

1.5 Research gap and objectives

Despite substantial efforts to identify and attribute coastal hydrometeorological extremes, several key limitations remain that hinder a comprehensive understanding of these events:

- (1) limited knowledge of coastal flooding under worst-case scenarios in Hong Kong;
- (2) limited research on emerging consecutive and concurrent events involving heatwaves and extreme sea levels; and
- (3) insufficient understanding of compound events involving heatwaves and tropical cyclones.

This dissertation aims to advance understanding of coastal hydrometeorological extremes, with a focus on coastal compound flooding and compound coastal hydrometeorological extremes, including consecutive heatwaves and extreme sea levels, concurrent heatwaves and extreme sea levels, as well as compound heatwaves and tropical cyclones. To achieve this aim, the dissertation is structured around the following specific objectives:

(1) to develop a hydrodynamic modeling-based framework for estimating economic losses from typhoon-induced coastal flooding;

(2) to investigate newly identified temporally compounding events involving both consecutive and concurrent heatwaves and extreme sea levels, hereafter termed consecutive HWESL and concurrent HWESL; and

(3) to conduct a global analysis of compound heatwaves and tropical cyclones.

1.6 Dissertation overview

As shown in Figure 1.1, this dissertation is structured to address the intricacies and challenges associated with coastal hydrometeorological hazards in a warming climate, focusing on two critical aspects: (1) coastal compound flooding and (2) coastal compound hydrometeorological extremes.

This dissertation is organized as follows. Chapter 2 lays the foundation by providing a detailed description of data acquisition and research methods used for coastal flooding modeling and the characterization of different coastal compound extremes. Chapter 3 develops an integrated framework that combines seamless hydrodynamic simulations, the storyline approach, and vulnerability assessment techniques to examine flood risk under various tidal levels and sea-level rise scenarios in Hong Kong. Chapter 4 presents a pilot study of compound heatwaves and extreme sea levels, specifically consecutive heatwaves and extreme sea levels across Europe, with a focus on their detection, attribution, and future projection. This regional-scale analysis is made possible by the availability of long-term simulation-based extreme sea-level datasets for historical detection and high-resolution CORDEX data under different warming scenarios for future projections. After demonstrating the feasibility of analyzing compound heatwaves and extreme sea levels, Chapter 5 extends the analysis to the global scale, examining concurrent heatwaves and extreme sea levels, their temporal interactions, underlying mechanisms, and projected future changes. This global perspective enables the identification of large-scale patterns and trends, offering a comprehensive understanding of these phenomena. Chapter 6 investigates the global time lag between heatwaves and tropical cyclones, as well as the influence of tropical cyclones on heatwaves. Building on insights from compound event impacts, it further explores how their characteristics and interactions may evolve in a warming climate. Finally, Chapter 7 synthesizes the key findings and outlines future research directions for advancing studies on coastal hydrometeorological extremes.

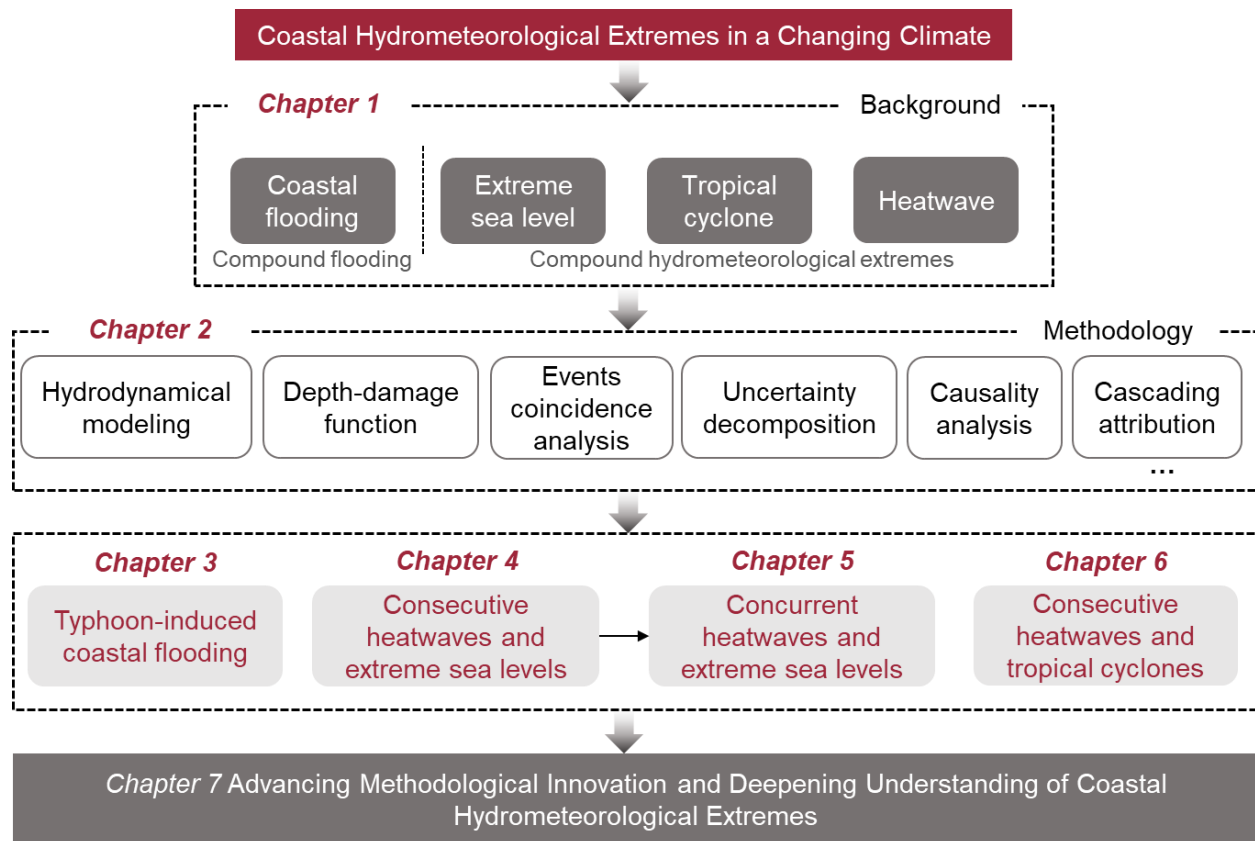


Figure 1.1 The framework of the dissertation.

Chapter 2. Data and methodology

This chapter presents both the data description and the research methodology used to analyze coastal hydrometeorological extremes, along with the proposed techniques for identifying and evaluating their compounding characteristics. First, the chapter provides a detailed description of the datasets, including the various types of reanalysis, projection, simulation, and observational data employed. It then introduces the analytical framework, which integrates wind and pressure modeling, tide-surge-wave simulation, and economic loss assessment for coastal flooding. Definitions and methodologies for identifying heatwaves and extreme sea levels are also outlined to facilitate understanding of their interactions. Finally, the chapter investigates the time lag between heatwaves and tropical cyclones, employing bootstrap resampling-based significance tests, correlation analysis, and causality analysis for compound event attribution.

2.1 Data descriptions

In this dissertation, I have employed a diverse range of datasets, broadly categorized into five groups: reanalysis data, projection data, simulation data, observational data, and other data.

2.1.1 Reanalysis data

Hourly 10-m u- and v-wind components and surface pressure fields obtained from the fifth-generation atmospheric reanalysis dataset (ERA5) [Hersbach, 2018a; b] of the European Centre for Medium-Range Weather Forecasts (ECMWF) with a spatial resolution of 0.25° were employed to construct wind and surface pressure patterns over Hong Kong during typhoon passages.

In addition, daily maximum 2-m air temperature (T_{max}), mean 2-m dew point temperature, surface pressure, total precipitation, surface solar radiation downward, convective available potential energy, total column water vapor, total cloud cover, 10 m u-wind component and v-wind component, vertical velocity at pressure levels, temperature at pressure levels, relative humidity at 700hPa, and geopotential at 500hPa, with a spatial resolution of 0.25° from ERA5, were used to calculate equivalent temperature, and adiabatic heat as well as analyze the atmospheric conditions.

2.1.2 Projection data

Projected 2-m air temperature and specific humidity used to calculate the equivalent temperature under global warming are based on 10 bias-corrected CMIP6 climate projections, including ACCESS-CM2, CanESM5, CNRM-CM6-1-HR, EC-Earth3-CC, EC-Earth3-Veg-LR, INM-CM4-8, INM-CM5-0, KIOST-ESM, MPI-ESM1-2-LR, and NorESM2-MM [Copernicus Climate Change Service, 2021]. These CMIP6 models were selected based on data availability and good performance in simulating meteorological variables to minimize the uncertainty originating from datasets [Di Virgilio *et al.*, 2022]. All future datasets at a global scale were gridded to 1° spatial resolution using the bilinear interpolation method.

The temperature projection dataset for Europe was obtained from EURO-CORDEX models [Copernicus Climate Change Service, 2019], considering data availability and good performance in simulating meteorological variables in Europe [Hosseinzadehtalaei *et al.*, 2020; Jacob *et al.*, 2013; Lhotka *et al.*, 2017], including NCC-NorESM1-M-DMI-HIRHAM5, MOHC-HadGEM2-ES-DMI-HIRHAM5, and ICHEC-EC-EARTH-DMI-HIRHAM5.

2.1.3 Simulation data

The simulation data refer to total water level outputs generated using the hydrodynamic Deltares Global Tide and Surge Model (GTSM, version 3.0) [Sanne Muis, 2022; Yan, 2020]. The simulations were driven by the ERA5 reanalysis dataset for the historical period 1979–2017 and by CMIP6 climate projections under the SSP5-8.5 emission scenario for the future period 2025–2049 on a global scale. The future total water level is based on five bias-corrected CMIP6 climate projections, including CMCC-CM2-VHR4, EC-Earth3P-HR, GFDL-CM4C192-SST, HadGEM3-GC31-HM, and HadGEM3-GC31-HM-SST [Sanne Muis, 2022].

For the European region, the regional climate model DMI-HIRHAM5 within the EURO-CORDEX framework was applied to simulate future extreme sea levels for 2042–2070 and 2072–2100 under high-emission (RCP8.5) and medium-emission (RCP4.5) scenarios, respectively.

The total water level dataset provides globally consistent water level data and features a finer spatial resolution for the European region. It is characterized by temporal stability, temporal continuity (no gaps or missing values), and spatial continuity, as it covers almost all the global

coastline. Globally, it has a temporal resolution of 10-minute and was aggregated to the daily total water level (W_t , cm) to identify extreme sea levels. It includes sea stations with a spatial resolution of 0.1° in the near coastal area and 0.25° in the ocean area within 100 km of the coastline.

2.1.4 Observational data

TC track data. The TC best track dataset is provided by the International Best Track Archive for Climate Stewardship (IBTrACS) v04r01 [Knapp *et al.*, 2018; Knapp *et al.*, 2010]. Multiple TC datasets from different institutions, such as the National Hurricane Center, Joint Typhoon Warning Center of US, China Meteorological Administration, Australian Bureau of Meteorology, Japan Meteorological Agency, have worked collaboratively to develop a complete global collection of TCs. For each TC track, I obtained its name, basin, as well as longitude, latitude, maximum sustained wind speed, radius, and translation speed at each observational time during its life span. Translation speed was calculated using the IBTrACS tracking algorithm based on storm-center position changes over successive time steps, with distances computed along great-circle paths and divided by the corresponding time interval. In this study, I used TCs with 6-hourly records for the period 1981–2022, which corresponds to the post-satellite era and is considered more reliable [Chand *et al.*, 2022; X Feng *et al.*, 2021].

I considered TCs with a record interval of 6 hours (at the standard observational times: 00, 06, 12, and 18 Coordinated Universal Times) from 1981 to 2022, which belongs to the post-satellite era and tends to be more reliable [Chand *et al.*, 2022; X Feng *et al.*, 2021]. Following previous studies, the 6-hourly TC records were linearly interpolated to an hourly resolution to better capture sub-daily variations [Bloemendaal *et al.*, 2022; Lavender and McBride, 2020]. I used TCs that were active for at least 72 hours and exceeded wind speeds of 34 knots for at least 36 hours [K Bhatia *et al.*, 2022; K T Bhatia *et al.*, 2019; Jing *et al.*, 2023]. I then removed TC records with wind speed less than 34 knots [K T Bhatia *et al.*, 2019]. This helps reduce the potential underestimation of weak and short-lived TCs occurring before or during the early satellite era. I only selected TC records within the range of 40°N – 40°S to minimize the influence of extra-tropical transition [K Bhatia *et al.*, 2022; Y. Li *et al.*, 2023b].

For the regional-scale analysis of Hong Kong, TC information was obtained from the best track dataset provided by the Tropical Cyclone Data Center of the China Meteorological

Administration (<https://tcdata.typhoon.org.cn/ziljsjj.html>) [Lu *et al.*, 2021; Ying *et al.*, 2014]. This dataset includes characteristics of TCs in the Western North Pacific since 1949. For each storm, the dataset provides parameters including storm name, date, latitude, longitude, 2-minute maximum sustained surface wind, minimum central pressure at sea level, radius of maximum wind speed (R_{max}), and a tropical system indicator that classifies the storm as a tropical depression, tropical storm, severe tropical storm, or typhoon. The dataset contains TC information at 6-hour intervals before 2018 and at 3-hour intervals thereafter. To enhance the temporal resolution, I linearly interpolated the data to hourly intervals, allowing for a more accurate representation of TC positions throughout their lifetimes.

MSWEP precipitation data. I employed precipitation data from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) version 2 dataset [Beck *et al.*, 2019] to obtain rainfall rates during typhoons in Hong Kong, which were incorporated into the coastal flooding simulation model. The MSWEP dataset has a spatial resolution of 0.01° and a temporal resolution of 3 hours.

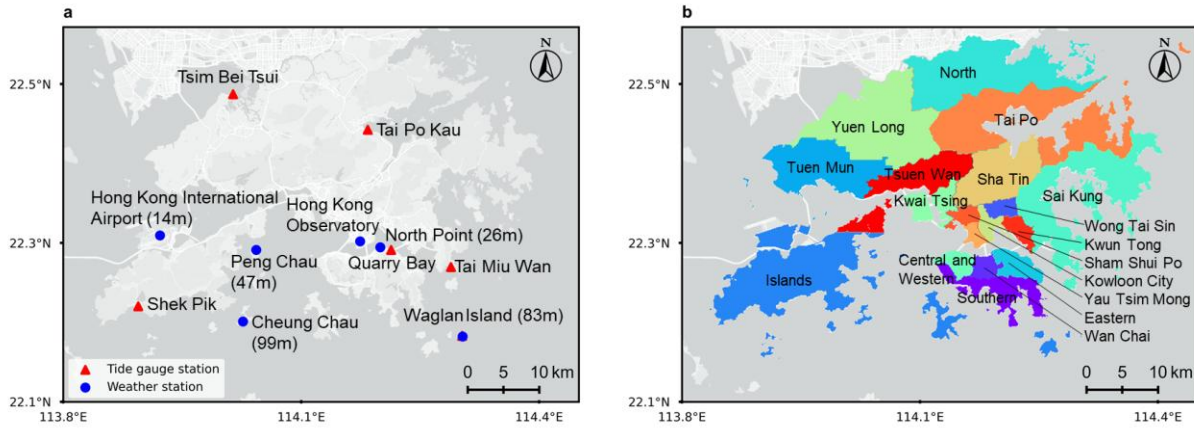


Figure 2.1 Stations and administrative districts in Hong Kong.

(a) Tidal gauge stations and weather stations in Hong Kong. The numbers in parentheses following the weather station names indicate the elevation of the anemometers. (b) Administrative districts in Hong Kong (a total of 18 districts).

Station observational data. Calibration and validation of the coastal flooding simulation model were performed using observational data collected from six tide gauge stations and six weather stations across Hong Kong (Figure 2.1a). Tide gauge stations provide hourly water levels,

while weather stations record hourly surface pressure and wind speeds during the passage of typhoons. The elevations of the anemometers at the weather stations vary and are not uniformly standardized to 10 meters (Figure 2.1a). To correct for this, the logarithmic wind-profile law [S-A Hsu, 2025] was applied to adjust the recorded wind speeds to a standard 10-meter elevation, ensuring consistency with the model outputs.

Global tide gauge data. To validate the results obtained from the ERA5 reanalysis dataset regarding extreme sea levels, I collected tide gauge observations from the Global Extreme Sea Level Analysis (GESLA) 3 dataset [Haigh *et al.*, 2022; P. L. Woodworth *et al.*, 2016]. I only considered tide gauges that had a minimum of 20 years of observations within the study period of 1979–2017. This selection process resulted in a total of 864 global tide gauges that were used for further analysis. To ensure consistency, I aggregated the hourly tide gauge observations into a daily mean total water level. Approximately 40% of these 864 tide gauges provided data spanning more than 35 years of total water level observations. The spatial distribution of these selected tide gauges is shown in Figure 2.2, which illustrates their concentration along the coastlines of Europe, Japan, America, Canada, and Australia. For the regional study of Europe, there is a total of 281 stations used for further analysis. Among these, approximately 50% provided records spanning more than 35 years of total water level observations. Stations are mainly concentrated in western and northern Europe.

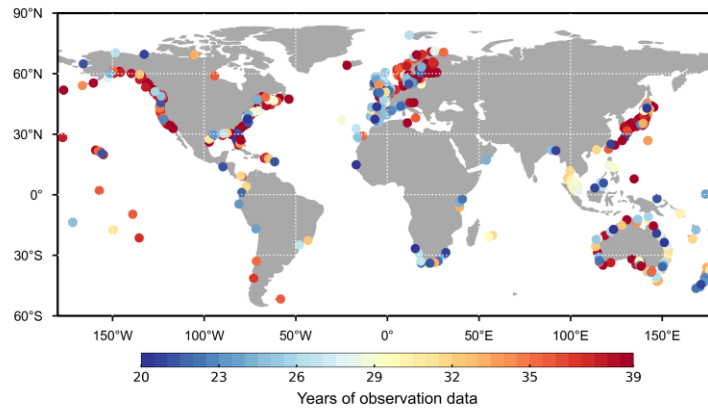


Figure 2.2 Distribution of global tide gauge stations.

A total of 864 global tide gauge stations with at least 20 years of observations during the study period of 1979–2017 are shown. Different colors indicate the length of the observational record at each station.

2.1.5 Other data

Topography, land, and tapping point data. Bathymetric data were derived from GEBCO's global 30 arc-second gridded dataset (https://www.gebco.net/data_and_products/). High-resolution topography data for Hong Kong, specifically the Digital Terrain Model (DTM) with a spatial resolution of 5 m and a vertical accuracy of ± 5 m, land cover type data with a resolution of 10 m, and building footprint data were sourced from the Hong Kong Government's Open Data Applications (<https://data.gov.hk/en/>) (Figure 2.3). The locations of stormwater tapping points in Hong Kong were also obtained from the Hong Kong Government's Open Data Applications. Coastal flooding in Hong Kong was described using the 18 administrative districts (Figure 2.1b). All water levels in this study are referenced to the Hong Kong Chart Datum, which is measured at 1.45 m below mean sea level and 0.146 m below the Hong Kong Principal Datum.

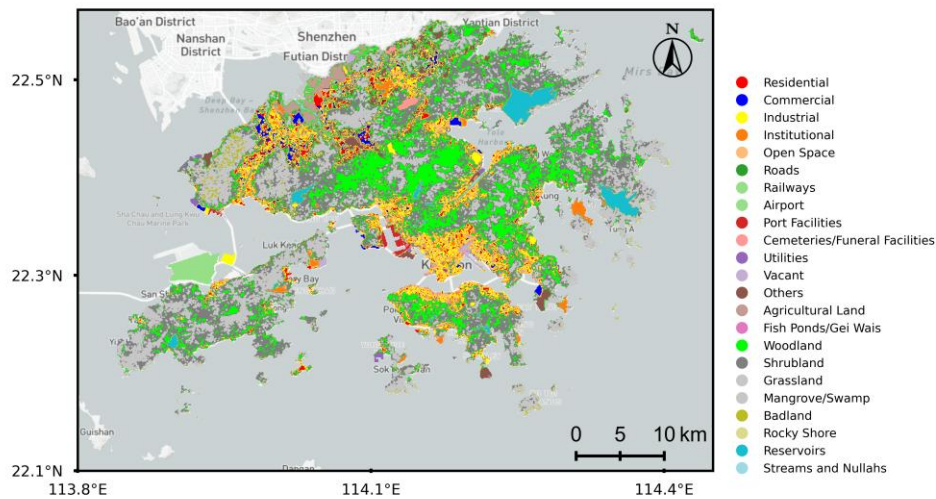


Figure 2.3 Land cover types in Hong Kong.

Astronomical tide data. Tidal data during the historical period were derived from eight major tidal constituents (K1, K2, M2, N2, O1, P1, Q1, and S2) extracted from the TPXO8-ATLAS dataset [Egbert and Erofeeva, 2002].

Future scenarios data. I used predicted tide data from the next 18.61-year lunar nodal tidal cycle, along with projected SLR (i.e., sea level rise) for the end of the century, to investigate future changes in flood hazard in Hong Kong. The predicted tide data were obtained from the Hong Kong

Observatory. The SLR projections for 2100 were sourced from the IPCC AR6 report, with a likely range between the 17th and 83rd percentiles, accounting for uncertainties in emissions scenarios and the relationships between temperatures and sea-level change drivers [Fox-Kemper *et al.*, 2021; Garner, 2021]. I used the upper and lower bounds of this range for averaged SLR projections at six tide gauge stations in Hong Kong (Table S2), reflecting a probability of at least 66% [Hsiao *et al.*, 2022]. Three emission scenarios from the Shared Socioeconomic Pathways (SSP) were considered: SSP126, SSP245, and SSP585.

Coastline shape data. The global coastline was derived from the Global Self-consistent, Hierarchical, High-resolution Geography database (GSHHG) [Wessel and Smith, 1996]. The GSHHG is a high-resolution geography dataset amalgamated from three databases in the public domain, including World Vector Shorelines (WVS), CIA World Data Bank II (WDBII), and Atlas of the Cryosphere (AC), and has been widely used in coastal studies [Marsooli and Lin, 2018; Qiu *et al.*, 2022].

Climate indices. I obtained two climate indices to examine the influence of natural climate variability on H-TC variability: the Niño 3.4 index, a widely used proxy for the El Niño–Southern Oscillation (ENSO), and the Pacific Decadal Oscillation (PDO). These indices represent dominant modes of natural climate variability operating primarily at interannual (e.g., Walker circulation) and decadal timescales, respectively [Chand *et al.*, 2022; Wahl and Chambers, 2015].

Population data. The population data of the Global Human Settlement Layer (GHSL) dataset used for exposure calculations has a spatial resolution of 30 arcseconds (approximately 900 m at the equator) and covers the period from 1975 to 2020 at five-year intervals.

2.2 Typhoon-Induced Coastal Flooding and Economic Losses

2.2.1 Wind and pressure modeling

Although wind and pressure data from the ERA5 reanalysis can be used to construct the wind and surface pressure fields in Hong Kong during the passage of typhoons, the spatial resolution of the ERA5 reanalysis dataset (approximately 25 kilometers) is too coarse to match the mesh grid of 5 kilometers offshore to 50 meters nearshore. Therefore, I used ERA5 to represent the

environmental background wind speed and pressure fields, and incorporated parametric wind-pressure models to calculate the surface wind and atmospheric pressure fields associated with the typhoons at a resolution of 50 meters. The combination of environmental wind and a symmetric gradient wind [Du et al., 2024] can be expressed in vector form as:

$$V_{10} = V_E(1 - e) + eV_G \quad 2-1$$

where V_E and V_G are the environmental background wind speed and symmetric gradient wind speed, respectively. They are superimposed with a weight coefficient e to construct a new typhoon wind field. e varies according to the distance between the calculation point and the typhoon center:

$$e = C^4 / (1 + C^4) \quad 2-2$$

where C represents the affected range of TCs, and is related to the distance r between the cyclone center and the target location, and the radius of maximum wind speed R_{max} :

$$C = r / (n \times R_{max}) \quad 2-3$$

The symmetric gradient wind speed V_G is calculated by the Holland wind model[Holland, 1980]:

$$V_G(r) = \left[\frac{B}{\rho_\alpha} \left(\frac{R_{max}}{r} \right)^B (P - P_0) \exp \left[- \left(\frac{R_{max}}{r} \right)^B \right] + \left(\frac{rf}{2} \right)^2 \right]^{0.5} - \frac{rf}{2} \quad 2-4$$

where B is the Holland pressure profile, ρ_α is the air density defined as 1.2 kg/m^3 , P is the outer pressure of a typhoon defined as 1010 hPa , P_0 is the typhoon center pressure, and f is the Coriolis parameter ($f = 2 \Omega \sin \varphi$; where $\Omega = 7.292 \times 10^{-5} \text{ rad/s}$ and φ is the geographical latitude in degrees). B can be expressed as:

$$B = 1.881 - 0.00557R_{max} - 0.01295\varphi \quad 2-5$$

where v_m and θ are the maximum wind speed and latitude of TC center, respectively.

There is no universal method to calculate R_{max} , but the empirical formula proposed by Willoughby and Rahn (2004) [Willoughby and Rahn, 2004] is a widely used method in storm surge simulation:

$$R_{max} = 51.6 \exp(-0.223v_m + 0.0281\theta) \quad 2-6$$

The direction of the gradient wind velocity was modified by the inflow angle [Bretschneider, April 1972] and can be expressed as:

$$\beta = \begin{cases} 10^\circ \left(1 + \frac{r}{R_{max}}\right), & 0 \leq r \leq R_{max} \\ 20^\circ + 25^\circ \left(\frac{r}{R_{max}} - 1\right), & R_{max} \leq r \leq 1.2R_{max} \\ 25^\circ, & r \geq 1.2R_{max} \end{cases} \quad 2-7$$

The surface wind stress τ_{wx} and τ_{wy} are calculated as:

$$\tau_{wx} = \rho_a C_d u_{10} \sqrt{u_{10}^2 + v_{10}^2} \quad 2-8$$

$$\tau_{wy} = \rho_a C_d v_{10} \sqrt{u_{10}^2 + v_{10}^2} \quad 2-9$$

where ρ_a is the air density. u_{10} and v_{10} are the x- and y-component of the wind velocity at 10-m height, respectively. Drag coefficient C_d is from Garratt's drag formula [Garratt, 1977].

The pressure field of the TC is also described by a parametric pressure field [Holland, 1980]:

$$P(r) = P_c + (P_n - P_c) e^{(-\frac{R}{r})^B} \quad 2-10$$

where P_c is the central pressure, and P_n is the ambient pressure. The combination of the environmental pressure field and the parametric pressure field is similar to the wind field.

2.2.2 Tide-surge-wave simulation

I utilized the Delft3D-Flow model to calculate sea surface levels and the velocity fields associated with storm surges and tidal currents. By utilizing the two-dimensional shallow water equations and assuming a constant fluid density along with depth-averaged horizontal velocity, the hydrodynamic Delft3D-Flow effectively computes long-period ocean surface disturbances induced by astronomical and meteorological forces, i.e., tides and storm surges [Silveira *et al.*, 2021]. The model numerically solves the Navier-Stokes equations for incompressible fluids, adhering to the shallow water and Boussinesq assumptions [Maymandi *et al.*, 2022; Veeramony *et al.*, 2017]. For incompressible fluids across the total depth, kinematic boundary conditions at the water surface and bed level are considered [C Lee *et al.*, 2019]. Consequently, the governing continuity equation can be expressed in the classical conservative form:

$$\frac{\partial h}{\partial t} + \frac{\partial Uh}{\partial x} + \frac{\partial Vh}{\partial y} = Q \quad 2-11$$

where U and V are the depth velocities, and Q is the contribution per unit area due to the discharge or withdrawal of water, precipitation and evaporation:

$$Q = \int_0^h (q_{in} - q_{out}) dz + P - E \quad 2-12$$

where q_{in} and q_{out} are the local sources and sink of water per unit of volume, respectively. P is the non-local source term of precipitation and E is the non-local sink term due to evaporation. I employed a rain-on-grid approach, incorporating rainfall data as a volume source term in each grid cell, while drainage data is considered a volume sink term at designated tapping point of the stormwaters, applied at the beginning of each time step [Gao *et al.*, 2023; Maymandi *et al.*, 2022]. The total rainfall amount is determined at the start of every timestep and added to the total volume source term for each grid cell. The momentum equations in x- and y-direction are given by:

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} + w \frac{\partial u}{\partial z} - fv = -\frac{1}{\rho_0} \frac{\partial P}{\partial x} + F_x + \frac{\partial}{\partial z} \left(v_v \frac{\partial u}{\partial z} \right) + M_x \quad 2-13$$

$$\frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} + w \frac{\partial v}{\partial z} - fu = -\frac{1}{\rho_0} \frac{\partial P}{\partial y} + F_y + \frac{\partial}{\partial z} \left(v_v \frac{\partial v}{\partial z} \right) + M_y \quad 2-14$$

where v_v is the vertical eddy viscosity coefficient, and $\frac{\partial P}{\partial x}$ and $\frac{\partial P}{\partial y}$ represent the pressure gradients. F_x and F_y are forces representing the imbalance of horizontal forces. M_x and M_y refer to the contributions due to external sources or sinks of momentum, such as wave stresses, discharge or withdrawal of stormwater.

I then used the Simulating Waves Nearshore (SWAN) model to simulate wave fields responding to TC events and run it with the Delft3D-Flow model in a coupled mode [Hasan Tanim and Goharian, 2021]. SWAN is a phase-averaged wave model that is used to simulate the evolution of random, short-crested wind waves [Veeramony *et al.*, 2017]. It is based on the discrete spectral action balance equation and accounts for refraction due to currents and bottom topography, dissipation due to white capping, depth limited wave breaking, and bottom friction, as well as nonlinear wave-wave interactions [Huang *et al.*, 2021]. The entire hydrodynamic simulation is conducted first, with the hydrodynamic output subsequently serving as input for the second wave simulation. This approach allows the hydrodynamic results to inform the control of structures or the simulation of wave dynamics. Such a coupling method is widely utilized and has demonstrated effective performance in numerous prior studies [Bakhtyar *et al.*, 2020a; Gutenson *et al.*, 2022; Jafarzadegan *et al.*, 2023]. The depth averaged wave-induced forcing F_x and F_y are given by the gradients of the radiation stress tensor S , or following Dingemans *et al.* [Dingemans *et al.*, 1987] approximated by wave energy dissipation:

$$F_x = -\frac{\partial S_{xx}}{\partial x} - \frac{\partial S_{yx}}{\partial y} = D \frac{k_x}{\omega} \quad 2-15$$

$$F_y = -\frac{\partial S_{xy}}{\partial x} - \frac{\partial S_{yy}}{\partial y} = D \frac{k_y}{\omega} \quad 2-16$$

where D is the dissipation rate, and S_{xx} , S_{yy} , and S_{xy} represent the components of the radiation stress. These are computed by the wave model, accounting for bottom friction (orbital motion), depth-induced breaking, and white-capping.

2.2.3 Construction of the Unstructured Mesh

Utilizing the mesh generation module of the Surface-water Modeling System (SMS), I developed a computational mesh that spans latitudes 21.2°N to 23.1°N and longitudes 112.9°E to 115.5°E (Figure 2.4). The computational domain comprises an unstructured triangular mesh with 88,545 nodes and 176,425 elements. The mesh resolution is finest at 50 meters nearshore and over land, gradually increasing to 5 kilometers offshore. This resolution is comparable to previous studies of Hong Kong's coastline and other coastal inundation assessments (Table 2.1), offering a good balance between accuracy and computational efficiency. To generate the computational mesh, I first created a series of feature arcs along the shorelines, continental slopes, and the deep ocean. Computational nodes were then distributed along the feature arcs at a prescribed density to achieve the mesh resolution described above [Marsooli and Lin, 2018].

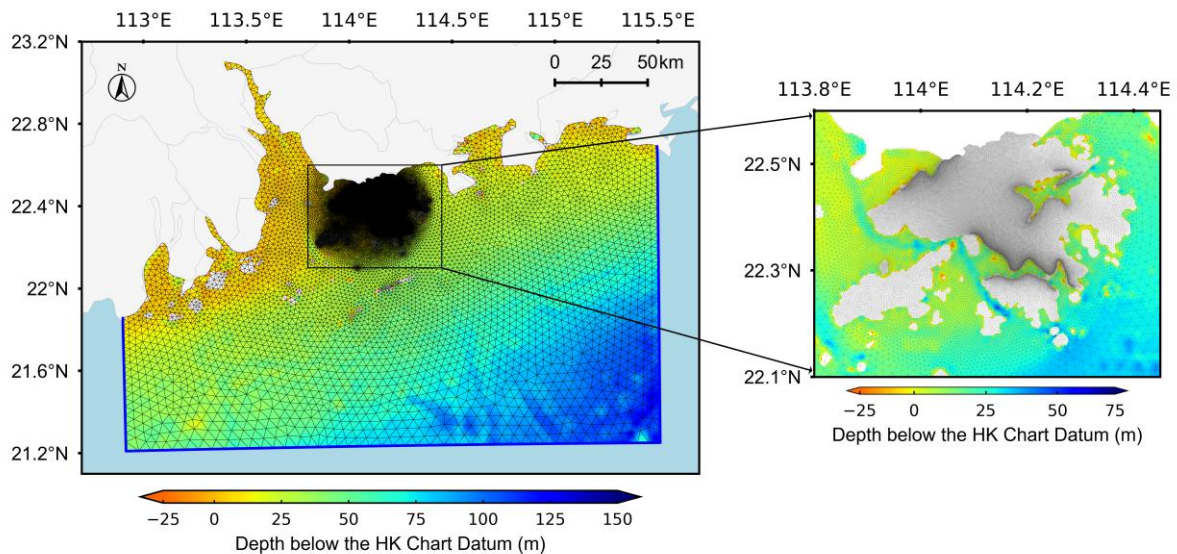


Figure 2.4 Computational mesh and bathymetry of the overall study area (left) and a zoomed-in view of Hong Kong (right).

Table 2.1 Spatial resolutions of mesh grids used in previous studies on Hong Kong’s coastline and similar coastal inundation assessments.

Study area	Spatial resolution of mesh	Source
South Sea	~50 km in the deep sea, ~1 km over the continental shelf, 20m in the vicinities of Macau and Kowloon Bay area in Hong Kong	Wang, J. H., and P. L. F. Liu (2021), Numerical study on impacts of a concurrent storm-tide-tsunami event in Macau and Hong Kong, Coastal Engineering, 170, doi:10.1016/j.coastaleng.2021.104000.
Haikou, China, ~2,237 km ²	Storm surge mesh grid: >=100m Overland flooding model: 50m	Liu, Q., H. Xu, and J. Wang (2022), Assessing tropical cyclone compound flood risk using hydrodynamic modelling: a case study in Haikou City, China, Natural Hazards and Earth System Sciences, 22(2), 665-675, doi:10.5194/nhess-22-665-2022.
Sabine–Neches Estuary, US, 2,500 km ²	1,000 m offshore to 40 m nearshore	Maymandi, N., M. A. Hummel, and Y. Zhang (2022), Compound Coastal, Fluvial, and Pluvial Flooding During Historical Hurricane Events in the Sabine–Neches Estuary, Texas, Water Resources Research, 58(12), doi:10.1029/2022wr033144.
Macau, China, 116 km ²	50 km in the deep sea to approximately 1 km over the continental shelf, and 10–20 m over the land area	Yang, J., et al. (2019), A Comparative Study of Typhoon Hato (2017) and Typhoon Mangkhut (2018)—Their Impacts on Coastal Inundation in Macau, Journal of Geophysical Research: Oceans, 124(12), 9590-9619, doi:10.1029/2019jc015249.
Île de Ré, France, 85 km ²	30 km in the deep ocean and 10m over land	Duong, T. M., R. Meynadier, R. Ranasinghe, M. A. D. Loaiza, J. D. Bricker, J. Reyns, A. Luijendijk, and J. Bamunawala (2024), On detailed representation of flood defences and flow-wave coupling in coastal flood modelling, npj Natural Hazards, 1(1), doi:10.1038/s44304-024-00016-9.
southwestern Taiwan, 10,847 km ²	5-m resolution on the terrestrial area and 1000-m resolution on the oceanic regions	Hsiao, S.-C., H.-S. Fu, H.-L. Wu, T.-Y. Liang, C.-H. Chang, Y.-M. Chen, L.-Y. Lin, and W.-B. Chen (2024), Impact assessment of sea level rise-induced high tide flooding and socioeconomic losses in a highly vulnerable coastal region, Journal of Hydrology: Regional Studies, 55, doi:10.1016/j.ejrh.2024.101921.

2.2.4 Identification of high tidal level

The coastline of Hong Kong experiences semi-diurnal tides, with two high tides and two low tides occurring each day. These tidal events can coincide with peak storm surges during typhoons, as they share similar time scales. I use the peak tidal level from the next 18.61-year lunar nodal tidal cycle as a representation of the extreme tidal level. Locations such as Hong Kong, which experience semi-diurnal tides, are expected to encounter peak tidal levels in 2025 during the next

18.61-year lunar nodal tidal cycle [Peng *et al.*, 2019]. Consequently, I used the predicted tidal levels at the TPK station for the year 2025 to identify extreme tidal events on an hourly timescale. The selection of the TPK station is based on its historical record of being the first to experience high water levels during typhoons. The maximum high tide (HHTide) is predicted to be 2.82 meters at 21:00 on December 6, 2025. Correspondingly, the minimum lower low tide (LLTide) on that day is expected to be 0.41 meters at 02:00 on the same day. Therefore, I conducted water level simulations at the HHTide and the LLTide by adjusting the arrival times of each typhoon to coincide with these tidal levels. I set the arrival time of each typhoon to 21:00 on 6 December 2025 for the HHTide and to 02:00 on 6 December 2025 for the LLTide.

2.2.5 Assessment of economic losses

The process of flooding risk assessment involves two key components: exposure and vulnerability. Exposure is represented through maps of built-up areas, identifying exposure zones for three categories—residential, commercial, and industrial—by utilizing land use data (Figure 2.3). Vulnerability refers to the susceptibility of exposure elements to damage, which is estimated using vulnerability curves (depth–damage functions) for each category [Tiggeloven *et al.*, 2020]. Constructing an empirical vulnerability curve is a commonly used method for conducting vulnerability assessments. The depth–damage function developed by Huizinga *et al.* (2017) at the Joint Research Centre (JRC) is widely employed to evaluate coastal flood risk [Huizinga, 2017; M. I. Voudoukas *et al.*, 2018; Yu *et al.*, 2024].

There are two key parameters in the depth–damage functions: the loss ratio, which represents the extent of damage, and the maximum economic loss per square meter, which indicates the potential economic loss. Both parameters are available for 214 countries and regions [Huizinga, 2017], with disparities based on socio-economic factors from the World Development Indicators database, such as Gross Domestic Product (GDP) and Purchasing Power Parity (PPP) for a given year. The loss ratio remains stable across years but varies across different exposure elements and inundation depths (0 to 6 meters), ranging from 0 to 1, where 0 indicates no damage and 1 represents complete damage. The loss ratio for Hong Kong is illustrated in Figure 2.5. As for the maximum economic loss, it can vary across years. To adjust for this, I use the consumer price index obtained from the World Bank to convert the maximum economic loss from the given year (2010) to the typhoon year. According to the JRC, the maximum loss for residential, commercial, and

industrial buildings in Hong Kong in 2010 was EUR 142, EUR 298, and EUR 243 per square meter, respectively. Using the consumer price index, the scale factors for monetary damage in the years of Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola are 1.28, 1.31, and 1.43, respectively, in relation to 2010. The exchange rate between the euro and the Hong Kong dollar (HKD) was calculated as 8.2.

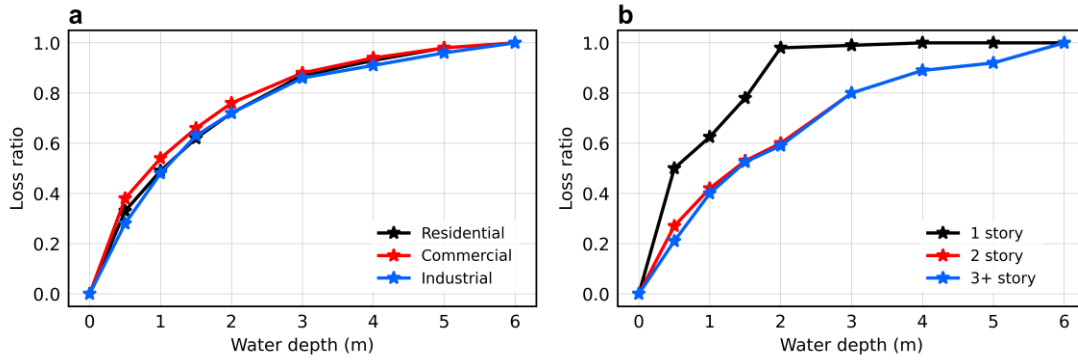


Figure 2.5 Depth–damage functions for coastal flooding.

(a) Depth–damage functions proposed by the JRC. (b) Adapted depth–damage functions for residential buildings in different floors.

I then use the maximum economic losses per square meter, the loss ratio, and the hazard-affected area, to calculate the actual economic loss:

$$E = \sum_{i=1}^n L_i R(d_i) A_i \quad 2-17$$

where E represent the estimated economic loss, n represents the number of exposure elements, and L_i is the maximum loss of the i th element. d_i refers to the inundation depth of the i th element, and $R(d_i)$ is the corresponding loss ratio. A_i refers to the area of the i th element affected by inundation.

Among the three types of elements, the risk of residential areas to coastal flooding is particularly sensitive to building heights. Consequently, an adapted loss ratio was developed to effectively assess their vulnerability to coastal flooding [Dabbeek *et al.*, 2020]:

$$\bar{R}(d) = \frac{1}{n} \sum_{j=1}^n r_j(d) \quad 2-18$$

where d refers to the inundation depth, and $r_j(d)$ represents the loss ratio at inundation depth d for j height category. $\bar{R}(d)$ is the average loss ratio for all heights.

2.3 Consecutive heatwaves and extreme sea levels along Europe's coastline

2.3.1 Identification of consecutive HWESL events

The consecutive HWESL events are identified by linking heatwaves with extreme sea levels during the summer season. I used a peak-over-threshold approach to identify heatwave and extreme sea level events. A heatwave is considered when the $T_{\max}$ (i.e., air temperature) exceeds the historical 90th percentile of $T_{\max}$ for no less than three calendar days during the extended summer season (May–September) [Mazdiyasni and AghaKouchak, 2015; Perkins-Kirkpatrick and Lewis, 2020]. Such 90th percentile was determined by ranking historical (1979–2017) data within a 15-day window (7 days before and after, i.e., total samples are $15 \times 39 = 585$ days) [J Wang et al., 2020a]. The thresholds on each day were calculated separately to identify hot extremes at different summer phases [Perkins and Alexander, 2013]. An extreme sea level event is considered when the $W_{\max}$ is higher than the 90th percentile of ranking historical (1979–2017) $W_{\max}$ for each grid cell ($365 \times 39 = 14235$ days). A consecutive HWESL event was identified as the occurrence of heatwaves followed by extreme sea levels within a 7-day period.

2.3.2 Characterization of consecutive HWESL events

In Chapter 4, consecutive HWESL events are characterized by their frequency, time lag, and probability. Frequency refers to the number of heatwaves followed by extreme sea levels in a year, and time lag represents the intervals between heatwaves and extreme sea levels. The frequency of both heatwaves and extreme sea levels is calculated analogously. The probability of consecutive HWESL events is determined by analyzing the likelihood of heatwaves being followed by extreme sea levels using event coincidence analysis (ECA), a widely used method for quantifying simultaneous or lagged coincidences of two series of extreme events [Y. Chen et al., 2021; He and Sheffield, 2020; Raymond et al., 2020]. I calculated the precursor coincidence rate by assessing the frequency of heatwaves being followed by extreme sea levels within a specific temporal window

(e.g., 7 days).

In the case of consecutive HWESL events, ECA can calculate how frequently heatwaves are followed by extreme sea levels within a specified time window (ΔT), by determining the trigger coincidence rate $P_{HW \Rightarrow ESL}(\Delta T)$:

$$P_{HW \Rightarrow ESL}(\Delta T) = 100 \times \frac{1}{N_{HW}} \sum_{j=1}^{N_{HW}} \Theta \times \left(\sum_{i=0}^{N_{ESL}} 1_{[0, \Delta T]}(t_i^{ESL} - t_i^{HW}) \right) \quad 2-19$$

where $P_{HW \Rightarrow ESL}$ is the probability of consecutive HWESL events, which represents the fraction of heatwaves followed by extreme sea levels within the time window. N_{HW} is the total number of heatwaves in this grid cell. Θ is the Heaviside function, which assigns a value of 0 when an extreme sea level does not follow a heatwave and a value of 1 when a extreme sea level follows a heatwave:

$$\Theta(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad 2-20$$

$1_{[0, \Delta T]}(\cdot)$ is the indicator function of the time window $[0, \Delta T]$:

$$1_{[0, \Delta T]}x = \begin{cases} 1, & \text{if } x \in [0, \Delta T] \\ 0, & \text{if } x \notin [0, \Delta T] \end{cases} \quad 2-21$$

t_i^{ESL} and t_i^{HW} are the timing of extreme sea levels and heatwaves, respectively, with a total number of events denoted as N_{ESL} and N_{HW} , respectively.

I used two methods to detect the decadal linear trend in frequency, including a moving window approach and a linear-fit approach. First, I used moving windows shifted by one year at each time step to derive characteristic data for a decade. Second, I calculated the slope coefficients of decadal linear trends in characteristics through a nonparametric Theil-Sen's slope estimator [Sen, 1968; Theil, 1950]. I chose a nonparametric Mann-Kendall trend test to identify the significance of decadal trends at a 95% confidence interval [Kendall, Griffin, 1948; Mann, 1945].

The area of each grid cell was estimated using the area of equatorial grid cell weighted by the cosine of its latitude, to account for the different sizes of grid cells between different latitudinal zones due to the convergence of lines of latitude towards the poles [Burke et al., 2018; Rousi et al., 2022]. If a value is aggregated for a certain region, all grid cells are weighted by the cosine of their

latitudes. To identify regional characteristics of consecutive HWESL events, Europe's coastlines were divided into eight geographical regions based on previous work but with minor modifications [M. I. Vousdoukas *et al.*, 2016] Figure 2.6.

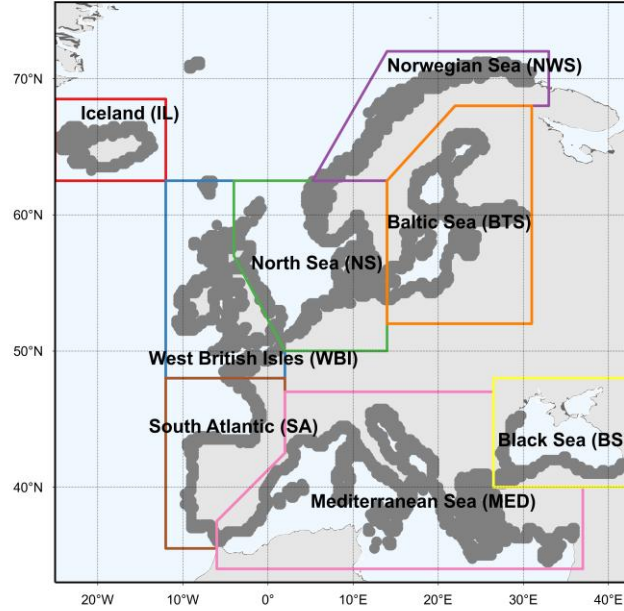


Figure 2.6 Map of Europe showing the coastlines (grey grid cells) and the spatial distribution of 8 different coastal regions defined in this study.

2.3.3 Bootstrap-resampling-based significance test

As compound heatwaves and extreme sea levels can be relatively rare and largely subject to chance, I used a resampling-based significance test [Sauter *et al.*, 2023; You and Wang, 2021] to investigate how the dependence between heatwaves and extreme sea levels influence the probability of consecutive HWESL events. The implementation of the resampling-based significance test for each grid cell involves the following steps: (a) Identify the heatwave and extreme sea level series from 1979 to 2017. The heatwave series is constructed by assigning a '1' label (indicating occurrence) to the end day of each heatwave. The extreme sea level series is constructed by assigning a '1' label to the onset day of each extreme sea level. (b) For each grid cell, 1,000 resampled heatwave series and extreme sea level series are generated using the bootstrap method. This method maintains the total frequency of heatwaves and extreme sea levels as in the original series, but allows them to occur on any day and in any year from 1979 to 2017.

(c) Calculate the probability of consecutive HWESL events for each round of 1,000 resampled heatwave series and extreme sea levels. (d) Compare the probability of consecutive HWESL events between the original series (referred to as “detected probability”) and the resampled series (referred to as “random probability”). Determine if the detected probability is significantly greater than the random probability at a 95% confidence interval. If the detected probability is significantly greater than the random probability at a 95% confidence interval, it indicates that the detected consecutive HWESL events are significantly different from what could be occurring by random coincidence at a 95% confidence interval. The difference between the detected probability and the random probability can be seen as the contribution of the dependence between heatwaves and extreme sea levels to the occurrence of consecutive HWESL events.

2.3.4 Decomposition of the effects of heatwaves and extreme sea levels

To investigate the specific impacts of changing heatwaves and extreme sea levels on the changes in the total frequency of consecutive HWESL events between the future period of 2042–2070 under RCP8.5 and the historical period of 1977–2005, I conducted a decomposition analysis. This enables the assessment of the relative contribution of changing heatwaves and extreme sea levels in shaping the changes of consecutive HWESL events. The methodology involved constructing three distinct time series realizations: (a) with changing heatwaves and changing extreme sea levels (consecutive HWESL events during the future period are identified based on future heatwaves and future extreme sea levels); (b) with changing heatwaves only and without changing extreme sea levels (consecutive HWESL events during the future period are identified based on future heatwaves and historical extreme sea levels); (c) with changing extreme sea levels only and without changing heatwaves (consecutive HWESL events during the future period are identified based on historical heatwaves and future extreme sea levels).

2.4 Concurrent heatwaves and extreme sea levels along the global coastline

2.4.1 Calculation of equivalent temperature

In Chapter 5, I used equivalent temperature (T_e) to investigate humid heatwaves along the global coastlines, as it can effectively capture changes in both air temperature and humidity. This responds to a recent demand to account for the influence of humidity on heat, as the equivalent

temperature is a more accurate measurement of thermal discomfort [Fischer and Schar, 2010]. The T_e is derived from the moist static energy (H) and calculated as:

$$T_e = \frac{H}{C_p} = T + \frac{L_v q}{C_p} \quad 2-22$$

where C_p is the specific heat of air at constant pressure ($1005 \text{ J}\cdot\text{kg}^{-1}\cdot\text{°C}^{-1}$), T is the 2-m air temperature (°C), L_v is the latent heat of vaporization ($\text{J}\cdot\text{kg}^{-1}$), and q is the specific humidity ($\text{kg}\cdot\text{kg}^{-1}$).

Here, q is calculated from 2-m dew point temperature (T_d , °C) and surface pressure (p , hPa) using the following equation[Bolton, 1980]:

$$e = 6.112 \exp\left(\frac{17.67T_d}{T_d + 243.5}\right) \quad 2-23$$

$$q = \frac{0.622e}{p - 0.378e} \quad 2-24$$

where e is the actual vapor pressure (hPa).

L_v is calculated as a linear function of T :

$$L_v = (2.501 - 0.00237T) \times 10^6 \quad 2-25$$

In addition, the relative humidity is calculated as the ratio of the e to the saturation vapor pressure (e_s , hPa) [Lawrence, 2005] as follows:

$$RH = 100 \times \frac{e}{e_s} \quad 2-26$$

$$e_s = 6.112 \exp\left(\frac{17.67T}{T + 243.5}\right) \quad 2-27$$

2.4.2 Pairing of land grid cells and sea stations in coastal areas

Heatwaves occur over land while extreme sea levels are defined based on sea stations. To identify concurrent HWESL events resulting from a combination of heatwaves and extreme sea levels, I paired land grid cells and sea stations using the following steps based on the minimum-distance method:

- (1) I converted the shapefile of the global coastline to a raster file with a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$.
- (2) For each grid cell in the raster file of the global coastline, I found the nearest land grid cell in the air temperature dataset based on the Euclidean distance.
- (3) Since multiple land grid cells might have been assigned to the same grid cell of coastlines, I removed duplicates. This results in a unique set of grid cell records for the coastal land grid cells.
- (4) I assigned each land grid cell in the coastal areas to the nearest sea station in the ERA5 reanalysis dataset of total water level based on the Euclidean distance. The pairing of land grid cells and corresponding sea stations is what I define as the coastal areas.
- (5) To conduct analyses of physical processes using sea-related atmospheric variables (i.e., 10-m wind and surface pressure), I assigned each sea station to the sea grid cell in these datasets (with a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$) that was closest to it.

After completing the pairing process, I identified 9,492 land grid cells. These land grid cells were paired with the nearest 9,492 sea stations in the ERA5 reanalysis dataset of total water level and 9,492 sea grid cells in the sea-related atmospheric variables dataset (i.e., surface pressure and 10-m wind). This pairing method results in a promising spatial proximity between the land grid cells and their corresponding paired sea stations (Figure 2.7). This allows us to investigate the risk of extreme sea levels for coastal communities threatened by heatwaves on the coast.

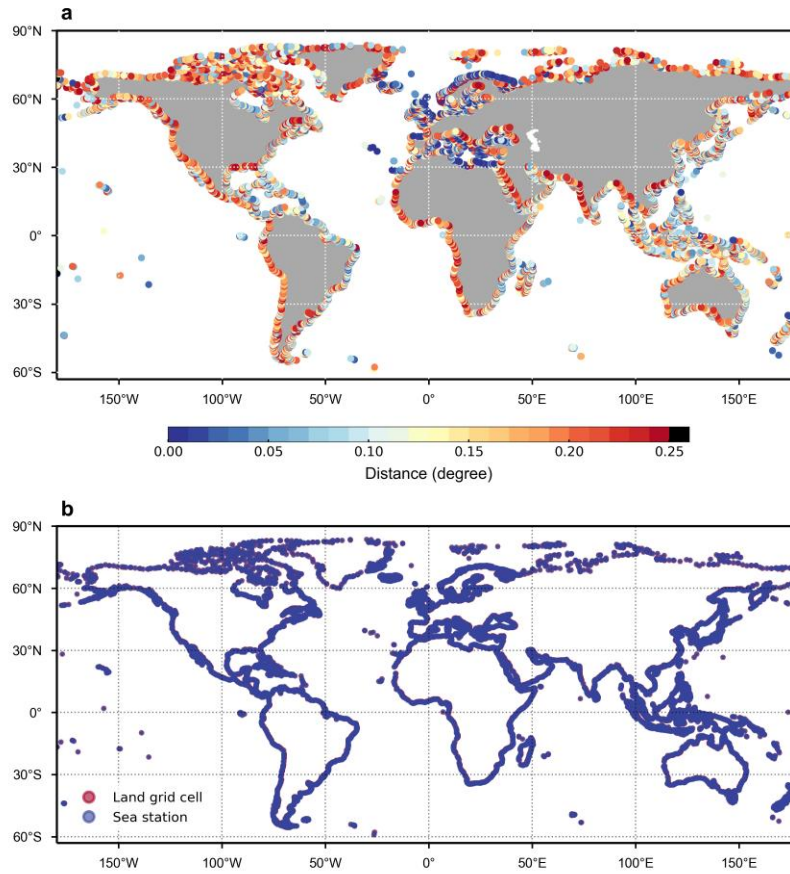


Figure 2.7 Pairing of land grid cells and sea stations in coastal areas.

(a) Distance between the land grid cell and its paired sea station. (b) Location of land grid cells and sea stations.

2.4.3 Definition, metrics, and likelihood of extreme events

Definition. The definitions of heatwave and extreme sea level are the same as those described in Section 2.3.2, except that the heatwave definition used in Chapter 5 is based on equivalent temperature. concurrent HWESL events in Chapter 5 are defined as the concurrence of heatwaves and extreme sea levels during the extended summer season, which spans from May to September in the Northern Hemisphere and from November to March in the Southern Hemisphere. To identify a concurrent HWESL day, I consider any day during a heatwave that is concurrent with any day of an extreme sea level event. A concurrent HWESL event is defined as having at least one concurrent HWESL day, and consecutive concurrent HWESL days are combined into a single

event. To separate adjacent events, I employed a window-based de-clustering method with a window size of three days [Bevacqua et al., 2019].

Metrics. In this Chapter, I used occurrence, total occurrence, and intensity to characterize extreme events. The occurrence is the number of days of extreme events within a year [Horton et al., 2015; Nairn and Fawcett, 2014]. Total occurrence refers to the sum of occurrences over multiple years. I quantified the intensity of a heatwave day as the percentile rank (ranging from the 90th to 99.5th percentile) of the T_e of that day. T_e is derived from 2-m air temperature and specific humidity. Therefore, a higher intensity indicates higher air temperature and higher specific humidity, corresponding to hotter and more humid conditions, respectively. Similarly, I determined the intensity of an extreme sea level day as the percentile rank of the W_t of that day. The use of a percentile-based intensity enables more meaningful comparisons between grid cells, thereby facilitating their integration into a unified assessment framework.

Likelihood. I used the likelihood to describe the probability of concurrent HWESL events. The likelihood of concurrent HWESL events during heatwaves is defined as the ratio between the number of heatwave days that are concurrent with extreme sea levels (i.e., concurrent HWESL events) and the total number of heatwave days. The likelihood of concurrent HWESL events during extreme sea levels was calculated analogously.

Trends. All linear trends were estimated using linear least-squares regression [Junde Li et al., 2022]. Trend uncertainties were represented by two-tailed 95% confidence intervals, assuming the residuals of the regression followed a normal distribution. To assess the significance of the regression slope, I applied the Wald test with a t-distribution of the test statistic to obtain a two-sided p -value [S Wang et al., 2020b].

The reference regions defined in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) [IPCC, 2013; Michalis I. Vourdoukas et al., 2020] were adopted, with minor modifications made to better represent the details of regional coastlines Figure 2.8. The order of coastal regions in this study was determined by the average latitude of each region. The area of each grid cell is estimated using the area of an equatorial grid cell weighted by the cosine of its latitude, to account for the different sizes of grid cells between different latitudinal zones due to the convergence of lines of latitude towards the poles [Burke et al., 2018; Rousi et al., 2022].

Daily anomalies were defined by removing the seasonal cycle, calculated as the climatological mean for each calendar day of each meteorological variable (e.g., 1979–2017) [T. Matthews *et al.*, 2019].

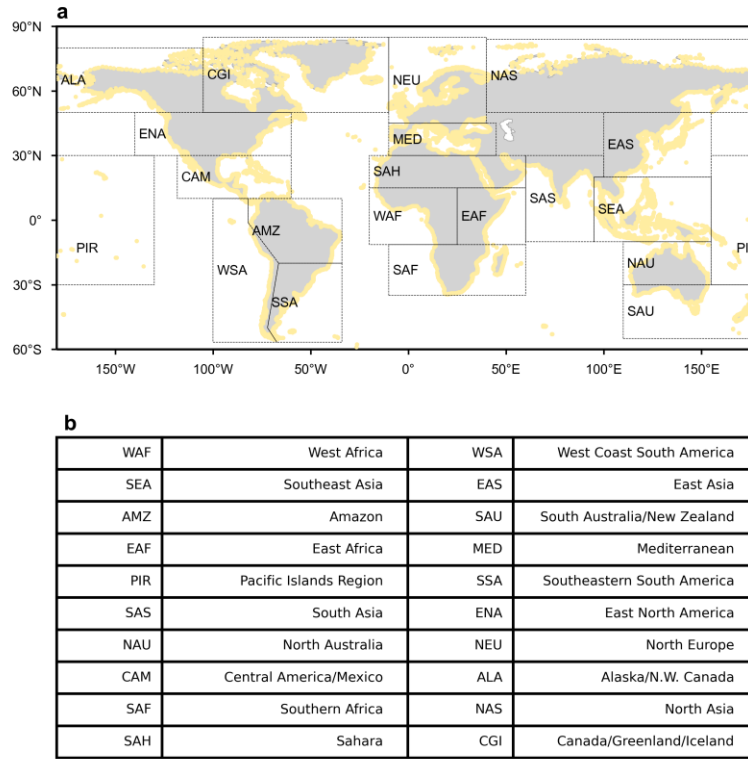


Figure 2.8 Map of coastlines and the spatial distribution of 20 different coastal regions.

2.4.4 Sensitivity of concurrent HWESL events to the intensity of individual extremes

To further analyze the characteristics of heatwaves and extreme sea levels, I classified them into 20 different levels of intensity. I then calculated the likelihood of concurrent HWESL events during heatwaves and extreme sea levels with varying intensities. This approach enables us to examine the sensitivity of the likelihood of concurrent HWESL events to the intensities of individual extremes. The 20 intensity levels range from 90th percentile to 99.5th percentile with a 0.5th percentile interval. An intensity level of the 90th percentile represents T_e or W_l greater than or equal to the 90th percentile value but less than the 90.5th percentile value. In the sensitivity analysis, the likelihood of concurrent HWESL events during heatwaves of a specific intensity is determined by calculating the ratio between the number of heatwave days concurrent with extreme

sea levels (i.e., concurrent HWESL events) and the total number of heatwave days at that specific intensity. I only consider the grid cells that experience concurrent HWESL events during all heatwaves with 20 intensity levels. The likelihood of concurrent HWESL events during extreme sea levels with a specific intensity was calculated analogously. I used the linear least-squares regression analysis to examine the sensitivity of the likelihood of concurrent HWESL events to the intensity of individual extremes.

2.4.5 Uncertainty decomposition

In this study, projected equivalent temperature derived from 10 CMIP6 models and projected total water level derived from five CMIP6 models were used. To quantify the total ensemble uncertainty in the projected concurrent HWESL events, an ANOVA-based variance decomposition method was applied [Jha *et al.*, 2023; Boen Zhang *et al.*, 2022]. This approach partitioned the total uncertainty into two components: one attributable to the climate models used to simulate equivalent temperature and the other attributable to the climate models used to simulate total water level. Here, total uncertainty is defined as the variance of the climate change signal, represented by the difference in concurrent HWESL event occurrence between the future period (2025–2049) and the historical period (1989–2013). Accordingly, an ANOVA model was constructed to decompose the total sum of squares (SST) into the sums of squares associated with the main effects of the two model groups (SSA and SSB) and their interaction term (SSI).

Because the ANOVA-based method tends to underestimate variance when applied to small sample sizes, a subsampling strategy was adopted [Déqué *et al.*, 2007; Y Zhao *et al.*, 2015]. In each subsampling iteration, 3 out of the 10 CMIP6 models for equivalent temperature were selected, yielding 120 possible combinations ($M = 120$), and the ensemble mean of the selected three models was calculated. Similarly, 3 out of the 5 CMIP6 models used to simulate total water level were selected, yielding 10 possible combinations ($N = 10$), and the ensemble mean of these three models was calculated for each iteration. This procedure produced a total of 1,200 ($M \times N$) combinations of CMIP6 models. concurrent HWESL events were then identified based on these 1,200 model combinations.

Taking the i th ($i=1, \dots, 1,200$) matrix as an example, $Y_i^{m,n}$ is the projected changes in the occurrence of concurrent HWESL events based on the m th equivalent temperature and the n th total

water level. $Y_i^{o,o}$ corresponds to the overall ensemble mean changes derived from the 1,200 combinations of CMIP6 models. $Y_i^{m,o}$ and $Y_i^{o,n}$ are the changes across M equivalent temperature subsampling and the changes across N total water level subsampling, respectively. The ANOVA model can be written as:

$$SSA_i = N. \sum_{m=1}^M (Y_i^{m,o} - Y_i^{o,o})^2 \quad 2-28$$

$$SSB_i = M. \sum_{n=1}^N (Y_i^{o,n} - Y_i^{o,o})^2 \quad 2-29$$

$$SSI_i = \sum_{m=1}^M \sum_{n=1}^N (Y_i^{m,n} - Y_i^{m,o} - Y_i^{o,n} + 2Y_i^{o,o})^2 \quad 2-30$$

$$SST_i = SSA_i + SSB_i + SSI_i \quad 2-31$$

where SSA_i , SSB_i , SSI_i , are the variances due to the effects of equivalent temperature models, total water level models, and the interactions between equivalent temperature models and total water level models. SST_i is the total variance.

This method enables the estimation of the proportion of the total uncertainty that can be attributed to each effect, which is expressed as the variance fraction η^2 :

$$\eta_{temperature}^2 = \frac{1}{I} \sum_{i=1}^I \frac{SSA_i}{SST_i} \quad 2-32$$

$$\eta_{total\ water\ level}^2 = \frac{1}{I} \sum_{i=1}^I \frac{SSB_i}{SST_i} \quad 2-33$$

$$\eta_{interactions}^2 = \frac{1}{I} \sum_{i=1}^I \frac{SSI_i}{SST_i} \quad 2-34$$

Values of 0 and 1 for η^2 represent a contribution of 0% and 100% to the total uncertainty, respectively.

2.5 Shortened time lag between heatwaves and subsequent landfalling tropical cyclones

2.5.1 Definition of heatwaves and landfalling TCs

The definition of a heatwave is the same as that described in Section 2.4.3. Heatwave duration was defined as the number of consecutive days (≥ 3 days) with temperatures exceeding the threshold. Heatwave intensity was quantified using the percentile rank of T_w relative to the samples used to calculate the threshold, enabling consistent comparisons across calendar dates and grid cells.

I used land grid cells from the ERA5 reanalysis data (0.25° spatial resolution) to identify coastal areas affected by TCs. Following previous studies [Dietrich *et al.*, 2011; S Wang and Toumi, 2021], TC landfall was defined as the first time when any land grid cell lies within 200 km of the TC center. This definition reflects the fact that TCs can cause damage through extreme winds and heavy rainfall well before direct contact with land, and in some cases without making direct landfall. Using this criterion, I identified 20,468 land grid cells affected by TCs during 1981–2022. TC counts were defined as the total number of distinct TCs affecting a grid cell within a given period, counting each TC only once, regardless of duration or repeated landfall.

2.5.2 Identification of H-TC events

H-TC events are defined as TCs making landfall within a specified temporal window following a heatwave. To account for potential lag effects between heatwaves and TC landfall, I adopted a seven-day impact-relevant time window, following previous studies on consecutive or temporally compounding extreme events [Y. Chen *et al.*, 2021; Jian Li *et al.*, 2025; You and Wang, 2021]. This lag is physically meaningful for identifying temporally linked H-TC events, as prolonged heat stress may persist into the pre-landfall period and influence human exposure and system vulnerability. Moreover, the seven-day window is consistent with typical evacuation and preparedness timeframes reported in TC evacuation studies [H C Wu *et al.*, 2012], during which heat stress may constrain evacuation efficiency and emergency response. Although this window is not intended as a climatological standard, it provides an impact-driven framework for capturing heatwave conditions most relevant to disaster preparedness and compound risk assessment. This

approach also enables a comparative analysis of H-TC events under shorter (≤ 3 days) versus longer (> 3 days) lag windows.

To enable comparison of translation speed across different grid cells, I calculated grid-cell specific percentiles of translation speed. Values in the top 30% were classified as fast translation speeds, whereas values in the bottom 30% were classified as slow translation speeds. The probability of H-TC events in each land grid cell was then assessed using the Event Coincidence Analysis (ECA) framework described in Section 2.3.2, which is widely applied to quantify lagged coincidences between event time series [Donges *et al.*, 2016; He and Sheffield, 2020; You and Wang, 2021].

2.5.3 Calculation of adiabatic warming

To estimate anomalies in near-surface adiabatic heating term during the heatwaves ($\Delta T_{\text{adiabatic}}$), I first calculated the adiabatic heating anomaly on different pressure layers, including 950hPa, 850hPa, 750hPa, and 650hPa, as follows,

$$\Delta T_{\text{adiabatic},pl} = \left(\frac{kT_{pl}}{p_s} - \frac{\partial T_{pl}}{\partial p} \right) \omega_{pl} \Delta t \quad 2-35$$

where pl is the index of air pressure level, k is the Poisson constant of 0.286, p_s is the surface pressure. T_{pl} and ω_{pl} represent temperature and vertical velocity at the respective pressure levels.

Adiabatic heating anomalies at 950hPa were used for heatwaves where the surface pressure ranges from 900 to 1100hPa, accounting for 90% of total heatwave days. Adiabatic heating anomalies at 850hPa, 750hPa, and 650hPa are used for heatwave days with surface pressures ranging from 800–900hPa (8% of heatwave days), 700–800hPa (2% of heatwave days), and 500–700hPa (1% of heatwave days), expressed as:

$$\Delta T_{\text{adiabatic}} = \begin{cases} \Delta T_{\text{adiabatic},950hPa} (p_s \geq 900hPa) \\ \Delta T_{\text{adiabatic},850hPa} (800hPa \leq p_s \leq 900hPa) \\ \Delta T_{\text{adiabatic},750hPa} (700hPa \leq p_s \leq 800hPa) \\ \Delta T_{\text{adiabatic},650hPa} (p_s \leq 700hPa) \end{cases} \quad 2-36$$

2.5.4 Trend analysis, field significance test, and correlation analysis

All linear trends were estimated using the robust non-parametric Theil–Sen slope estimator, and trend significance was assessed using the Mann–Kendall test [Kendall, Griffin, 1948; Mann, 1945].

To address the issue of multiple hypothesis testing across spatially distributed grid cells and to assess field significance, I controlled the false discovery rate (FDR) using the Benjamini–Hochberg procedure [Ford and Schoof, 2017; Jain et al., 2021; You et al., 2023]. Controlling the FDR limits the expected proportion of false positives (type I errors) among all rejected null hypotheses when multiple tests are performed simultaneously, thereby increasing confidence in the robustness of detected trends. Following previous studies, I adopted a conservative global significance threshold by defining the global significance level (α_{global}) as half of the FDR threshold (α_{FDR}). In this study, α_{global} was set to 0.05.

In addition, Pearson correlation analysis was used to quantify relationships between variables.

2.5.5 Granger causality test and impulse–response functions

To evaluate the potential causal influence of TC translation speed on the time lag, I applied a two-variable Granger causality (GC) model combined with impulse–response functions (IRFs).

GC is now widely used in climate science to assess causality in complex weather and climate systems [Fan and Li, 2022; Sun et al., 2016]. This method identifies causal relationships by testing whether past values of one variable, X , can predict future changes in another variable, Y , using vector autoregression models. A statistically significant causal pathway ($p < 0.05$) is denoted as " $X \rightarrow Y$ " when variable X exhibits a predictive influence on variable Y .

I first tested the stationarity of the time series for TC translation speed and time lag across different coastal regions. The augmented Dickey–Fuller (ADF) test [Dickey and Fuller, 1981], a widely used unit root test, was employed for this purpose. The analysis demonstrates that both TC translation speed and time lag remain stationary over the period 1981–2022, with statistical significance at the 95% confidence level.

A two-variable causal model for two stationary time series X_t and Y_t can be expressed as:

$$X_t = \sum_{j=1}^{m_1} a_j X_{t-j} + \sum_{i=1}^{m_2} b_i Y_{t-i} + \varepsilon_t \quad 2-37$$

$$X_t = \sum_{j=1}^{m_1} r_j X_{t-j} + \varepsilon'_t \quad 2-38$$

where X and Y are time series of translation speed and time lag of H-TC events, t is the length of the time series, a , b , and r are the regression coefficients, and ε_t and ε'_t are error terms. Equation 2-37 represents the unrestricted model, which includes both X and Y variables. Equation 2-38 denotes the restricted model, in which only the lagged values of the dependent variable X itself are included. m_1 and m_2 represent the optimal lag order for X and Y , respectively.

GC model results are sensitive to the choice of lag order. I used the Bayesian Information Criterion (BIC) to determine the optimal lag order for each region by identifying the lag with the minimum BIC value. The selected lag order is 9 (Figure 2.9).

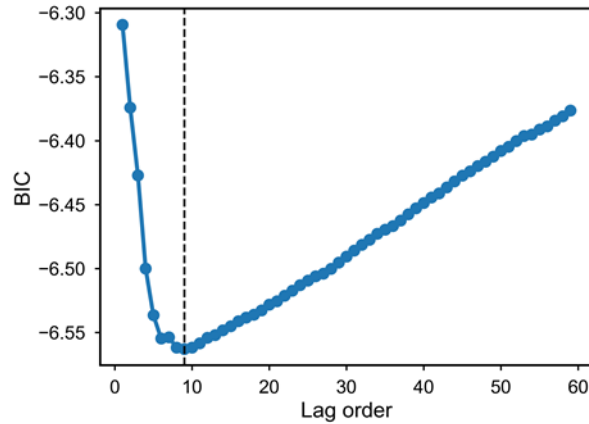


Figure 2.9 Relationship between the Bayesian Information Criterion (BIC) and lag order in the Granger Causality model.

The optimal lag order was determined by identifying the lag with the minimum BIC value, indicated by dashed lines.

Building on the GC results, I quantitatively characterized the dynamic response of the H-TC time lag to perturbations in TC translation speed using IRFs derived from the fitted bivariate linear system. I considered a one-time pulse (shock) in translation speed around an equilibrium state and

tracked the subsequent evolution of the time-lag response. For a linear time-invariant system, the IRF can be interpreted as the Green's function $G(t)$, which gives the output response to a unit impulse applied to the input at $t=0$ [Millar *et al.*, 2017]. The IRF can be approximated by a sum of exponentials:

$$G(t) = \sum_{i=1}^n a_i \exp(-\lambda_i t), \quad t \geq 0 \quad 2-39$$

where a_i are amplitude coefficients, and $\lambda_i > 0$ are decay rates. Equivalently, $\tau_i = 1/\lambda_i$ denotes the e-folding time scale of the i -th component, defined as the time required for that component to decay to 1/e of its initial magnitude

When translation-speed anomalies are viewed as a sequence of consecutive pulse-like inputs $x(t)$, the corresponding time-lag anomaly $y(t)$ can be written as the convolution of the input history with the Green's function [Kirchner, 2022]:

$$y(t) = \int_0^t G(t - t')x(t') dt' \quad 2-40$$

where $x(t')$ denotes the translation-speed perturbation at time t' , and $G(t - t')$ quantifies the remaining contribution of that perturbation to the time-lag response after a delay $(t - t')$.

2.5.6 Cascading attribution framework

To rigorously quantify the causal links within the H-TC cascading process, I implemented a cascading attribution framework based on a comparison of factual and counterfactual scenarios. This framework, widely utilized in epidemiology and compound climate extreme studies, allows for the quantification of exposure–outcome relationships while accounting for potential confounders[Mukherjee *et al.*, 2023]. I applied this framework to two distinct aspects of the H-TC interaction: (1) the intensification of heatwaves attributable to TCs, and (2) the influence of TC translation speed on the time lag of H-TC events.

I first employed the framework to quantify the cascading effect (CE) on the intensification of heatwaves followed by TCs. In this application, the exposure X was defined as the occurrence of a subsequent TC within a specific time lag (1–3 days) after a heatwave. The outcome Y was defined

as the occurrence of extreme heat exceeding a specific intensity threshold (e.g., $p \geq 95$ th percentile). I defined heatwave intensity as the average intensity over the final three days of each event. Since all identified heatwaves in our study lasted at least three days, this fixed 3-day window ensures consistency across all cases. To isolate the TC's impact, I converted the occurrences of TCs and extreme heatwaves into binary (0/1) time series at each time step and adjusted for confounders Z , including latitude and longitude. I fitted a logistic regression model for Y as a function of X while adjusting for Z . For binary exposure and outcome, AF is defined as

$$AF = 1 - \frac{P(Y_0 = 1)}{P(Y = 1)} \quad 2-41$$

where $P(Y_0 = 1)$ is the counterfactual probability of the outcome if the exposure were eliminated (i.e., setting $X = 0$), and $P(Y = 1)$ is the factual probability of the outcome in the population. Conditioning on confounders, this can be written as

$$AF = 1 - \frac{P(Y = 1|X = 0, Z = z)}{P(Y = 1|Z = z)} \quad 2-42$$

In this context, AF measures the specific proportion of extreme heat occurrences that is attributable to the TC's presence. A higher AF indicates a stronger cascading effect, where the TC systematically shifts the probability distribution of heatwave intensity toward more extreme values.

Secondly, I extended this framework to evaluate the cascading effect of fast TC translation speed (top 30%) on the occurrence of H-TC events with a time lag $\leq d$. For this analysis, fast translation speed was treated as the exposure X , while the occurrence of an H-TC event with time lag $\leq d$ was the outcome Y . Confounders Z included latitude, longitude, and TC maximum sustained wind speed. Following the same mathematical logic as described in Equations 2-41 and 2-42, I quantified the attributable contribution of fast translation speed using the AF under a counterfactual scenario where translation speed is fixed at a slower baseline. Here, AF represents the proportion of observed short-lag events that would theoretically not occur if fast translation speeds were eliminated, assuming the model is correctly specified and relevant confounders are adequately controlled.

2.5.7 Calculation of the exposure to H-TC events

I quantify changes in population exposure to extreme events from 1981 to 2022 using a risk assessment framework [*Jian Li et al.*, 2025] and it is defined as:

$$Exposure = \sum_{igrid=1}^n Population_{igrid} \times Counts_{TC} \quad 2-43$$

where $Population_{igrid}$ represents the total population within grid cell $igrid$, and $Counts_{TC}$ represents the total number of TC-alone or H-TC events affecting that grid cell during the corresponding period.

Chapter 3. Typhoon-Induced Coastal Flooding and Economic Losses

Typhoon Hato (2017), Typhoon Mangkhut (2018), and Typhoon Saola (2023) are among the most destructive typhoons to have struck Hong Kong in recent years, resulting in intense coastal flooding and severe damage. However, comprehensive flood risk assessments remain limited due to scarce data from inundation field surveys and damage assessments. In this chapter, I develop an integrated framework combining a wind-pressure model, a hydrodynamic model, and a depth-damage function to estimate coastal flood hazards from tropical cyclones in Hong Kong. This framework incorporates worst-case scenarios of short-term extreme tidal levels and long-term sea level rise. This quantitative risk assessment can support the government in implementing effective flood prevention measures and optimizing land use planning, potentially reducing economic losses in coastal areas.

3.1 A framework for coastal flooding risk assessment

Hong Kong, located on the southeast coast of China, is a densely populated city with over 7 million residents across an area of 1,180 km² and a coastline exceeding 1,000 km [Choy *et al.*, 2020]. It has been identified as the city with the highest natural disaster risk in Asia according to the inaugural Sustainable Cities Index [ARCADIS, 2015]. This vulnerability stems from its geographical location, which exposes the region to TCs from May to November each year. As a result, Hong Kong frequently experiences extreme flooding caused by these storms, with at least one super typhoon occurring every three years [T C Lee, Cheng, Y.Y., 2012]. Low-lying coastal regions such as Yuen Long North West and Tai Po are particularly vulnerable to storm surges and overtopping waves [Drainage Services Department]. Additionally, the city's existing infrastructure may struggle to manage the changing patterns and intensities of flooding [Civil Engineering and Development Department, 2022; Qiang *et al.*, 2021]. The high population density and extensive infrastructure in such urbanized areas heighten the potential economic impacts of high storm tides, making them more significant than in less developed cities and rural regions with lower property values [You *et al.*, 2024]. Therefore, Hong Kong serves as a critical case study for assessing the risk of megacities to coastal flooding [Sim *et al.*, 2018].

I focus on Typhoon Hato (2017), Typhoon Mangkhut (2018), and Typhoon Saola (2023), which were among the most destructive events in recent history, with their tracks and intensities shown in Figure 3.1. All three typhoons intensified to Super Typhoon status (colored as purple), with wind speeds reaching the highest extreme wind signal, No. 10, as they approached Hong Kong. These typhoons set records for maximum sustained winds, storm tides, and the extent of affected areas. While they share the commonality of being highly destructive and record-setting, they differ in characteristics such as maximum intensity, proximity, and size, enabling a comprehensive assessment of the varied impacts of typhoons on Hong Kong. This diversity provides a unique opportunity to study the effects of climate change on the dynamic mechanisms of coastal flooding. This study can generate flood risk maps that exhibit flood characteristics, which will be valuable for informed coastal engineering planning and managing the growing risk associated with coastal flooding under a warming climate.

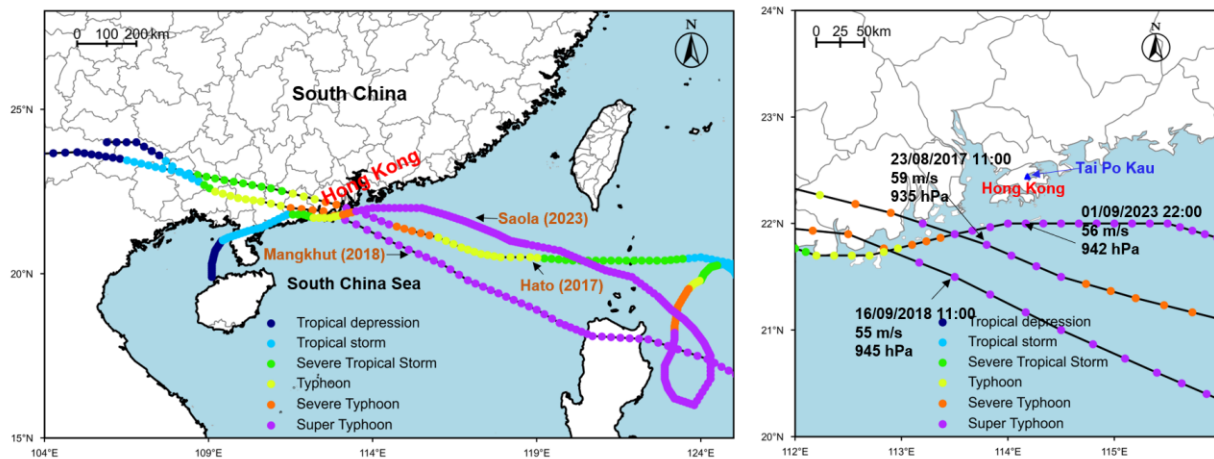


Figure 3.1 The tracks and intensities of Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola are presented.

The right panel shows the location and details of the TC at the time of its minimum distance to the tide gauge station at Tai Po Kau (TPK), whose location is represented by a blue triangle in the right panel. These details include the local time, 2-minute maximum sustained surface wind, and minimum central pressure at sea level.

I aim to quantitatively assess the tangible damage across Hong Kong through a systematic approach that includes hazard assessment, vulnerability assessment, and risk assessment.

Specifically, a flowchart illustrating this procedure is presented in Figure 3.2, with detailed sequential steps and the relationships between the various components of the framework illustrated in the following sections.

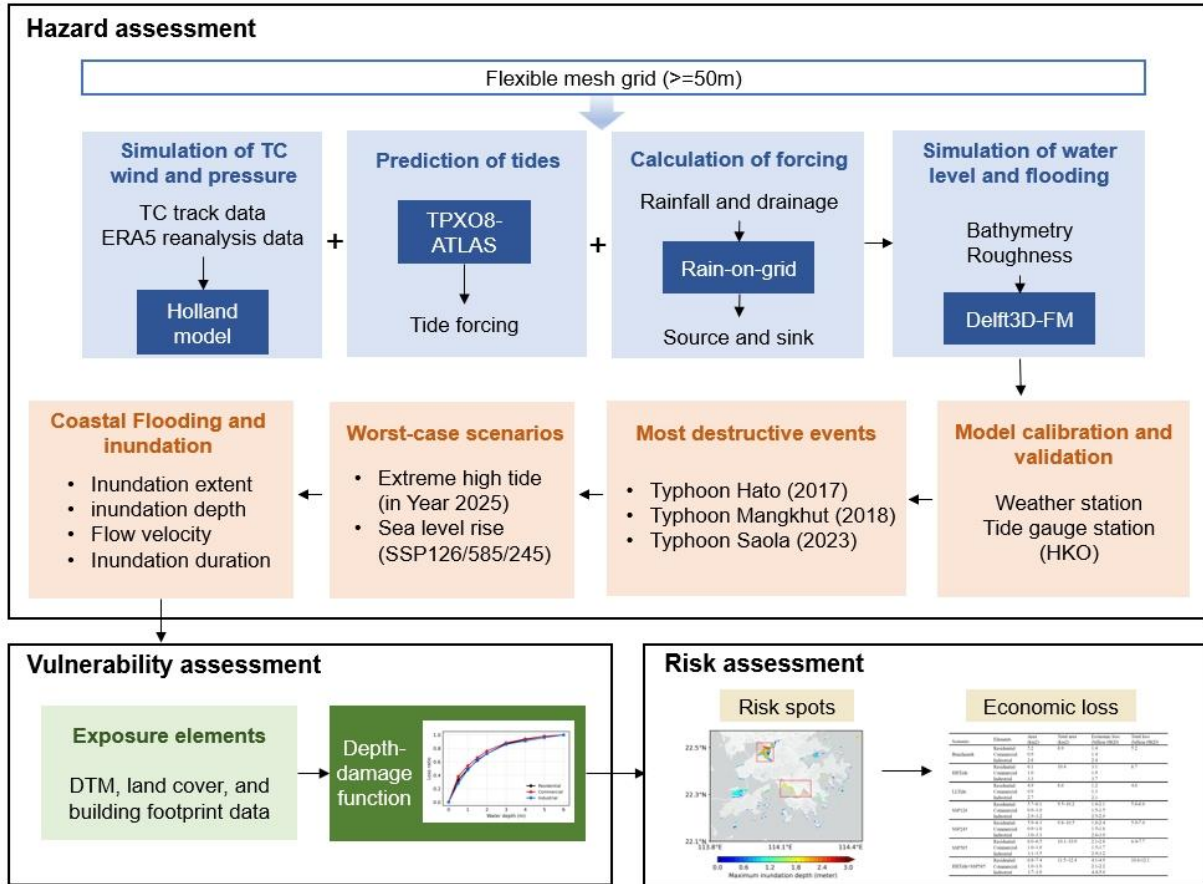


Figure 3.2 Framework for assessing the coastal flooding risk.

3.2 Calibration and validation for the hydrodynamic model

3.2.1 Calibration

Model calibration was performed during a non-extreme period of December 2023 to examine variations in water levels and tidal properties along the Hong Kong coastline. For the offshore sea, I tested various Manning's n coefficients and ultimately determined that the calibrated value is 0.01, consistent with previous studies on coastal inundation in cities within South China [J Yang *et al.*, 2019]. The relatively low Manning's n values for the open sea were selected because

the sediment in the Pearl River Estuary is predominantly very fine sand [Jiang *et al.*, 2014]. For inland areas, spatially variable Manning's n coefficients (Figure 3.1) were assigned based on land cover type (Figure 2.3), in accordance with previous studies [Gao *et al.*, 2023; Hasan Tanim and Goharian, 2021]. As a result, the model performs well at all tide gauge stations, with an average RMSE of 0.15 m and an NSE of 0.89. These results demonstrate a strong reproduction of the hydraulic characteristics along the Hong Kong coastline (Figure 3.3).

The calibrated numerical model was subsequently applied to reproduce coastal flood water levels during the typhoon events and to demonstrate the model validation. The validated wind and pressure (Figure 3.4–Figure 3.6) were used as inputs for water level simulations during Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola over a period of 8 days, with the first day designated as the spin-up period.

Table 3.1 Manning's coefficients assigned based on land cover data.

Class	Description	Manning's coefficient
1/2/3	Residential	0.120
11	Commercial	0.050
21/22/23	Industrial	0.150
31	Institutional	0.150
32	Open Space	0.100
41	Roads	0.032
42	Railways	0.032
43	Airport	0.032
44	Port Facilities	0.100
51	Cemeteries/Funeral Facilities	0.100
52	Utilities	0.100
53	Vacant	0.120
54	Others	0.130
61	Agricultural Land	0.060
62	Fish Ponds/Gei Wais	0.045
71	Woodland	0.140
72	Shrubland	0.070
73	Grassland	0.035
74	Mangrove/Swamp	0.040
81	Badland	0.030
83	Rocky Shore	0.040

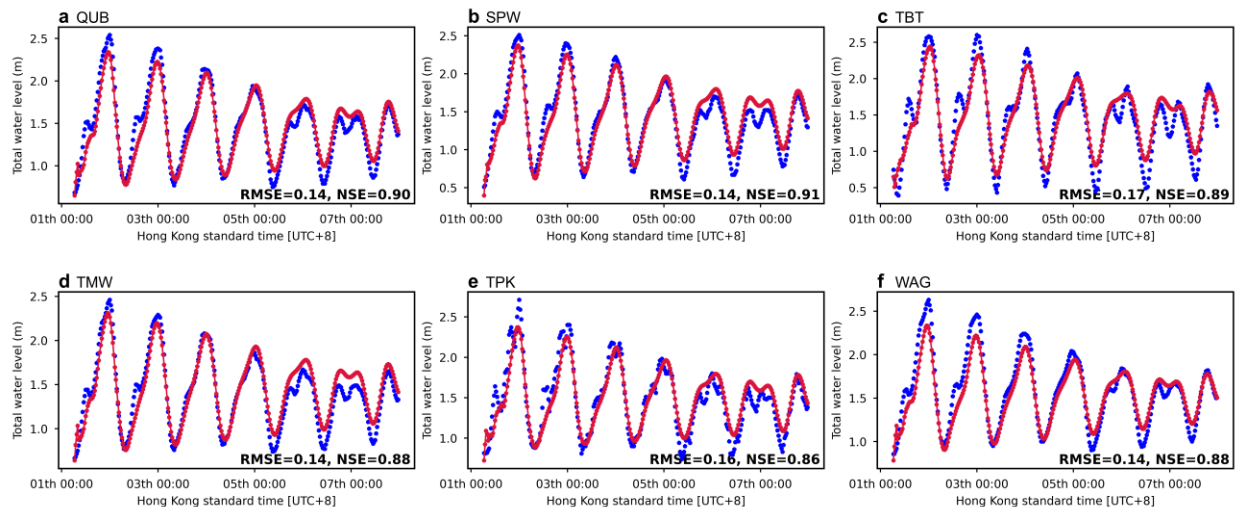


Figure 3.3 Time series of observed (blue) and modeled (red) water levels at six tide gauge stations for the non-extreme period of December 2023.

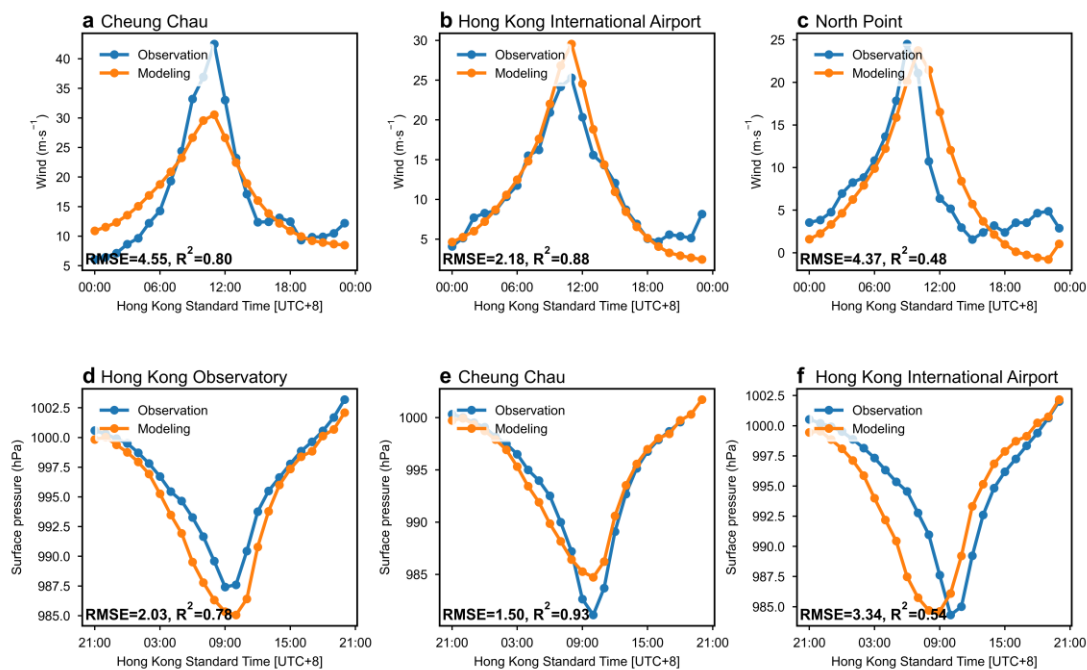


Figure 3.4 Time series of observed and modeled wind (top row) surface pressure (bottom column) at weather stations during Typhoon Hato.

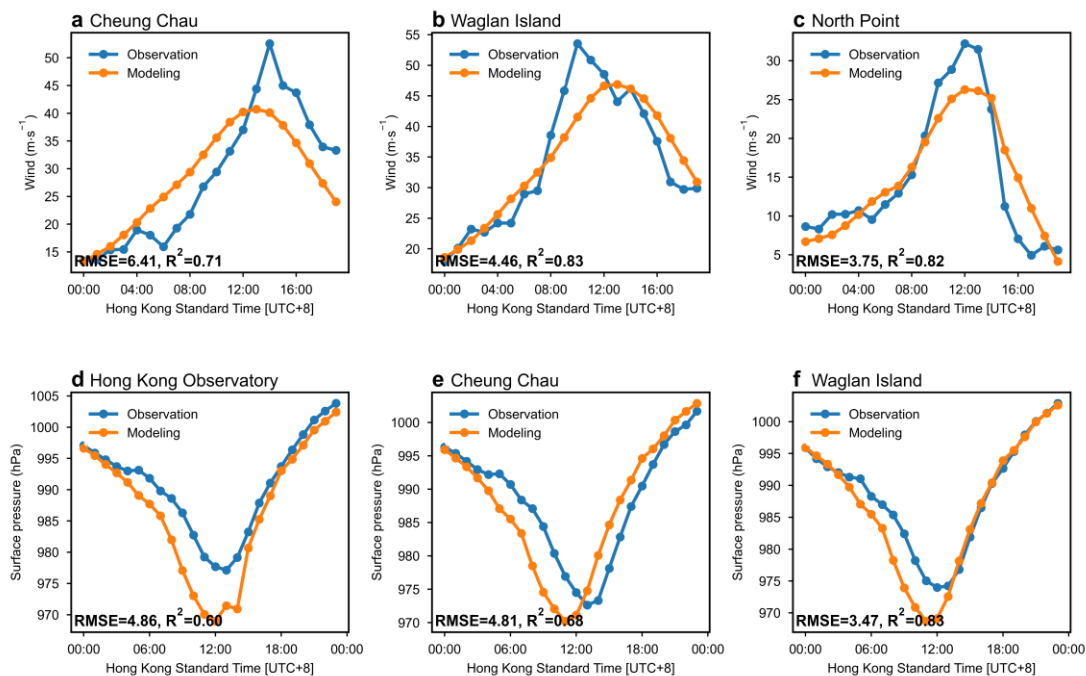


Figure 3.5 Same as Figure 3.4 but for Typhoon Mangkhut.

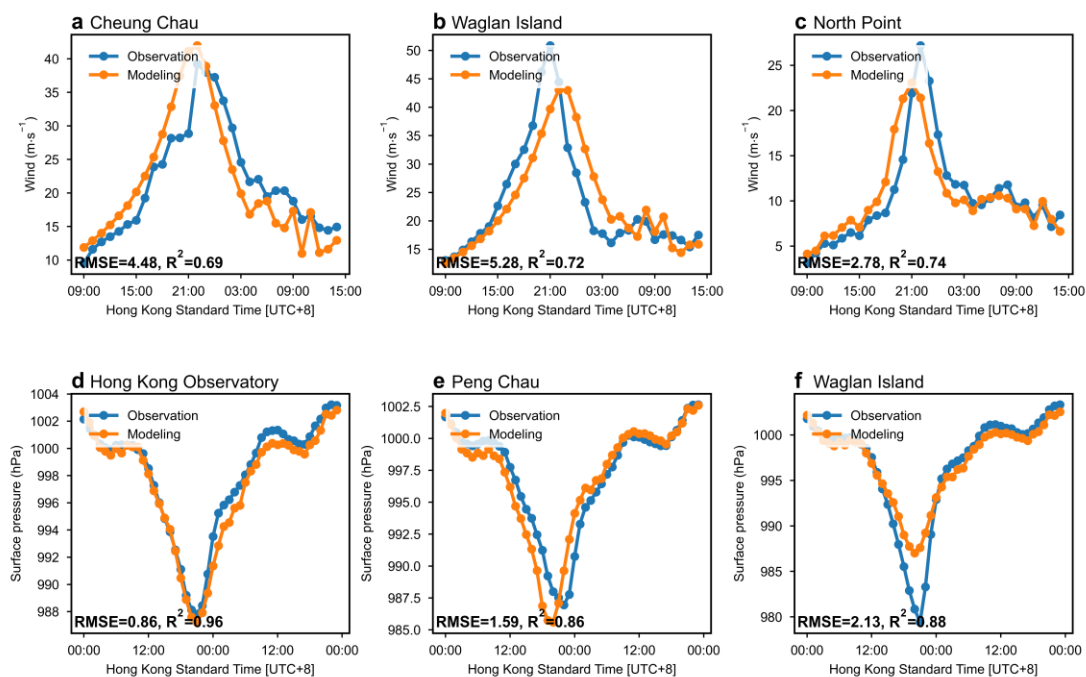


Figure 3.6 Same as Figure 3.4 but for Typhoon Saola.

3.2.2 Validation

The numerical results for water levels generated by Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola are compared with measurements from observation stations in Hong Kong (Figure 3.7). These comparisons reveal that the simulated water levels, in both magnitude and timing, closely match the observed data. This alignment indicates that the numerical model effectively captures the dominant dynamics of major tidal constituents, storm surges, and wave patterns along the Hong Kong coast. For example, the modeled maximum water level is 3.4 m at the Shek Pik (SPW) station, which agrees well with the observed value of 3.1 m (Figure 3.7b). The RMSE and NSE values between the hourly water level observations and simulations at the tide gauge stations during the three typhoons range from 0.30 to 0.42 m and from 0.70 to 0.88, respectively. However, some discrepancies are observed before and after the peak levels. These disparities may arise from factors such as errors in the wind product, small-scale coastal features, and inaccuracies or uncertainties in bathymetric and topographic data [K Parker *et al.*, 2023; Yin *et al.*, 2021], which may not be fully captured in the regional models.

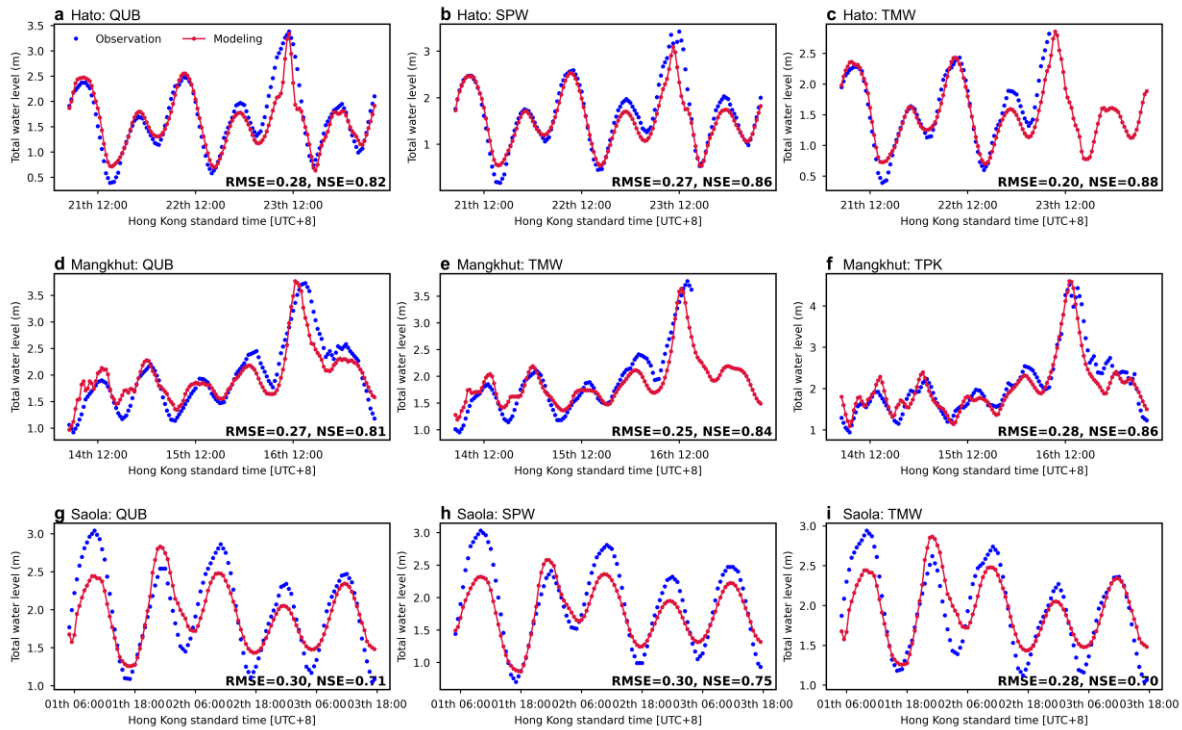


Figure 3.7 Time series of observed (blue) and modeled (red) water levels at three tide gauge stations for Typhoon Hato (a–c), Typhoon Mangkhut (d–f), and Typhoon Saola (g–i).

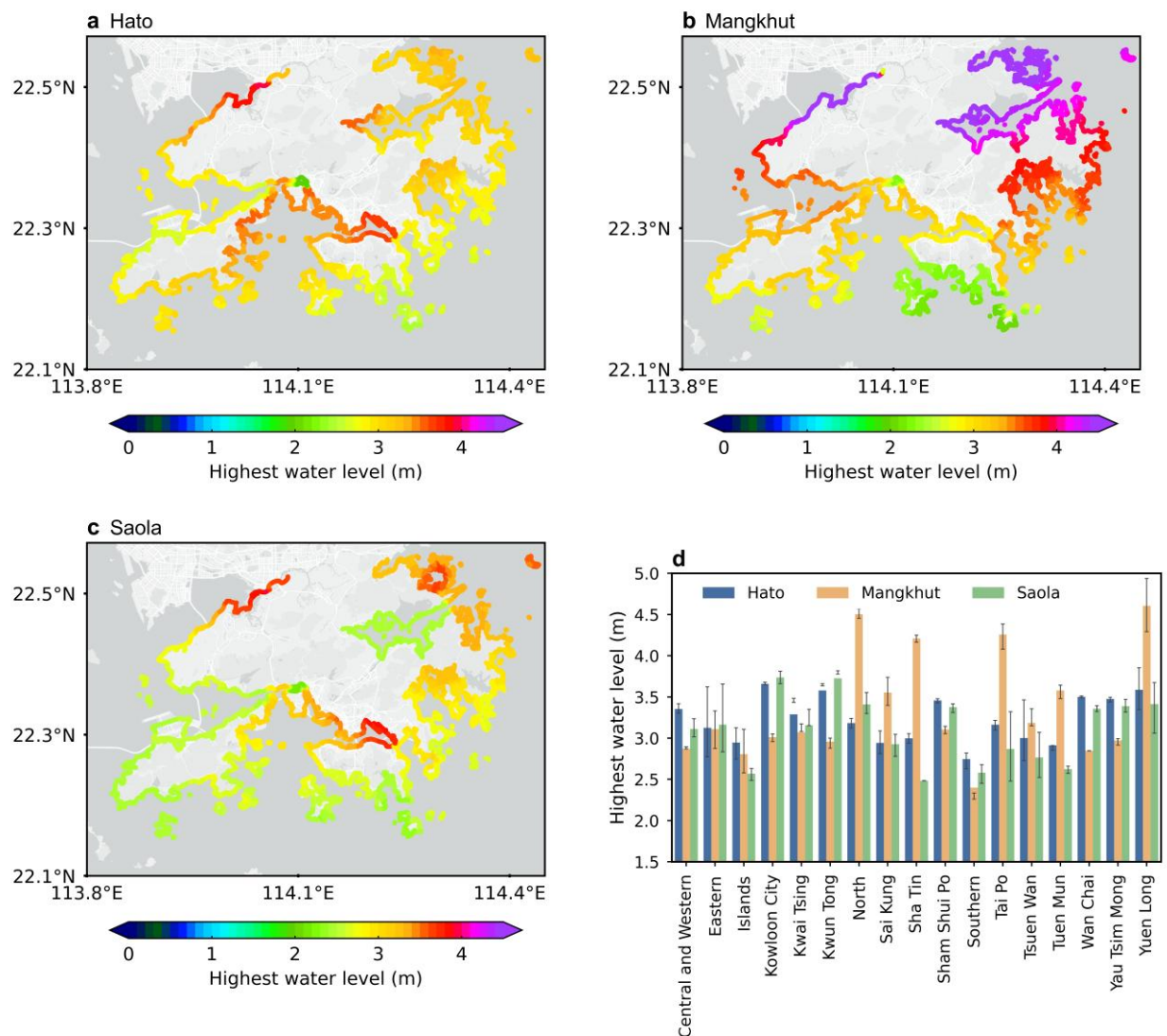


Figure 3.8 Modeled highest water levels during Typhoon Hato (a), Typhoon Mangkhut (b), and Typhoon Saola (c), and comparison across the 18 districts of Hong Kong (d).

The spatially continuous distributions of the highest water levels during Typhoon Mangkhut, Typhoon Hato, and Typhoon Saola along the Hong Kong coast are shown in Figure 3.8. Generally, most coastlines experienced water levels exceeding 2.5 m during these three typhoons. The maximum water levels range from 1.9 to 3.9 m for Typhoon Hato, 2.0 to 5.0 m for Typhoon Mangkhut, and 2.1 to 3.9 m for Typhoon Saola (Figure 3.8d). Notably, Typhoon Mangkhut, being the largest in size [J Yang and Chen, 2022; J Yang et al., 2019], generated the strongest winds (Figure 3.5), resulting in the highest water levels among the three typhoons (Figure 3.8b).

Specifically, the northern coastline of Hong Kong, including the districts of North, Tai Po, and Yuen Long, recorded maximum water levels surpassing 4.0 m during Typhoon Mangkhut. Typhoon Saola, characterized by its high intensity and closest proximity to Hong Kong (Figure 3.1), induced water levels exceeding 3.5 m in districts such as Kowloon City, Kwun Tong, North, and Yuen Long (Figure 3.8c). In contrast, Typhoon Hato induced lower water levels, with Kowloon City and Kwun Tong experiencing higher water levels (Figure 3.8a). This spatially continuous distribution of simulated water levels along the coast can provide enhanced detail and accuracy for flood hazard assessments compared to methods that rely on interpolating water levels from sparsely distributed tide gauges.

3.3 Flood inundation mapping during the most destructive typhoon events

By subtracting the topographical elevation data obtained from the Digital Terrain Model in Hong Kong from the simulated water levels, I constructed maps of maximum inundation (local water depth above ground level) for Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola (Figure 3.9). The northwest region of Hong Kong (i.e., Yuen Long) is the most vulnerable (upper box in Figure 3.9), experiencing the deepest and most widespread inundation during all three typhoons. Among them, the deepest inundation in Yuen Long was recorded during Typhoon Mangkhut, reaching 2.5 meters (Figure 3.9b). Additionally, severe inundations are observed in the coastal areas of Tolo Harbour in the Tai Po district (right box in Figure 3.9b) and in the northern part of the Islands (bottom box in Figure 3.9b). For Typhoon Hato and Typhoon Saola, the maximum inundation depth and spatial extent are comparable (Figure 3.9a, c). The inundation spots are slightly different from those observed during Typhoon Mangkhut, as Kowloon City, Kwai Tsing, and Yau Tsim Mong, located in the southern part of the Kowloon Peninsula (bottom box in Figure 3.9a, c), also experienced deeper inundation.

The simulation results are consistent with the inundation depths recorded in field surveys and real-time observations. For example, outlying islands such as Kat O and Tap Mun experienced inundation depths during Typhoon Mangkhut ranging from approximately 0.4 to 0.9 m based on post-event measurements [Choy *et al.*, 2020], while the simulations indicate an average inundation depth of 0.7 m in these areas. Additionally, a previous study showed good agreement with post-field surveys, indicating that the inundation depth at Tseung Kwan O town reached up to 2.0 m on

16th September 2018 [Qiang *et al.*, 2021], which aligns with the simulation result of a maximum inundation depth of 2.0 m on that day.

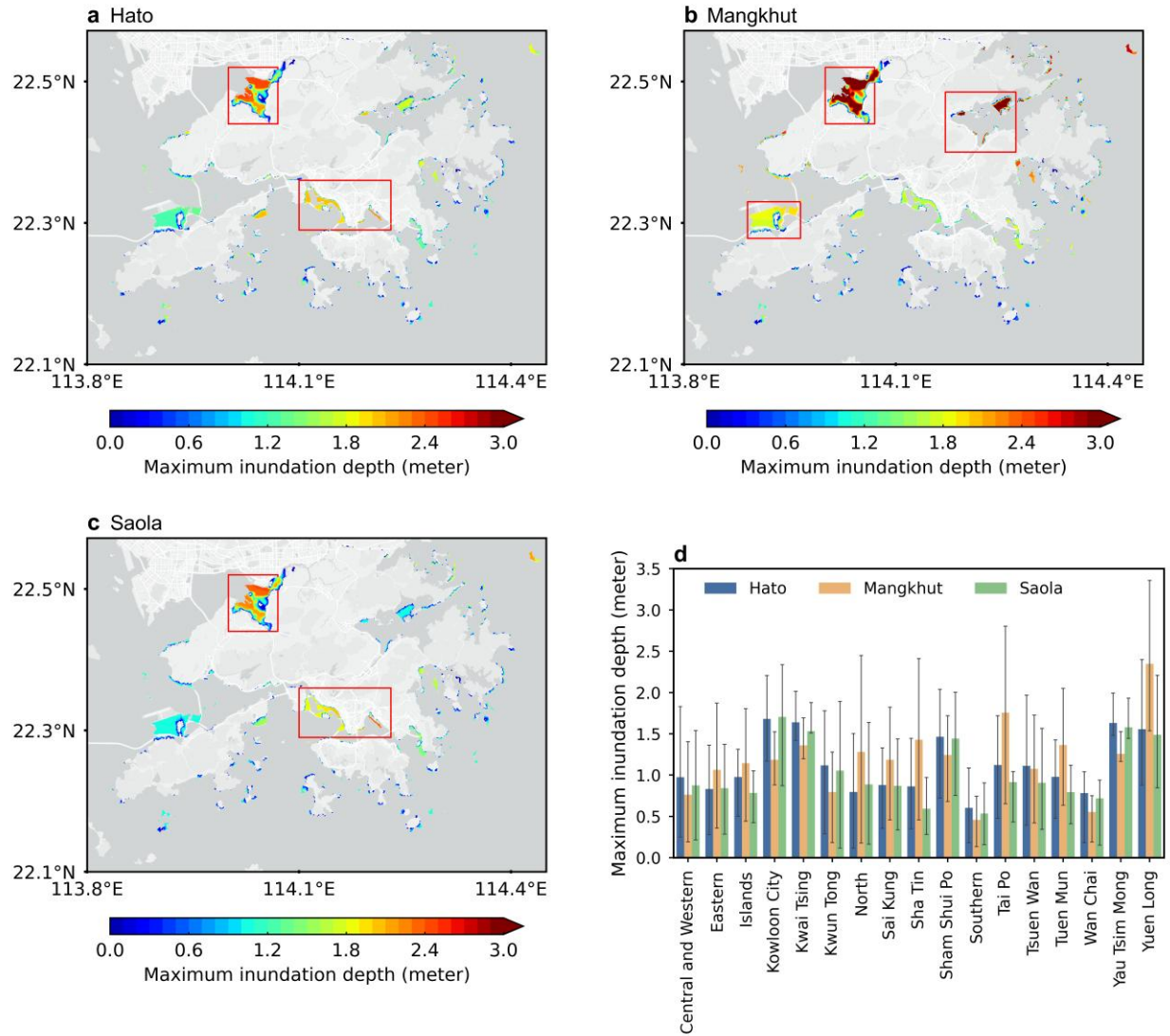


Figure 3.9 Maximum inundation depth during Typhoon Hato (a), Typhoon Mangkhut (b), and Typhoon Saola (c), and comparison across the 18 districts of Hong Kong (d).

Besides the inundation depth and inundation extent revealed from the inundation maps, the inundation duration is another important aspect in assessing hazard risk and potential damage. During the flooding process, injuries or fatalities can occur when the inundation depth surpasses a certain threshold. In simulations based on bare-ground topography, the average inland flow

velocity is 0.30 m/s for the three typhoons (Figure 3.10). According to a study by Martínez-Gomariz et al. [Martínez-Gomariz et al., 2016], a flow velocity of 0.30 m/s corresponds to a maximum flood depth of approximately 1.67 m, which is the limit for an adult to maintain stability in floodwaters. To provide a spatial overview of the duration of hazardous flood depths, I calculated the inundation duration for depths greater than 1.67 meters, as shown in Figure 3.11.

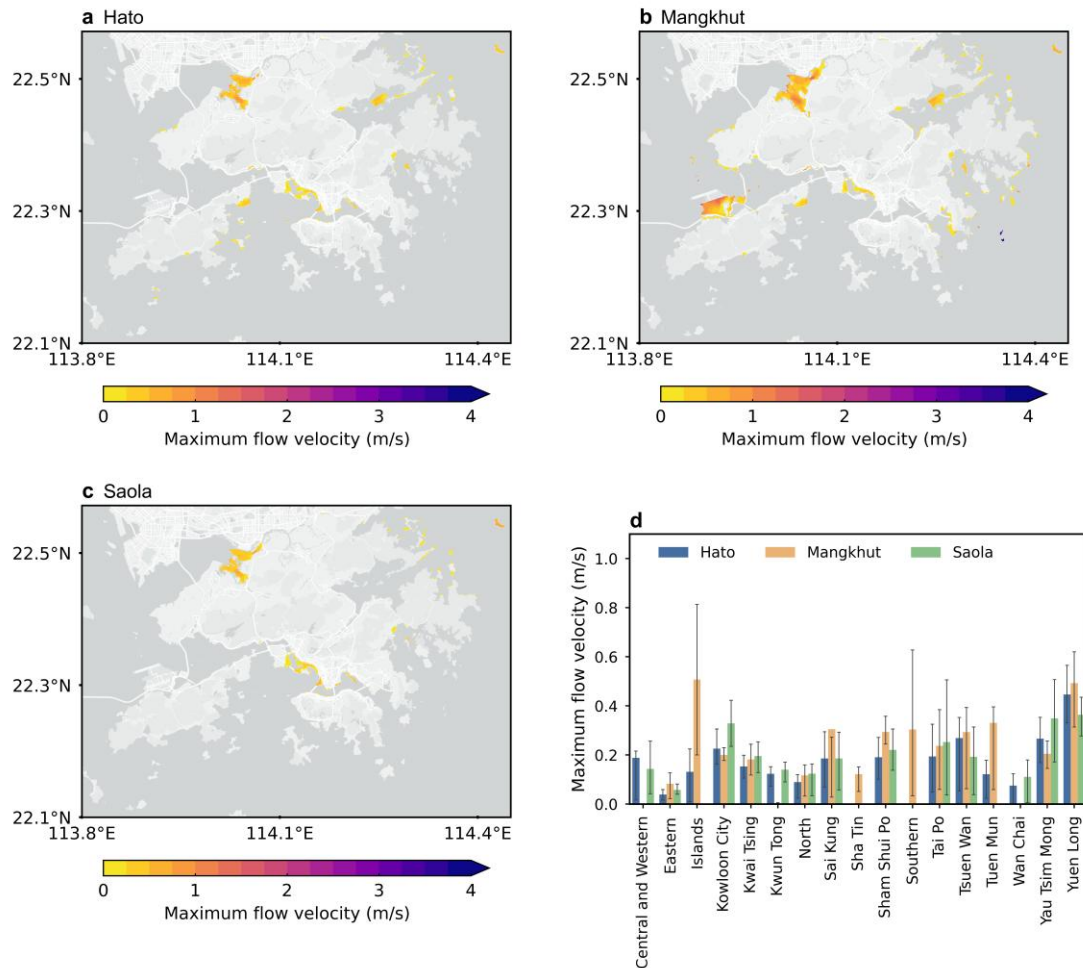


Figure 3.10 Maximum flow velocity of the inland flow during Typhoon Hato (a), Typhoon Mangkhut (b), and Typhoon Saola (c), and comparison across the 18 districts of Hong Kong (d).

I observe that the inundation duration during Typhoon Mangkhut is longer than during Typhoon Hato and Typhoon Saola, with an average inundation duration of 3.2 hours (Figure 3.11b). Among all the affected areas, the low-elevation regions in Yuen Long (the northwest region of Hong Kong) experience the longest flood durations. Specifically, the inundation durations in Yuen

Long are 1.0–2.0 hours during Typhoon Hato (Figure 3.11a), 2.4–6.5 hours during Typhoon Mangkhut (Figure 3.11b), and 1.7–3.0 hours during Typhoon Saola (Figure 3.11c). Besides Yuen Long, 10 other districts also experience inundation lasting over one hour, with a hazardous flood depth of 1.67 m during three typhoons (Figure 3.9d and Figure 3.11d). Such prolonged exposure to flood can significantly increase the risk of flooding-related hazards, including property damage, contamination of drinking water supplies, and added strain on power system restoration and the recovery of normal living conditions, highlighting the critical importance of robust seawall construction [Y Wu *et al.*, 2022].

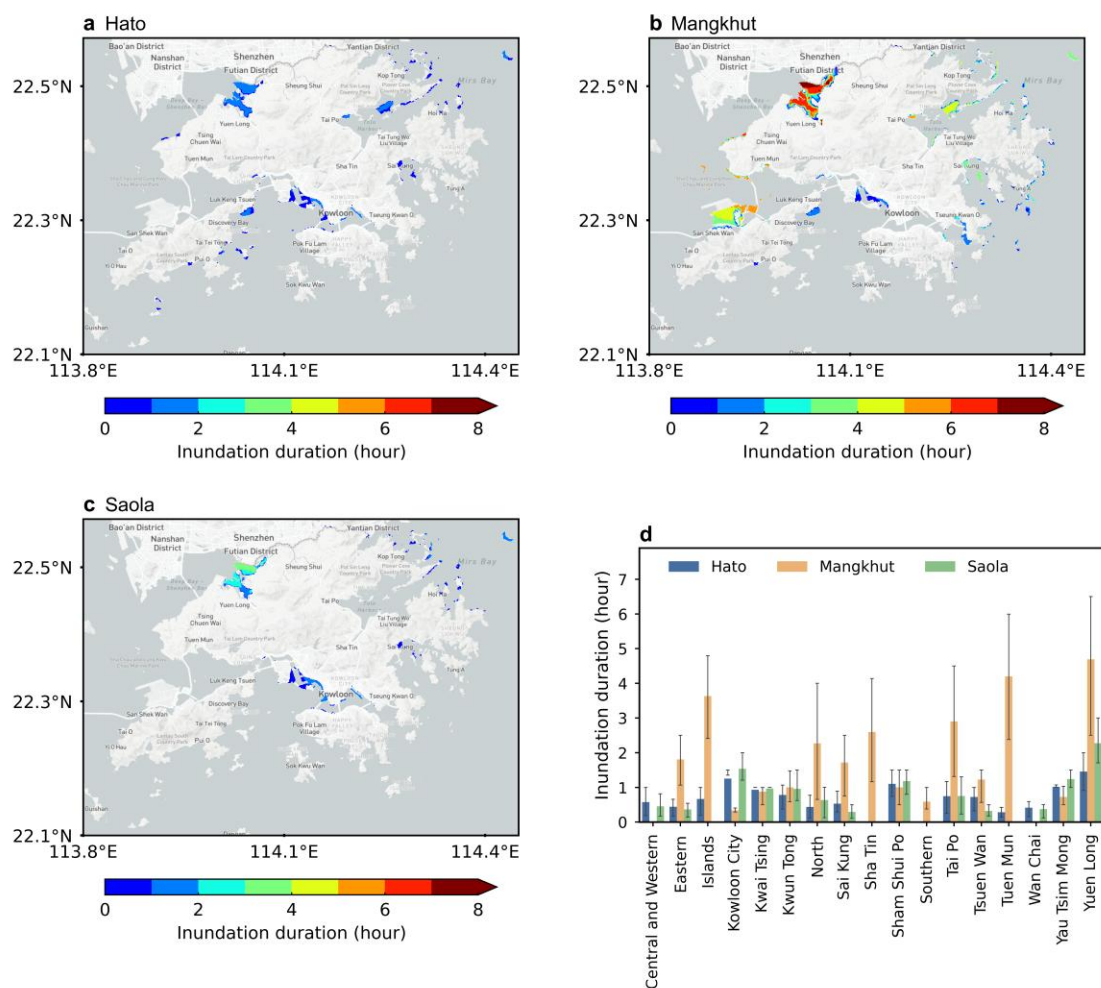


Figure 3.11 Envelopes of inundation duration (inundation depth > 1.67 m) during Typhoon Hato (a), Typhoon Mangkhut (b), Typhoon Saola (c), and comparison across the 18 districts of Hong Kong (d).

3.4 Effects of tidal level on the water level

The impacts of typhoons can be amplified when they coincide with higher astronomical tides [J Yang and Chen, 2022]. Therefore, I extracted the tidal levels and compared them with the tidal levels at the times of typhoon landfall to provide a basis for investigating the influence of tidal levels on water levels during typhoon events. Specifically, I used predicted extreme high tide data from the next lunar nodal tidal cycle, as it reflects the influence of tidal levels on high water events, which are expected to occur and recur regularly in the future. I set the arrival time of each typhoon to 21:00 on 6 December 2025 for the HHTide (i.e., higher high tide) and to 02:00 on 6 December 2025 for the LLTide to consider the effects of tidal level.

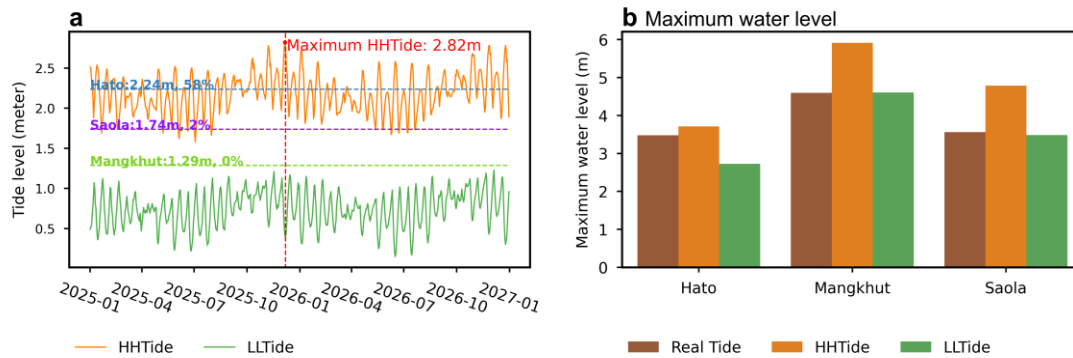


Figure 3.12 Predicted extreme high tide in the next lunar nodal tidal cycle and simulated water levels using extreme tidal levels.

(a) Predicted tide obtained from the HKO compared with the maximum tidal levels recorded during three historical typhoons. (b) Simulated maximum water levels during the three typhoons under three scenarios: benchmark scenario, HHTide scenario, and LLTide scenario.

I first compared the maximum HHTide in 2025 with the highest tidal level during three typhoons (Figure 3.12). I find that the maximum tidal levels during Typhoon Hato, Typhoon Saola, and Typhoon Mangkhut were higher than 58%, 2%, and did not exceed the maximum HHTide, respectively (Figure 3.12a). The coincidence of astronomical high tide and storm surge can be a crucial factor contributing to the widespread flooding in Hong Kong during Typhoon Hato. This is indicated by the higher tidal levels (Figure 3.12a), as the tidal component contributed more significantly to the water level during Typhoon Hato than during Typhoon Saola and Typhoon

Mangkhut. The impact of Typhoon Mangkhut was primarily due to its intensity and size, with little contribution from tidal levels, as the timing did not align with the peak tidal levels (Figure 3.12a).

I integrated extreme tidal levels into water level simulations and evaluated the associated risk of economic losses. I compared the simulated maximum water levels under different tidal scenarios at the TPK station (Figure 3.12b). Generally, high tidal levels lead to higher water levels. However, due to the nonlinear interactions between tide and storm surge, the magnitude of the rising water level can be less than the magnitude of the rising tidal level [Arns *et al.*, 2020]. For example, during Typhoon Hato, the rising water level is 0.58 m while the rising tidal level is 0.23 m, indicating a counteracting effect of 60% due to the interactions. Conversely, low tidal levels correspond to lower water levels, but the decrease in water level is smaller than the decrease in tidal level.

3.5 Flood inundation mapping under worst-case future scenarios

Based on the flood inundation model for the most destructive typhoon events, I further assess the impacts of tidal levels and SLR (i.e., sea level rise) on flooding, treating these potential future conditions as worst-case scenarios. For tidal levels, I consider both extreme high tide and low tide scenarios. For the SLR, I consider projected sea level changes by 2100 under three emission scenarios: SSP126, SSP245, and SSP585, which represent the lowest, moderate, and highest values, respectively, in terms of anthropogenic radiative forcing, global CO₂ concentration, and emissions, as well as socioeconomic factors.

HHTide greatly expands inland flooding, particularly in regions that saw limited inundation during past benchmark typhoons. Compared to the benchmark scenario, the average maximum inundation depths under HHTide scenario increased by 0.08 m (12%), 0.67 m (94%), and 0.63 m (118%) for Typhoon Hato (Figure 3.13a), Typhoon Mangkhut (Figure 3.14a), and Typhoon Saola (Figure 3.15a), respectively. The substantial increases observed for Typhoon Mangkhut and Typhoon Saola are attributed to its coinciding with lower tidal levels during the historical period (Figure 3.12a). This highlights the potential risks associated with the alignment of astronomical tides and typhoon landfall. Given that Typhoon Mangkhut and Typhoon Saola are already the most severe typhoons to impact Hong Kong, its overlap with high astronomical tides could significantly exacerbate flooding. Correspondingly, the LLTide can significantly reduce the risk of coastal flooding, resulting in a decreased extent of flooding and lower inundation depths, and less

economic losses (Figure 3.13b, Figure 3.14b, and Figure 3.15b). Compared with HHTide, the effect of SLR on coastal flooding during Typhoon Mangkhut and Typhoon Saola is relatively limited (Figure 3.14c–e and Figure 3.15c–e).

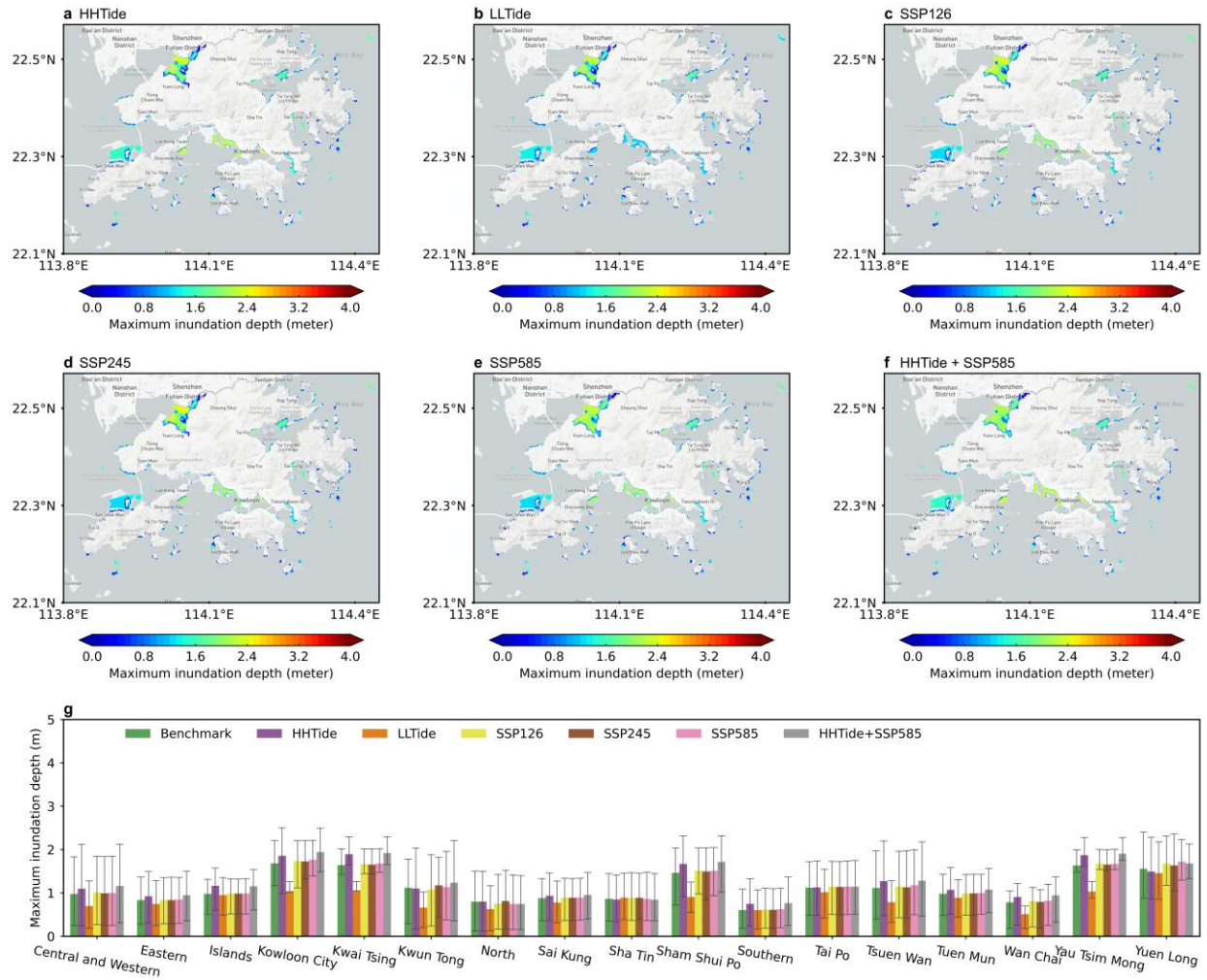


Figure 3.13 Maximum inundation depths under different scenarios using Typhoon Hato as the benchmark, and comparison across the 18 districts of Hong Kong.

(a) HHTide. (b) LLTide. (c) 2100 sea-level rise under SSP126. (d) 2100 sea-level rise under SSP245. (e) 2100 sea-level rise under SSP585. (f) Combined HHTide and 2100 sea-level rise under SSP585. (g) Comparison of maximum inundation depths across 18 districts in Hong Kong under six different scenarios.

Although I have verified the nonlinear tide-surge interactions can reduce surge height during high tide (Figure 3.12b), the difference in tidal levels in the HHTide scenario cannot fully

counteract this effect (Figure 3.13a, Figure 3.14a, and Figure 3.15a), leading to additional inundation that is more severe than SLR under the SSP585 scenario (Figure 3.13e, Figure 3.14e, and Figure 3.15e), compared to the flood depth in the benchmark scenario. Therefore, for Hato-like typhoons, the effects of extreme high tide and SLR are comparable in contributing to coastal flooding. However, for Mangkhut-like and Saola-like typhoons, extreme high tide can significantly increase the risk of flooding. The most severe worst-case scenario is expected to occur when a TC approaches during high tide under the high-emission scenario SSP585 in 2100 (Figure 3.13f, Figure 3.14f, and Figure 3.15f). Under this scenario, the maximum inundation depth could increase by 48–83%, 133%–181%, and 169–210% for Typhoon Hato, Typhoon Mangkhut, and Typhoon Saola, respectively.

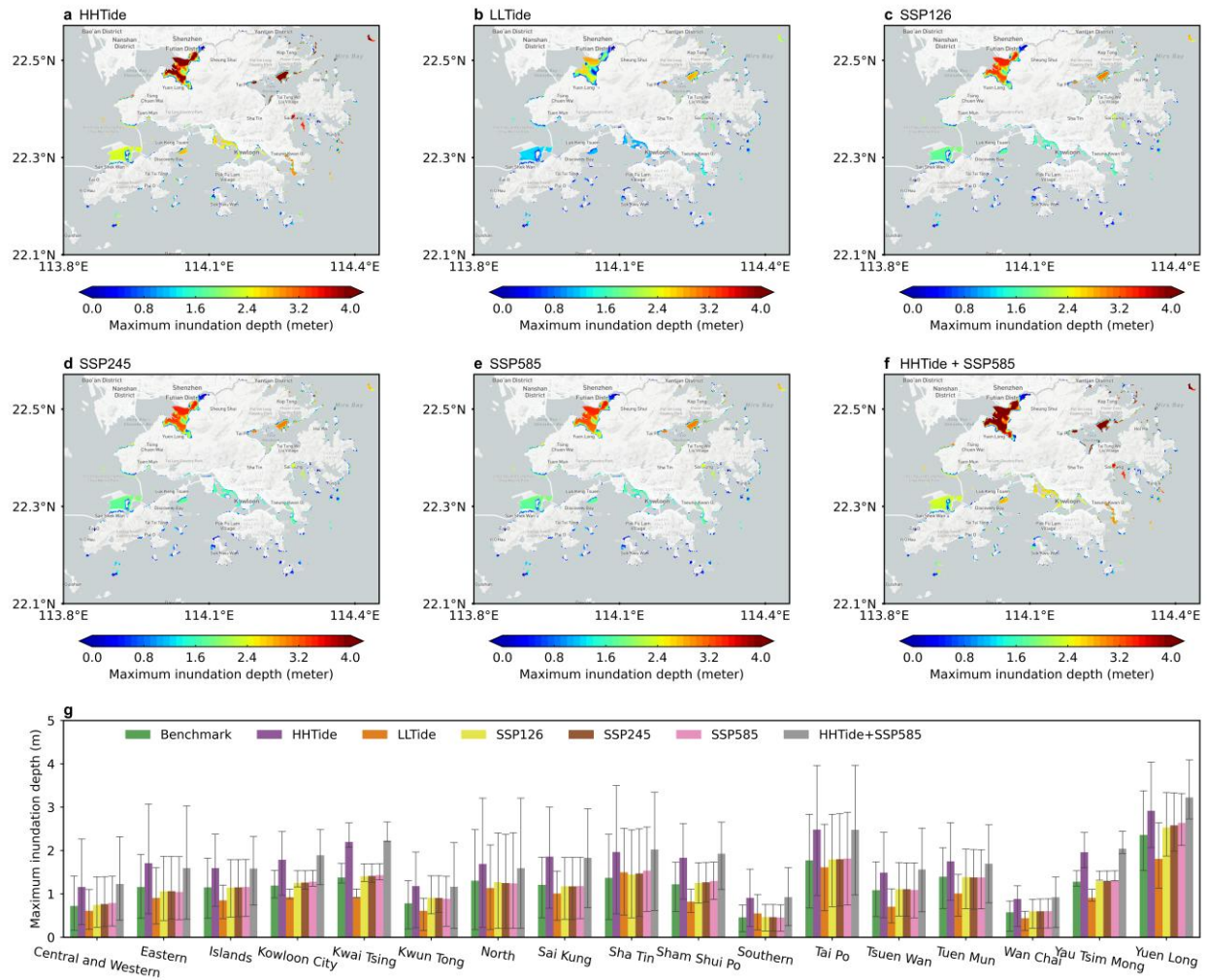


Figure 3.14 Same as Figure 3.13 but using Typhoon Mangkhut as the benchmark.

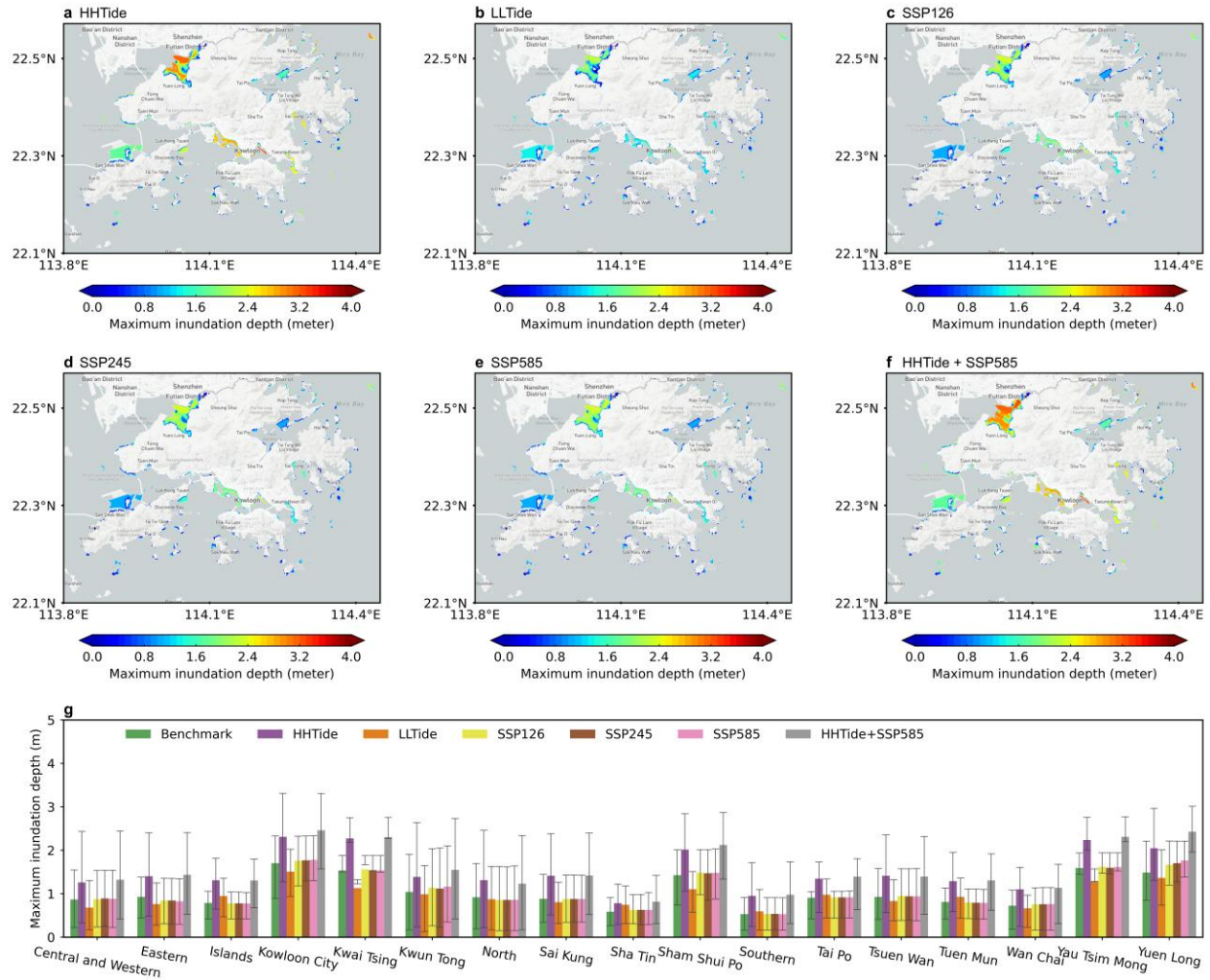


Figure 3.15 Same as Figure 3.13 but using Typhoon Saola as the benchmark.

3.6 Assessment of economic losses under worst-case future scenarios

Using the depth–damage functions, I estimated the corresponding economic losses from coastal flooding for each typhoon and scenario, aiming to provide a comprehensive assessment of the risk that climate change poses to typhoon-induced flooding.

Table 3.2 Risk assessment for six scenarios using Typhoon Hato as the benchmark.

Scenario	Elements	Area (km ²)	Total area (km ²)	Economic loss (billion HKD)	Total loss (billion HKD)
Benchmark	Residential	5.2	9.0	1.4	5.4
	Commercial	0.9		1.5	
	Industrial	2.9		2.5	
HHTide	Residential	5.2	9.1	1.6	5.8
	Commercial	0.9		1.6	
	Industrial	3.0		2.6	
LLTide	Residential	5.0	8.7	1.1	4.4
	Commercial	0.8		1.1	
	Industrial	2.9		2.2	
SSP126	Residential	5.5–6.1	9.4–10.4	1.6–2.0	5.7–6.5
	Commercial	0.9–1.0		1.5–1.5	
	Industrial	3.0–3.3		2.6–2.9	
SSP245	Residential	5.7–5.2	9.7–9.0	1.7–1.4	6.0–5.4
	Commercial	0.9–0.9		1.5–1.5	
	Industrial	3.1–2.9		2.8–2.5	
SSP585	Residential	6.0–6.4	10.2–11.0	1.9–2.5	6.3–7.4
	Commercial	1.0–1.0		1.5–1.6	
	Industrial	3.2–3.6		2.9–3.3	
HHTide+SSP585	Residential	6.2–6.6	10.4–11.2	2.1–2.7	6.8–7.9
	Commercial	1.0–1.0		1.6–1.7	
	Industrial	3.2–3.6		3.1–3.5	

Table 3.3 Risk assessment for six scenarios using Typhoon Mangkhut as the benchmark.

Scenario	Elements	Area (km ²)	Total area (km ²)	Economic loss (billion HKD)	Total loss (billion HKD)
Benchmark	Residential	6.1	10.7	2.9	7.9
	Commercial	0.9		1.3	
	Industrial	3.6		3.7	
HHTide	Residential	7.0	12.0	4.7	11.9
	Commercial	1.0		1.9	
	Industrial	4.0		5.4	
LLTide	Residential	5.2	9.0	1.6	5.5
	Commercial	0.8		1.1	
	Industrial	3.0		2.7	
SSP126	Residential	6.4–6.8	11.1–11.6	3.2–3.7	8.5–9.6
	Commercial	0.9–1.0		1.4–1.5	
	Industrial	3.7–3.9		3.9–4.4	
SSP245	Residential	6.5–7.0	11.2–12.0	3.3–4.0	8.9–10.0
	Commercial	1.0–1.0		1.4–1.5	
	Industrial	3.7–4.0		4.1–4.5	
SSP585	Residential	6.6–7.3	11.5–12.5	3.6–4.3	9.4–10.6
	Commercial	1.0–1.0		1.5–1.5	
	Industrial	3.9–4.2		4.3–4.8	
HHTide+SSP585	Residential	7.8–8.3	13.2–14.0	5.4–6.1	13.4–14.8
	Commercial	1.0–1.1		2.0–2.1	
	Industrial	4.4–4.6		6.0–6.6	

Table 3.4 Risk assessment for six scenarios using Typhoon Saola as the benchmark.

Scenario	Elements	Area (km ²)	Total area (km ²)	Economic loss (billion HKD)	Total loss (billion HKD)
Benchmark	Residential	5.2	8.9	1.4	5.2
	Commercial	0.9		1.4	
	Industrial	2.8		2.4	
HHTide	Residential	6.1	10.4	3.1	8.7
	Commercial	1.0		1.9	
	Industrial	3.3		3.7	
LLTide	Residential	4.9	8.6	1.2	4.6
	Commercial	0.9		1.3	
	Industrial	2.7		2.1	
SSP126	Residential	5.7–6.1	9.5–10.2	1.6–2.1	5.6–6.6
	Commercial	0.9–1.0		1.5–1.5	
	Industrial	2.9–3.2		2.5–2.9	
SSP245	Residential	5.9–6.3	9.8–10.5	1.8–2.4	5.9–7.0
	Commercial	0.9–1.0		1.5–1.6	
	Industrial	3.0–3.3		2.6–3.0	
SSP585	Residential	6.0–6.5	10.1–10.9	2.1–2.8	6.4–7.7
	Commercial	1.0–1.0		1.5–1.7	
	Industrial	3.1–3.5		2.9–3.2	
HHTide+SSP585	Residential	6.8–7.4	11.5–12.4	4.1–4.9	10.6–12.1
	Commercial	1.0–1.0		2.1–2.2	
	Industrial	3.7–3.9		4.4–5.0	

I estimated the total economic losses from coastal flooding caused by historical Typhoon Hato (Table 3.2), Typhoon Mangkhut (Table 3.3), and Typhoon Saola (Table 3.4) to be 5.4, 7.9, and 5.2 billion HKD, respectively. However, because the economic losses derived from the depth-damage function are based solely on inundation depth and do not account for the duration of flooding—which varies considerably across the three typhoon benchmarks (Figure 3.11)—the estimated losses cannot be directly compared with actual damages. As a result, this analysis places greater emphasis on the relative variations in economic losses under different worst-case scenarios. Compared to the benchmark scenario, except for the LLTide scenario, economic losses under the SLR and HHTide scenarios show varying degrees of increase. Particularly, under the most severe worst-case scenario—when a TC approaches during the extreme high tide under the high-emission SSP585 scenario in 2100—economic losses could increase by 1.4–2.5, 5.5–6.9, and 5.4–6.9 billion HKD for Typhoon Hato, Mangkhut, and Saola, respectively. These economic losses are approximately 1.3–1.5, 1.7–1.9, and 2.0–2.3 times higher than those under the benchmark scenario. This highlights the critical need for robust disaster preparedness and mitigation strategies.

In terms of inundated building types, the inundated area of residential buildings is particularly large—seven times greater than that of commercial buildings and twice that of industrial buildings.

This is due to Hong Kong's world-leading high-density residential usage along the coastline [Yu *et al.*, 2024]. Economic losses of residential buildings and industrial buildings are comparable; both are approximately twice those of commercial buildings. The high economic loss in industrial buildings is associated with the highest maximum loss, as the coastline serves as an important harbor and fish breeding area in Hong Kong (Figure 2.3). Industrial buildings are primarily constructed by the seaside to facilitate better turnover, making these waterfront structures particularly vulnerable to inundation and storm impacts. Overall, the inundated area experienced by residential buildings is twice as large as that of industrial buildings, and the economic losses are twice as high as those of commercial buildings. This disparity highlights the severe impact of flooding on residential areas, which often house vulnerable populations that may lack the resources to recover from such disasters. Therefore, when designing engineering measures, it is essential to implement proactive policies and adaptive strategies to address the potential for worsening flooding in the future.

3.7 Discussion and summary of the chapter

To investigate coastal flooding and potential risks in Hong Kong under future climate scenarios, I primarily utilize a hydrodynamic model to reproduce water levels along the coastline and assess inland flooding. I focus on the three most destructive typhoons: Typhoon Hato (2017), Typhoon Mangkhut (2018), and Typhoon Saola (2023). Using these events as benchmarks, I incorporate extreme high tides and sea level rise as worst-case scenarios and estimate economic losses based on a depth-damage function. The simulation model results show good agreement with observed records and provide abundant data on spatial and temporal variations.

Through an integrated framework to estimate coastal flood hazards, I reveal that the northwestern region of Hong Kong (Yuen Long District) is the most vulnerable to coastal flooding caused by all three typhoons. In addition, the coastlines along the Islands District, Tai Po, Sai Kung, Kowloon City, and Kwai Tsing experience greater inundation depth, wider inundation extent, and longer inundation duration. 11 districts experienced inundation lasting over one hour during the three typhoons, with a hazardous flood depth reaching 1.67 meters. For Typhoon Hato, the effects of extreme high tide and SLR are comparable in contributing to coastal flooding. However, for Typhoon Mangkhut and Typhoon Saola, extreme high tide plays a more critical role in

exacerbating flooding. The most severe worst-case scenario is expected to occur when extreme high tide coincides with the high-emission SSP585 scenario in 2100. Under this condition, economic losses are projected to be approximately 1.3–1.5, 1.7–1.9, and 2.0–2.3 times higher than those under the benchmark scenario for the three typhoons. Particularly, residential areas account for the highest risk in Hong Kong when facing coastal flooding.

The Hong Kong Drainage Services Department (DSD) has identified several low-lying and exposed residential areas as particularly vulnerable to the highest risks of overtopping water and sea inundation during extreme weather events (see https://www.dsd.gov.hk/EN/Flood_Prevention/Our_Flooding_Situation/Coastal_Low_lying_or_Windy_Residential_Areas/index.html), covering most of the locations I identified as high-risk for flooding. However, these findings highlight that the southern area of the Kowloon Peninsula, particularly the coastline in Kowloon City and Kwai Tsing, should also be recognized as increasingly vulnerable to coastal flooding. Focusing improvement works and management measures exclusively on existing storm surge hotspots may leave this southern area susceptible to compounded flooding risks due to potential oversights.

The increases in inundation depth due to HHTide and SLR can vary across different districts and depend on the benchmarks of three typhoons (Figure 3.13g, Figure 3.14g, and Figure 3.15g). The spatially and temporally non-uniform increments in inundation can be attributed to the nonlinear response of storm surge to SLR [*Bilskie et al.*, 2016; *L Li et al.*, 2018]. Storm surges during typhoons can worsen the effects of SLR, as stronger winds push a disproportionately large amount of water inland, heightening the risk from the most destructive storms in a warming climate. This situation underscores the critical need for context-specific, robust disaster preparedness and mitigation strategies.

This study enhances the understanding of extreme coastal flooding in Hong Kong caused by TC-induced storm surges, astronomical tides, and sea level rise. It also lays the groundwork for estimating the evolution of flood hazards resulting from sea level rise and changes in tidal patterns in a changing climate. The framework developed here is applicable to any coastal city vulnerable to TC surge flooding and rising sea levels, particularly in megacities.

Chapter 4. Consecutive heatwaves and extreme sea levels along Europe's coastline

Consecutive heatwaves and extreme sea levels (consecutive HWESL) are sequential extremes in which an extreme sea level closely follows a heatwave, affecting water availability, human societies, and ecosystems. However, current research lacks comprehensive spatiotemporal analyses examining the interplay between heatwaves and extreme sea levels, particularly in the context of climate change. In this study, I utilize ERA5 reanalysis data, GESLA observational data, and EURO-CORDEX climate model simulations to investigate the frequency, dependence, and potential indicators of these compound events over Europe's coastal areas. Specifically, I investigate the spatiotemporal characteristics and dynamics of consecutive HWESL events along Europe's coastline during 1979–2017, as well as the future changes of consecutive HWESL events during the period of 2042–2070. I also explore the underlying physical processes associated with heatwaves followed by extreme sea levels. This study will not only shed light on the understanding of emerging compound extremes but also provide insights for informing disaster risk management strategies, thereby enhancing resilience and adaptation to consecutive HWESL hazards under a warming climate.

4.1 Changes in the characteristics of consecutive HWESL events

I examined the total frequency of consecutive HWESL events during 1979–2017. As shown in Figure 4.1a, 90% of Europe's coastal regions have experienced compound heatwave and extreme sea level events except for some places near the Baltic Sea (BTS). The western and southern regions of Europe experience more frequent consecutive HWESL events, which corresponds to the higher total frequency of heatwaves and extreme sea levels in these areas (Figure 4.1b and Figure 4.1c). The total frequency of consecutive HWESL events in the West British Isles (WBI) and South Atlantic (SA) is approximately 28 and 36 events, respectively. I calculated the time lag between heatwaves and extreme sea levels (Figure 4.1d). The average time lag is 3 days for most of Europe's coastal regions. About 15% of consecutive HWESL events exhibit a time lag of 0 days in WBI and SA (Figure 4.2). The proportion of consecutive HWESL events with a time lag of 0 days can reach up to 23% in the Mediterranean Sea (MED). These results suggest a sudden occurrence of extreme sea levels following the end of a heatwave. This

abrupt shift from heatwaves to extreme sea levels may increase the risk of consecutive HWESL events, as coastal communities may struggle to adapt quickly.

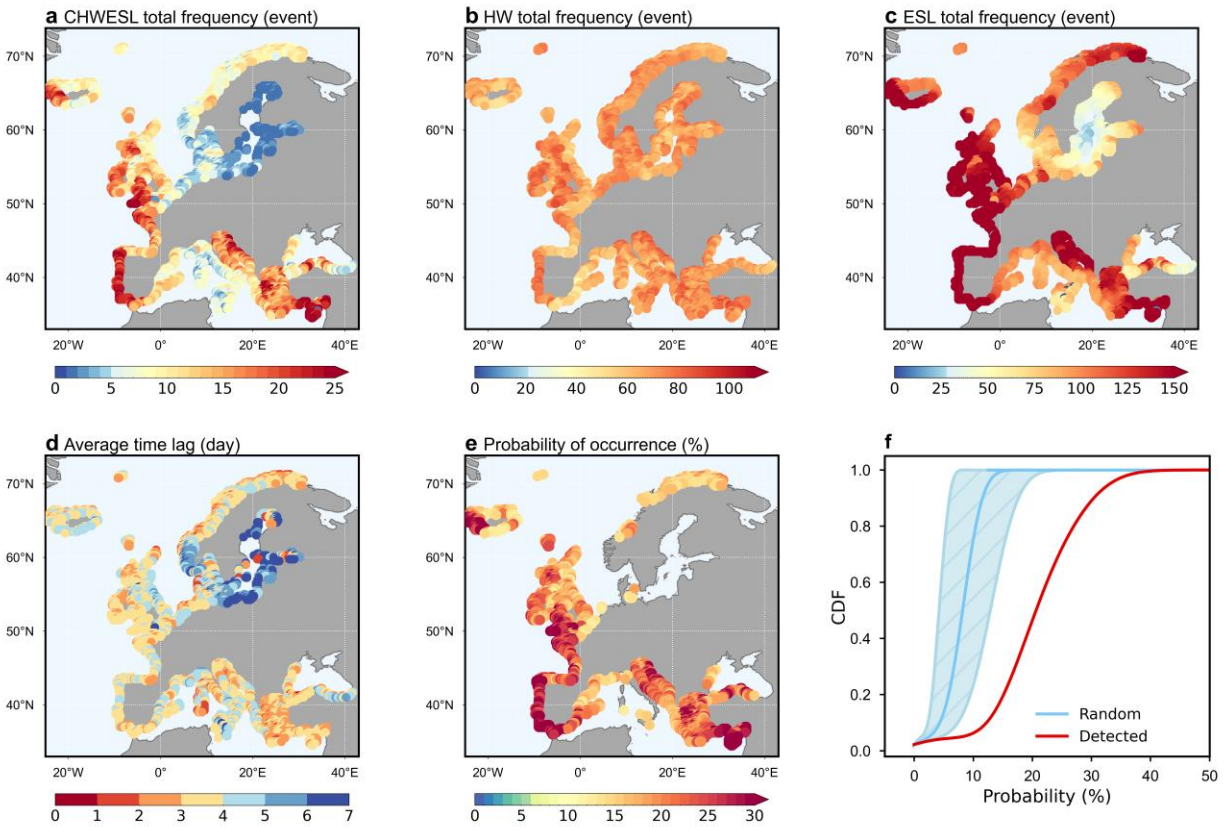


Figure 4.1 Characteristics of consecutive HWESL events during the period of 1979–2017.

(a–c) Total frequency (event) of consecutive HWESL events (a), heatwaves (b), and extreme sea levels (c) during 1979–2017. (d) Average time lag (day) between heatwaves and extreme sea levels. (e) Probability is defined as the likelihood of heatwaves being followed by extreme sea levels. Grid cells with detected probability of consecutive HWESL events significantly ($p < 0.05$) lower than the probability obtained from 1,000 resamples in the significance test are excluded from the probability analysis. (f) Comparisons between the detected probability of consecutive HWESL events and the median value of random probability derived from 1,000 resamples. Hatched shading is the 95% confidence interval of random variability simulated by 1,000 times of bootstrap iteration.

Figure 4.1e shows the probability of consecutive HWESL events during 1979–2017, showing 23% of heatwaves are followed by extreme sea levels. This indicates for every five heatwaves, there is one following extreme sea level within 7 days during 1979–2017 along Europe’s coastlines.

Heatwaves in WBI, SA, and MED are more likely to be followed by extreme sea levels, with probabilities of consecutive HWESL events of 22%, 26%, and 20%, respectively. I validated that the probability of consecutive HWESL events is greater than what would be expected by chance through a resampling-based significance test. The detected probability of consecutive HWESL events significantly exceeds ($p<0.05$) the random probability based on 1,000 resamples in the significance test for Europe's coastlines (Figure 4.1f). This finding confirms the interaction between heatwaves and extreme sea levels, potentially nearly tripling the probability of consecutive HWESL events from 9% to 23% and consequently increasing the risks associated with such compound events.

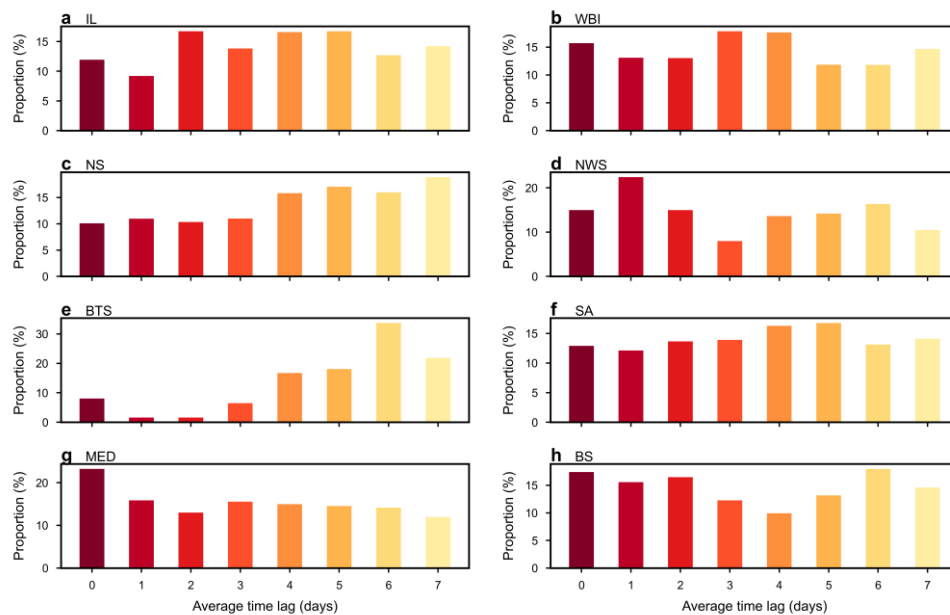


Figure 4.2 Average time lag (day) between heatwaves and extreme sea levels during 1979–2017 for different coastal regions.

I analyzed the decadal trends in the frequency of consecutive HWESL events and individual extremes during 1979–2017 to reveal long-term changes (Figure 4.3). In recent decades, 48% of coastal areas experienced more frequent consecutive HWESL events due to the increased frequency of heatwaves and extreme sea levels (Figure 4.3b and Figure 4.3c), with an average rate of 0.4 events per decade. The rising trend in the frequency of consecutive HWESL events is notably concentrated in the MED and Iceland (IL). Conversely, the slight decreasing trends observed in the frequency of consecutive HWESL events in the WBI and SA can be attributed,

respectively, to the decreasing frequency of heatwaves and extreme sea levels. These trends in the frequency of individual extremes align with findings from previous studies [Rousi *et al.*, 2022; Philip L. Woodworth *et al.*, 2011; Sijia Wu *et al.*, 2023].

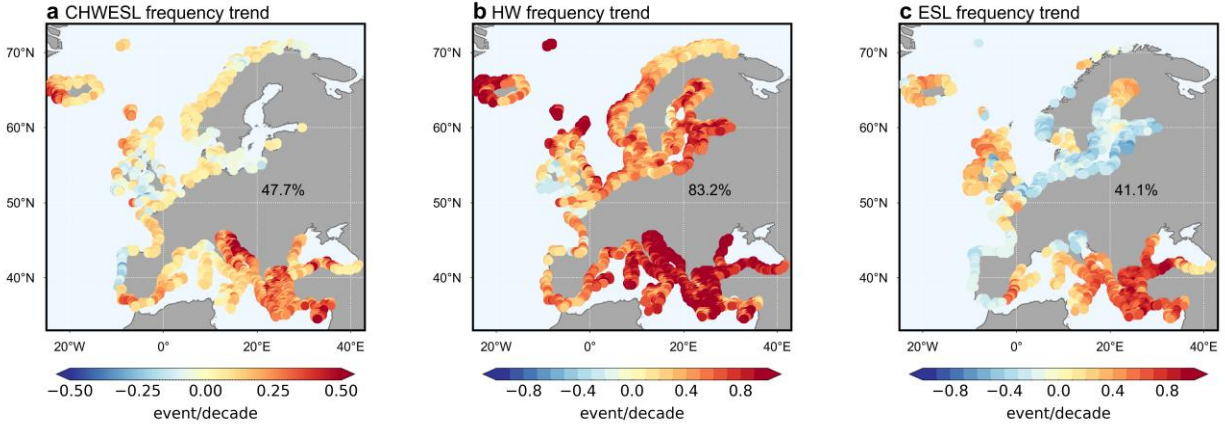


Figure 4.3 Decadal trends in the frequency of consecutive HWESL events and individual extremes for the period from 1979 to 2017.

(a) consecutive HWESL events. (b) Heatwaves. (c) Extreme sea levels. Trends were estimated using the Theil–Sen slope estimator, and their statistical significance was assessed using the Mann–Kendall (MK) trend test at the 95% confidence level. Only grid cells with statistically significant trends are shown. The number in each panel indicates the percentage of coastal areas with a significant increasing trend.

4.2 Comparison between heatwaves followed by and not followed by extreme sea levels

I used the composite meteorological maps [Hendry *et al.*, 2019; Zscheischler *et al.*, 2020] to investigate the differences in synoptic preconditions between heatwaves followed by extreme sea levels (consecutive HWESL) and those not followed by extreme sea levels (NHW). I find that hotter heatwaves are more likely to be followed by extreme sea levels. There is a significant difference in air temperature between consecutive HWESL and NHW. consecutive HWESL (Figure 4.4a) has higher air temperatures than NHW (Figure 4.4b) along Europe's coastlines, with an average air temperature difference of 0.3°C and a maximum difference of 4.7°C. This indicates I need a more holistic view by considering not only the heatwave itself, but also the intensity of the heatwave as an indicator of potential following extreme sea level events. Additionally, I compared the time series of air temperature for the consecutive HWESL events and the NHW

events, following the approach used by Chen et al. (2022) [Yang Chen et al., 2022]. I verified that the hotter consecutive HWESL are not just a signal of general warming, but that such a contrast in air temperature actually occurs in most years (Figure 4.5), rather than being dictated by recent warmer periods or strong internal variability regimes.

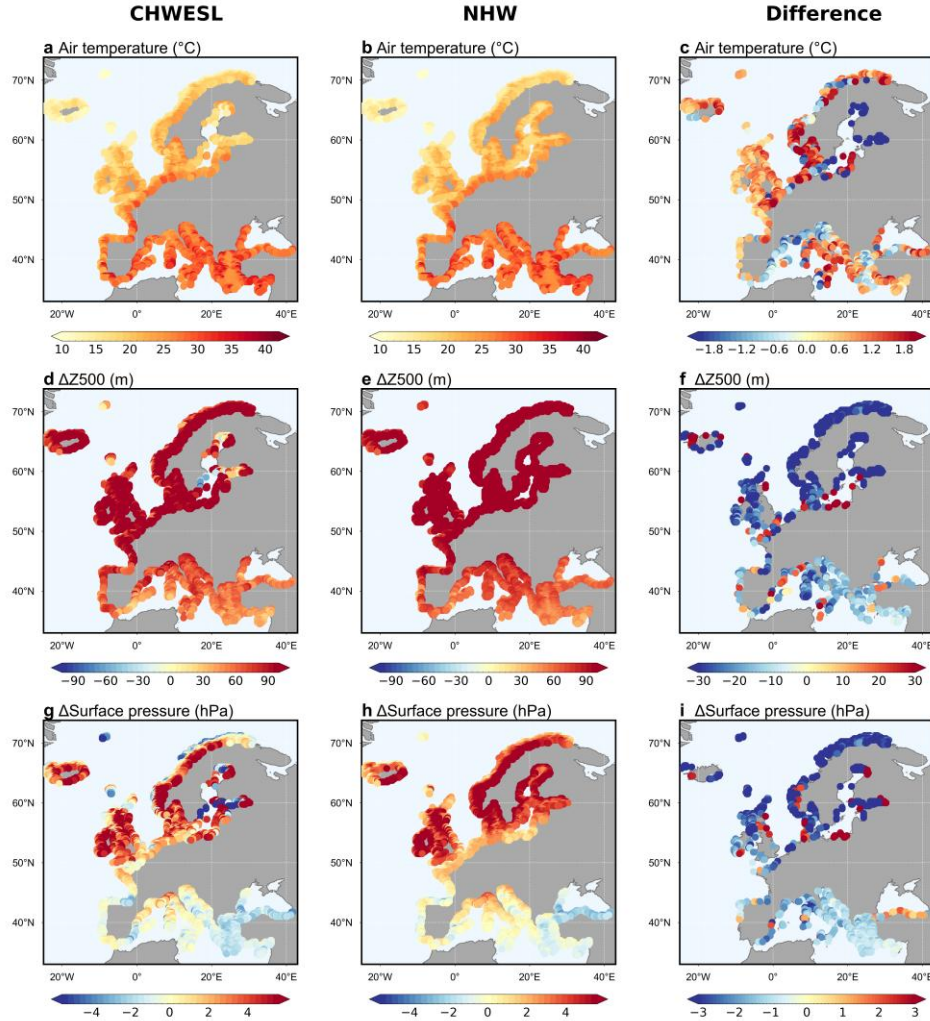


Figure 4.4 Composites of large-scale variables.

Large-scale variables include air temperature ($^{\circ}\text{C}$) in the first row, anomalies of geopotential height at 500 hPa (Z500, m) in the second row, and anomalies of surface pressure (hPa) in the third row. The left, middle, and right columns represent conditions during heatwaves followed by extreme sea levels (consecutive HWESL), heatwaves not followed by extreme sea levels (NHW), and their differences, respectively. Grid cells with insignificant differences at a 95% confidence level are not shown. The differences were assessed using a Student's t -test.

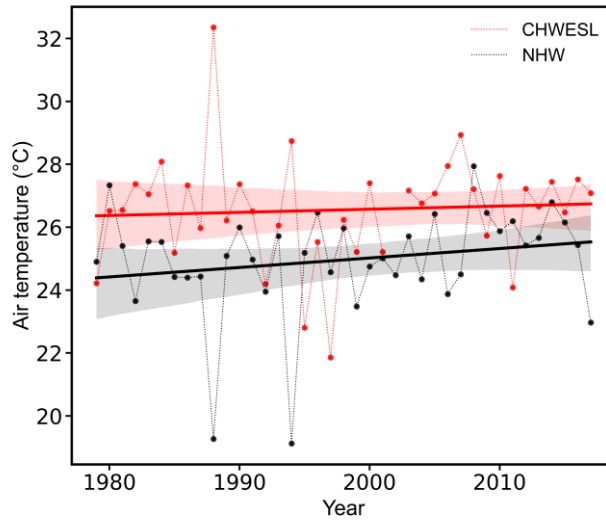


Figure 4.5 Time series of air temperature of consecutive HWESL events and NHW events.

Corresponding to the warmer conditions during consecutive HWESL and NHW, positive Z500 anomalies, which represent anomalous anti-cyclonic flows [Ha *et al.*, 2022], cover nearly all coastal regions (Figure 4.4d and Figure 4.4e). In comparison, the geopotential height anomalies during consecutive HWESL are significantly lower than those during NHW (Figure 4.4f). The reduced geopotential height anomalies observed during consecutive HWESL may be linked to the lower surface pressure (Figure 4.4g). The anomalous low surface pressure may mitigate the anti-cyclonic condition by slightly reducing the anomalies of geopotential height, whereas the anomalies of geopotential height remain at a high level (Figure 4.4d). Such a difference in surface pressure anomalies between consecutive HWESL and NHW is particularly evident when comparing the surface pressure anomalies on the end day of consecutive HWESL and NHW (Figure 4.6c). By the end of the consecutive HWESL event, the low surface pressure intensifies and encompasses almost all coastal areas (Figure 4.6a), which contrasts with the conditions observed on the end day of NHW (Figure 4.6b). The low surface pressure can create a pressure gradient that favors stronger winds, generating waves and storm surges that drive seawater toward coastlines, ultimately elevating the total water level and leading to extreme sea levels [Muis *et al.*, 2020; Tebaldi *et al.*, 2021]. Overall, these findings show that the low surface pressure during hotter heatwaves may be an important indicator of compound heatwaves and extreme sea levels along Europe's coastlines.

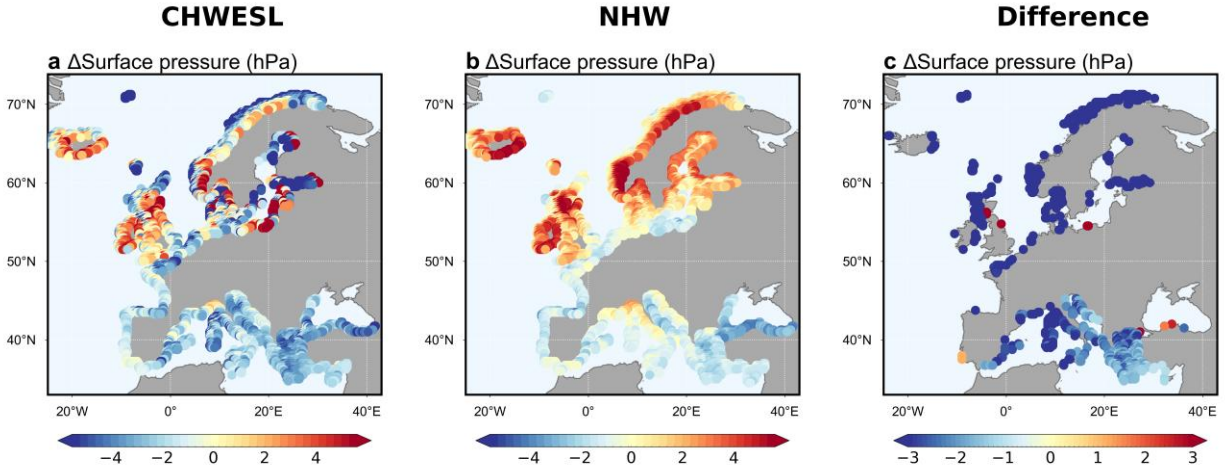


Figure 4.6 Composite anomalies of surface pressure (hPa) on the end day of heatwaves.

(a) Heatwaves followed by extreme sea levels. (b) Heatwaves not followed by extreme sea levels. (c) Differences between the two composites. Grid cells with insignificant differences at a 95% confidence level are not shown. The differences were assessed using a Student's *t*-test.

4.3 Projected characteristics of consecutive HWESL events

Figure 4.7 illustrates the changes in the characteristics of consecutive HWESL events between the future period of 2042–2070 under the high-emission scenario of RCP8.5 and the historical period of 1977–2005. I find that 83% of Europe's coastal regions are projected to experience a higher total frequency of consecutive HWESL events during the future period, with an average increase of 46 events (Figure 4.7a), indicating an eightfold increase compared to the historical period. A warmer climate may simultaneously cause more heatwaves and extreme sea levels (Figure 4.8a and Figure 4.8b) along Europe's coastlines, thereby resulting in a higher total frequency of consecutive HWESL events. To elucidate the increasing total frequency of consecutive HWESL events in the future, I conducted a decomposition analysis to evaluate how the total frequency of consecutive HWESL events would change when considering either the changing heatwaves or the changing extreme sea levels alone. I find that the changing heatwaves and extreme sea levels may jointly influence the changing frequency of consecutive HWESL events, as the increasing frequency of consecutive HWESL events cannot be reproduced by considering the influence of heatwaves and extreme sea levels alone (Figure 4.8c and Figure 4.8d). In comparison, the primary factor driving future changes in the total frequency of consecutive

HWESL events seems to be changes in heatwaves. When considering changes in heatwaves alone (Figure 4.8a), 90% of coastal regions show significant positive changes in the total frequency of consecutive HWESL events, amounting to 20 events (Figure 4.8c). The impact of heatwave changes is pronounced in the regions of SA and IL. Conversely, when only considering changes in extreme sea levels, the proportion of coastal regions with significantly increasing consecutive HWESL events decreases to 71% (Figure 4.8d). The average increase in the frequency of consecutive HWESL events is 7 events.

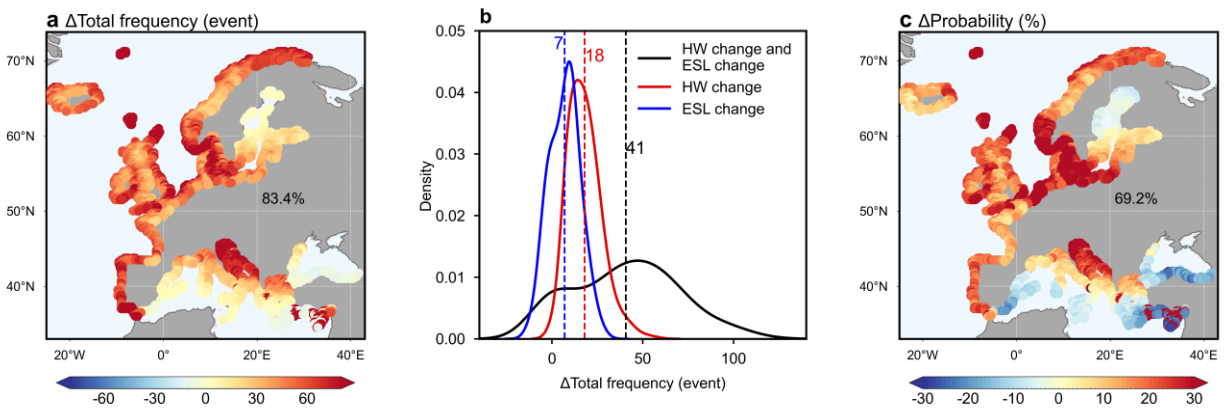


Figure 4.7 Projected changes of consecutive HWESL events and the decomposition of changes in the total frequency of consecutive HWESL events.

(a) Projected changes in the total frequency (event) of consecutive HWESL events between the future period of 2042–2070 under RCP8.5 and the historical period of 1977–2005. The results are considered significant only when all models consistently indicate an increase (or decrease) in the change. Grid cells with insignificant changes are excluded from the analysis. The number represents the percentage of coastal areas with significant positive changes. (b) Decomposition of the changes in total frequency of consecutive HWESL events due to changes in the frequency of heatwaves and changes in the frequency of extreme sea levels. It shows the probability density function of the average changes in the frequency of consecutive HWESL events between the future period and the historical period. consecutive HWESL events during the future period are identified based on future heatwaves and future extreme sea levels (black), future heatwaves and historical extreme sea levels (red), historical heatwaves and future extreme sea levels (blue). (c) Same as (a) but for the projected changes in the probability of consecutive HWESL events.

The higher risk for Europe's coastline is also reflected in the increases in the probability of consecutive HWESL events during the future period (Figure 4.7c). Furthermore, the increasing trends of consecutive HWESL events from 2042 to 2070 (Figure 4.9d–f) are larger than those observed during the historical period from 1977 to 2005 (Figure 4.9a–c), serving as additional stressors for coastal communities. This indicates that in a warmer climate, heatwaves are more likely to be followed by extreme sea levels. Despite the region North Sea having few consecutive HWESL events during the historical period (Figure 4.1a), it shows the most prominent increase in both frequency and probability during the future period (Figure 4.7a and c). This emphasizes the need for emergency response systems to prepare for consecutive HWESL events, even though some regions have not yet experienced such compound extremes during the historical period.

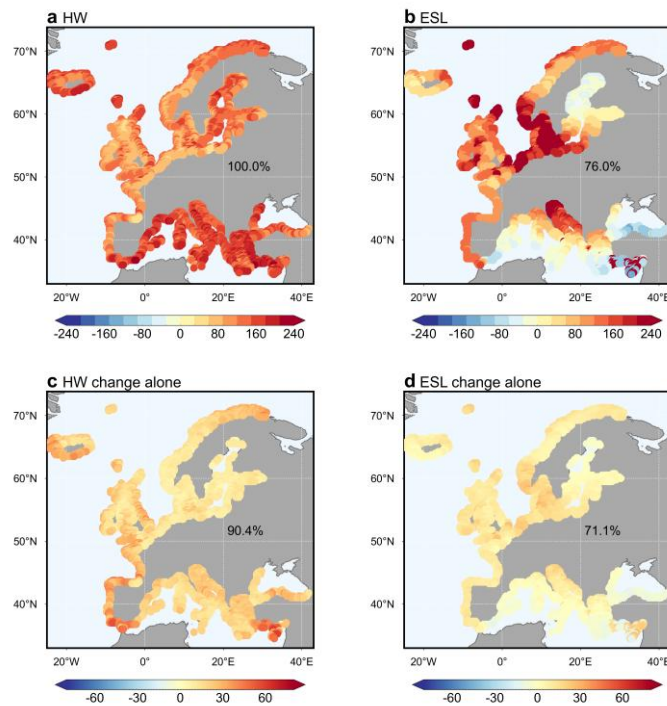


Figure 4.8 Projected changes in the total frequency (events) between the future period of 2042–2070 under RCP8.5 and the historical period of 1977–2005.

(a–b) Projected changes in the total frequency of heatwaves (a) and extreme sea levels (b). (c–d) Projected changes in the total frequency of consecutive HWESL events when consecutive HWESL events during the future period are identified based on future heatwaves and historical extreme sea levels (c), and historical heatwaves and future extreme sea levels (d). The number represents the percentage of coastal areas with positive changes.

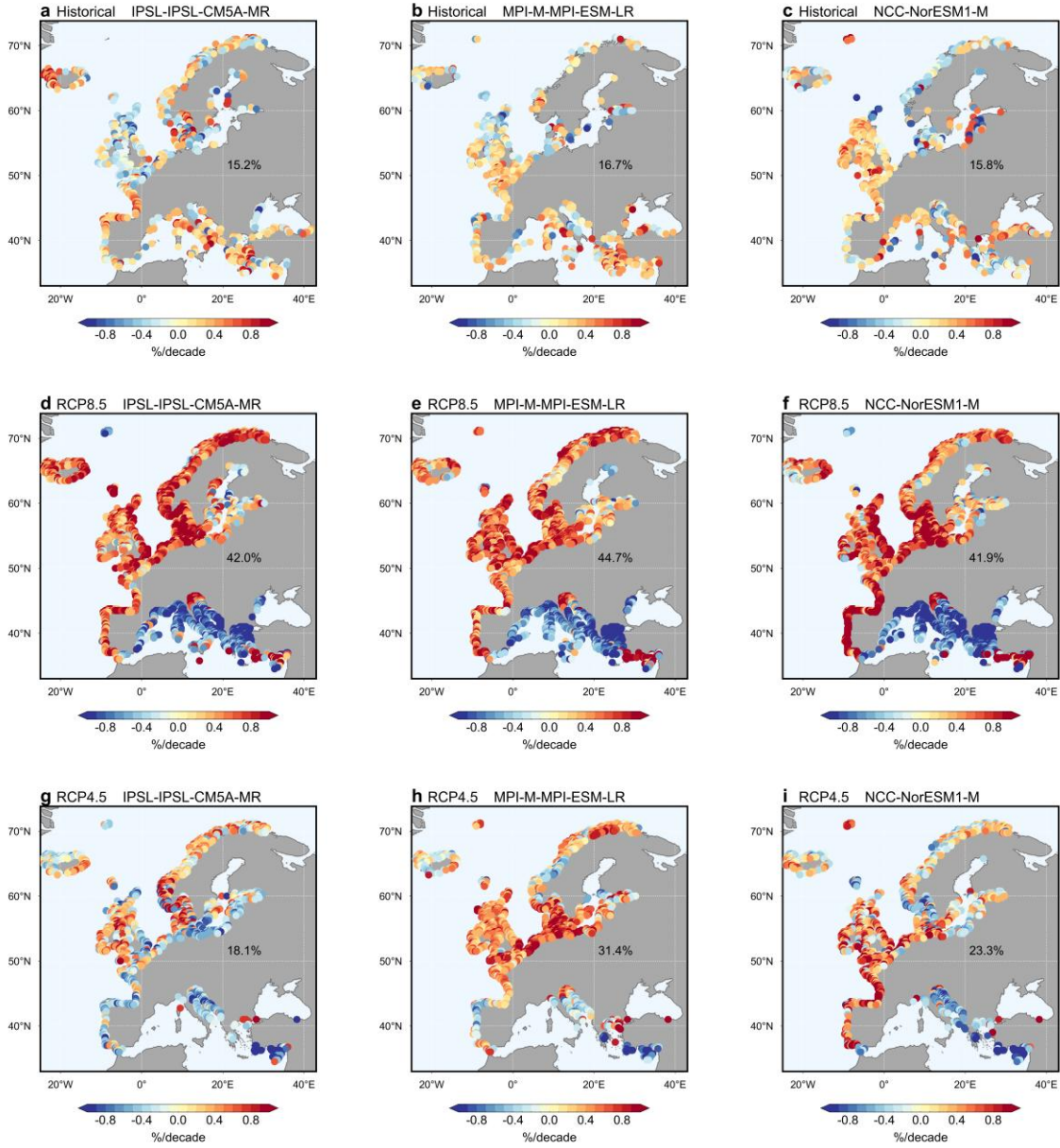


Figure 4.9 Decadal trends in the frequency of consecutive HWESL events based on different EURO-CORDEX models.

(a–c) Historical period of 1977–2005. (d–f) Future period of 2042–2070 under RCP8.5. (g–i) Future period of 2072–2100 under RCP4.5. Displayed trends are derived from the Theil-Sen slope estimator. The statistical significance of trends is estimated by the Mann-Kendall (MK) trend test at a 95% confidence level. Only grid cells with statistically significant increasing or decreasing trends are shown in the figure. The number represents the percentage of coastal areas with a significant increasing trend.

4.4 Verification of findings using different datasets and thresholds

4.4.1 Historical reproduction of consecutive HWESL events

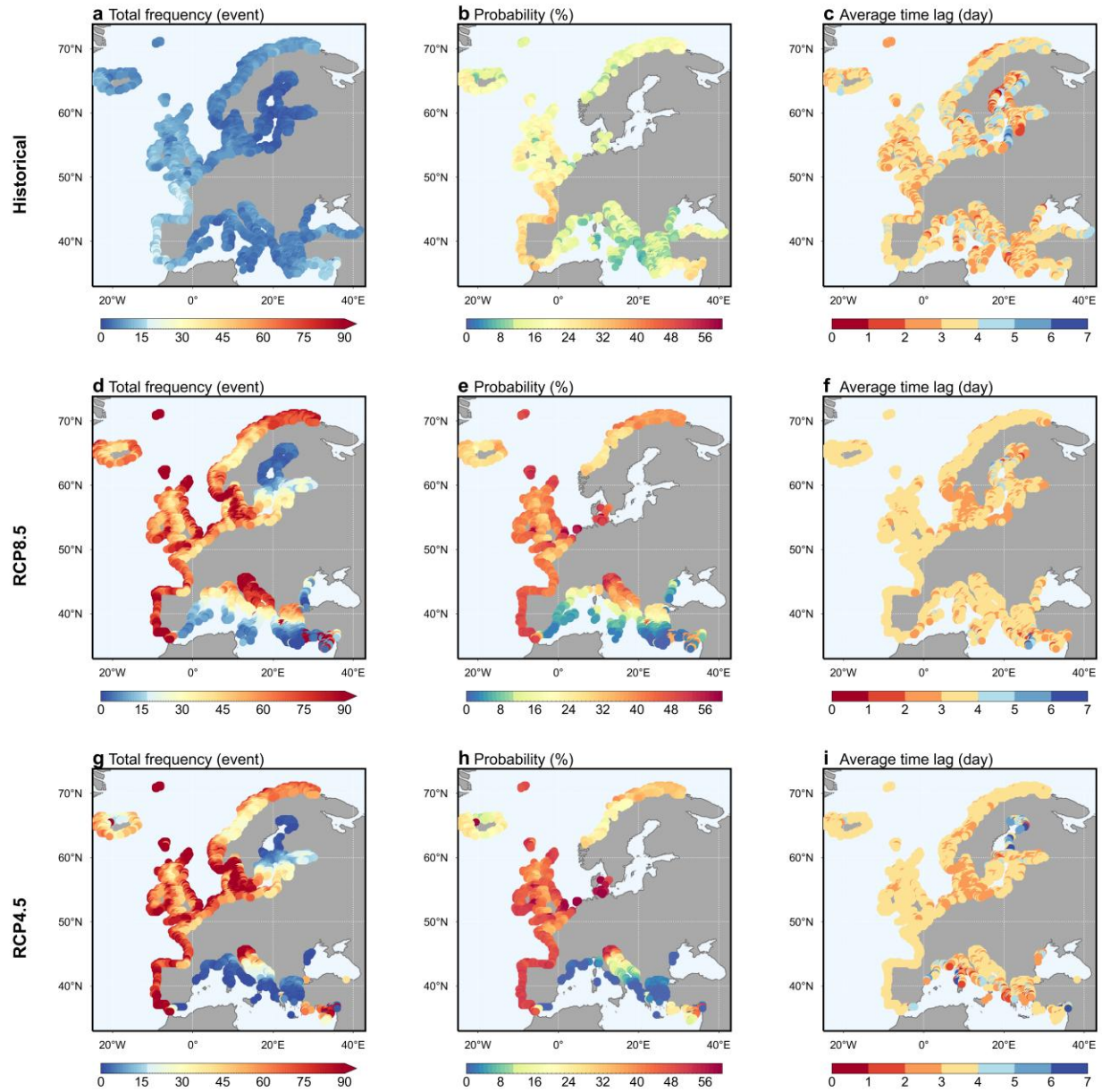


Figure 4.10 Characteristics of consecutive HWESL events during. (a–c) Historical period (1977–2005). (d–f) Future period (2042–2070) under RCP8.5. (g–i) Future period (2072–2100) under RCP4.5.

To assess future changes in the characteristics of consecutive HWESL events relative to the historical period, historical consecutive HWESL events were first reproduced using EURO-CORDEX models and then compared with reanalysis results. This evaluation was carried out to confirm that the models can reliably capture consecutive HWESL events along coastlines. In general, the EURO-CORDEX models show good skill in representing the characteristics of consecutive HWESL events, as reflected by the agreement in spatial patterns between the model simulations (Figure 4.10) and the reanalysis results (Figure 4.10) and reanalysis results (Figure 4.1). Furthermore, the simulated characteristics of consecutive HWESL events are broadly consistent among the different EURO-CORDEX models (Figure 4.11).

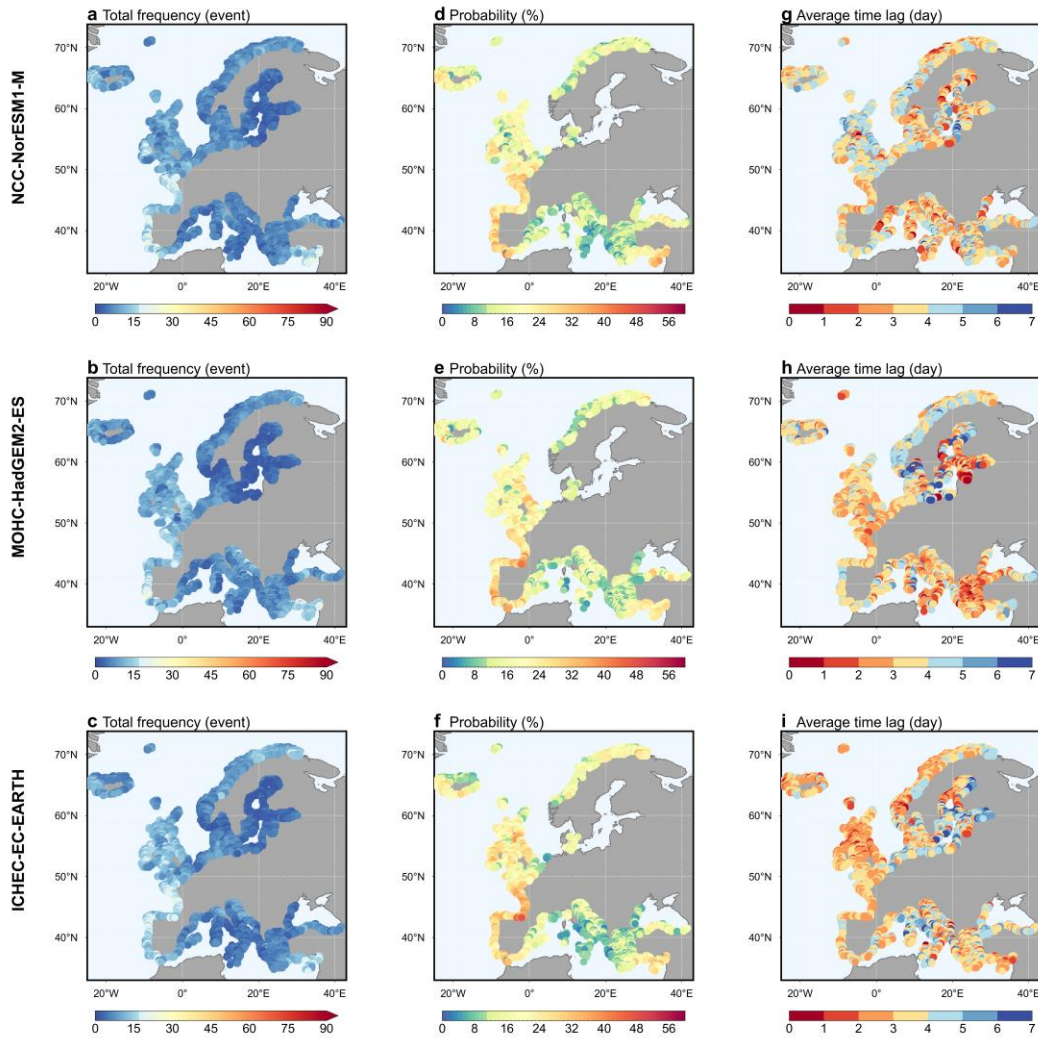


Figure 4.11 Characteristics of consecutive HWESL events for the historical period from 1977 to 2005 using the temperature projection dataset derived from individual EURO-CORDEX models.

4.4.2 Verification of findings using different datasets, thresholds, and time lags

I used an observational dataset of total water levels to validate the results. While differences in the characteristics of consecutive HWESL events may exist between the two datasets (Figure 4.1 and Figure 4.12) due to variations in temporal length (Figure 4.12d) and missing data, the spatial patterns of consecutive HWESL events derived from reanalysis and observational data show consistency.

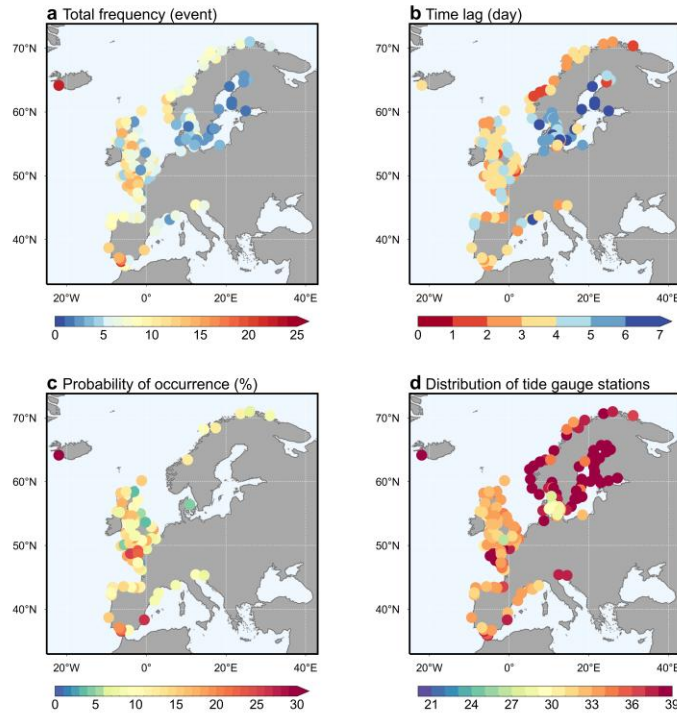


Figure 4.12 Characteristics of consecutive HWESL events based on the observational total water levels.

(a) Total frequency (event) of consecutive HWESL events. (b) Average time lag (day) between heatwaves and extreme sea levels. (c) Probability of occurrence of consecutive HWESL events. Probability is defined as the likelihood of heatwaves being followed by extreme sea levels. Grid cells with detected probability of consecutive HWESL events significantly ($p < 0.05$) lower than the probability obtained from 1,000 resamples in the significance test are excluded from the probability analysis. (d) Distribution of 281 tide gauge stations that have a minimum of 20 years of observations within the study period of 1979–2017. Different colors show the temporal length of observation data in each tide gauge station.

Climatic threshold is linked to the level of tolerance to extremes, which can be altered by adaptation and risk management efforts [Ranasinghe *et al.*, 2021]. To help inform risk management decisions on consecutive HWESL events, I performed a sensitivity analysis using different threshold levels (90th and 95th percentiles) to identify heatwave and extreme sea level events (Figure 4.13 and Figure 4.14). The spatial patterns of consecutive HWESL characteristics are consistent across different thresholds. As expected, using a higher percentile threshold can largely reduce the frequency and probability of consecutive HWESL events.

I also conducted a sensitivity analysis using different lag intervals of 1 and 3 days (Figure 4.15 and Figure 4.16) to account for the potential impact of varying lag connections between heatwaves and extreme sea levels. The results consistently demonstrate patterns of consecutive HWESL events across varying time intervals.

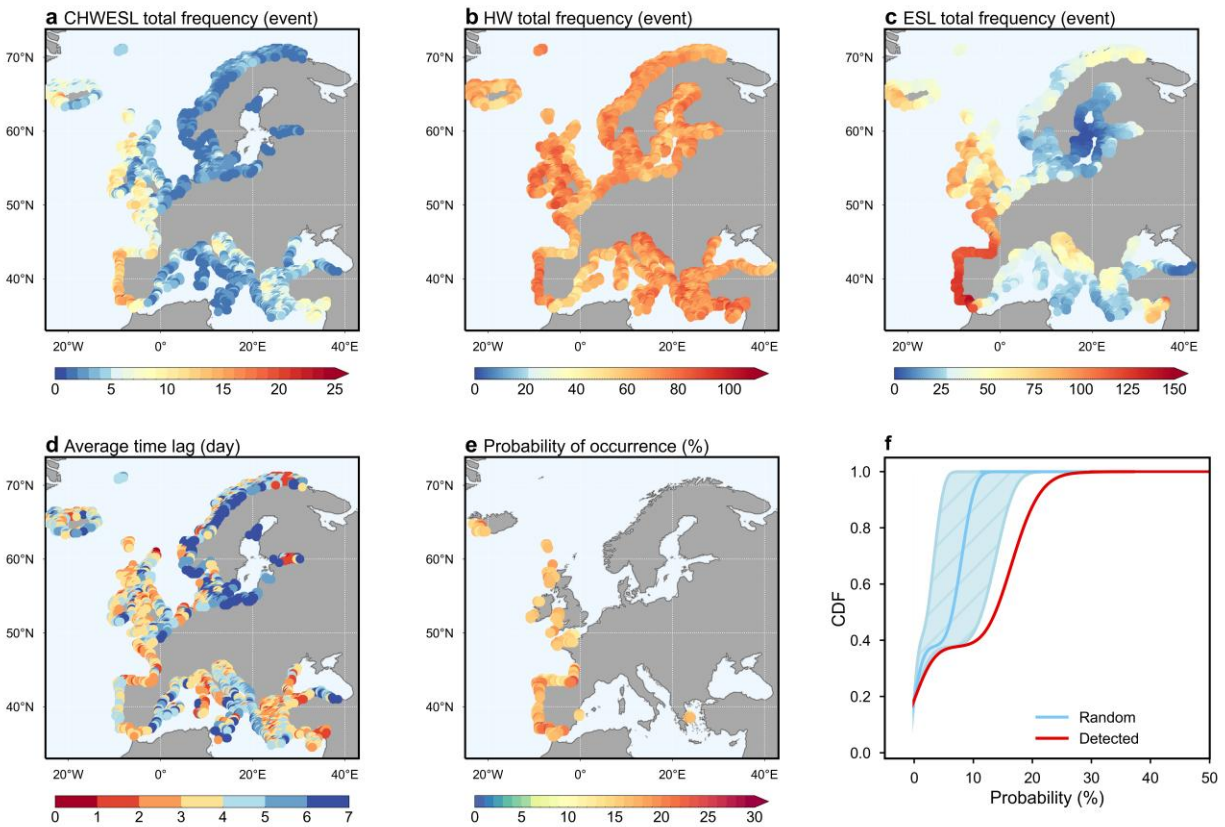


Figure 4.13 Same as Figure 4.1 but the heatwaves and extreme sea levels are identified based on 90th and 95th percentile thresholds, respectively.

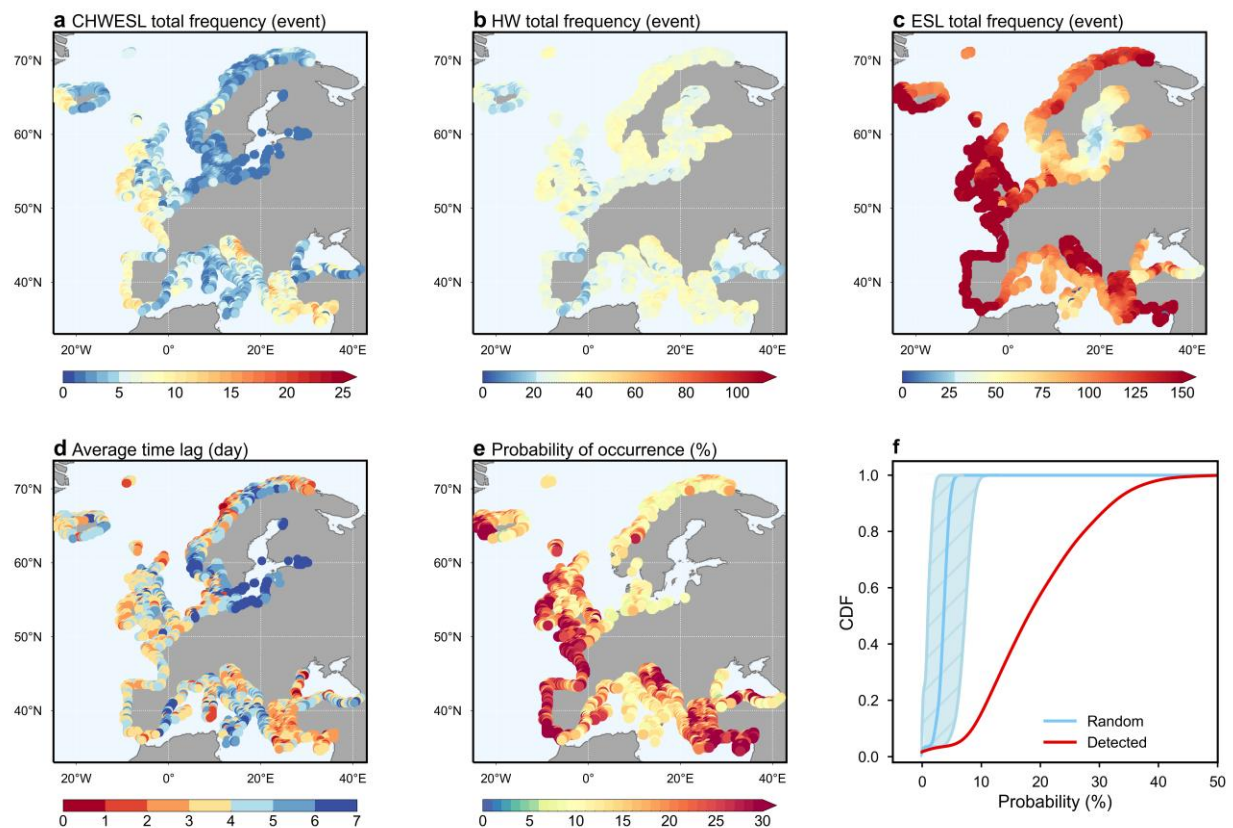


Figure 4.14 Same as Figure 4.1 but the heatwaves and extreme sea levels are identified based on 95th and 90th percentile thresholds, respectively.

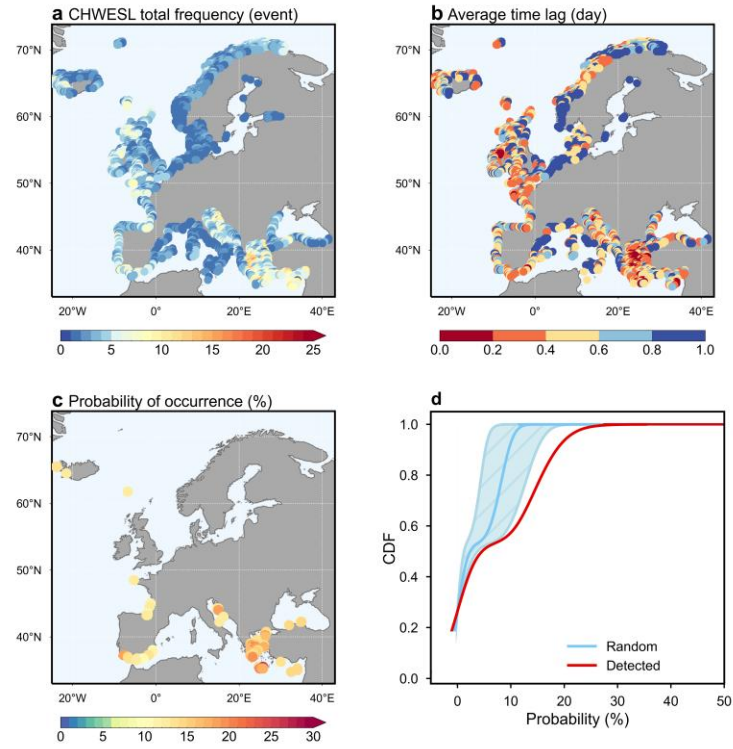


Figure 4.15 Same as Figure 4.1a, d–f, but the time lag is 1 day.

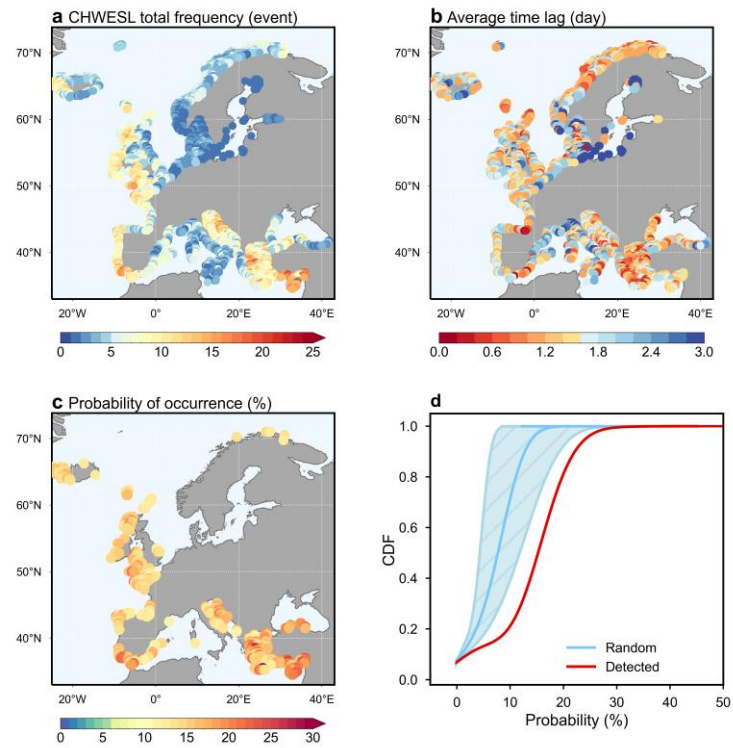


Figure 4.16 Same as Figure 4.15 but the time lag is 3 days.

4.4.3 consecutive HWESL events under different emission scenarios and adaptation levels

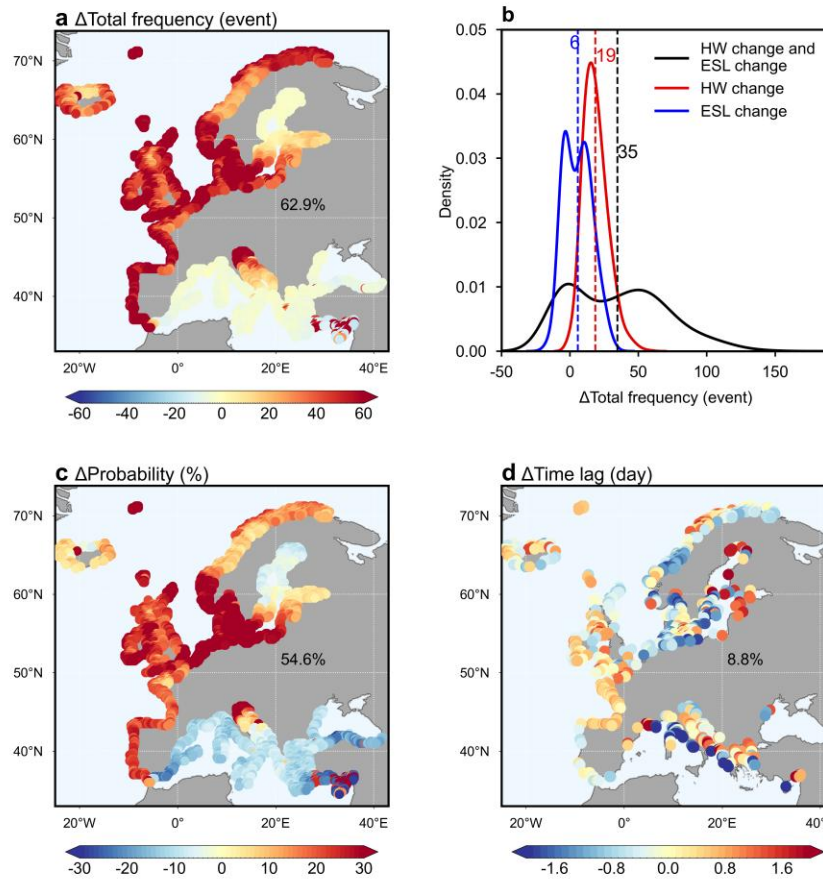


Figure 4.17 Same as Figure 4.7 but the projected changes between the future period of 2072–2100 under RCP4.5 and the historical period.

I considered the potential impact of both emission mitigation efforts and adaptation strategies that can enhance society's tolerance and resilience to consecutive HWESL events. First, besides the highest emission scenario of RCP8.5, I also examined the projected characteristics of consecutive HWESL events for the future period of 2072–2100 under the RCP4.5 scenario (Figure 4.17 and Figure 4.10g–Figure 4.10i). The results show that even under a medium-emission scenario, most of Europe's coastlines are also projected to experience consecutive HWESL events that are more frequent and higher probability by the end of this century relative to the historical period of 1977–2005. These results provide critical information that highlights the urgent need for more ambitious emission mitigation efforts and accelerated climate action plans. Second, I also used heatwaves and extreme sea levels identified based on the thresholds derived from $T_{\max}$ and

W_{max} of the future period to represent a lower-bound estimation of the future risk of consecutive HWESL events. Despite my optimistic assumption that future societies will be better adapted to both heatwaves and extreme sea levels, the projections indicate that 15% of Europe's coastlines will still face increased risks of consecutive HWESL events due to climate warming (Figure 4.18d).

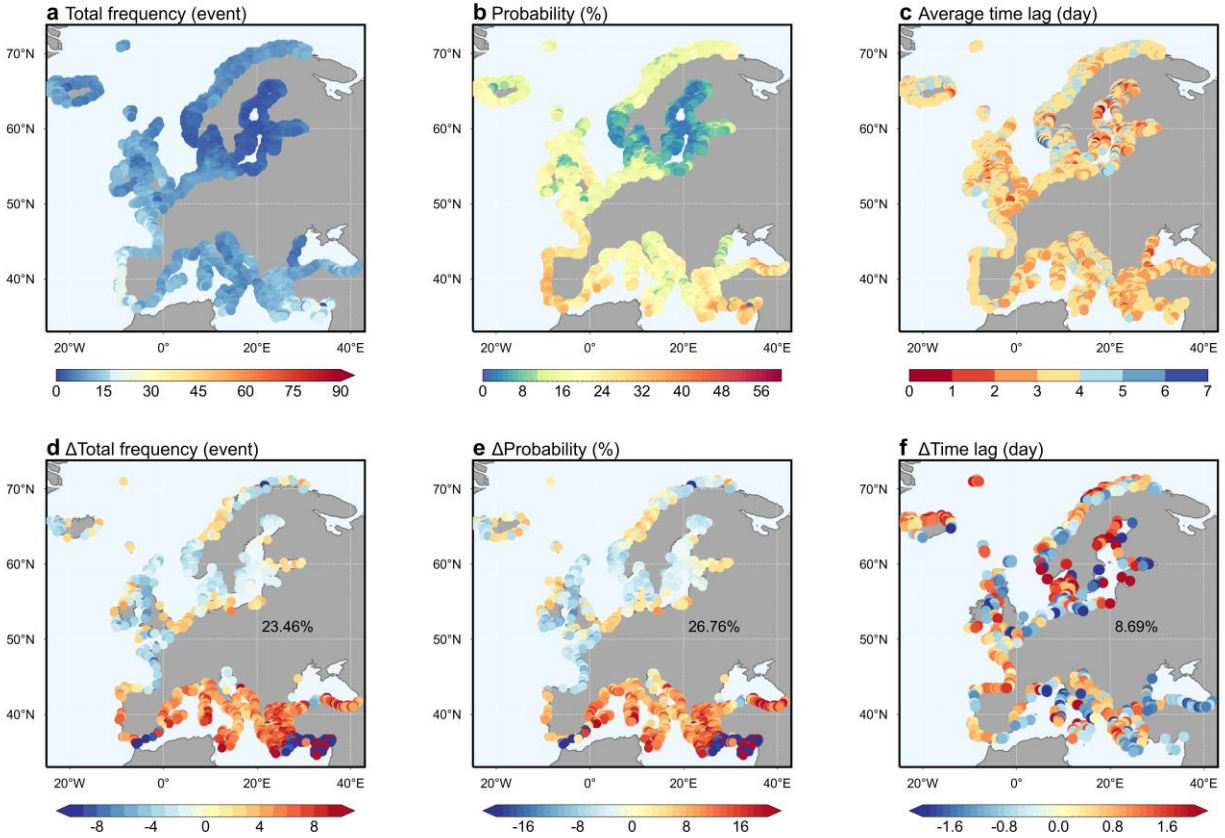


Figure 4.18 consecutive HWESL events during the future period of 2042–2070 under RCP8.5.

(a–c) Characteristics of consecutive HWESL events during the future period of 2042–2070. consecutive HWESL events are identified using heatwaves and extreme sea levels based on the threshold derived from T_{max} and W_{max} of the future period. (d–f) Projected changes in the characteristics of consecutive HWESL events between the future period of 2042–2070 under RCP8.5 and the historical period of 1977–2005.

4.5 Discussion and summary of the chapter

Although previous studies have reported heatwaves [Garcia-Leon et al., 2021; Guerreiro et al., 2018] and extreme sea levels [M. I. Vousedoukas et al., 2017; Weisse et al., 2014] separately in

Europe, the characteristics of compound heatwaves and extreme sea levels as well as their dynamic evolution in response to the warming climate remain poorly understood. This study provides an in-depth assessment of compound heatwave and extreme sea level (consecutive HWESL) events in Europe's coastal regions. I investigated the spatiotemporal changes in consecutive HWESL characteristics (frequency, time lag, probability), and underlying mechanisms of consecutive HWESL events during the summer season. Although this study focuses on Europe, the proposed framework can also be applied to examine the occurrence of consecutive HWESL events in other parts of the world, provided that reliable datasets with long-term records of temperature and total water level are available.

I find that most of coastal areas have experienced consecutive HWESL events during 1979–2017. For every five heatwaves, there is one following extreme sea level within 7 days during 1979–2017 along the Europe's coastline. There are significant dependencies between heatwaves and extreme sea levels, and these dependences can increase the occurrence of compound events by threefold. This is evidenced by comparing the probability of consecutive HWESL events in random tests with the observed probabilities. For half of the coastal area, the frequency of consecutive HWESL events increases in response to more heatwaves and extreme sea levels in a changing climate. Hotter heatwaves compared to other heatwaves are more likely to be followed by extreme sea levels. The anticyclone flows and low surface pressure may be important indicators of compound heatwaves and extreme sea levels. In addition, consecutive HWESL events are projected to become more frequent under RCP8.5, increasing the risk of compound heatwaves and extreme sea levels along Europe's coastlines as the climate warms.

Previous studies also provide evidence supporting the potential occurrence of consecutive HWESL events. Extreme sea levels on a daily basis are often associated with storm surges and waves, which are mainly caused by low atmospheric pressure and strong winds during cyclones, thunderstorms, or other intense convective systems [Arns *et al.*, 2020; Couasnon *et al.*, 2020; Haslett *et al.*, 2009; Marcos *et al.*, 2019; Paprotny *et al.*, 2020]. Heatwaves can be closely linked to these circulation anomalies, as rising temperatures can increase air humidity and atmospheric instability [L Gu *et al.*, 2022; W Zhang and Villarini, 2020], and they may result from anticyclones induced by the outer circulation of a low-pressure system [P Y Wang *et al.*, 2023a; D Zhao *et al.*, 2021a].

This study offers valuable insights for policymakers and stakeholders seeking to mitigate the risks arising from the transition between extreme heatwaves and extreme sea levels. It is particularly relevant for developing effective mitigation and adaptation strategies to reduce the impacts of such compound extremes on Europe's coastal communities. These findings also contribute to improving early warning systems and emergency preparedness for the increasing occurrence of consecutive HWESL events in the coming decades.

Chapter 5. Concurrent heatwaves and extreme sea levels along the global coastline

In the previous chapter, I showed that heatwaves and extreme sea levels can occur not only in close succession but also simultaneously. Building on this finding, this chapter focuses on the concurrent occurrence of these two hazards. Moreover, rather than limiting the analysis to Europe, I extend the study domain to the global coastline to explore how these compound events may evolve worldwide. Under climate change, concurrent heatwaves and extreme sea levels (concurrent HWESL events) may pose a serious threat to coastal communities. However, their spatiotemporal characteristics and dynamic evolution along the global coastline remain poorly understood. To address this knowledge gap, this chapter provides an in-depth assessment of both historical patterns and future changes in concurrent HWESL characteristics on a global scale, based on reanalysis datasets and CMIP6 projections. Furthermore, I investigate the sensitivity of concurrent HWESL events to the intensity of individual extremes and explore the underlying physical mechanisms driving these compound events. This study will not only contribute to a deeper understanding of the emerging type of compound extremes, but also provide crucial insights into the implementation of adaptation and early warning systems that can help mitigate the negative consequences of such extreme events.

5.1 Characteristics of concurrent heatwaves and extreme sea levels

The occurrence of concurrent HWESL events is defined as the number of concurrent HWESL days within a year. Using extreme sea levels derived from the ERA5 reanalysis dataset (ESL reanalysis), I calculated the total occurrence of concurrent HWESL events during 1979–2017. Most of the coastlines (88%) have been affected by concurrent events during the period of 1979–2017, with a concentration of these events in the tropical region (Figure 5.1a). Specifically, tropical coastlines, which account for only 47% of the total coastal area, have experienced 70.30% of all concurrent HWESL events worldwide. For each grid cell in the tropical region, the average total occurrence of concurrent HWESL events is 75 days during 1979–2017. In contrast, subtropical and temperate zones show a lower occurrence of concurrent HWESL for only 39 and 11 days, respectively. Results derived from the GESLA observation dataset (ESL observation) support the same finding that lower-latitude regions are more prone to concurrent events (Figure 5.2c, d).

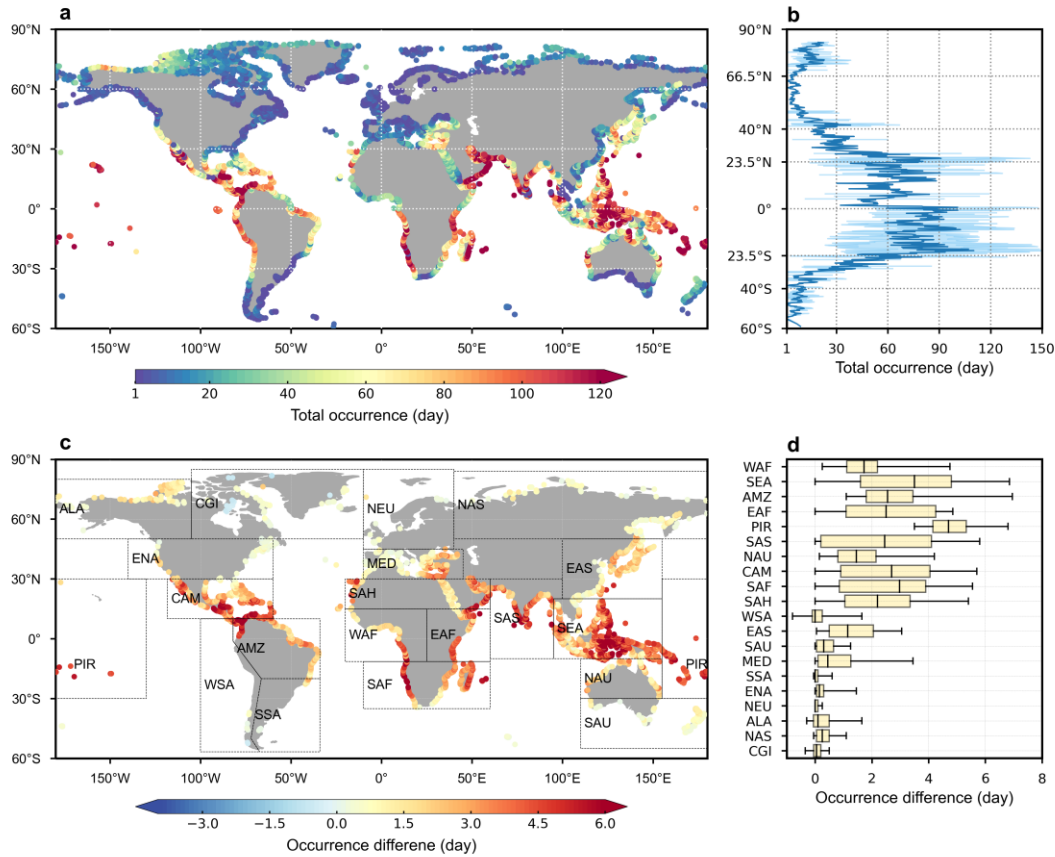


Figure 5.1 Characteristics of concurrent HWESL events during 1979–2017.

(a) Total occurrence (day) of concurrent HWESL events during 1979–2017. (b) Total occurrence (day) of concurrent HWESL events for grid cells at different latitudes. The shading spans an anomaly of ± 1 s.e.m. To enable comparisons between grid cells at different latitudes, the total occurrence of all grid cells is averaged for each latitude. (c) Differences in the concurrent HWESL occurrence (day) between 1998–2017 and 1979–1998. Statistical significance of the difference is estimated by the Student's *t* test at a 95% confidence level. Grid cells with insignificant differences are excluded from the change analysis. (d) Occurrence difference (day) for each divided region. Each box represents the distribution of occurrence difference across all grid cells within that region. The box is bounded by the 25th and 75th percentiles of the data, and the whisker is bounded by the 5th and 95th percentiles of the data. The order of coastal regions is determined by the average latitude of each region.

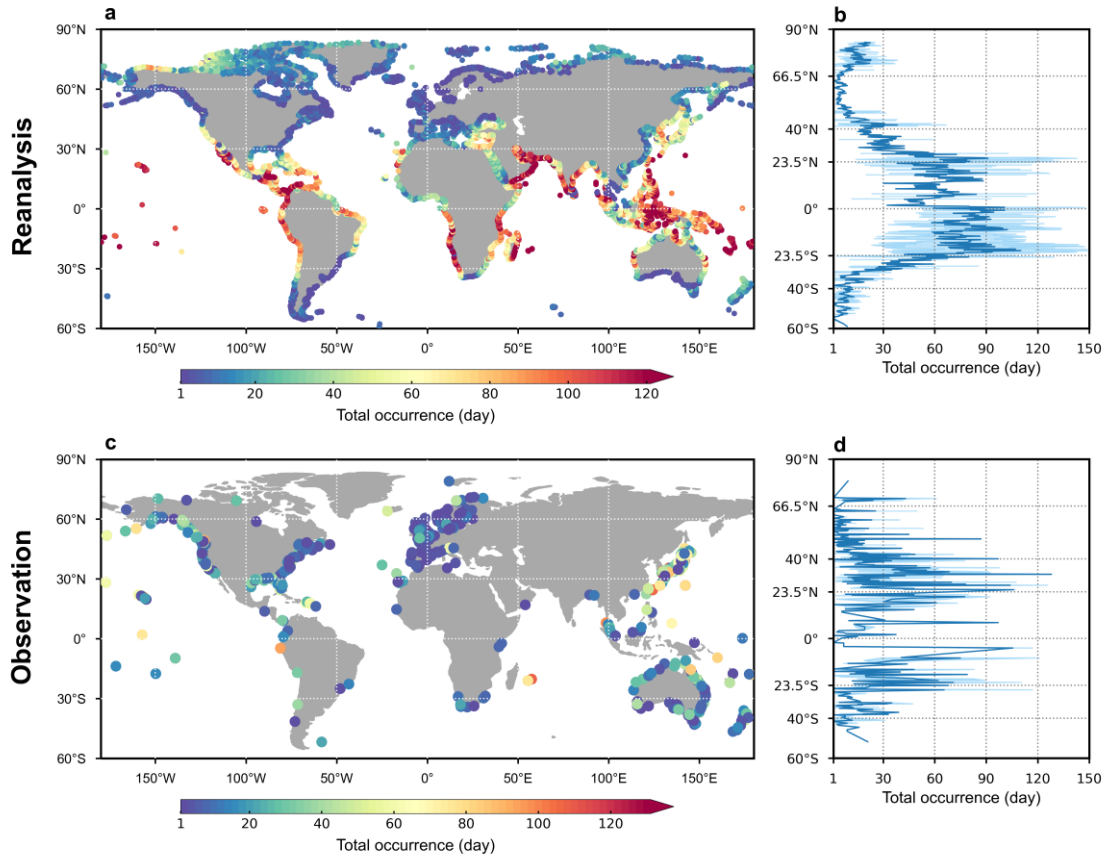


Figure 5.2 Comparison of the characteristics of concurrent HWESL events based on the ERA5 reanalysis dataset (a, b) and the GESLA observation dataset (c, d) of total water level.

(a, c) Total occurrence (day) of concurrent HWESL events during 1979–2017. (b, d) Total occurrence (day) of concurrent HWESL events for grid cells at different latitudes. To enable comparisons between grid cells at different latitudes, the total occurrence of all grid cells is averaged for each latitude.

I divided the period from 1979 to 2017 into two 20-year periods (1998–2017 and 1979–1998) and calculated the changes in the occurrence of concurrent HWESL events during these two periods. The evolution of concurrent HWESL events varies across global coastal areas. The results indicate that 39% of the world’s coastal areas have experienced a significant increase in the occurrence of concurrent HWESL events in recent 20 years, with an average increasing occurrence of 4 days (Figure 5.1c). Lower-latitude regions, such as West Africa (WAF), Southeast Asia (SEA), East Africa (EAF), and the Pacific Islands Region (PIR), show a more pronounced increase in the

occurrence of concurrent HWESL events (Figure 5.1d). However, there is a significant decrease of concurrent HWESL events in Canada, Greenland, and Iceland (CGI) and the West Coast of South America (WSA). The decreasing concurrent HWESL events in CGI corresponds to the decreasing extreme sea levels (Figure 5.3d), which is due to the fact that the land beneath the ice sheet rises in this region as the substantial weight of ice sheet is removed when Greenland losing ice under a warmer climate [Wade, 2016]. And the decreasing concurrent HWESL events in WSA is due to the decreasing humid heatwave (Figure 5.3b). This agrees with the results of previous studies [Rogers *et al.*, 2021; Speizer *et al.*, 2022]. Nevertheless, the WSA is expected to experience increasing concurrent HWESL events during the future period of 2025–2049. Thus, coastal communities without emergency response systems may face a significant threat from the increasing concurrent HWESL occurrence in the future.

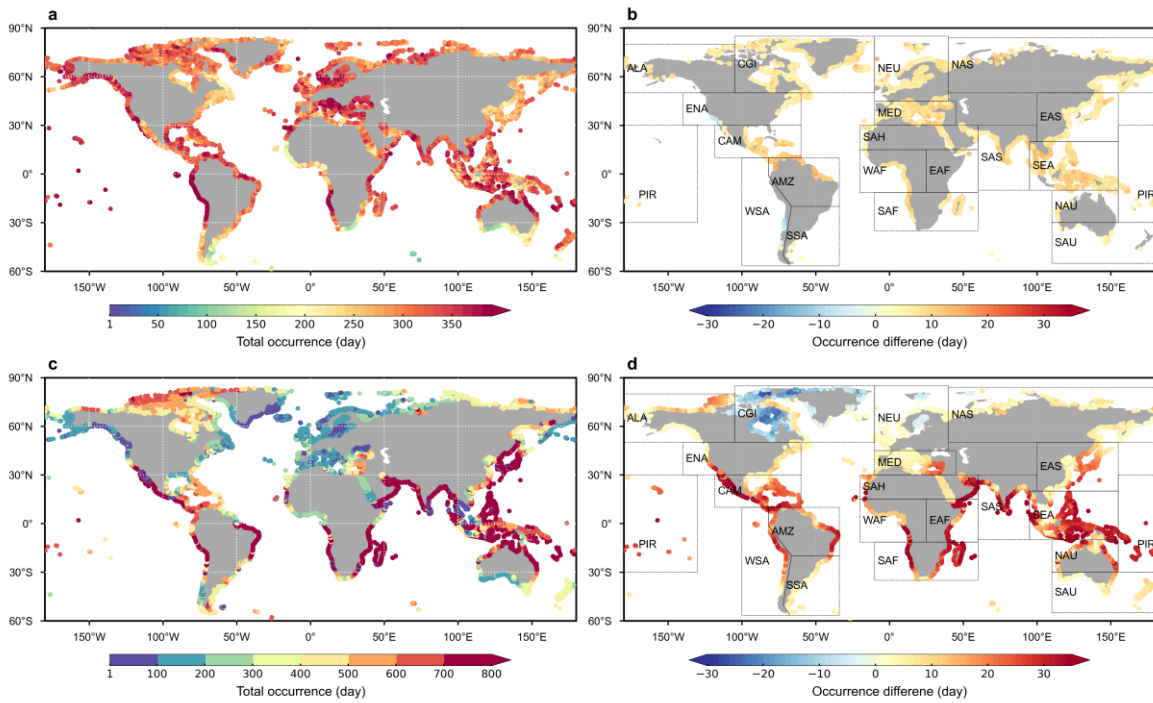


Figure 5.3 Characteristics of heatwaves and extreme sea levels.

(a, c) Total occurrence (day) of heatwaves (a) and extreme sea levels (c) during 1979–2017. (b, d) Differences in the occurrence (day) of heatwaves (b) and extreme sea levels (d) between 1998–2017 and 1979–1998. Statistical significance of the difference is estimated by the Student’s *t* test at a 95% confidence level. Grid cells with insignificant differences are excluded from the change analysis.

To assess whether the occurrence of concurrent HWESL events is purely a coincidence, I used the bootstrap-resampling-based significance test [You *et al.*, 2023] to generate random concurrent HWESL events and compared these with the detected concurrent HWESL events based on the ERA5 reanalysis dataset (Figure 5.4). The total occurrence of detected concurrent HWESL events is significantly higher than the concurrent HWESL events expected due to random coincidence at a 95% confidence level. Assuming heatwaves and extreme sea levels are concurrent by chance, the average total occurrence of concurrent HWESL events would drop from 41 days to 23 days. This indicates that the interaction between heatwaves and extreme sea levels contributes an additional 78% to the total occurrence of concurrent HWESL events.

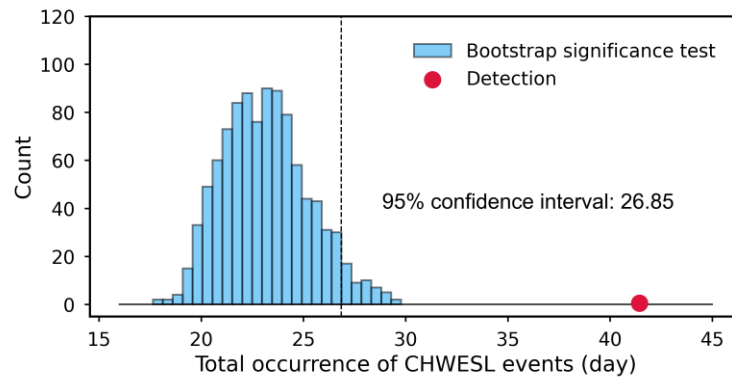


Figure 5.4 Bootstrap significance test of the total occurrence of concurrent HWESL events.

The histogram represents the empirical distribution of the global-average total occurrence of concurrent HWESL events using the 1,000 resampled series based on the bootstrap resampling. The 95% confidence interval is indicated by a vertical dashed line. The red dot represents the average total occurrence of concurrent HWESL events detected based on the ERA5 dataset.

5.2 Sensitivity of concurrent HWESL events to the intensity of individual extremes

Given that regions with a higher risk of concurrent HWESL events are primarily concentrated in the tropical region, which is typically characterized by hotter and more humid conditions, I hypothesize that these conditions may be associated with the occurrence of concurrent HWESL events. To test this hypothesis, I conducted sensitivity experiments by categorizing heatwaves into 20 levels based on their intensities and examined the likelihood of concurrent HWESL events during heatwaves with varying intensities. The intensity of a heatwave day is determined by the

percentile of the equivalent temperature on that day. Equivalent temperature is derived from air temperature and specific humidity. Therefore, a higher intensity indicates higher air temperature and higher specific humidity, corresponding to hotter and more humid conditions, respectively. The likelihood of concurrent HWESL events during heatwaves of a specific intensity is determined by calculating the ratio between the number of heatwave days that are concurrent with extreme sea levels (i.e., concurrent HWESL events) and the total number of heatwave days with that specific intensity.

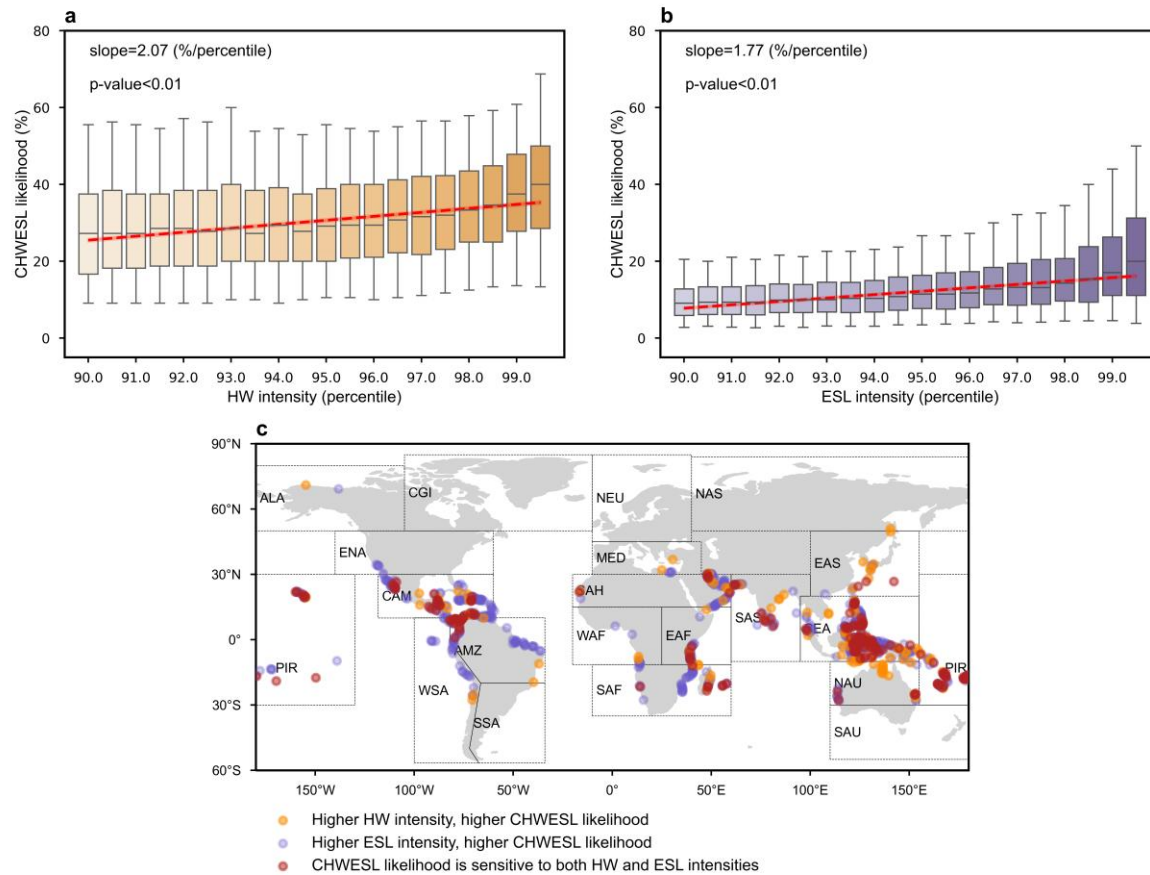


Figure 5.5 Sensitivity of concurrent HWESL events to the intensity of individual extremes.

(a) Changes in the likelihood of concurrent HWESL events during heatwaves with increasing intensities. Intensity of a heatwave day is determined by the percentile of the equivalent temperature on that day. I have defined 20 levels of intensity ranging from the 90th to the 99.5th percentile, with an interval of 0.5th percentile. Heatwaves with a 90th intensity refer to those where the equivalent temperature on that day is equal to or greater than the 90th percentile but less than

the 90.5th percentile. Boxplots show the distribution of concurrent HWESL likelihood during heatwaves with a specified intensity across all grid cells. Boxes in the boxplot are bounded by the 25th and 75th percentiles of the data, and the whiskers represent the 5th and 95th percentiles of the data. The red dashed line represents the fitted linear regression between the heatwave intensity (x-axis) and the median values of concurrent HWESL likelihood (y-axis). (b) Same as (a) but concurrent HWESL likelihood is calculated during extreme sea levels with increasing intensities. Intensity of an extreme sea level day is determined by the percentile of the total water level on that day. c Sensitivity of concurrent HWESL likelihood to the intensity of heatwaves (yellow) and extreme sea levels (purple) for each grid cell. Grid cells where the concurrent HWESL likelihood shows significant sensitivity to the intensities of both heatwaves and extreme sea levels will be marked in red. Grid cells with insignificant trends are excluded from the sensitivity analysis.

Generally, the findings indicate a significant increase in the likelihood of concurrent HWESL events as heatwaves become more intense (Figure 5.5a and Figure 5.6a). On average, a one-percentile increase in heatwave intensity corresponds to a 2% increase in the likelihood of heatwaves that are concurrent with extreme sea levels. Specifically, I observed that 17–38% of heatwaves with the 90.0th percentile intensity is concurrent with extreme sea levels, while this likelihood increases to 29–50% for heatwaves with the 99.5th percentile intensity. These findings suggest that more intense heatwaves, characterized by higher air temperature and specific humidity, are more likely to occur simultaneously with extreme sea levels, thereby amplifying the risk of concurrent HWESL events. This is particularly concerning considering that heatwaves with the 99.5th intensity are already unbearable for coastal communities. Additionally, I calculated the absolute number of concurrent HWESL days during heatwaves with varying intensities (Figure 5.7a and Figure 5.6c). This analysis reveals a notable increase in the number of concurrent HWESL days as heatwaves become more intense. This verifies my findings that more intense heatwave could amplify the risk of concurrent HWESL events.

I also examined the sensitivity of the likelihood of concurrent HWESL events to the intensity of extreme sea levels (Figure 5.5b and Figure 5.6b), using analogous percentile-based intensities. This likelihood was determined by calculating the ratio between the number of extreme sea level days that are concurrent with heatwaves and the total number of extreme sea level days at a specific intensity. I find that the likelihood of concurrent HWESL events increases by 2% when the

intensity of extreme sea levels increases by one percentile. This implies that both more intense heatwaves and more intense extreme sea levels can increase the likelihood of concurrent HWESL events. Notably, SEA, EAF, PIR, and the Central America and Mexico (CAM) are particularly exposed to the synergistically amplified risk (Figure 5.5c). The results obtained from the ESL observation consistently demonstrate the sensitivity of concurrent HWESL events to the intensity of two individual extremes, as shown in Figure 5.7c, d. These synergistic amplification effects are further evident in the correlation between the intensities of heatwaves and extreme sea levels (Figure 5.8).

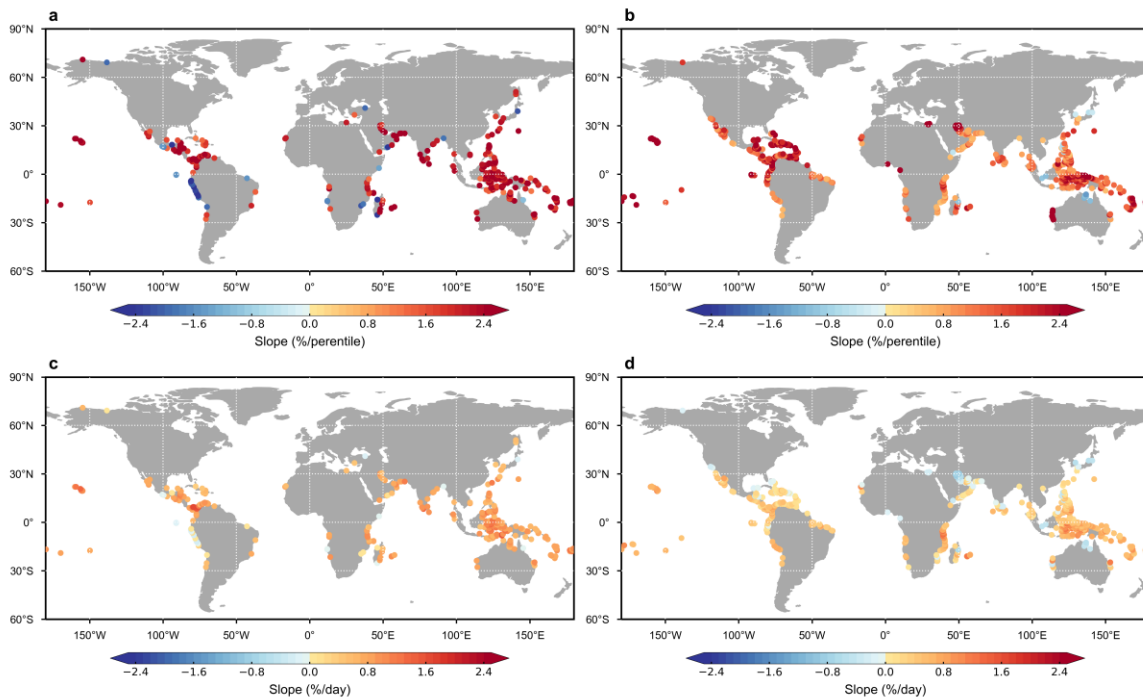


Figure 5.6 Spatial map of the sensitivity of concurrent HWESL events to the intensity of individual extremes.

(a) Slope (%/percentile) of the fitted linear regression between the intensity of heatwaves and the likelihood of concurrent HWESL events. (b) Slope (%/percentile) of the fitted linear regression between the intensity of extreme sea levels and the likelihood of concurrent HWESL events. (c) Slope (%/day) of the fitted linear regression between the intensity of heatwaves and the total occurrence of concurrent HWESL events. (d) Slope (%/day) of the fitted linear regression between the intensity of extreme sea levels and the total occurrence of concurrent HWESL events.

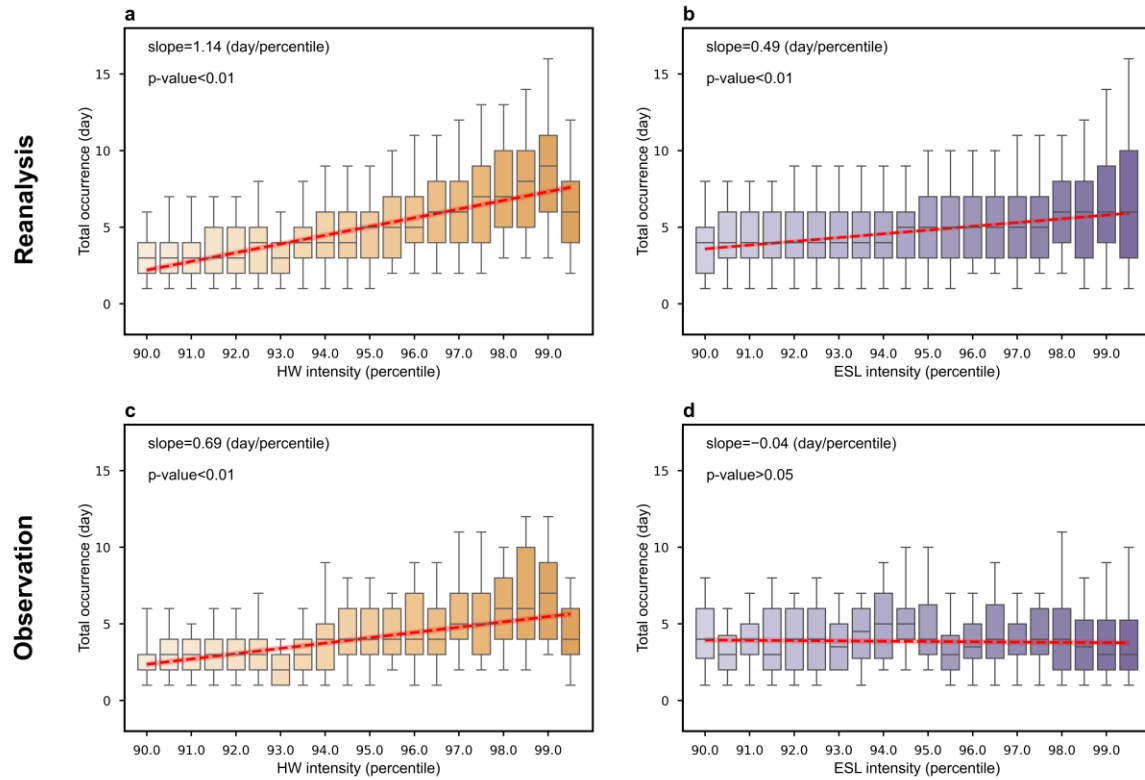


Figure 5.7 Total occurrence of concurrent HWESL events during heatwaves and extreme sea levels with different intensities.

(a) Changes in the total occurrence of concurrent HWESL events during heatwaves with increasing intensities. Intensity of a heatwave day is determined by the percentile of the equivalent temperature on that day. I have defined 20 levels of intensity ranging from the 90th to the 99.5th percentile, with an interval of 0.5th percentile. Heatwaves with a 90th intensity refer to those where the equivalent temperature on that day is equal to or greater than the 90th percentile but less than the 90.5th percentile. Boxplots show the distribution of the total occurrence of concurrent HWESL events during heatwaves with a specified intensity across all grid cells. Boxes in the boxplot are bounded by the 25th and 75th percentiles of the data, and the whiskers represent the 5th and 95th percentiles of the data. The red dashed line represents the fitted linear regression between the heatwave intensity (x-axis) and the median values of concurrent HWESL likelihood (y-axis). (b) Same as (a) but is the change in the total occurrence of concurrent HWESL events during extreme sea levels with increasing intensities. a, b are the results based on the ESL reanalysis while c, d are the results based on the ESL observation.

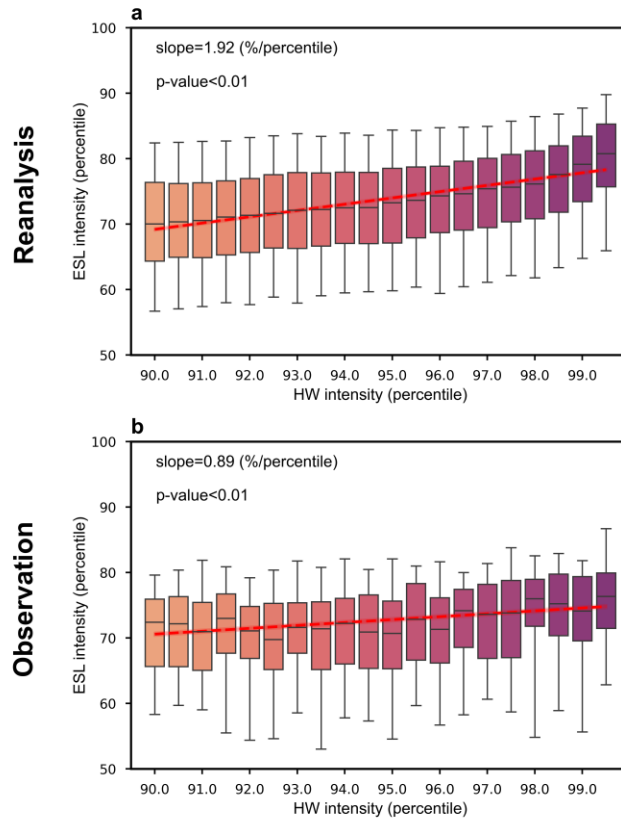


Figure 5.8 Correlation between the intensity of heatwaves and the intensity of extreme sea levels.

The intensity of a heatwave day is determined by the percentile of the equivalent temperature on that day. Intensity of an extreme sea level day is determined by the percentile of the total water level on that day. I have defined 20 levels of heatwave intensity ranging from the 90th to the 99.5th percentile, with an interval of 0.5th percentile. Heatwaves with a 90th intensity refer to those where the equivalent temperature on that day is equal to or greater than the 90th percentile but less than the 90.5th percentile. Boxplots show the distribution of the extreme sea level intensity during heatwaves with a specified intensity across all grid cells. Boxes in the boxplot are bounded by the 25th and 75th percentiles of the data, and the whiskers represent the 5th and 95th percentiles of the data. The red dashed line represents the fitted linear regression between the heatwave intensity (x-axis) and median values of extreme sea level intensity (y-axis). (b) Same as a but is the result derived from the ESL observation, and a is the result based on the ESL reanalysis.

5.3 Future projection of concurrent HWESL events

To assess the potential impacts of climate change on concurrent HWESL events, future occurrences during the period 2025–2049 were projected under the SSP585 scenario using an ensemble of CMIP6 (Coupled Model Intercomparison Project Phase 6) model outputs. To ensure the reliability of these projections, historical concurrent HWESL events were first reproduced using multiple CMIP6 models and then evaluated against reanalysis datasets. The same predefined thresholds were applied to both the historical and future periods to ensure the comparability of projected changes in concurrent HWESL event characteristics. Overall, the model simulations agree well with the reanalysis results in terms of the likelihood of concurrent HWESL events during the historical period (Figure 5.9), indicating that the CMIP6 models are capable of capturing the characteristics of concurrent HWESL events.

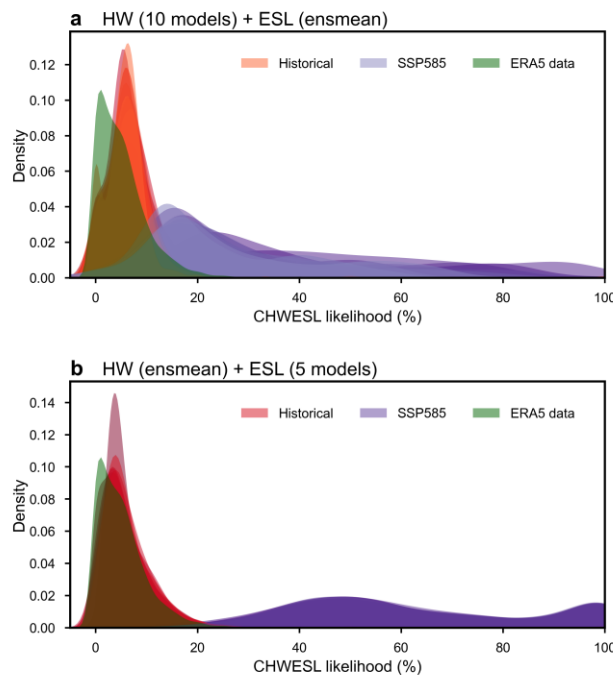


Figure 5.9 Distribution of the likelihood of concurrent HWESL events.

(a) concurrent HWESL events are based on heatwaves derived from 10 CMIP6 simulation models of equivalent temperature and extreme sea levels derived from the ensemble mean of five CMIP6 simulation models of total water level. (b) concurrent HWESL events are based on heatwaves derived from the ensemble mean of 10 CMIP6 simulation models of equivalent temperature and extreme sea levels derived from five CMIP6 simulation models of total water level. The likelihood

of concurrent HWESL events during the future period is statistically greater than that during the historical period based on a Student's t test at a 95% confidence level. Note that the results of the likelihood of concurrent HWESL events based on ERA5 reanalysis dataset in a and b are the same and calculated for the historical period of 1989–2013.

Furthermore, the results of the uncertainty decomposition are shown in Figure 5.10. The interaction between the climate models for equivalent temperature and those for total water level constitutes the largest source of uncertainty, particularly in grid cells exhibiting larger differences in concurrent HWESL event occurrence between the future and historical periods. In contrast, the average contribution of uncertainty from the equivalent temperature models to the total uncertainty (22%) is slightly greater than that from the total water level models (16%). This indicates that the uncertainty associated with the climate forcing used to drive the hydrodynamic model for total water level simulation is comparatively limited.

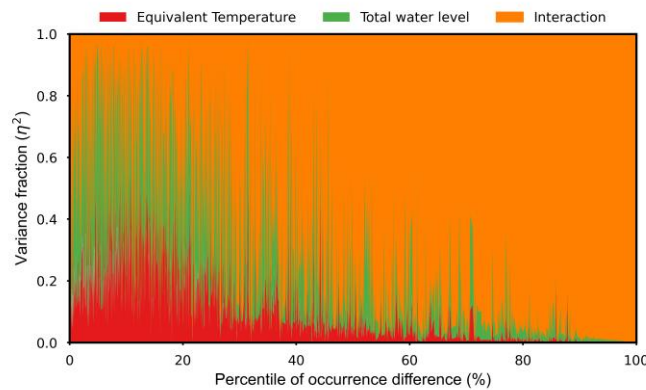


Figure 5.10 Variance decomposition of uncertainty in the projected changes in the occurrence of concurrent HWESL events between the future period of 2025–2049 and the historical period of 1989–2013.

The percentile of occurrence difference is determined by ranking the occurrence difference for each grid cell along the global coastline.

The projection results reveal that global coastal communities are expected to experience 38 days of concurrent HWESL events each year during the future period of 2025–2049, representing an average increase of 31 days compared to the historical period of 1989–2013 (Figure 5.11a, b).

This increase is primarily attributed to a warming climate under the highest-emission scenario (SSP585). Particularly, the tropical coastal regions, such as WAF, SEA, and Amazon (AMZ), witness the strongest increase in the occurrence of concurrent HWESL events (Figure 5.11b and Figure 5.12). These findings imply that coastal communities will face a disproportionately increasing risk of concurrent HWESL events, with tropical regions facing the most serious threat from such a concurrent extreme.

The projected increase in the likelihood of concurrent HWESL events during heatwaves is statistically significant, and most climate models agree on the changes in each region (Figure 5.11c and Figure 5.12). On average, the likelihood of global concurrent HWESL events during the future period is projected to increase by fivefold compared to the historical period. This increase is particularly prominent in lower-latitude coastal regions. For instance, in SEA, the likelihood of concurrent HWESL events is expected to be up to eight times higher than that in the historical period. This indicates that under a warmer climate, heatwaves are more likely to be concurrent with extreme sea levels, which is consistent with my findings that hotter and more humid heatwaves may amplify the risk of concurrent HWESL events.

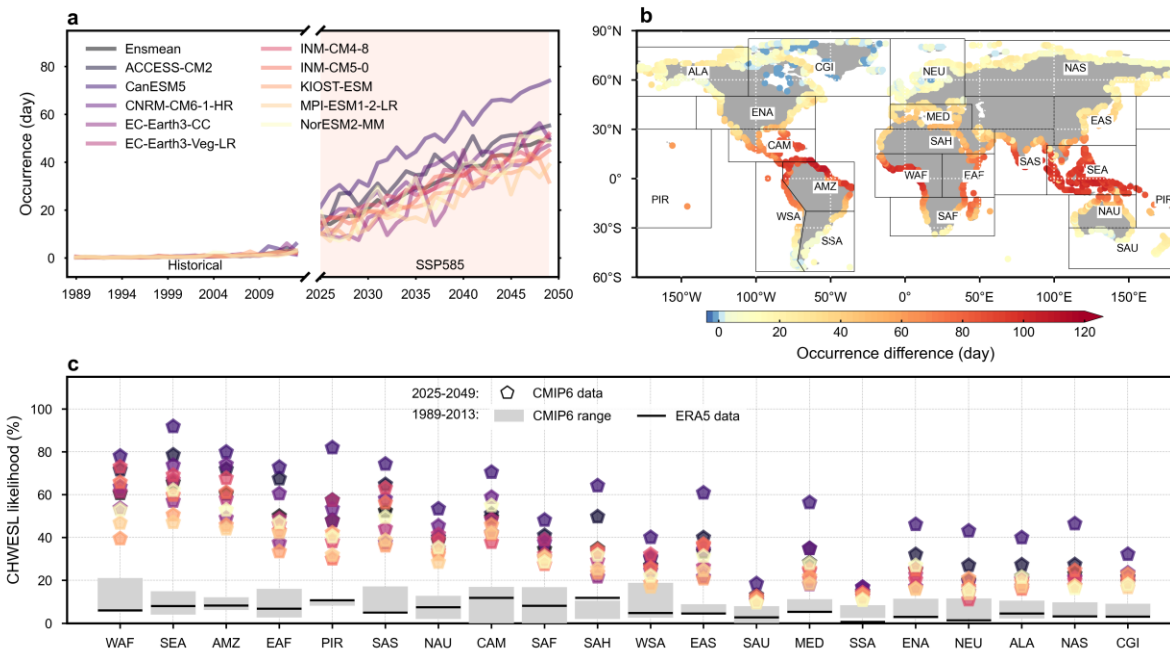


Figure 5.11 Projected changes in the characteristics of concurrent HWESL events.

(a) Occurrence (day) of concurrent HWESL events during the future period of 2025–2049 and the historical period of 1989–2013 based on 10 CMIP6 simulation models. (b) Average differences in the concurrent HWESL occurrence (day) between the future period (2025–2049) and the historical period (1989–2013) across 10 CMIP6 simulation models. For each simulation model, the statistical significance of the difference is estimated by the Student's t test at a 95% confidence level. Only grid cells that exhibit a significant difference across all 10 CMIP6 simulation models are included in the change analysis. (c) Likelihood of concurrent HWESL events for each coastal region during the historical and future periods. The stars represent the average likelihood of concurrent HWESL events during the future period in each region. The 10 stars represent the 10 CMIP6 simulation models. The gray shading illustrates the 95% uncertainty range of CMIP6 historical simulations. The lower and upper bounds of the gray shading represent the 2.5th and 97.5th percentile estimates of the likelihood of concurrent HWESL events across the 10 CMIP6 models, respectively. The black line is the likelihood of concurrent HWESL events identified based on ERA5 reanalysis data during the same historical period of 1989–2013. The order of coastal regions is determined by the average latitude of each region.

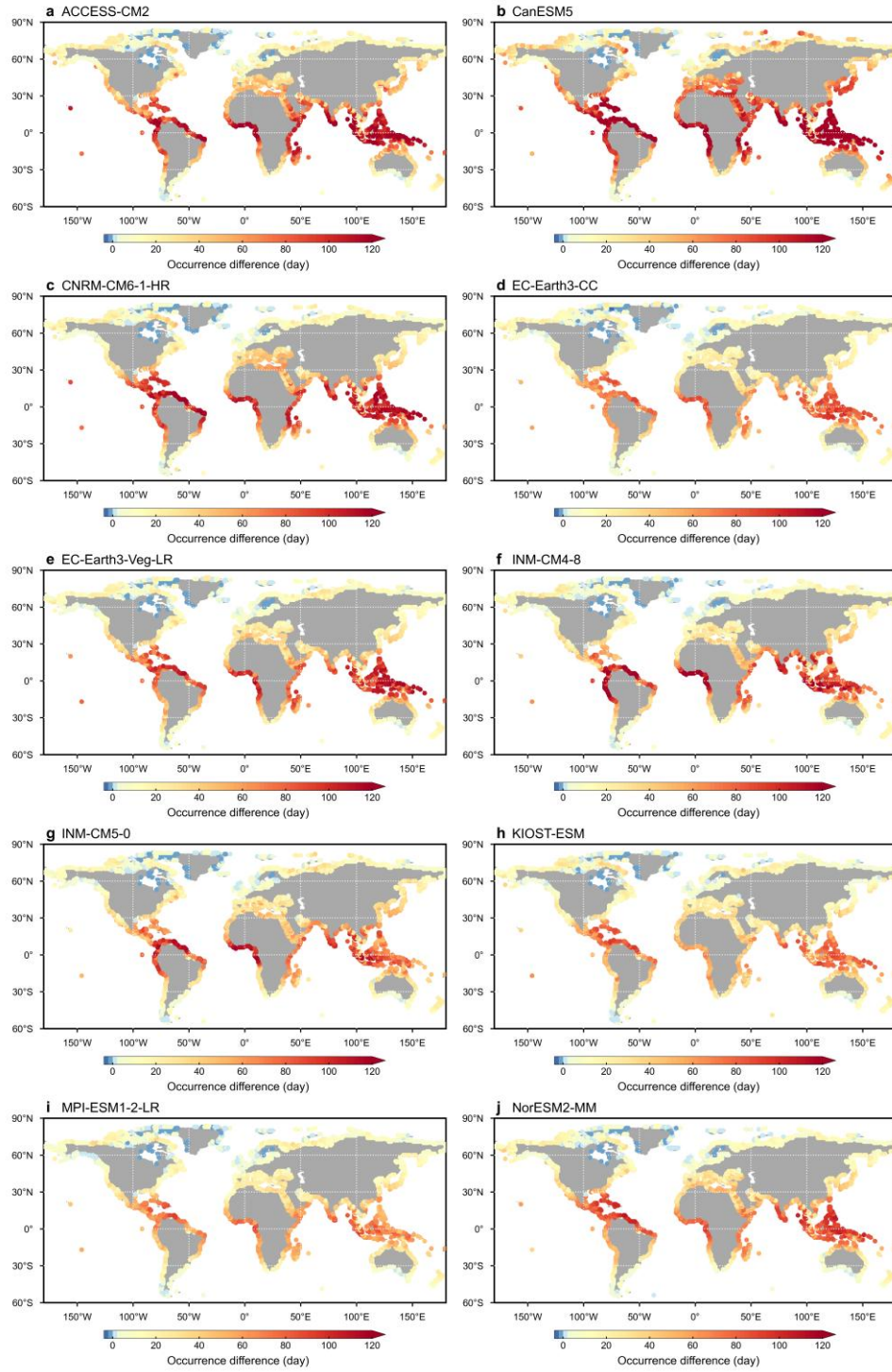


Figure 5.12 Occurrence difference of concurrent HWESL events between the future period of 2025–2049 and the historical period of 1989–2013 based on heatwaves derived from 10 CMIP6 simulation models of equivalent temperature and extreme sea levels derived from the ensemble mean of five CMIP6 simulation models of total water level.

5.4 Atmospheric conditions associated with concurrent HWESL events

The days experiencing heatwaves and extreme sea levels were categorized into three groups, including concurrent HWESL days, heatwave days that are not concurrent with extreme sea levels (referred to as “HWN days”), and extreme sea level days that are not concurrent with heatwaves (referred to as “ESLN days”). I used the composite of large-scale atmospheric variables [Hendry *et al.*, 2019; Zscheischler *et al.*, 2020] to disentangle the effects of atmospheric conditions on concurrent HWESL events.

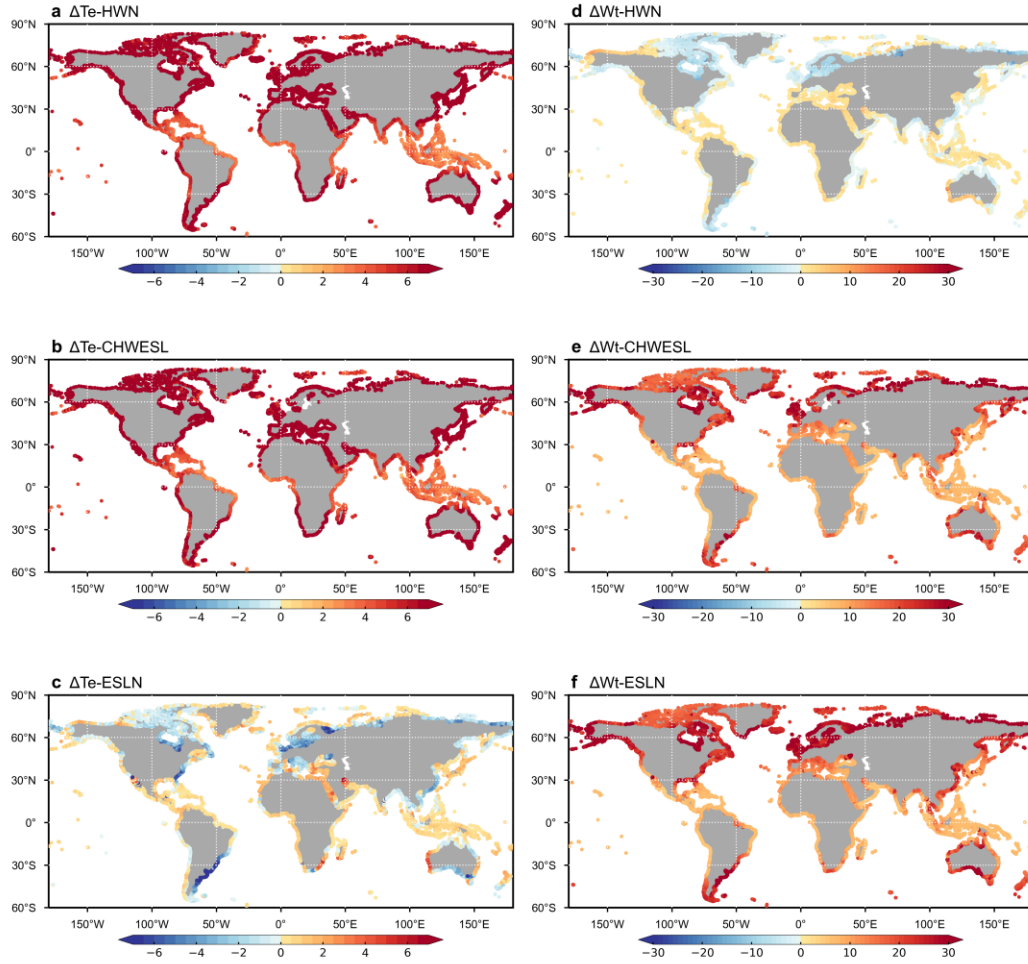


Figure 5.13 Composite of anomalies of equivalent temperature (ΔT_e , °C) and total water level (ΔW_t , cm) during extreme days.

(a–c) ΔT_e during HWN days (a), concurrent HWESL days (b), and ESLN days (c). (d–f) ΔW_t during HWN days (d), concurrent HWESL days (e), and ESLN days (f).

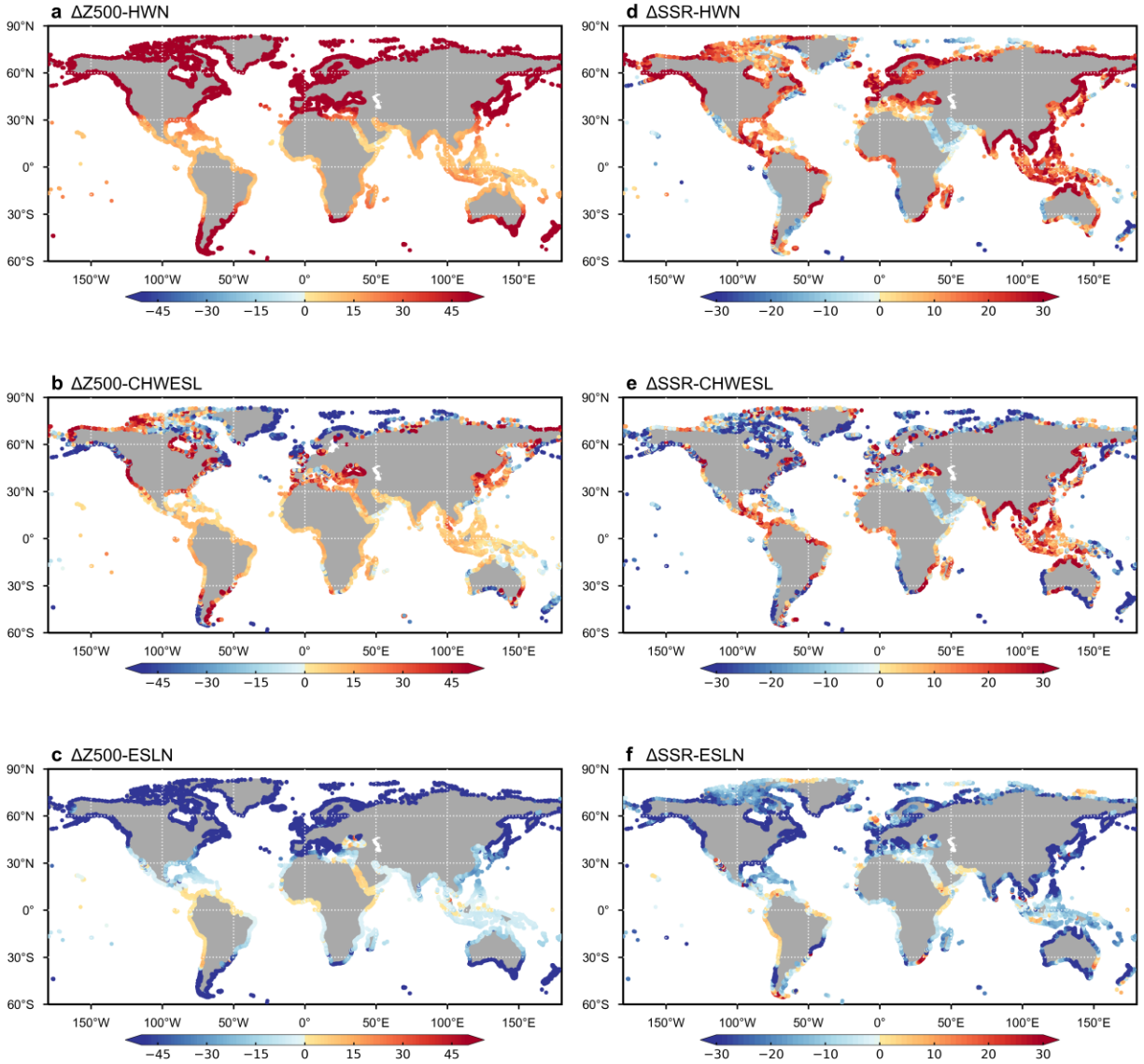


Figure 5.14 Composite of anomalies of atmospheric variables that are associated with heatwaves.

(a–c) Anomalies of geopotential height at 500 hPa ($\Delta Z500$, m) during HWN days (a), concurrent HWESL days (b), and ESLN days (c). (d–f) Anomalies of surface solar radiation (ΔSSR , $W \cdot m^{-2}$) during HWN days (d), concurrent HWESL days (e), and ESLN days (f).

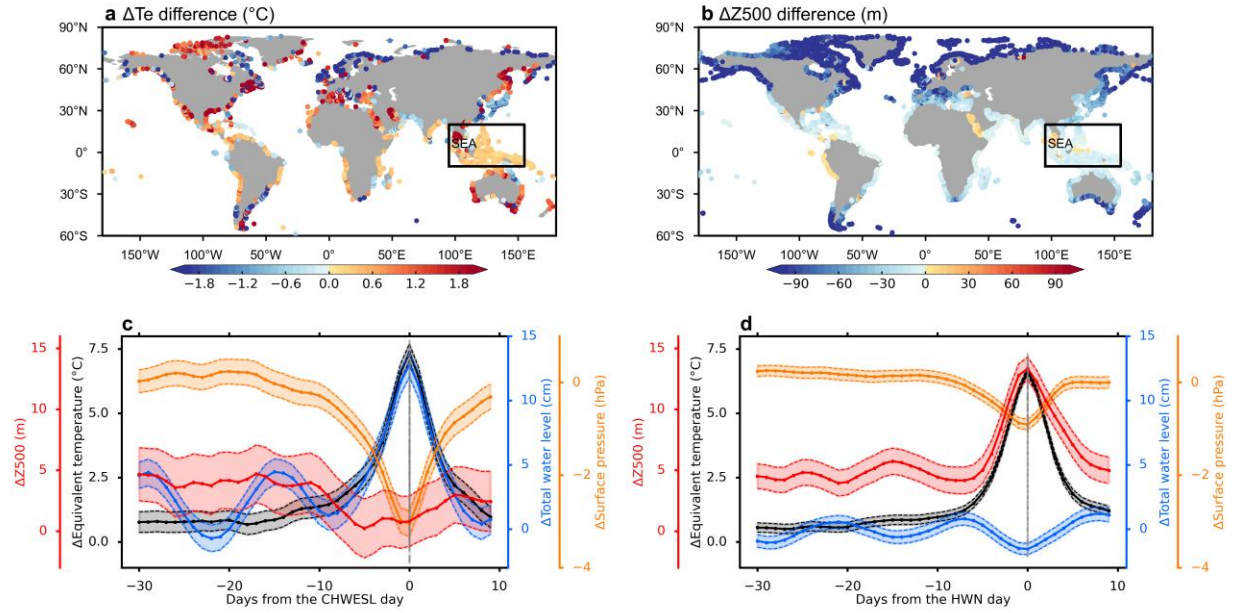


Figure 5.15 Anomalies of atmospheric variables during concurrent HWESL days and HWN days.

(a) Difference in the anomalies of equivalent temperature (ΔT_e) during concurrent HWESL days and HWN days. The statistical significance of the difference is estimated by the Student's t test at a 95% confidence level. Grid cells with insignificant differences are excluded from the difference analysis. (b) Same as (a) but for the difference in the anomalies of geopotential height (ΔZ_{500}). c Evolution of anomalies in atmospheric variables from 30 days before the concurrent HWESL day to 10 days after the concurrent HWESL day in the SEA region. (d) Evolution of anomalies in atmospheric variables from 30 days before the concurrent HWESL day to 10 days after the HWN day in the SEA region.

The concurrent HWESL days along the global coastline are characterized by simultaneous warm temperature anomalies (Figure 5.13b) and high sea level anomalies (Figure 5.13e), similar to what is observed during HWN days (Figure 5.13a) and ESLN days (Figure 5.13f), respectively. Corresponding to warm temperature anomalies, both concurrent HWESL days and HWN days are characterized by elevated geopotential height at 500 Pa (Z500) (Figure 5.14a, b) and increased surface solar radiation (Figure 5.14d, e). The high Z500 in the atmosphere is typically linked to anticyclonic systems generating warm air, and the heightened surface solar radiation supplies abundant energy for land surface heating [R Chen and Lu, 2015; Ha et al., 2022]. Despite the equivalent temperature anomalies during concurrent HWESL days are comparable to, and even

higher than, those during HWN days along most coastlines (Figure 5.15a), I observe lower Z500 values during concurrent HWESL days (Figure 5.15b).

Through the analysis of the evolution of atmospheric variables in the SEA region during the 30 days prior to the concurrent HWESL day (Figure 5.15c) and the HWN day (Figure 5.15d), I find that the discrepancy in Z500 between concurrent HWESL days and HWN days can be attributed to the different evolution of Z500 prior the concurrent HWESL day and HWN day. Specifically, there is a slight decreasing trend in Z500 starting from 10 days prior to the concurrent HWESL day, accompanied by an obvious decrease in surface pressure (Figure 5.15c). Surface pressure continuously decreases during that time, reaching its lowest value on the concurrent HWESL day. This indicates that the blocking highs responsible for generating warm air are weakening before the concurrent HWESL day and transitioning into a surface low-pressure system. In contrast, Z500 exhibits a significant increasing trend from 10 days prior to the HWN day. On the HWN day, Z500 reaches its peak and surface pressure remains relatively stable. These results indicate that the distinct evolution of Z500 before the concurrent HWESL day and the HWN day may be closely linked to the variations in surface pressure.

This low surface pressure during concurrent HWESL days (Figure 5.16b) resembles what is observed during ESLN days (Figure 5.16c). Such a surface low-pressure system is often observed during tropical cyclones or other intense weather systems [*Avantika Gori et al.*, 2022; *Needham et al.*, 2015], and it can contribute to the generation of strengthening winds [*Lin et al.*, 2012] (Figure 5.16e, f). These winds can trigger storm surges by driving water towards the coast. Therefore, the combination of a surface low-pressure system, intensifying winds, and the resulting storm surge can elevate total water levels, leading to extreme sea levels [*Muis et al.*, 2016]. The findings indicate that the weakening of blocking highs and their transition into a surface low-pressure system may serve as important indicators for the occurrence of concurrent HWESL events. Figure 5.17 illustrates the same analysis of atmospheric variable evolution for the regions of EAF and PIR, and the results align with my findings.

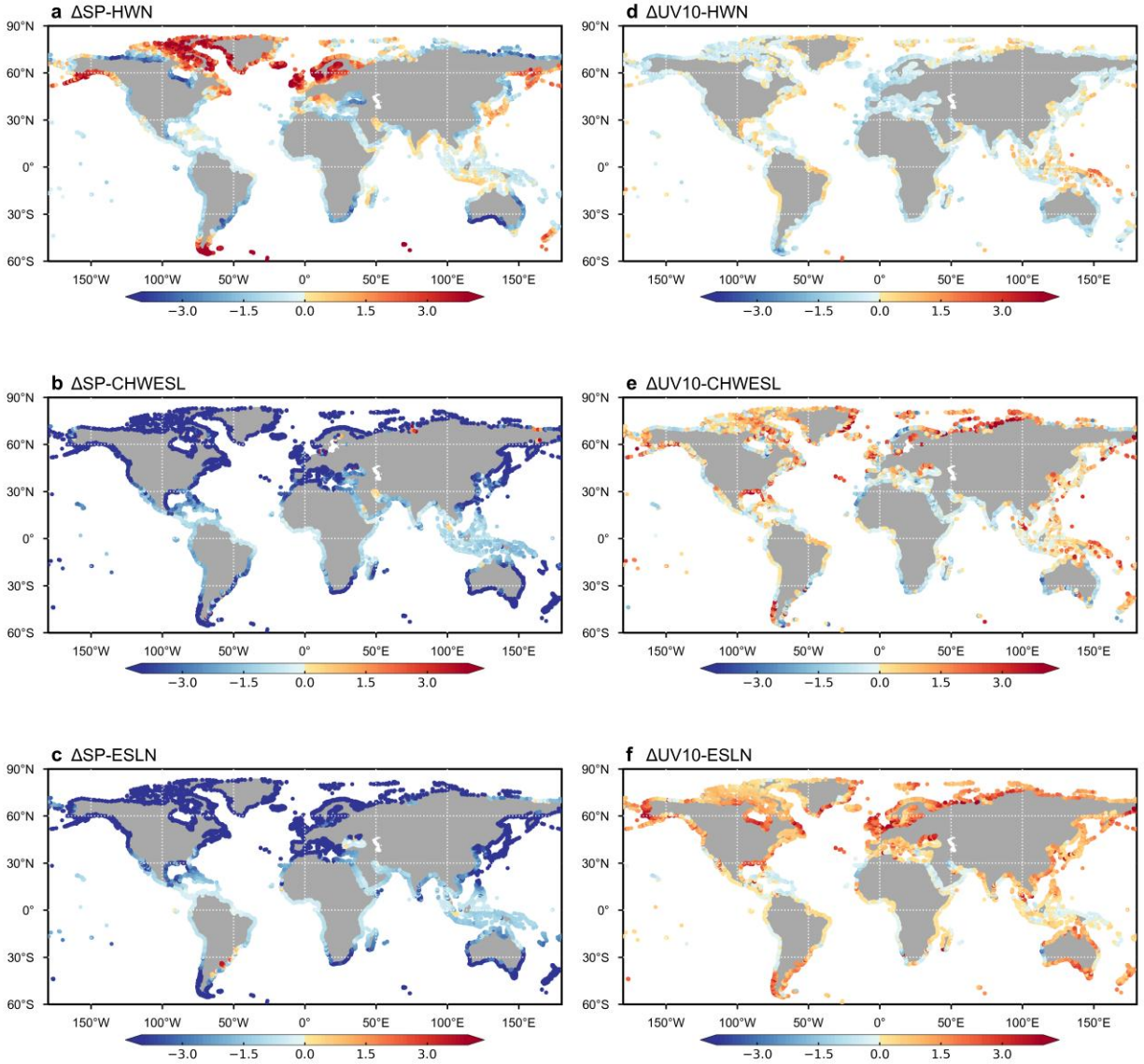


Figure 5.16 Composite of anomalies of atmospheric variables that are associated with extreme sea levels.

(a–c) Anomalies of surface pressure (ΔSP , hPa) during HWN days (a), concurrent HWESL days (b), and ESLN days (c). (d–f) Anomalies of 10-m wind ($\Delta UV10$, $m \cdot s^{-1}$) during HWN days (d), concurrent HWESL days (e), and ESLN days (f).

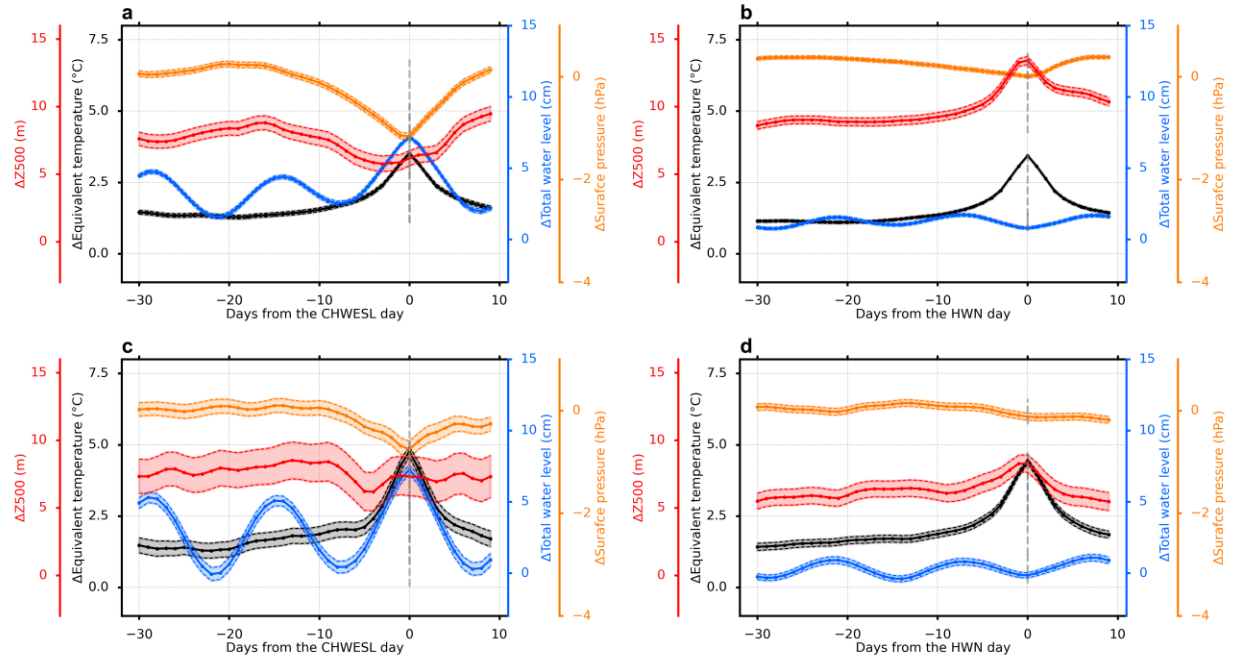


Figure 5.17 Evolution of anomalies of atmospheric variables.

Evolution of anomalies of atmospheric variables from 30 days before the concurrent HWESL day to 10 days after the concurrent HWESL day in the EAF region (a) and PIR region (c). Evolution of anomalies in atmospheric variables from 30 days before the HWN day to 10 days after the HWN day in the EAF region (b) and PIR region (d).

5.5 Discussion and summary of the chapter

The climate-induced heatwave and extreme sea level have been receiving increasing attention in recent years due to their adverse effects on coastal communities, but they are usually treated individually. This study provides a comprehensive investigation of concurrent heatwave and extreme sea level events along the global coastline. I identified global hotspots of concurrent HWESL events and explored their dynamic evolution in response to the warming climate. I also examined the sensitivity of the likelihood of concurrent HWESL events to the intensity of individual extremes. In addition, I investigated the potential physical processes linked to the occurrence of concurrent HWESL events.

The findings reveal that the global coastline experienced a significant increase in the occurrence of concurrent HWESL events during the period of 1979–2017. Coastlines in the

tropical region are at higher risk for concurrent HWESL events, as evidenced by both a higher occurrence of concurrent HWESL events and a larger occurrence difference between two 20-year periods. Furthermore, I find that hotter and more humid heatwaves are more likely to be concurrent with extreme sea levels globally. More intense heatwaves and more intense extreme sea levels may synergistically increase the likelihood of concurrent HWESL events in SEA, EAF, and PIR. Under the highest emission scenario of SSP585, the global coastline is expected to experience a higher occurrence and a higher likelihood of concurrent HWESL events. Weakening of geopotential height at 500hPa accompanied by the emergence of a surface low-pressure system may serve as a crucial indicator for concurrent HWESL events.

This chapter primarily focused on the highest emission scenario to evaluate the potential risks and impacts of concurrent HWESL events. I recognize that different emission scenarios can lead to varying outcomes. In more optimistic emission scenarios, characterized by stronger mitigation efforts and reduced greenhouse gas emissions, it is plausible to expect a decrease in the frequency and intensity of concurrent HWESL events. Future research that explores alternative emission scenarios and their effects on concurrent HWESL events would be valuable in providing a comprehensive understanding of the full range of potential outcomes.

The atmospheric conditions associated with concurrent HWESL events suggest that a weakening anticyclonic circulation and a simultaneous surface low-pressure system may contribute to extreme sea levels during heatwaves. These low-pressure systems, which induce extreme sea levels, are often considered important features of tropical cyclones [Avantika Gori *et al.*, 2022; Needham *et al.*, 2015]. Previous studies have suggested that anomalous warm and humid conditions can precede the occurrence of tropical cyclones, as these cyclones can modulate atmospheric circulations and trigger anomalous descending motion [T. Matthews *et al.*, 2019; P Y Wang *et al.*, 2023a; D C Zhao *et al.*, 2021b]. As a result, hot weather conditions can persist until the tropical cyclones make landfall. However, it is worth noting that surface pressure can decrease several days before the landfall of a tropical cyclone, even if the hot conditions are still ongoing [T. Matthews *et al.*, 2019]. Therefore, it is reasonable to consider the potential overlap between ongoing heatwaves and upcoming extreme sea levels, as these two phenomena may be interconnected.

However, while weakened geopotential height and reduced surface pressure are closely linked to extreme sea levels, these conditions alone cannot fully explain the enhanced heatwave intensity observed during compound events. From a dynamical perspective, intense heatwaves are more commonly associated with anticyclonic circulation and elevated geopotential heights. This suggests that additional processes, particularly horizontal advection, may play an important role [Sousa *et al.*, 2020]. The approach of a low-pressure system can induce warm and moist air advection, transporting heat and humidity into coastal regions. Such advective forcing may compensate for the reduced thermodynamic support associated with weakened anticyclonic conditions, thereby sustaining or even intensifying heatwave conditions prior to landfall [Bartusek *et al.*, 2022; L Hu, 2021; D Wang and Lin, 2020]. Nevertheless, land–ocean–atmosphere interactions remain highly complex, and further work is needed to quantify the relative contributions of circulation changes, advection, and local thermodynamic processes to the development of concurrent HWESL events.

The concurrent HWESL event could pose a significant threat to coastal communities in terms of beach activities and power supply. On the one hand, individuals who seek relief from hot weather by engaging in beach activities may potentially increase their exposure to extreme sea levels during heatwaves. Low- and middle-income countries, such as Indonesia and Mexico, are particularly vulnerable to such a risk since the majority of households do not have access to space-cooling devices to alleviate the effects of hot weather [Davis *et al.*, 2021; Pavanello *et al.*, 2021]. On the other hand, even in high-income countries where air conditioners are more widely available during heatwaves, the flooding caused by extreme sea levels can disrupt power supplies [Panteli and Mancarella, 2015], worsening the existing thermal risks.

The potential impacts of concurrent HWESL events for each region are also determined by a combination of the characteristics of extreme events and the inherent vulnerabilities of the region. Approximately 40% of the world's population (3 billion people) is living in the tropics [Biardeau *et al.*, 2019] where are the hotspots of concurrent HWESL events and are already experiencing the highest temperatures and greatest sea-level rise [Hooijer and Vernimmen, 2021; T. Matthews, 2018]. Countries located in the tropics are major contributors to global population growth [CIA, 2022; Jones and O'Neill, 2016], which can further increase exposure risk and exacerbate the vulnerability of communities in these regions to concurrent HWESL events. Moreover, people

living in low-lying islands in the tropics, such as those in the Caribbean, Pacific, and Southeast Asia (i.e., CAM, PIR, and SEA) are far more likely to be harmed by concurrent HWESL events. This is due to many people living there have low- or middle-income and reside in developing countries [Jones and O'Neill, 2016]. concurrent HWESL events could impose more adverse impacts on developing countries due to a lack of adaptive capacity [King and Harrington, 2018]. My findings indicate that there is a pressing need to inform adaptation planning of concurrent HWESL events in the tropics. Therefore, this study is crucial in advancing our understanding of the evolution and mechanisms of concurrent HWESL events along the global coastline, as well as in developing effective risk mitigation strategies.

Chapter 6. Shortened time lag between heatwaves and subsequent landfalling tropical cyclones

Extreme heatwaves and tropical cyclones (TCs) are among the deadliest and most damaging weather events, posing severe threats to society. When these events interact, their combined impacts can exceed those of individual events, especially in cases where heatwaves precede TCs (H-TC events). This is a critical concern because evacuations—often involving millions—may increase health vulnerability to heat extremes. However, the time lag between heatwaves and following TCs, which offers a window for safe evacuation, has not been systematically studied. In this study, I explore the evolving time lag of H-TC events using the TC best track data and reanalysis datasets. I examine historical trends in this time lag and investigate its relationship with variations in the characteristics of TCs. The results highlight an increasing threat from compound H-TC events, particularly in terms of the growing challenge of ensuring safe evacuations.

6.1 Global climatology of H-TC events

Figure 6.1a provides a global overview of TC tracks making landfall in coastal regions during 1981–2022. During this period, 1,003 unique named TCs made landfall worldwide, with each TC represented by a single track (Figure 1A). These tracks are primarily concentrated over land in East Asia, Southern North America–Caribbean, Mozambique–Madagascar, and Australia. Using TC tracks, I examined whether at least one time point experienced a heatwave prior to TC landfall and identified 390 TCs that were preceded by heatwaves (shown as red tracks in Figure 6.1a). These TCs are primarily concentrated in East Asia, located along the Northwestern Pacific, the most active ocean basin for TC formation [Klotzbach *et al.*, 2022; Z-Q Shen *et al.*, 2023], and home to some of the world’s most populated coastal cities [Barragán and de Andrés, 2015]. I then calculated the counts of TCs preceded by heatwaves (i.e., H-TC events) during 1981–2022 for each grid cell (Figure 6.1c–f). TC counts was defined as the total number of distinct TCs affecting a grid cell within a given period, counting each TC only once regardless of duration or repeated landfall. Coastal areas in East Asia, especially Taiwan, the Philippines, the Korean Peninsula, and Japan exhibit particularly high exposure to H-TC events (Figure 6.1c).

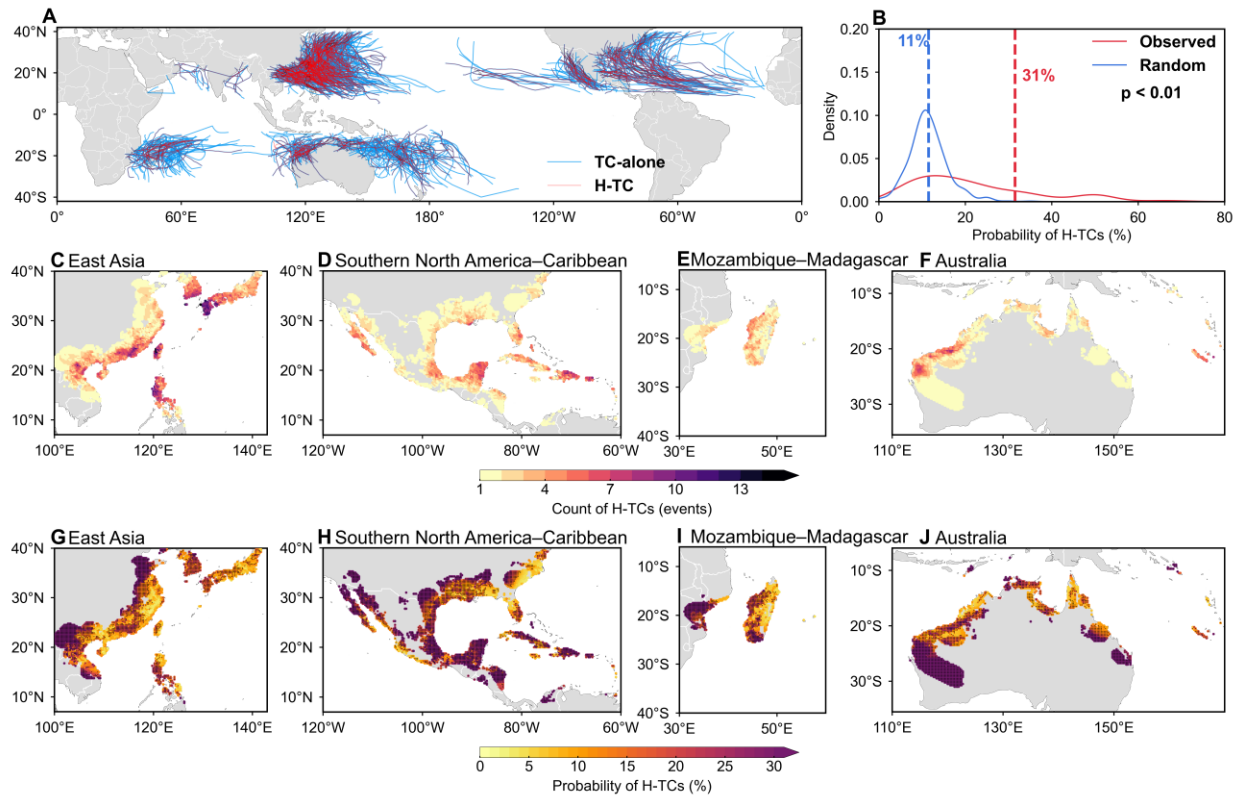


Figure 6.1 Characteristics of TC and H-TC events during 1981–2022.

(a) A total of 1,003 unique named TCs made landfall worldwide, with each TC represented by a single track. TCs preceded by a heatwave are shown in red, whereas those not preceded by a heatwave are shown in blue. (b) Comparison of the observed probability of H-TC events with the random probability assuming independence between heatwaves and TCs. The blue dashed line represents the mean random probability, and the red dashed line indicates the mean observed probability of H-TC events. Statistical significance between the two distributions was assessed using the Kolmogorov–Smirnov (K–S) test; a p -value < 0.01 indicates that the observed probability differs significantly from the random probability. (c–f) Counts represent the total number of distinct TCs preceded by heatwaves in each grid cell during 1981–2022, with each TC counted only once regardless of its duration or repeated landfall. Panels correspond to East Asia (c), Southern North America–Caribbean (d), Mozambique–Madagascar (e), and Australia (f). (g–j) Probability of H-TC events across four coastal regions, defined as the likelihood that TCs are preceded by heatwaves within a specified time window. Grid cells with statistically significant probabilities are marked by black dots, indicating that the observed probability exceeds that expected from the random test.

I calculated the probability of H-TC events for each coastal grid cell using the counts of H-TC events (Figure 6.1c–f) to that of all TCs (Figure 6.2), providing an intuitive measure of how often TCs are preceded by heatwaves and enabling comparisons across coastal regions. On average, this probability is 31%, meaning that roughly one in every four TCs is preceded by a heatwave (Figure 6.1b). The average probability exhibits regional variability, with values of 23% in East Asia, 28% in the Southern North America–Caribbean, 24% in Mozambique–Madagascar, and 39% in Australia (Figure 6.1g–j). Although Australia experiences relatively fewer H-TC events in terms of absolute counts (Figure 6.1f), it exhibits the highest probability (Figure 6.1j), indicating a stronger conditional association between heatwaves and subsequent TCs. For the Southern North America–Caribbean region, in addition to the higher probability of H-TC events in, TCs in this region also exhibit the greatest intensity (Figure 6.3), which suggests a particularly elevated risk associated with H-TC events. Some inland grid cells exhibit low counts of H-TC events but high probabilities of occurrence, as indicated by the dark-colored regions in Figure 6.1g–j. This suggests that although these areas experience fewer TCs overall, the TCs that do occur are much more likely to be preceded by heatwaves.

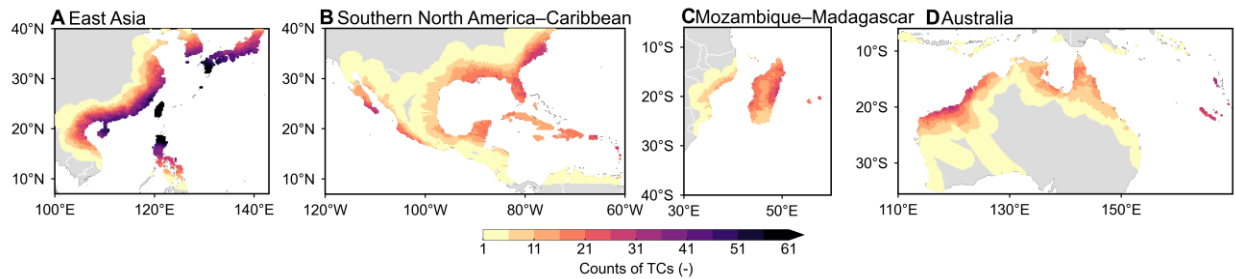


Figure 6.2 Counts represent the total number of distinct TCs in each grid cell during 1981–2022. Each TC counted only once regardless of its duration or repeated landfall. Panels correspond to East Asia (a), Southern North America–Caribbean (b), Mozambique–Madagascar (c), and Australia (d).

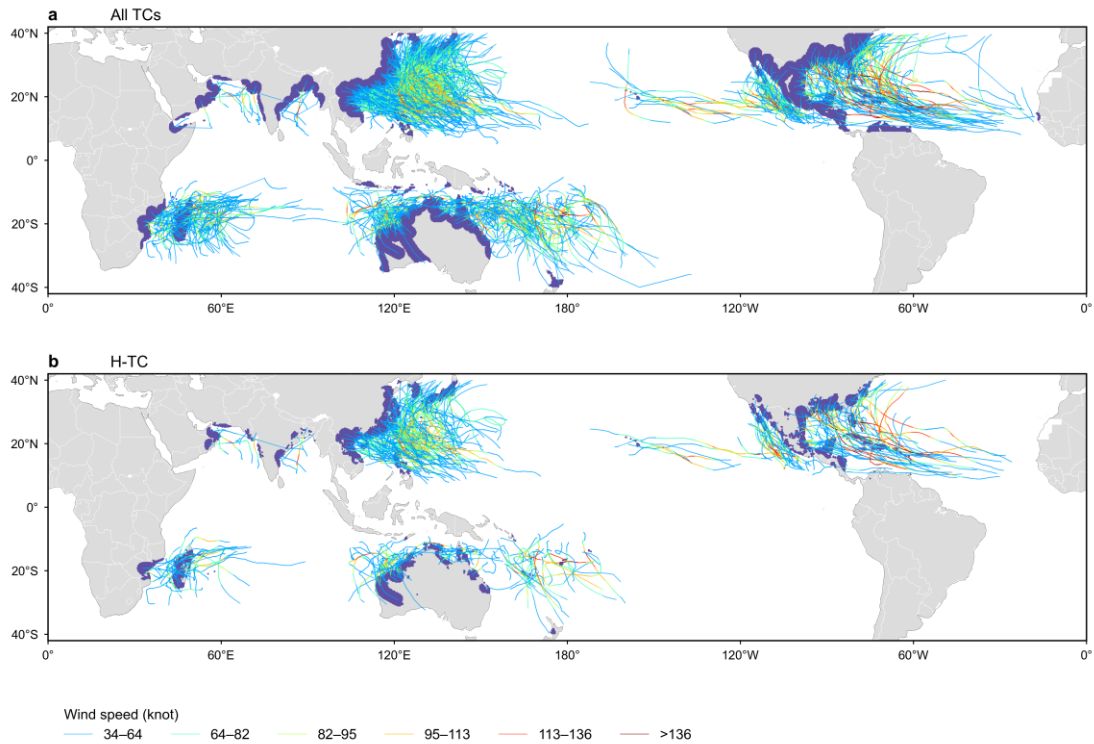


Figure 6.3 Intensity of all landfalling TCs (a) and TCs following heatwaves (b).

Track colors represent the wind speed of each TC at each recorded time step. Blue dots indicate land grid cells affected by TCs.

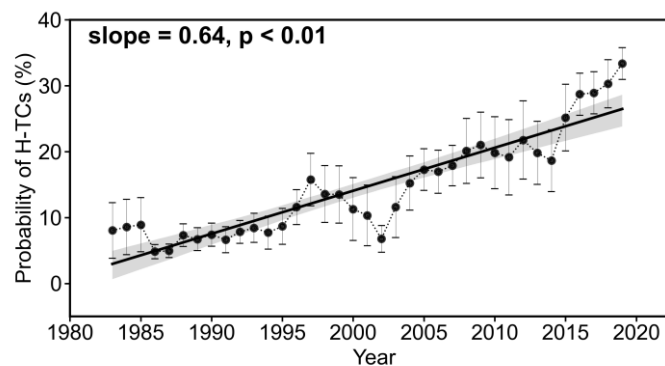


Figure 6.4 Linear trend in the probability of H-TC events.

The shaded region denotes the 95% confidence interval of the regression. Scatter points represent the annual mean probability, and vertical bars indicate ± 1 standard error of the mean (s.e.m.), calculated within a 5-year moving window centered on each year.

Temporally, the probability of H-TC events increased from 1981 to 2022 at an average rate of 0.64% per year ($p < 0.01$) (Figure 6.4), indicating an elevated risk of H-TC events in recent years. I used a bootstrap resampling test to evaluate whether the probability of H-TC events differs from that expected under independence between TCs and heatwaves. In this test, the heatwave time series was randomly shuffled. The expected probability under random coincidence is ~11%, about one-third of the observed probability (Figure 6.5 and Figure 6.1b), indicating that the TC and heatwave association is unlikely to arise by chance and warrants further investigation of the underlying physical mechanisms.

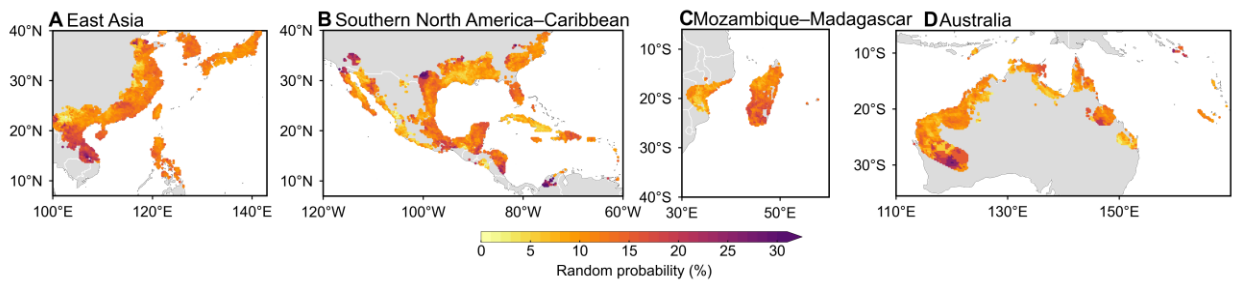


Figure 6.5 Random probability of H-TC events during 1981–2022 across four coastal regions, estimated using a bootstrap resampling-based significance test.

6.2 Shortened time lag of H-TC events

I examined the time lag between TCs and preceding heatwaves, as it represents the potential lead time for H-TC event preparedness and provides a critical window for evacuation planning of TCs. Globally, the average time lag of H-TC events varies across the four coastal regions, with East Asia having the shortest average time lag of 3.2 days and Australia the longest at 3.8 days (Figure 6.6A). In East Asia, more than half (54%) of H-TC events occur with a time lag of no more than three days, and particularly, those with a one-day lag account for the highest proportion (25%), indicating that TCs often make landfall immediately after a heatwave ends, leaving little to no time for recovery or safe evacuation.

I calculated the temporal trend in time lag for each coastal grid cell. To assess the significance of these trends, spatial autocorrelation was examined in the residuals of the linear trend models for time lag (Figure 6.6c–f). Significant spatial autocorrelation was identified in the regression residuals (Figure 6.7a), consistent with the inherent spatial dependence of climate fields [Jain *et al.*, 2021; Madakumbura *et al.*, 2021]. If not properly accounted for, such spatial autocorrelation

may lead to a slight overestimation of statistical significance [Meier *et al.*, 2021]. Considering the trends in time lag, I find that while 2,328 grid cells achieve local statistical significance at the conventional $p < 0.05$ level, 1,732 grid cells meet the Benjamini–Hochberg FDR criterion, indicating statistical significance at the field level (Figure 6.7b). Then, only trends meeting this criterion are reported as statistically significant in Figure 6.6.

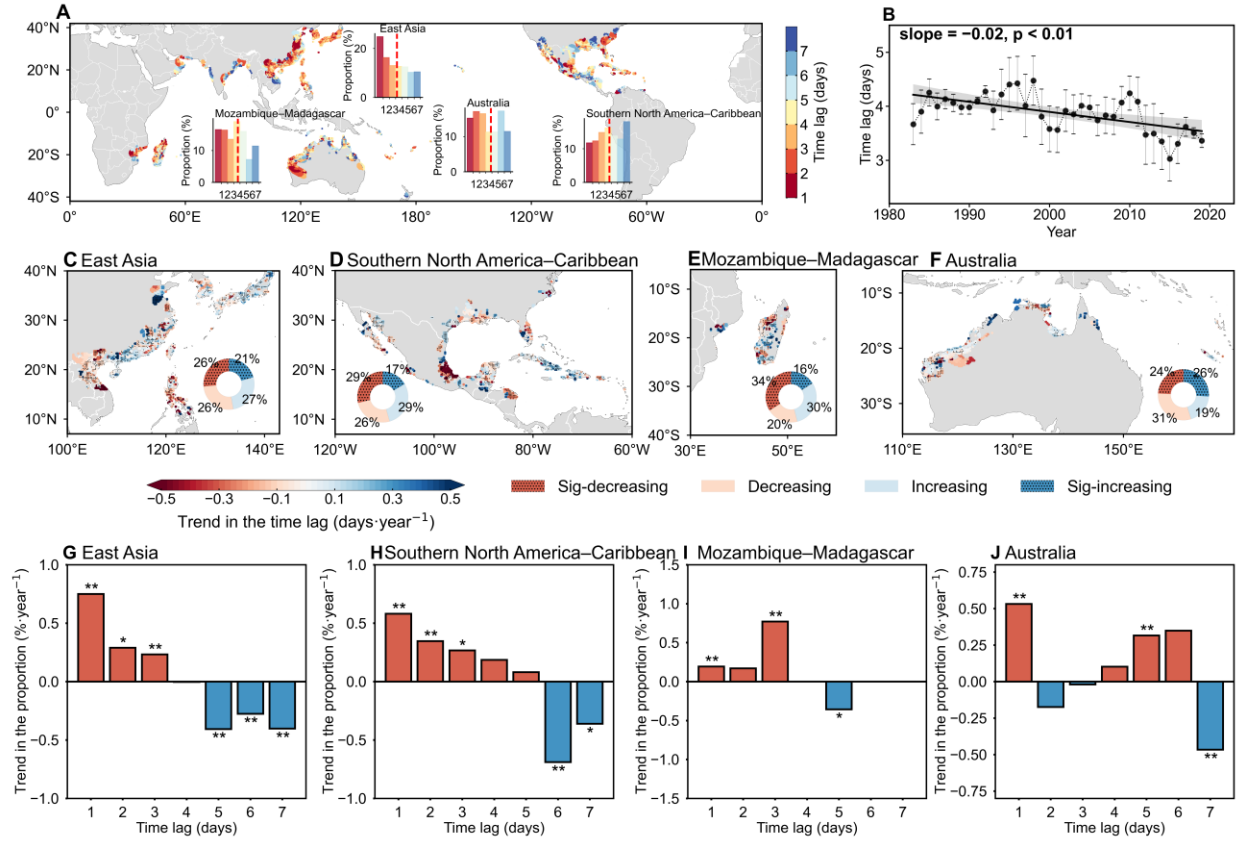


Figure 6.6 Spatial patterns and temporal evolution of the H-TC time lag.

(a) Average time lag of H-TC events from 1981 to 2022. The four inset panels show the mean time lag (red dashed line) and the distribution of time lags for H-TC events across the four coastal regions. (b) Linear trend in the time lag of H-TC events. The shaded region denotes the 95% confidence interval of the regression. Scatter points represent the annual mean time lag, and vertical bars denote ± 1 standard error of the mean (s.e.m.), calculated within a 5-year moving window centered on each year. (c–f) Linear trend in the time lag of H-TC events for individual coastal grid cells. The inset panels summarize the proportions of grid cells classified by the direction and statistical significance of the regression trends. Grid cells with statistically significant

trends ($p < 0.05$) are marked by black dots. Significance was determined using the MK test, with multiple testing controlled at the field level using the Benjamini–Hochberg false discovery rate (FDR) to account for spatial autocorrelation. (g–i) Linear trends in the proportion of each time-lag category during 1981–2022. Only grid cells exhibiting a decreasing trend in time lag (i.e., red grid cells in C–F) are included in the calculation. Bars are colored red and blue to indicate increasing and decreasing trends, respectively. Asterisks denote statistical significance: * for $p < 0.05$ and ** for $p < 0.01$.

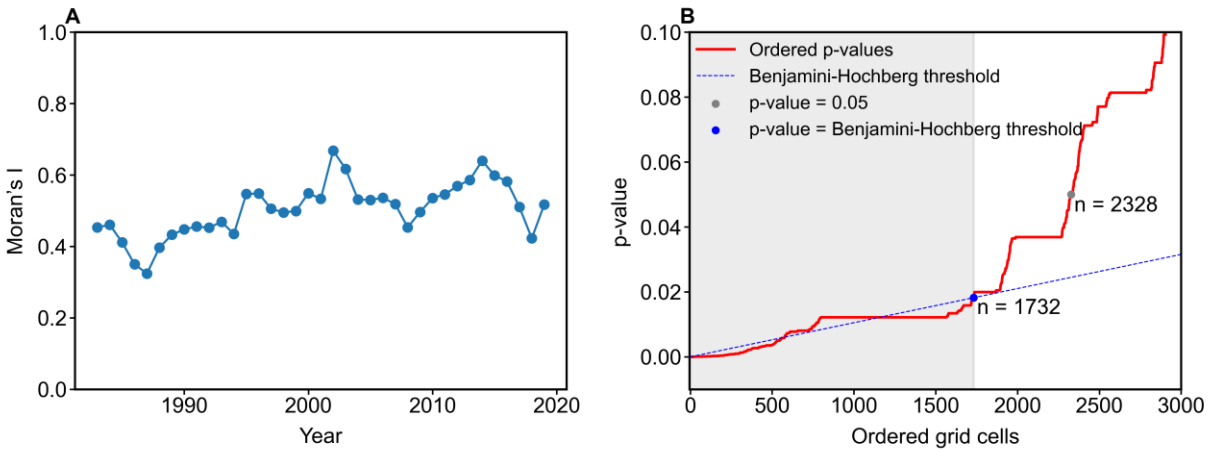


Figure 6.7 Temporal evolution of spatial autocorrelation and Benjamini–Hochberg field significance of time-lag trends.

(a) Year-specific global Moran's I values calculated for the residuals of the linear trends in time lag, using a k-nearest-neighbor spatial weights matrix ($k = 8$) on the 0.25° grid. Moran's I remains consistently positive across all years, indicating persistent spatial autocorrelation of moderate-to-strong magnitude. (b) Ordered p-values of linear trends across all coastal grid cells (red solid line), compared with the Benjamini–Hochberg false discovery rate (FDR) threshold (blue dashed line). Grid cells are ranked in ascending order of p-values. The grey shaded region highlights the range of ranks for which the ordered p-values fall below the FDR threshold, indicating grid cells that satisfy the FDR criterion. The blue point indicates the number of grid cells that remain statistically significant after field-level correction for multiple testing using the FDR approach ($n = 1,732$). The grey point denotes the number of grid cells that achieve local statistical significance at the conventional $p < 0.05$ level ($n = 2,328$).

More than half of coastal areas show a decreasing trend in time lag (Figure 6.6c–f), with a statistically significant rate of $-0.02 \text{ days} \cdot \text{yr}^{-1}$ ($p < 0.01$; Figure 6.6b), leading to an overall reduction of about 16% (0.8 days) from 1981 to 2022. These results indicate that the preparedness and evacuation window between the end of a heatwave and TC landfall has been shortening in recent decades. Among the four coastal regions, the Southern North America–Caribbean exhibits the most pronounced decrease ($-0.06 \text{ days} \cdot \text{yr}^{-1}$; Figure 6.8b), corresponding to an overall reduction of approximately 2.5 days over the study period. In contrast, the trend in Australia is weak and not statistically significant ($-0.01 \text{ days} \cdot \text{yr}^{-1}$, $p = 0.12$; Figure 6.8d). The time lag remains relatively stable over the study period, with substantial year-to-year fluctuations. This reflects pronounced regional heterogeneity in H-TC time-lag trends, with decreasing trends largely confined to areas with relatively few events (Figure 6.1f and Figure 6.6f).

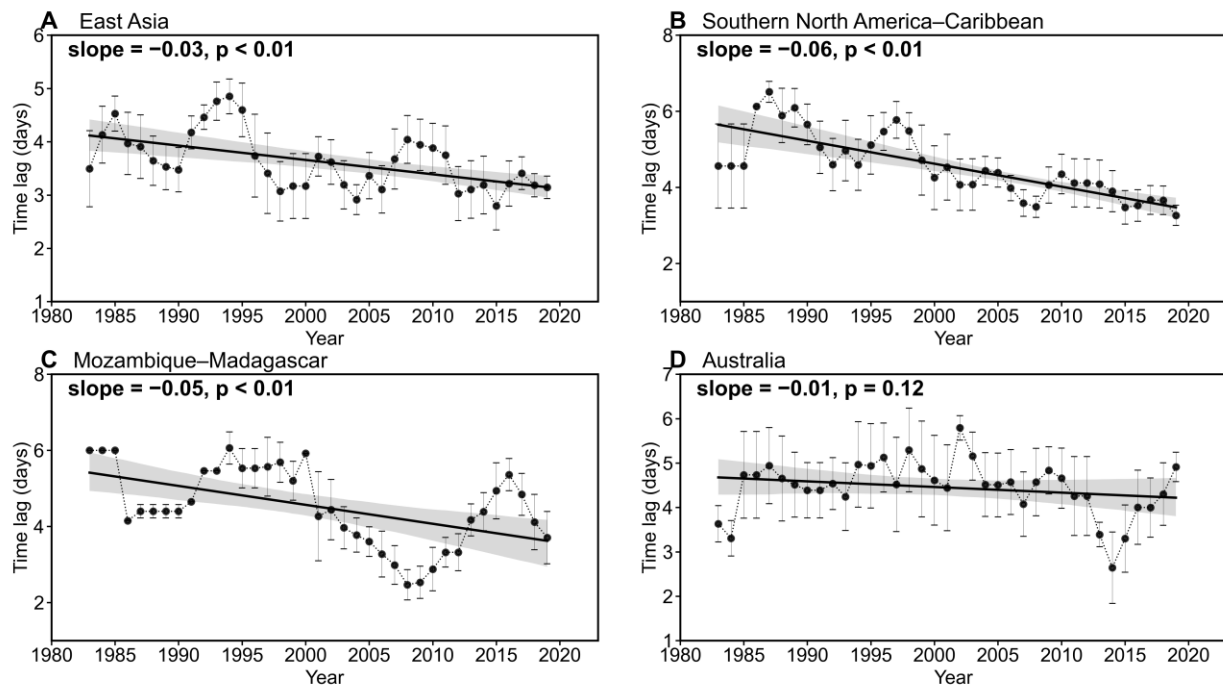


Figure 6.8 Linear trend in the time lag of H-TC events in East Asia (a), Southern North America–Caribbean (b), Mozambique–Madagascar (c), and Australia (d).

The shaded region denotes the 95% confidence interval of the regression. Scatter points represent the annual mean time lag, and vertical bars indicate ± 1 standard error of the mean (s.e.m.), calculated within a 5-year moving window centered on each year.

I further analyzed the linear trends in the proportion of each time-lag category within grid cells exhibiting decreasing time lags (Figure 6.6c–f) to investigate category-specific changes. The results reveal a clear shift toward shorter time lags, characterized by an increasing proportion of events with short lags (≤ 3 days) and a decreasing proportion of events with longer lags (> 3 days) (Figure 6.6g–j). Notably, all four coastal regions exhibit a significant increase in the proportion of 1-day lag events, indicating a rapid rise in cases where TCs make landfall shortly after heatwave termination. Except for the Mozambique–Madagascar region, the most pronounced increases are consistently observed for 1-day lag events, with rates of 0.75, 0.58, and 0.53 $\% \cdot \text{yr}^{-1}$ in East Asia, Southern North America–Caribbean, and Australia, respectively. These trends underscore the growing risk associated with rapidly successive H-TC events, which leave limited time for recovery, preparedness, and emergency evacuation.

The total proportion of events with shorter time lags (≤ 3 days) shows a significant ($p < 0.05$) increasing trend of 0.21% per year, corresponding to an overall increase of about 9% from 1981 to 2022 (Figure 6.9a). The contribution of the rising proportion of shorter time lag events to the overall shortening of time lag is also evident in the strong negative correlation ($r = -0.87$, $p < 0.01$) between the trend in the proportion of short-lag events (Figure 6.10) and the trend in the time lag of H-TC events (Figure 6.6c–f), as shown in Figure 6.9b. These results further verify that the increasing proportion of shorter time-lag events contributes to the overall reduction in time lag. Accordingly, in the following analysis, I focus on H-TC events with short time lags (i.e., ≤ 3 days) to investigate the potential linkage between heatwaves and TCs, as such events have increasingly dominated the observed shortening of time lag in recent years.

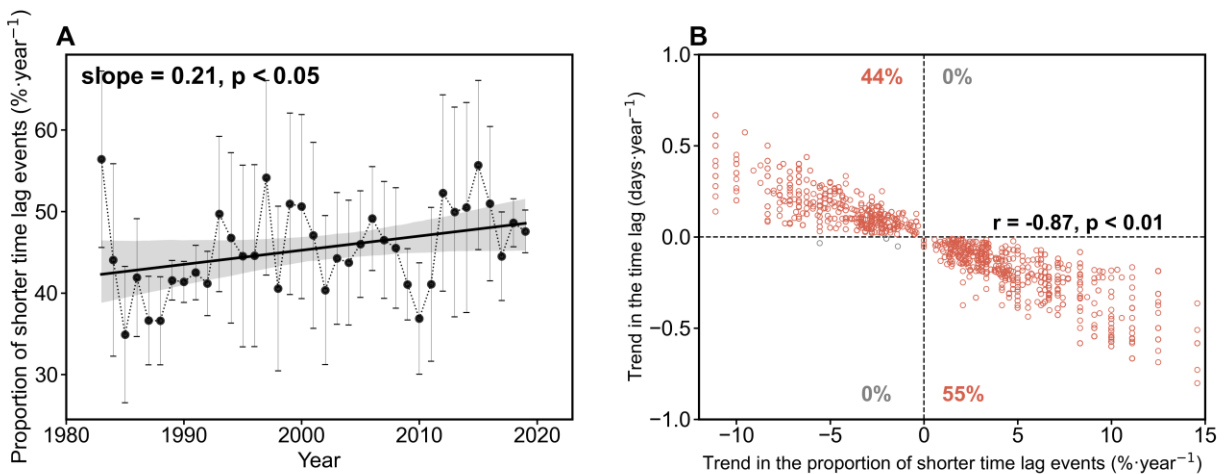


Figure 6.9 Linear trend in the proportion of shorter time lag H-TC events and its relationship with the trend in the time lag of H-TC events.

(a) Linear trend in the proportion of H-TC events with shorter time lags (≤ 3 days). The shaded region denotes the 95% confidence interval of the regression. Scatter points represent the annual mean proportion, and vertical bars indicate ± 1 standard error of the mean (s.e.m.), calculated across all grid cells using a 5-year moving window centered on each year. (b) Relationship between the trend in the proportion of short-lag H-TC events and the trend in the H-TC time lag. Correlations are assessed using the Pearson correlation test. Each point represents a grid cell, with grid cells exhibiting opposite trends highlighted in red. Percentages indicate the fraction of grid cells in each quadrant.

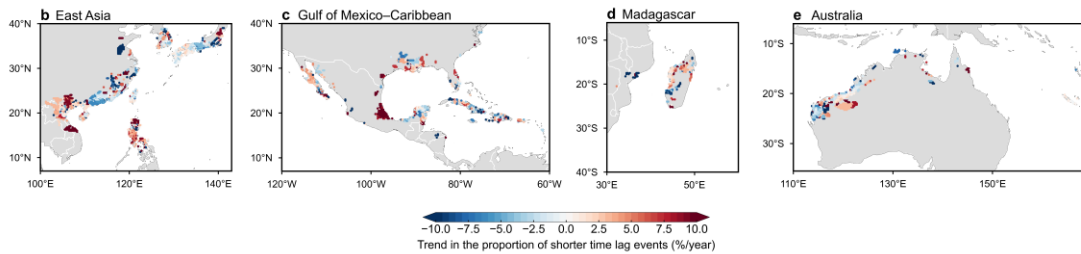


Figure 6.10 Linear trend in the proportion of shorter time lag events (i.e., ≤ 3 days) for individual coastal grid cells.

6.3 Linkages between heatwaves and TCs

To examine the potential linkages between heatwaves and subsequent TCs, I conducted a comparative analysis of heatwaves followed by TCs (H-TC events) and those without subsequent TCs (H-alone events). I find that H-TC events generally have shorter durations and exhibit greater intensity on their final stage compared with heatwaves not followed by TCs.

As shown in Figure 6.11a–d, in most coastal regions of East Asia, the Southern North America–Caribbean, Mozambique–Madagascar, and Australia, H-TC events are on average shorter in duration. To ensure consistency across events, intensity comparisons were restricted to the final three days of each heatwave, as all identified events lasted at least three days. While H-TC events exhibit intensity levels that are slightly weaker two days prior and merely comparable one day prior to termination, they undergo an amplification at the end (Figure 6.11e). H-TC events

exhibit significantly higher intensity than H-alone events on the final day of the heatwave. This is consistent with previous studies showing that, as TCs approach the coastline, the associated heatwaves may gradually intensify [P Y Wang et al., 2023a].

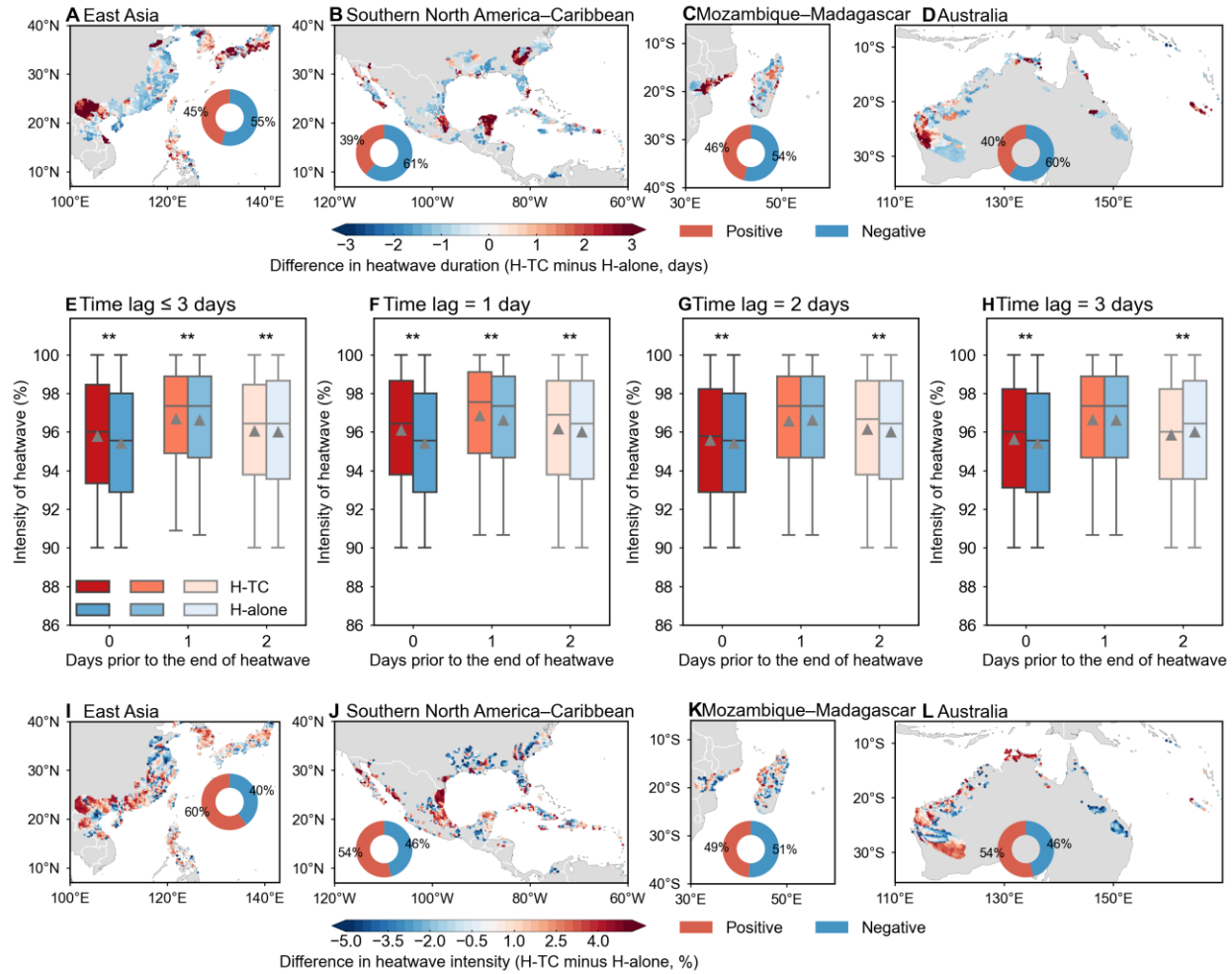


Figure 6.11 Comparison of heatwave duration and intensity between heatwaves that are followed by TCs (i.e., H-TC events) and those not followed by TC (i.e., H-alone events).

(a–d) Difference in heatwave duration between H-TC and H-alone events across the four coastal regions, calculated as H-TC minus H-alone. The inset pie charts illustrate the proportion of positive (red) and negative (blue) differences. (e) Comparison of heatwave intensity on the final day of heatwaves, as well as one and two days prior to termination. Heatwave intensity is defined as the percentile rank of wet-bulb temperature relative to a centered 15-day moving window during 1981–2010 used to compute thresholds ($30 \text{ years} \times 15 \text{ days} = 450 \text{ samples}$; see Methods), enabling

consistent comparisons across calendar dates and grid cells. Boxplots show the distribution of heatwave intensity, with boxes representing the interquartile range (25th–75th percentiles), triangles indicating mean values, and whiskers extending from the 5th to the 95th percentiles. Statistical significance between H-TC and H-alone events is assessed using the K–S test, with $**p < 0.01$ and $*p < 0.05$. (f–h) Comparison of heatwave intensity across different time-lag categories of H-TC events, including one-day (f), two-day (g), and three-day (h) lags. For each time-lag category, heatwave intensity is shown for the final day of the heatwave as well as one and two days prior to termination. Boxplots for H-alone events are identical across all time-lag categories and serve as a consistent reference for comparison with H-TC events. (g–i) Difference in heatwave intensity between H-TC and H-alone events across the four coastal regions, calculated as H-TC minus H-alone. The inset pie charts illustrate the proportion of positive (red) and negative (blue) differences.

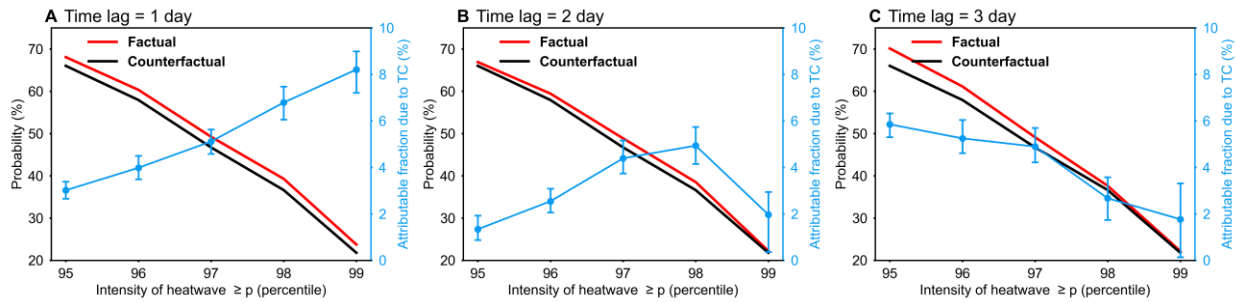


Figure 6.12 Cascading attribution of heatwave intensity to TCs.

Panels (a–c) show the results for time lags of 1, 2, and 3 days, respectively. For each heatwave intensity threshold p (where intensity $\geq p$ percentile), the plots display the probability that a heatwave event occurs under the factual scenario (red dots; under the influence of a TC) and the counterfactual scenario (black dots; with the TC influence removed). The specific contribution of TCs to heatwave intensification at each intensity level is quantified by the attributable fraction (AF, %, blue markers), with higher AF values indicating a stronger cascading effect of TCs on heatwave magnitude. The error bars represent the 5th–95th percentile confidence intervals.

I confirm that H-TC events are systematically associated with stronger heatwaves than H-alone events on the final stage of the heatwave across all time-lag categories (Figure 6.11f–h). The intensity contrast increases monotonically as the H-TC time lag shortens, indicating progressively

stronger heat amplification under rapidly successive events. The largest contrast occurs for the 1-day lag cases (Figure 6.11f), and this amplification also appears earlier in the heatwave lifecycle, emerging up to three days before heatwave termination. Using a cascading attribution framework that compares factual conditions (heatwaves preceded by TCs) with a counterfactual scenario without TC influence, I further quantify this intensification. The results demonstrate that TC occurrence significantly increases the probability of extreme heat (Figure 6.12). This effect is most pronounced at a 1-day lag, with attributable fractions (AF) ranging from 1.0% to 8.2% for heatwaves exceeding the 95th percentile, and reaching its peak for the most extreme events (>99th percentile). These findings suggest that TCs do not merely coexist with heatwaves but systematically shift the probability distribution toward higher intensities during the late stages of these events. Collectively, our results indicate that closely coupled H-TC events are characterized by both intensified late-stage heatwaves and a clear amplification as the time lag narrows.

I further examined the large-scale atmospheric conditions associated with H-TC and H-alone events and identified two distinct pathways through which TCs can intensify heatwaves over land. As wet-bulb temperature depends on both air temperature and relative humidity, increases in either factor can enhance heatwave intensity. In coastal regions of East Asia and Mozambique–Madagascar, TCs primarily strengthen heatwaves by increasing air temperature, whereas in the Southern North America–Caribbean and coastal Australia, the intensification is mainly driven by elevated atmospheric moisture.

Most of grid cells in East Asia and Mozambique–Madagascar experience higher air temperatures and lower relative humidity during H-TC events compared with H-alone events (Figure 6.13a, c, e, and g). The rise in temperature can stem from both diabatic and adiabatic warming. When a TC approaches land during a heatwave, enhanced surface solar radiation is observed in 62% of grid cells in East Asia and 72% in Mozambique–Madagascar (Figure 6.13i and k), favoring diabatic heating [Bieli *et al.*, 2015; Domeisen *et al.*, 2022]. In addition, the upper-level divergent outflow from TCs may promote subsidence in surrounding regions, as indicated by strengthened vertical velocity (Figure 6.13m and o), which can transport dry air from the upper troposphere downward and induces adiabatic warming (Figure 6.13q and s) [Rothlisberger and Papritz, 2023]. Together, these diabatic and adiabatic processes can reinforce the hot and dry conditions, thereby intensifying the heatwave.

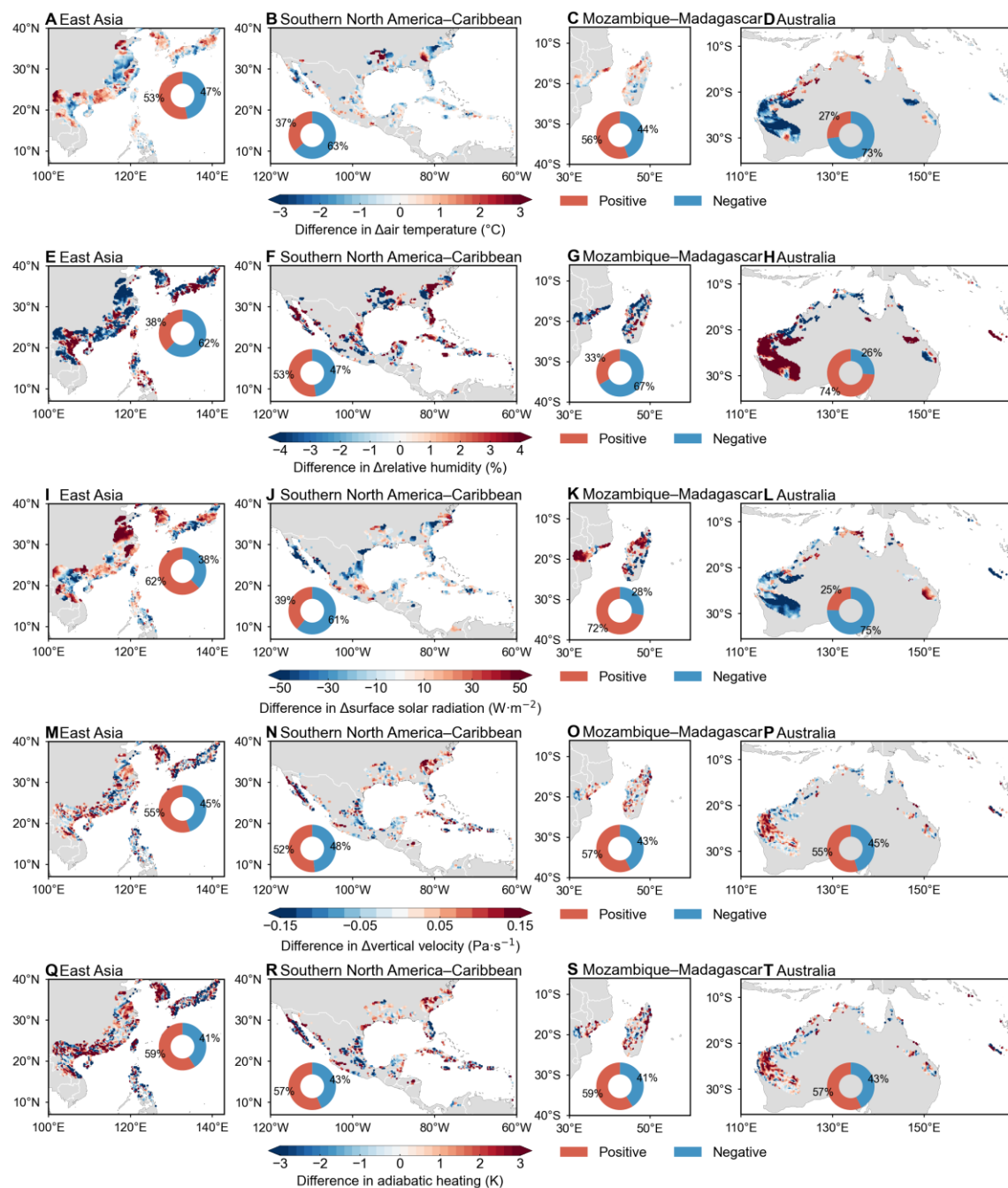


Figure 6.13 Composite differences in large-scale atmospheric conditions between H-TC and H-alone events.

Large-scale atmospheric variables include anomalies in air temperature (a–d), anomalies in relative humidity (e–h), anomalies in surface solar radiation (i–l), anomalies in vertical velocity (m–p), and adiabatic heating (q–t). Inset pie charts indicate the proportions of positive and negative differences.

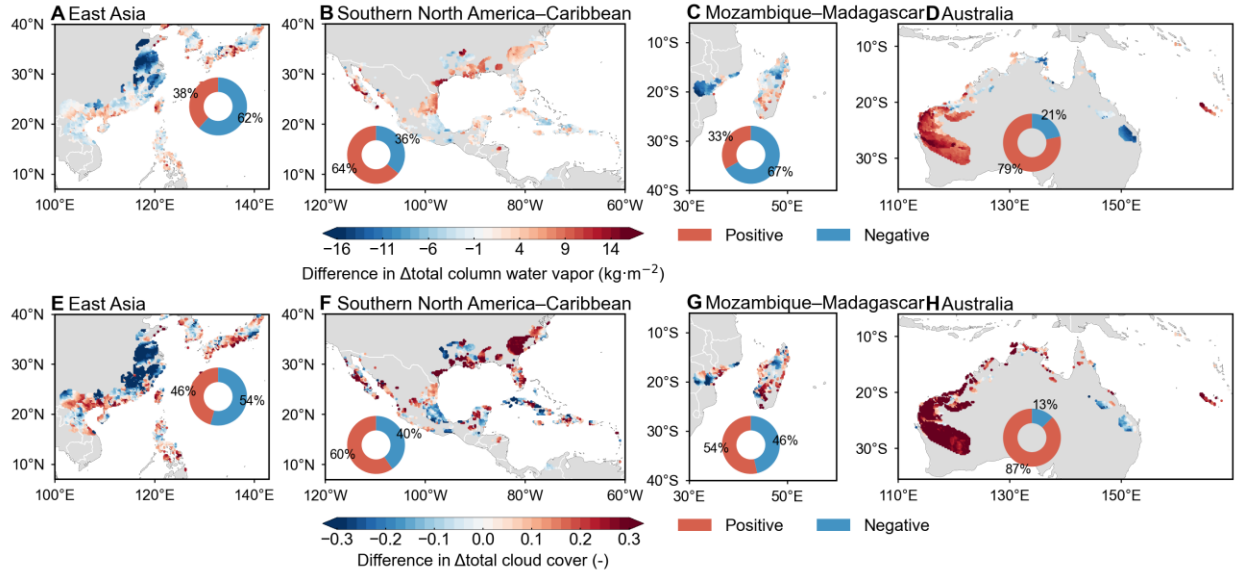


Figure 6.14 Composite differences in large-scale atmospheric conditions between H-TC and H-alone events.

Large-scale atmospheric variables include anomalies in total column water vapor (a–d), anomalies in total cloud cover (e–h). Inset pie charts indicate the proportions of positive and negative differences.

In contrast, across the coastal regions of the Southern North America–Caribbean and Australia, air temperature decreases during H-TC events in 63% and 73% of coastal grid cells, respectively (Figure 6.13b and D). Despite lower air temperatures, these regions exhibit elevated relative humidity (Figure 6.14f and h) and increased total column water vapor (Figure 6.14b and S9d). This suggests that when a TC remains over the ocean while approaching land, moisture transport from the ocean to the coast can intensify humid heatwave conditions. The associated increase in total cloud cover (Figure 6.14f and h) can reduce the amount of solar radiation reaching the surface (Figure 6.14j and 4l), thereby limiting near-surface temperature increases [S. Wu *et al.*, 2025; X Zhou *et al.*, 2025]. Overall, the influx of moisture increases atmospheric water vapor over these coastal regions, thereby amplifying heatwave intensity primarily through enhanced humidity.

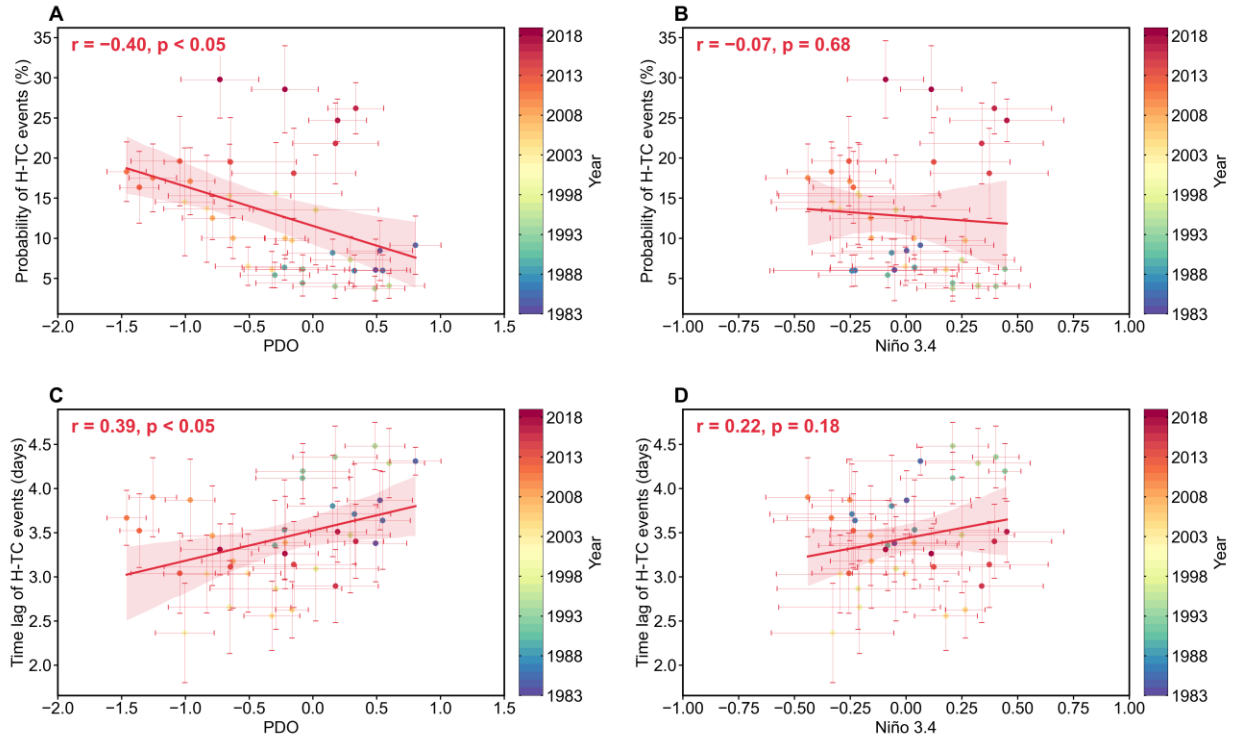


Figure 6.15 Relationships between climate indices and H-TC occurrence characteristics in East Asia.

(a) Correlation between the annual probability of H-TC events and the Pacific Decadal Oscillation (PDO). (b) Correlation between the annual probability of H-TC events and the Niño3.4 index. (c) Correlation between the H-TC time lag and PDO. (d) Correlation between the H-TC time lag and the Niño3.4 index. Correlations are assessed using the Pearson correlation test. Each scatter point represents an annual mean value, with colors indicating year. Horizontal and vertical bars denote ± 1 standard error of the mean (s.e.m.), calculated within a 5-year moving window centered on each year.

Beyond synoptic-scale conditions, heatwaves and subsequent TCs may also be linked at interannual to decadal timescales through modulation of the large-scale ocean–atmosphere background state. Our results show that such climate variability plays a key role in shaping H-TC events over East Asia. Specifically, H-TC probability is significantly negatively correlated with the Pacific Decadal Oscillation (PDO; $r = -0.40$, $p < 0.05$; Figure 6.15a), while the H-TC time lag is positively correlated with PDO ($r = 0.39$, $p < 0.05$; Figure 6.15c). This suggests that negative PDO phases, which are associated with a warmer western North Pacific and a strengthened subtropical circulation background [Deng et al., 2022; X Y Yang et al., 2021], favor more frequent

H-TC events and shorter time lags. These conditions likely act by simultaneously supporting heatwave development over land and enhancing TC activity and landfall [Yi Li *et al.*, 2023a; Y. Li *et al.*, 2023b; Mukherjee *et al.*, 2020; Song *et al.*, 2020]. By contrast, no statistically significant relationship is found with the Niño3.4 index (Figure 6.15b and d), which is consistent with the seasonally dependent and often opposing influences of ENSO on heat extremes and TC activity [Fu *et al.*, 2025; Luo *et al.*, 2025; Lyu *et al.*, 2025; Tong *et al.*, 2025; P Y Wang *et al.*, 2023a; Sijia Wu *et al.*, 2023; D Zhang *et al.*, 2025]. These influences do not consistently reinforce one another, resulting in a weak net effect on H-TC compound events.

6.4 Causes for the shortened time lag of H-TC events

The results confirm that TCs can be associated with atmospheric conditions that favor heatwave intensification prior to landfall. However, this enhancement is often disrupted once TCs make landfall, as TC-related cooling processes can suppress extreme heat and may even terminate ongoing heatwaves, leading to shorter heatwave durations. I therefore hypothesize that faster TC translation speeds may accelerate this transition by advancing landfall, thereby reducing the time lag between heatwaves and subsequent TCs. To test this hypothesis, I examine long-term changes in H-TC translation speeds and analyze their relationship with the H-TC time lag. Here, I focus on East Asia, as this region experiences the most frequent of H-TC events and exhibits the shortest average time lag during 1981–2022. TC translation speed was calculated at the time of landfall for H-TC events.

I first evaluated the sensitivity of H-TC time lag to TC translation speed. At the event level, time lag decreases significantly with increasing translation speed. A linear fit indicates a reduction of approximately 0.02 days in time lag for each one-percentile increase in translation speed ($p < 0.01$; Figure 6.16a). I used the bivariate Granger causality analysis to identify a significant directional influence from translation speed to time lag ($p < 0.05$), whereas the reverse direction is not significant (Figure 6.16b). The impulse–response functions further quantify this asymmetry by showing how the time lag responds to a translation-speed shock over time. A positive shock to translation speed causes an immediate drop in time lag of ~ 0.5 standardized units, and this effect decays to near zero within a few years, indicating a short-lived response (Figure 6.16b). This transient behavior is consistent with the discrete, episodic nature of compound H-TC events. In contrast, a positive shock to time lag does not generate a measurable response in translation speed.

Together, these results indicate that perturbations in translation speed exert a prompt influence on time lag, providing evidence for a causal effect from translation speed to time lag.

Distributional evidence supports the same conclusion. The time-lag distribution differs markedly between faster-moving and slower-moving events (Figure 6.16c; $p < 0.01$). Short-lag events (≤ 3 days) occur more frequently among faster H-TC events, whereas slower-moving events exhibit a heavier tail toward longer lags, extending to about 6–7 days. I further quantified the causal contribution of fast translation speed to short time lags using a cascading attribution analysis. Across time-lag thresholds d , the factual probability that time lag is $\leq d$ is consistently higher than the counterfactual probability when the effect of fast translation speed is eliminated, indicating the occurrence of short-lag events attributable to fast translation speed (Figure 6.16d). For short-lag events (time lag ≤ 3 days), the attributable fraction (AF) ranges from 3.1% to 10.8%. The AF reaches 10.8% (95% CI: 8.8%–13.0%) at the shortest-lag threshold, suggesting that fast translation speed contributes most strongly to 1-day lag H-TC events. This is consistent with the pronounced increase in 1-day cases among fast-moving events (Figure 6.16c).

Here I identify faster TC translation speed as an important factor associated with the shortening of H-TC time lags. Although previous studies reported a long-term slowdown in TC translation speed [Kossin, 2018], this apparent discrepancy can be explained by differences in data coverage and analytical perspective. Focusing on the satellite era (1981–2022), our analysis reveals no significant decreasing trend in global TC translation speed; instead, I find a weak increasing tendency ($0.01 \text{ km h}^{-1} \text{ yr}^{-1}$, $p = 0.31$; Figure 6.17a). A slightly stronger increase is evident over the western North Pacific ($0.02 \text{ km h}^{-1} \text{ yr}^{-1}$, $p = 0.20$; Figure 6.17c), which aligns with several recent regional studies [Gong *et al.*, 2022; Song *et al.*, 2024]. More importantly, our analysis adopts a grid-based exposure perspective rather than focusing solely on instantaneous translation speed along storm tracks. By accounting for the frequency and speed at which TCs affect individual land grid points, this framework is more directly relevant for assessing H-TC time lags. Using this approach, I further demonstrate that many coastal areas in East Asia have experienced increasing TC translation speeds (Figure 6.18a), with more pronounced acceleration for TCs preceded by heatwaves (Figure 6.18e). This provides a plausible mechanistic explanation for the observed shortening of H-TC time lags.

Together, these results indicate that faster-moving TCs warrant particular concern, as they can shorten the response window for coastal communities facing consecutive heatwaves and TCs within a short timeframe.

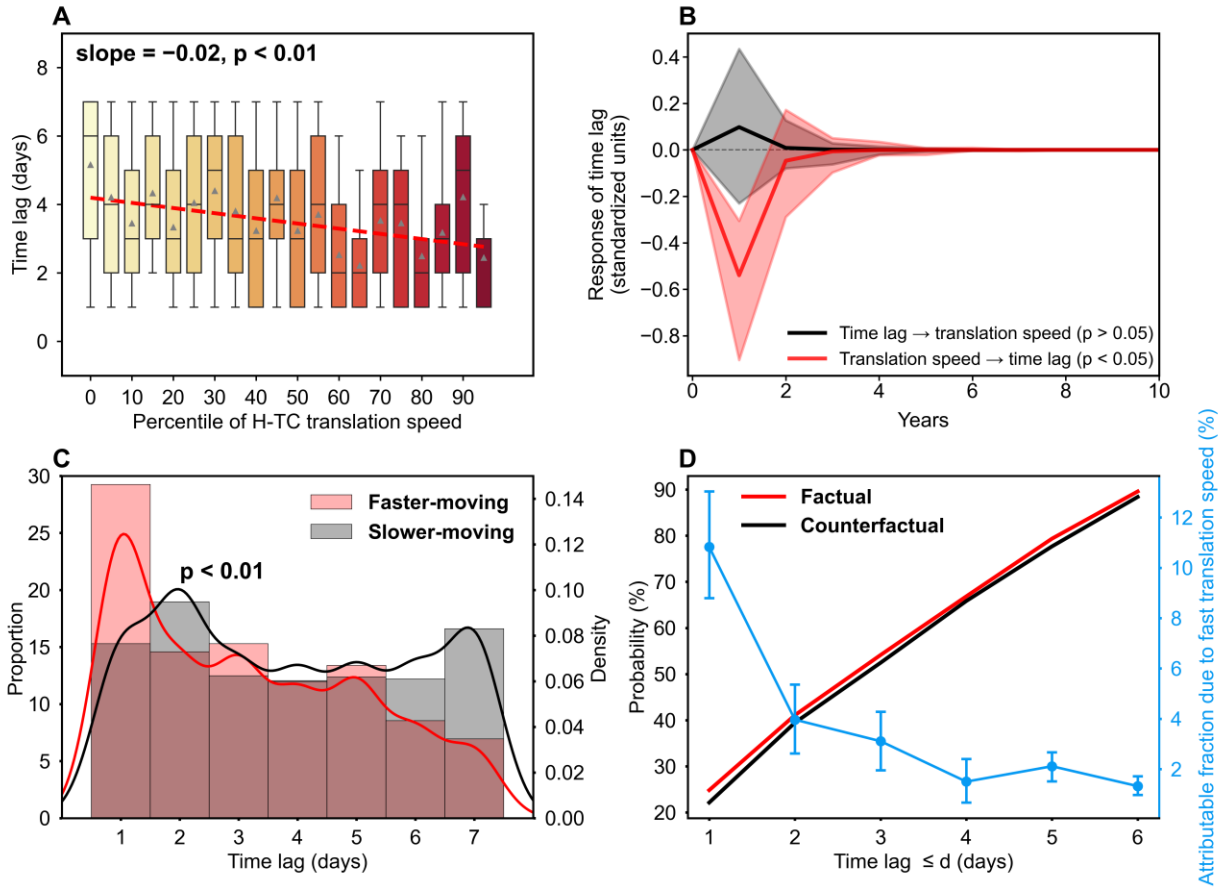


Figure 6.16 Causal analyses of translation speed and time lag of H-TC events.

(a) Changes in the time lag of H-TC events with increasing translation speed. Translation speeds are divided into 20 percentile bins (0–95th percentile in 5-percentile increments; e.g., the 0th bin represents >0–5th percentile). Boxplots show the interquartile range (25th–75th percentiles), triangles indicate mean values, and whiskers span the 5th–95th percentiles. The red dashed line denotes the fitted linear regression between translation speed (x-axis) and mean time lag (y-axis).

(b) Impulse-response functions showing the response of H-TC time lag to a positive shock in translation speed (red) and the response of translation speed to a shock in time lag (black). Shaded areas represent 95% confidence intervals. P-values are derived from Granger causality tests.

(c) Distributions of the H-TC time lag for events with faster (top 30%) and slower (bottom 30%)

translation speeds. Translation speeds are expressed as percentiles within each grid cell to enable comparison across coastal regions. Statistical significance of the difference between the two groups is assessed using the K–S test. (d) Cascading attribution of short time lags to fast translation speed (top 30%). For each time-lag threshold d (time lag $\leq d$), I show the probability that an H-TC event meets the threshold under the factual scenario (red; observed fast translation speed) and the counterfactual scenario (black; with the effect of fast translation speed removed). The contribution of fast translation speed to short time lags at each threshold is quantified by the attributable fraction (AF, %, blue markers), with higher AF indicating stronger cascading effects. The error bars represent the 5th–95th percentile confidence intervals.

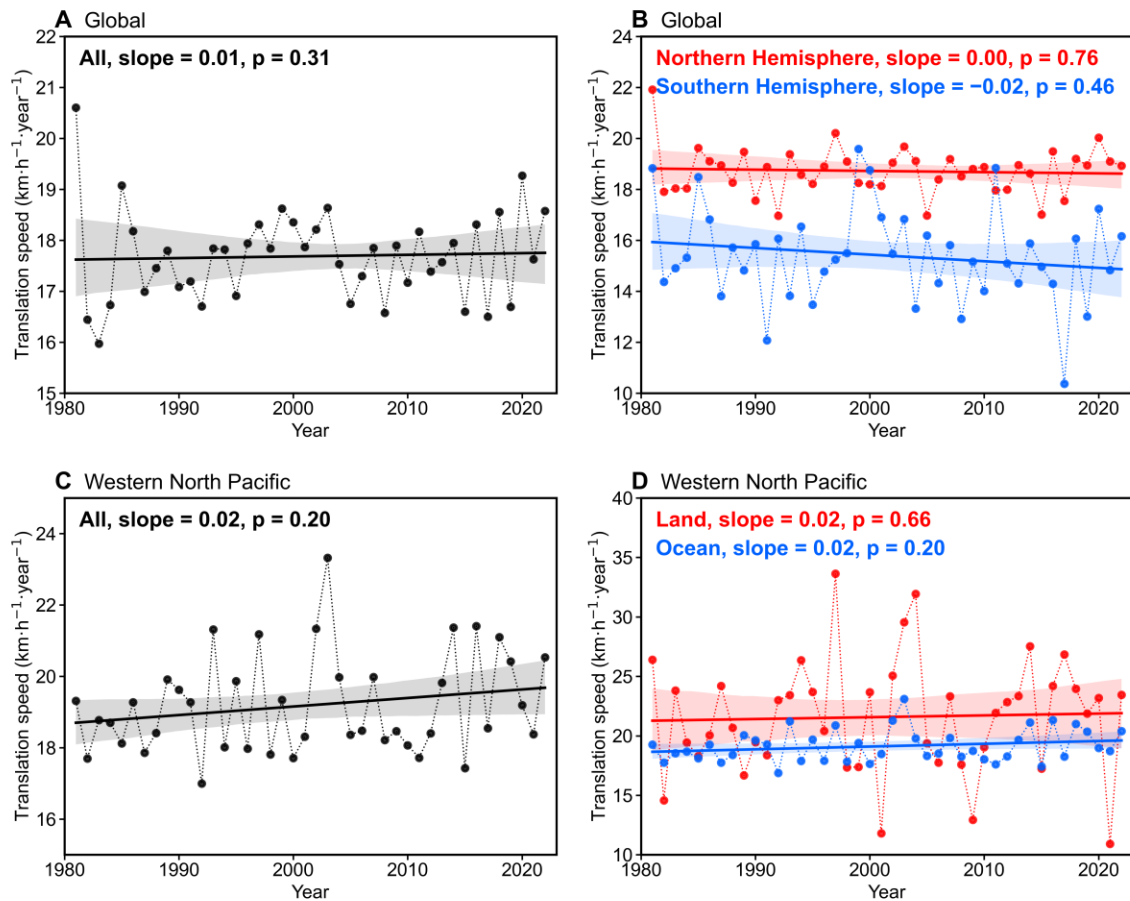


Figure 6.17 Global and regional trends in TC translation speed, including hemispheric and land–ocean contrasts.

The shaded region represents the 95% confidence interval of the regression. Scatter points represent the annual mean time lag, and vertical bars represents ± 1 standard error of the mean (s.e.m.), calculated within a 5-year moving window centered on each year.

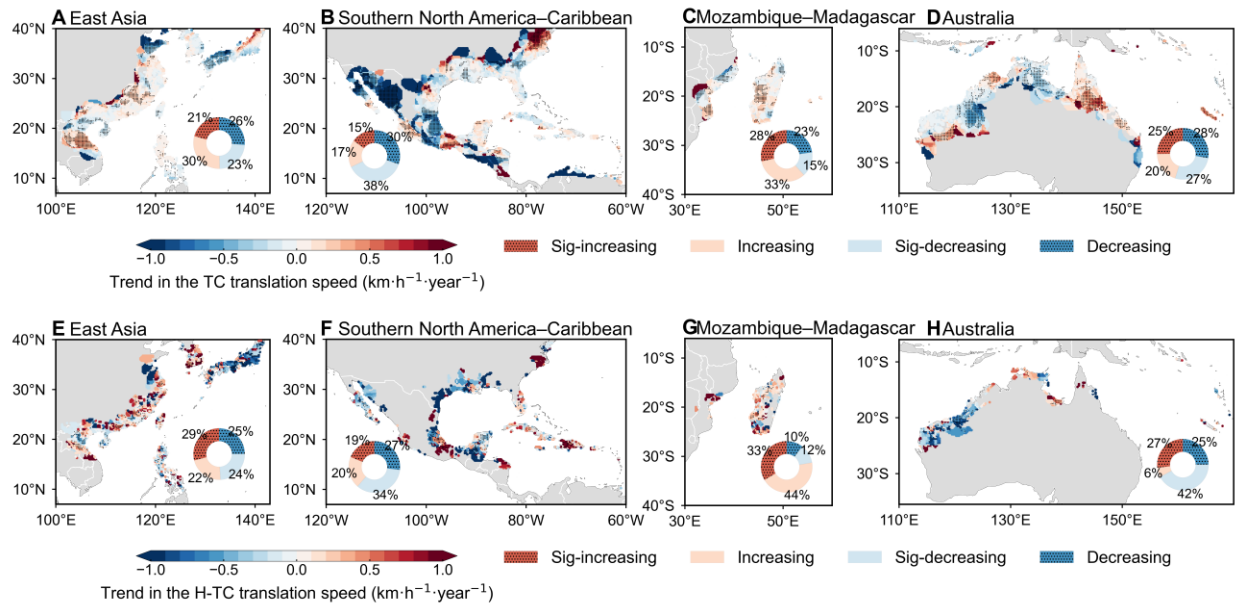


Figure 6.18 Linear trends in the translation speed of tropical cyclones (TCs; a–d) and tropical cyclones preceded by heatwaves (H-TCs; e–h) for individual coastal grid cells.

The inset panels summarize the proportions of grid cells classified by the direction and statistical significance of the regression trends. Grid cells with statistically significant trends ($p < 0.05$) are marked by black dots.

6.5 Global population and exposure to H-TC events

The societal relevance of H-TC events varies markedly across regions. Here, I calculate population exposure to H-TC events to better understand their spatial distribution and impacts. East Asia stands out as a major hotspot, exhibiting both the highest frequency of H-TC events (Figure 6.1c) and the shortest time lag (Figure 6.6a), coinciding with dense coastal populations (Figure 6.19a), resulting in elevated H-TC exposure and approximately 72% of coastal grid cells showing increasing exposure trends (Figure 6.19i). In the Southern North America–Caribbean region, stronger TCs (Figure 6.3b), pronounced time-lag shortening (Figure 6.8b), and high coastal population density (Figure 6.19b) have also led to substantially increasing exposure (Figure 6.19j).

By contrast, although shortening time lags are evident over parts of inland Australia, low population density limits the societal consequences of these hazards (Figure 6.19h). Consequently, large hazard signals in these regions do not necessarily translate into proportionally large societal consequences. This is likely due to fewer compound events and stronger interannual variability influenced by large-scale climate modes. This emphasizes the need for regionally targeted adaptation strategies that reflect local exposure and vulnerability.

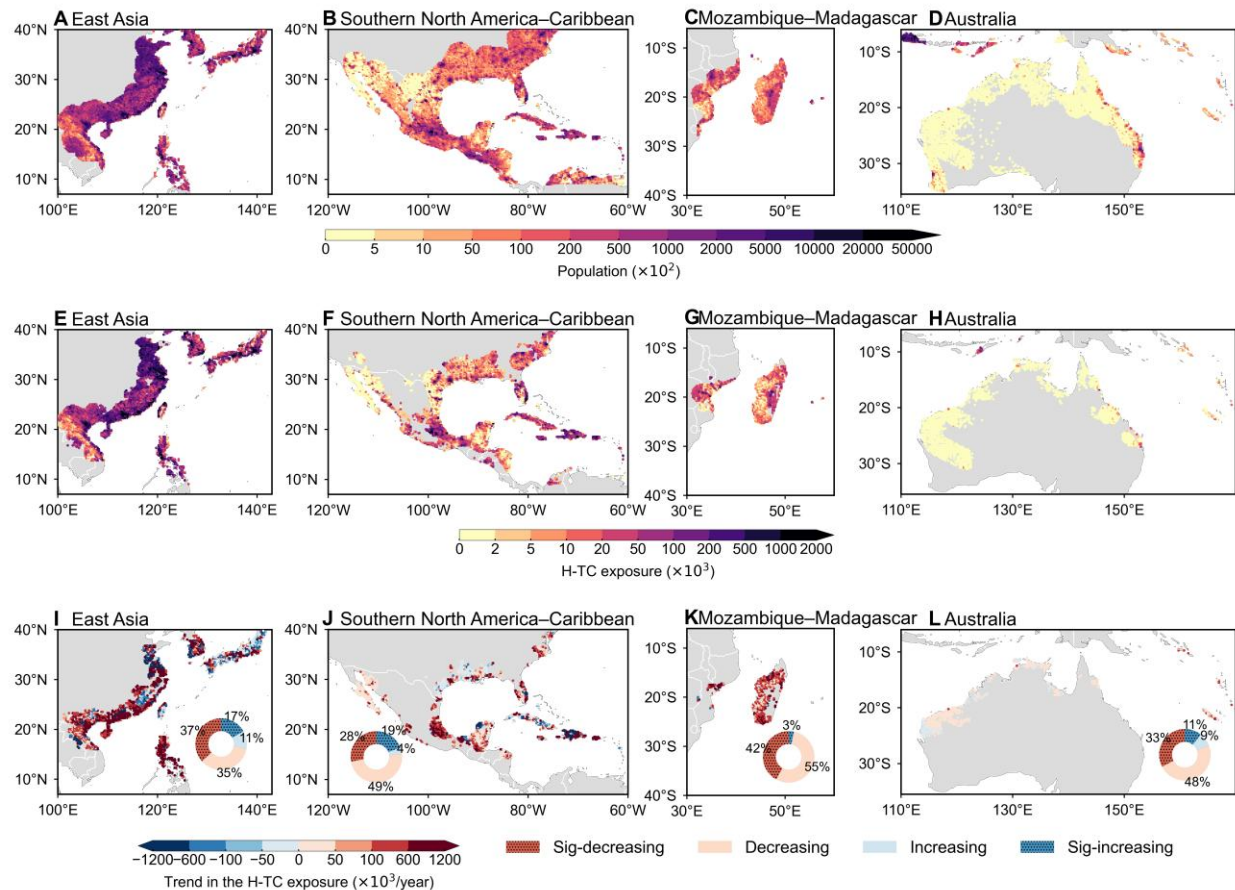


Figure 6.19 Global population and exposure to H-TC events.

(a–d) Spatial distribution of the global population across four coastal regions: East Asia (a), Southern North America–Caribbean (b), Mozambique–Madagascar (c), and Australia (d). (e–h) Spatial patterns of population exposure to H-TC events. (i–l) Linear trend in population exposure to H-TC events ($\times 10^3$ per year) for individual coastal grid cells. The inset panels summarize the proportions of grid cells classified by the direction and statistical significance of the regression trends. Grid cells with statistically significant trends ($p < 0.05$) are marked by black dots.

6.6 Sensitivity analyses and detrending analyses

I evaluated the robustness of our results using a comprehensive sensitivity analysis that varies the heatwave threshold (90th vs. 95th percentile), TC landfall distance (200, 300, and 400 km), and the length of the impact-relevant time window (5, 7, 9, and 11 days; Figure 6.20–Figure 6.22). From an impact perspective, a higher temperature threshold (95th percentile) represents populations operating closer to physiological or infrastructural heat-tolerance limits, while longer TC landfall distances imply earlier and more spatially extensive pre-landfall influences, thereby expanding exposure to compounding hazards. In contrast, shorter time windows (e.g., 5 days) signals the need for faster, more constrained evacuations. Across all tested parameter combinations, the results reveal a robust and consistent signal. While the mean H-TC time lag scales with the chosen time-window length (Figure 6.20A), its long-term evolution indicates a progressive shortening of the interval between heatwaves and TC landfall, with all cases exhibiting negative trends (Figure 6.20b and Figure 6.21).

Stricter definitions, such as higher temperature thresholds, shorter time windows, or smaller TC landfall distances, can reduce the absolute number of identified H-TC events (Figure 6.20C). However, these choices exert only a limited influence on the compound occurrence probability, which ranges from approximately 16% to 37% and consistently exceeds the random expectation of 11% (Figure 6.20d and Figure 6.22). The relatively lower probability arises under the strictest definition, defined by a 95th-percentile heatwave threshold combined with a 400 km landfall distance, because this setting markedly reduces the number of detected heatwaves while increasing the number of TC landfall cases, thereby lowering the conditional probability. These results indicate that the reported global occurrence rate is not an artifact of parameter selection but instead reflects a robust feature of H-TC interactions.

I also performed a detrending analysis to confirm that the observed shortening of the time lag is not simply a consequence of more frequent heatwaves under global warming. After removing the long-term air temperature trend and re-identifying heatwaves and H-TC events, I find that the time lag still shows a significant decreasing trend in recent years (Figure 6.23b). This indicates that the shortening of the time lag between heatwaves and TCs is jointly driven by dynamic factors, such as varying TC translation speeds, rather than by purely thermodynamic changes.

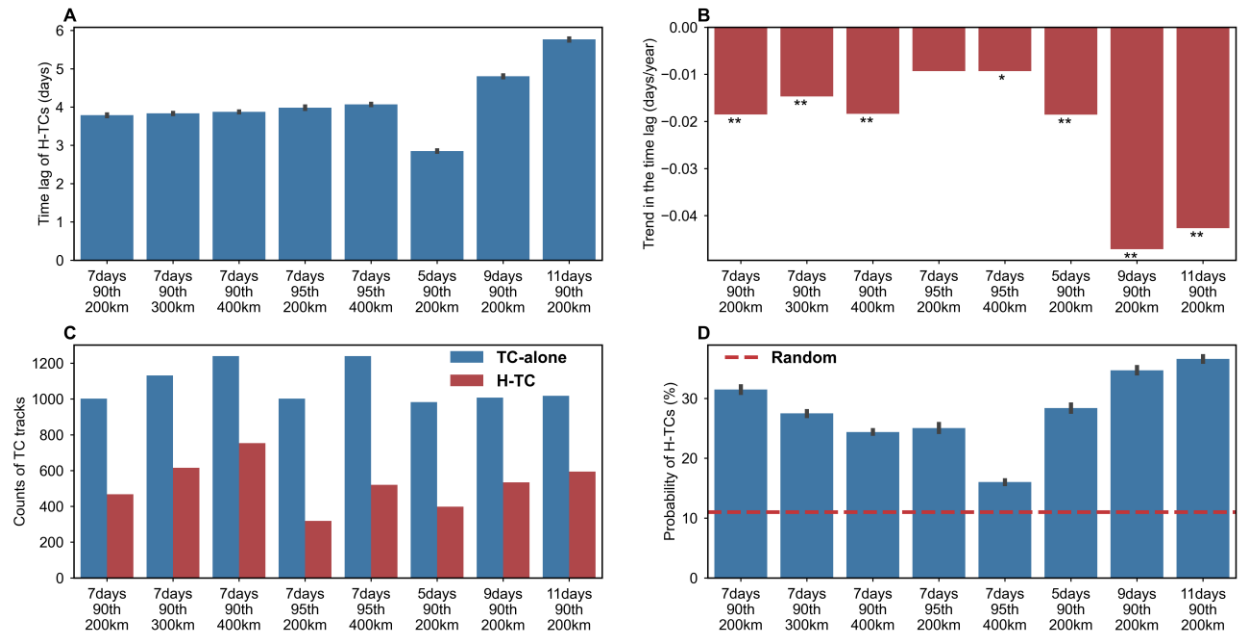


Figure 6.20 Sensitivity of H-TC compound event characteristics to definition choices.

(a) Average time lag between heatwaves and TC landfall under different scenarios of heatwave thresholds, landfall distances, and impact-relevant time windows. (b) Long-term trends in the H-TC time lag during 1981–2022; asterisks denote statistical significance, with $**p < 0.01$ and $*p < 0.05$. (c) Counts of tracks of TC-alone and compound H-TC. (d) Probability of compound H-TC occurrence, with the red dashed line indicating the random expectation.

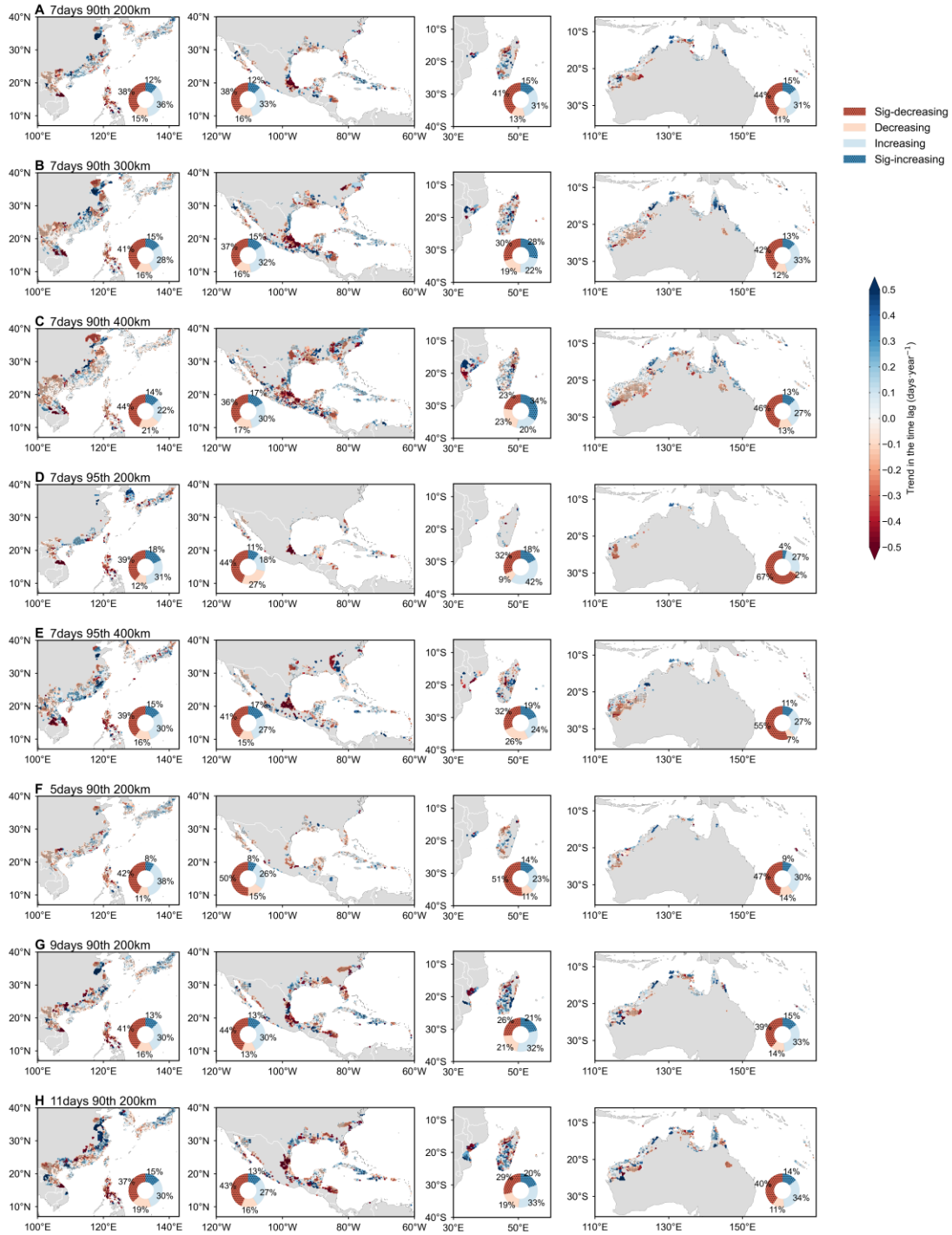


Figure 6.21 Sensitivity of H-TC time lag to temperature thresholds, time windows, and TC landfall distances.

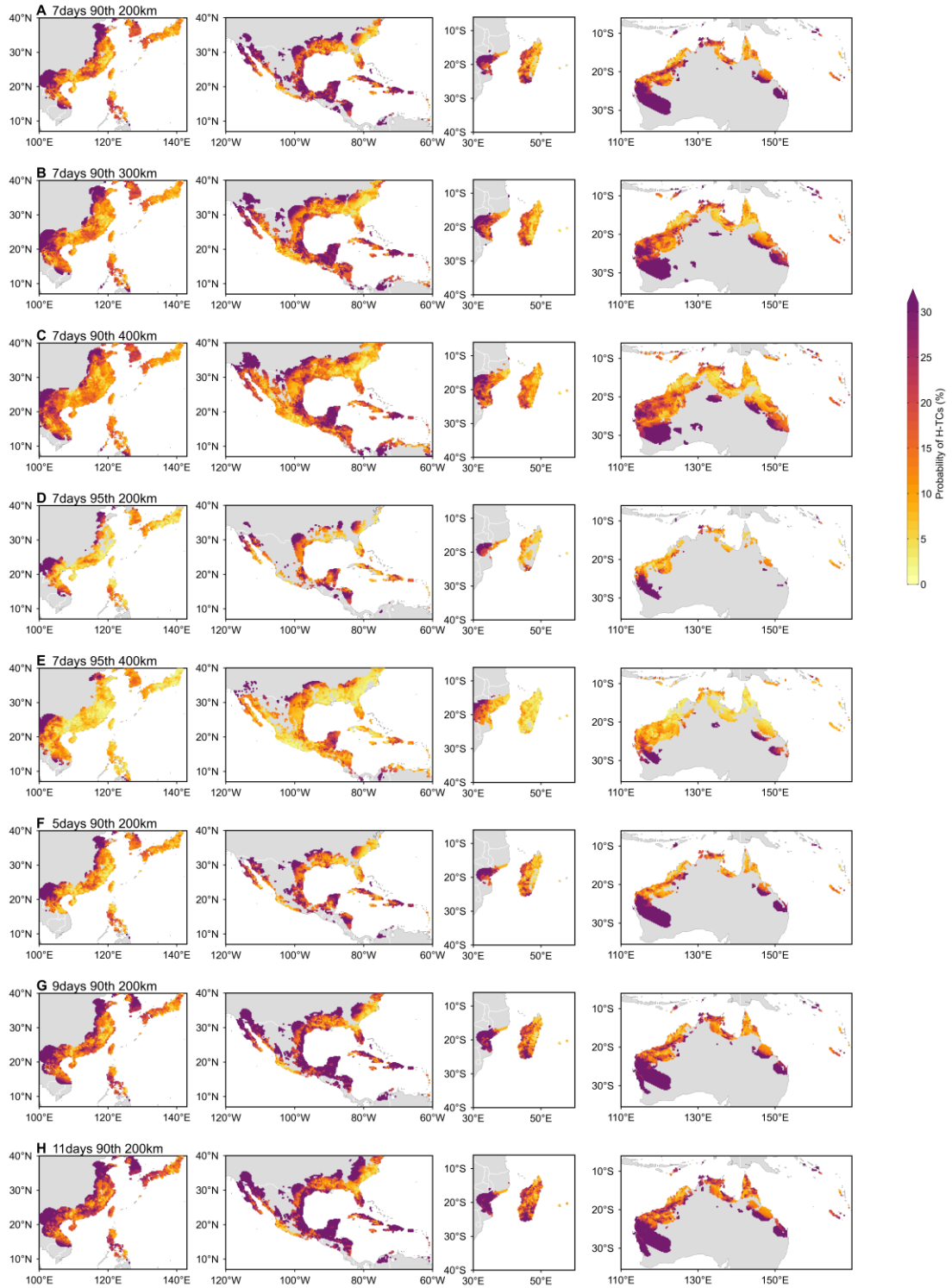


Figure 6.22 Sensitivity of H-TC event probability to temperature thresholds, time windows, and TC landfall distances.

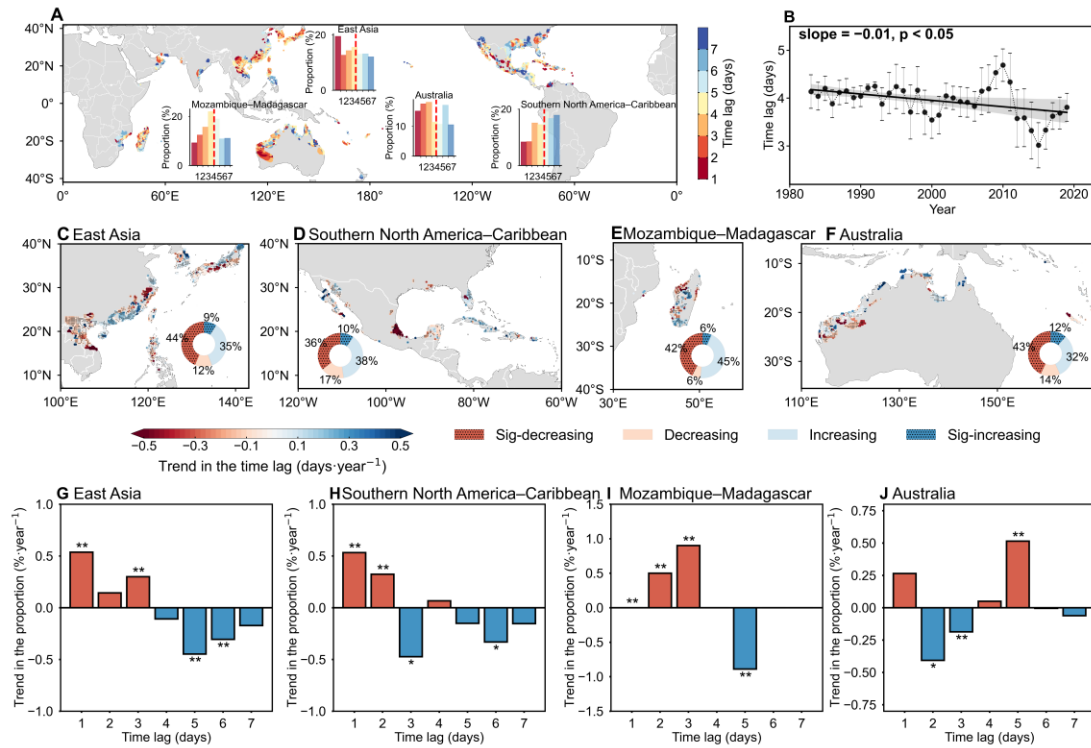


Figure 6.23 Same as Figure 6.6, but based on detrended air temperature time series, in which heatwaves and H-TC events are re-identified after removing the long-term air temperature trend.

6.7 Discussion and summary of the chapter

This study highlights the consecutive occurrence of heatwaves and landfalling TCs (i.e., H-TC events), with emphasis on the shortening of the time lag between these hazards in recent decades. Heatwaves followed by TCs tend to be shorter in duration yet more intense, reflecting enhanced thermal stress before TC landfall, likely associated with TC-related hot and moisture conditions. Faster TC translation speeds can cause shorter H-TC time lags, thereby leaving coastal communities with a progressively narrower window for preparedness and evacuation.

I identified two primary pathways through which short time-lag (≤ 3 days) H-TC compound events are intensified over land, shaped by regional circulation systems. In East Asia, these events are characterized by elevated temperatures, drier conditions, enhanced solar radiation, and subsidence-induced adiabatic warming. These features are closely linked to variations in the Western Pacific Subtropical High (WPSH), the dominant large-scale circulation system that governs summer weather and monsoon activity in the region [Y N Wang *et al.*, 2023b; M Zhang *et*

al., 2024]. A northward or westward displacement of the WPSH can simultaneously create favorable conditions for extreme heat over land. Meanwhile, approaching TCs from lower latitudes can promote the northward extension of this anticyclonic system [*J Hu and Chen*, 2024; *P Y Wang et al.*, 2023a], leading to their close temporal succession. This dual control by large-scale circulation provides a physically consistent explanation for the observed H-TC sequencing in East Asia. Such circulation configurations promote the close temporal succession of heatwaves and landfalling TCs, which explains why East Asia exhibits the most frequent H-TC pairs, beyond the effect of higher TC occurrence alone.

In contrast, over the Southern North America–Caribbean region, H-TC heatwaves are dominated by moisture accumulation and enhanced humidity. Here, TC-associated moisture transport in the pre-landfall environment can amplify heat stress primarily through increased humidity rather than direct temperature increases. Such moisture-driven heat stress has been documented during past U.S. evacuation events, in which populations were exposed to extreme humidity prior to landfall [*Baker*, 2018].

Our results highlight growing concerns over the escalating risks of H-TC events. TC-related evacuations often involve millions [*Shultz et al.*, 2020; *H Wang et al.*, 2019], including approximately four million evacuees during Cyclone Amphan (India, 2020) and around one million during both Typhoon Shanshan (Japan, 2024) and Hurricane Milton (United States, 2024). In China, 56.4 million people were evacuated due to TCs between 2005 and 2016 [*H Wang et al.*, 2019]. A shorter time lag forces at-risk population to evacuate in extreme heat or delay until it subsides, risking overcrowded, less efficient evacuations in a compressed timeframe. Mitigation requires protecting evacuees from heat stress, ensuring evacuation centers and routes provide cool refugia even during power outages. Heat-related deaths on gridlocked roads during Hurricane Rita in 2005—when travel times were up to 20 times longer than expected [*Baker*, 2018]—underscore the need to maintain traffic flow to minimize heat exposure during evacuations.

Our findings have important implications under projected climate change. CMIP6 projections indicate continued intensification of extreme heat, with more frequent and longer-lasting heatwaves [*K Feng et al.*, 2025; *X Gu et al.*, 2025; *M Zhou and Wang*, 2024], while TCs are expected to become more hazardous, with an increased likelihood of intense storms and rapid

intensification, despite remaining uncertainties in overall frequency [Hülsen *et al.*, 2025; Kropf *et al.*, 2025; H Zhao *et al.*, 2024]. In this context, the observed shortening of the H-TC time lag may compress early warning and evacuation windows, amplifying risks to human health, infrastructure, and emergency response. More broadly, our results highlight the importance of considering large-scale background conditions, including ocean warming and circulation variability, in assessments of future compound risk. These factors may jointly influence both heat extremes and TC behavior [Choi *et al.*, 2024; X Gu *et al.*, 2025; L Hu, 2021; Radfar *et al.*, 2024; X Zhou *et al.*, 2025], shaping their temporal overlap. However, these processes remain uncertain and regionally dependent, motivating further investigation using CMIP6 ensembles and high-resolution regional simulations.

Overall, our findings indicate that H-TC events, which are arguably the most severe compound weather events threatening society, are evolving. The compound risk has become more common, and the hazards are becoming more closely spaced in time, with major implications for evacuations and therefore the safety of millions who are regularly forced to flee. These changes must urgently be factored into disaster risk reduction planning if potentially very severe losses of human life are to be avoided.

Chapter 7. Conclusion and future work

7.1 Research conclusions

In this dissertation, a range of approaches has been developed to enhance the detection and attribution of emerging coastal hydrometeorological risks. These include the simulation and loss estimation of coastal flooding, the examination of consecutive and concurrent heatwaves and extreme sea levels, and the investigation of interactions between heatwaves and tropical cyclones. A comprehensive framework integrating hydrodynamic modeling and a depth–damage function was established to assess the risk and economic loss associated with coastal flooding. Furthermore, the spatial and temporal patterns of compound heatwaves and extreme sea levels, as well as compound heatwaves and tropical cyclones, were analyzed using event coincidence analysis, bootstrap-resampling-based test, decomposition analysis, and trend test. Causality analysis, cascading attribution framework and large-scale atmospheric composite mapping were also employed to unravel the underlying mechanisms driving these compound events.

I have the following findings:

(1) Through an integrated framework combining a wind-pressure model, a hydrodynamic model, and a depth-damage function to estimate coastal flood hazards from tropical cyclones in Hong Kong, I reveal that the northwestern region of Hong Kong (Yuen Long District) is the most vulnerable to coastal flooding caused by all three typhoons. In addition, the coastlines along the Islands District, Tai Po, Sai Kung, Kowloon City, and Kwai Tsing experience greater inundation depth, wider inundation extent, and longer inundation duration. 11 districts experienced inundation lasting over one hour during the three typhoons, with a hazardous flood depth reaching 1.67 meters. For Typhoon Hato, the effects of extreme high tide and SLR are comparable in contributing to coastal flooding. However, for Typhoon Mangkhut and Typhoon Saola, extreme high tide plays a more critical role in exacerbating flooding. The most severe worst-case scenario is expected to occur when high tide coincides with the high-emission SSP585 scenario in 2100. Under this condition, economic losses are projected to be approximately 1.2–1.5, 1.7–1.9, and 2.0–2.3 times higher than those under the benchmark scenario for the three typhoons. Particularly, residential areas account for the highest risk in Hong Kong when facing coastal flooding.

(2) Most of coastal areas have experienced consecutive heatwaves and extreme sea levels during 1979–2017. For every five heatwaves, there is one following extreme sea level within 7 days during 1979–2017 along the Europe’s coastline. There are significant dependencies between heatwaves and extreme sea levels, and these dependences can increase the occurrence of compound events by threefold. For half of the coastal area, the frequency of such consecutive events increases in response to more heatwaves and extreme sea levels in a changing climate. Hotter heatwaves compared to other heatwaves, are more likely to be followed by extreme sea levels. The anticyclone flows and low surface pressure may be important indicators of compound heatwaves and extreme sea levels. In addition, consecutive HWESL are projected to become more frequent under RCP8.5, increasing the risk of compound heatwaves and extreme sea levels along Europe’s coastlines as the climate warms.

(3) The global coastline experienced a significant increase in the occurrence of concurrent heatwaves and extreme sea levels during the period of 1979–2017. Coastlines in the tropical region are at higher risk for concurrent extremes, as evidenced by both a higher occurrence of such concurrent events and a larger occurrence difference between the two 20-year periods. Furthermore, I find that hotter and more humid heatwaves are more likely to be concurrent with extreme sea levels globally. More intense heatwaves and more intense extreme sea levels may synergistically increase the likelihood of concurrent HWESL events in three regions including SEA, EAF, and PIR. Under the highest emission scenario of SSP585, the global coastline is expected to experience a higher occurrence and a higher likelihood of concurrent HWESL events. Weakening of geopotential height at 500hPa accompanied by the emergence of a surface low-pressure system may serve as a crucial indicator for concurrent HWESL events.

(4) My findings show that approximately one-third of TCs is preceded by a heatwave, forming what I define as H-TC events. These events are primarily concentrated in East Asia, the world’s most active basin for TC genesis. Notably, East Asia also exhibits the shortest average time lag between heatwaves and following TCs. The time lag of H-TC events shows a significant decreasing trend in recent years, marked by an increasing proportion of short-lag events (≤ 3 days) and a declining proportion of longer-lag events (> 3 days). When comparing heatwaves followed by TCs to those that are not, H-TC events tend to be shorter in duration but higher in intensity. This intensification of heatwaves results from TCs supplying heat that reinforces heatwaves over

land in regions such as East Asia and Madagascar, while contributing moisture that exacerbates heatwaves in the Gulf of Mexico-Caribbean and Australia. Importantly, faster TC translation speeds emerge as a critical factor in shortening the safety evacuation window, leaving coastal communities with less time to respond between extreme heat and approaching TCs.

7.2 Future work

In this dissertation, I developed an integrated framework to assess tropical-cyclone-induced coastal flood hazards. Although the framework already accounts for the combined effects of pluvial flooding, storm surge, and drainage interactions, it can be further extended to incorporate fluvial processes into compound coastal flooding modeling. This allows for quantifying the contribution of each factor and examining their complex interplay. Such integration enables a more realistic assessment of compound flooding and the nonlinear interactions among multiple drivers. Considering climate change, the framework can also include rainfall-induced landslides, recognizing that intense precipitation not only amplifies flooding but also triggers slope failures. The extended framework thus provides a comprehensive tool for multi-hazard risk evaluation and climate-resilient planning in coastal regions.

In studying compound heatwaves and extreme sea levels, recent efforts have focused on the influence of large-scale atmospheric variables such as geopotential height, surface pressure, wind fields, and solar radiation divergence. It has been observed that hotter and more humid heatwaves often coincide with extreme sea levels. This linkage is crucial for improving the understanding of coupled atmospheric–oceanic dynamics and for enhancing early warning capabilities. Building on these findings, future work can focus on developing real-time early warning systems for compound-event forecasting. Such systems would integrate high-frequency hydroclimatic data streams and employ rapid data assimilation and predictive modeling to issue timely alerts for the occurrence of consecutive heatwaves, heavy rainfall, and coastal flooding events.

In my study on temporally compounding events involving heatwaves and tropical cyclones, the crucial role of tropical cyclones in transporting heat and moisture has been emphasized. However, despite this important finding, a comprehensive understanding of the physical mechanisms that exacerbate heatwaves remains challenging. Future studies should aim to explore these mechanisms in greater depth. On shorter time scales, this could involve using numerical

weather models such as the Weather Research and Forecasting model (WRF) to simulate representative compound events and clarify the pathways of heat and moisture transport by tropical cyclones. In addition, particle trajectory models can be employed to analyze long-term sequences and trace air-mass movements. Such investigations are essential for advancing our understanding of these complex processes and improving the prediction and management of their impacts.

Finally, future work can conduct in-depth assessments of the socio-economic impacts of compound hydrometeorological events through real-world case studies. In the research on compound heatwaves and tropical cyclones, I have identified that the time lag between these hazards poses a serious threat to evacuation effectiveness, which is one of the most critical strategies for cyclone response. However, most existing studies remain conceptual and have not yet considered multivariate hazards or adopted impact-based methodologies. Future research should therefore move beyond meteorology and hydrology to integrate perspectives from social sciences, economics, and public health. Such interdisciplinary approaches are essential to fully understand how extreme hydrometeorological events threaten societies and to develop more inclusive and effective adaptation and risk management strategies.

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