

IMPERIAL

The Decay of Wind Speed in Tropical Cyclones

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Abstract

The decay of tropical cyclones (TCs), characterized by a weakening of TC wind speed, is a key stage prior to landfall and is therefore essential for risk management in coastal regions. A full description of the decay of global TCs over the ocean using a new modified empirical model (the β model) has been established, which captures the decay feature with time using two characteristic parameters: a scale parameter α (the decay scale) and a shape parameter β (which determines whether the decay rate decelerates or accelerates over time). Global fits indicate that most TCs (about 60%) show accelerating decay ($\beta > 1$) over the ocean and that decay scales are larger at lower latitudes.

Next, the mechanisms behind the decay of a well-developed TC moving to the Equator are investigated using idealized simulations. Under reduced latitude, a deeper inflow layer and strengthened downdrafts in the outer rainbands enhance the entrainment of mid-level dry air into the boundary layer. This causes a decrease in boundary layer θ_e and suppresses the deep convection in the eyewall, leading to TC weakening.

Last but not least, large synthetic TC datasets are generated by simulating the decay of TC wind speed from the point of lifetime maximum intensity (LMI) in a stochastic model (IRIS) for reliable landfall risk assessment. Using this framework,

the increased intensity of North Atlantic hurricanes from 1979 to 2024 is analysed. The model attributes the increasing trend in LMI ($0.08 \text{ m s}^{-1} \text{ yr}^{-1}$) to comparable contributions from rising potential intensity and southward shifts in TC tracks, with little sensitivity to changes in relative intensity to date. The model also predicts a southward shift in landfall ($-0.10^\circ \text{ yr}^{-1}$), which is hard to detect.

Statement of Originality

I declare that this thesis is my own work and that all else is appropriately referenced.

The main body of this thesis have been published in three papers:

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Chapter 1

Introduction

1.1 Background and motivation

Tropical cyclones (TCs), also known as hurricanes in the North Atlantic and typhoons in the Western North Pacific, are warm-cored cyclonic vortices that develop over warm tropical oceans and are characterized by deep convection and an organized near-surface circulation. They are among the most destructive natural hazards, causing substantial loss of life and economic damage through strong winds, storm surge, and heavy rainfall.

Maximum surface wind speed is commonly used to classify TCs into intensity categories based on the Saffir–Simpson hurricane wind scale, providing an efficient estimate of potential wind-related damage. On this scale, TCs are classified from Category 1 ($33\text{--}42\text{ m s}^{-1}$) to Category 5 ($\geq 70\text{ m s}^{-1}$) based on their maximum sustained 1-minute surface wind speed. Categories 3–5 are collectively referred to as major TCs, reflecting their substantially greater destructive potential. Before reaching 33 m s^{-1} , systems are classified as tropical depressions (maximum sustained

winds $< 17 \text{ m s}^{-1}$) or tropical storms ($17\text{--}32 \text{ m s}^{-1}$).

Figure 1.1 shows a schematic diagram of an idealized mature TC. A mature TC consists of several distinguishing features. Its inner-core structure is often close to axisymmetric, with a ring of maximum winds surrounding a relatively calm eye (typically 20–100 km in diameter). The eye is surrounded by deep convective clouds that rise from near the sea surface to the tropopause and slope outward with height, and the strongest winds are located near the eyewall. Outside the eyewall are spiral rainbands with active updrafts and mesoscale downdrafts. A more detailed structure of the outer-core rainbands is shown in Figure 1.2.

The basic structure of a TC can be described as a nearly axisymmetric primary circulation with a secondary circulation superimposed. The primary circulation refers to the dominant swirling flow around the storm center, characterized by strong tangential winds that are in gradient-wind balance above the boundary layer. The secondary circulation is an overturning in–up–out flow, including low-level inflow toward the center, updrafts in the eyewall and rainbands, and upper-level outflow near the top of the troposphere. The location of the updrafts is controlled by boundary-layer frictional convergence, while their strength is largely determined by latent heat release in deep convection.

The decay stage is typically the final stage before a TC makes landfall and can substantially affect landfall intensity. Wang and Toumi (2022b) concludes that TCs decay on average by 25% from lifetime maximum intensity (LMI) to landfall intensity. Understanding the decay from LMI is therefore of great importance for reliable landfall intensity estimates and TC risk assessments. However, despite its importance, the behaviour of TC decay remains poorly understood and has received

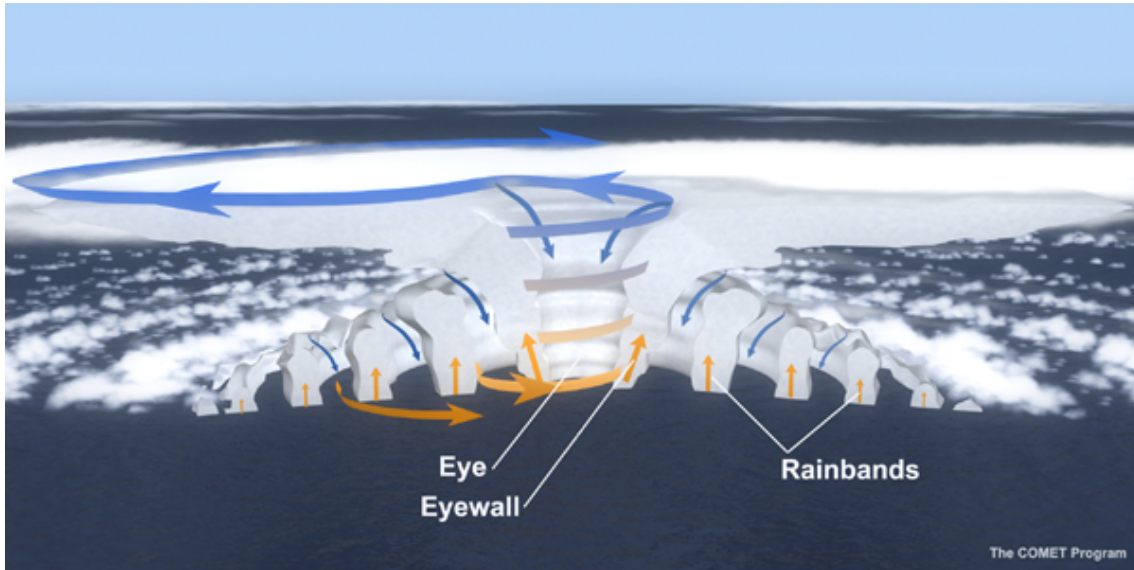


Figure 1.1: Schematic structure of a mature tropical cyclone, showing the eye, eyewall, and rainbands, with low-level inflow, upper-level outflow, and strong convective updrafts in the eyewall and rainbands. From the COMET Program.

relatively limited systematic investigation. The main goal of this thesis is to improve understanding of TC decay and support more effective TC risk assessments in the context of climate change.

1.2 Physics underlying TC intensity decay

1.2.1 Theory

Energetic basis: potential intensity theory

In TC theory, a Carnot engine provides an idealized framework for how a storm converts heat energy from the ocean into kinetic energy of the winds, where the heat input is supplied by surface enthalpy (sensible and latent heat) fluxes from the ocean. It is also assumed that the TC system loses energy through surface friction.

Based on this Carnot-engine analogy, a theoretical model for steady-state hurricanes was proposed (Emanuel, 1986, 1995; Bister and Emanuel, 1998), in which the maximum potential intensity (MPI) that a TC can attain is constrained by the thermodynamic efficiency of the cycle and can be estimated from environmental conditions. From Eq. 21 in Bister and Emanuel (1998), MPI can be expressed as:

$$V_{max}^2 = \frac{C_k}{C_D} \left(\frac{T_s - T_0}{T_0} \right) (h_0^* - h^*), \quad (1.1)$$

where C_k and C_D are the enthalpy and momentum surface exchange coefficients, respectively; T_s is the sea surface temperature (SST); T_0 is the mean outflow temperature; h_0^* is the saturation moist static energy at the sea surface; and h^* is the moist static energy of the free troposphere. $\frac{T_s - T_0}{T_0}$ is the efficiency term, which depends mainly on the outflow temperature: the lower the outflow temperature, the greater the thermodynamic efficiency. $h_0^* - h^*$ is the disequilibrium term, which depends primarily on SST and relative humidity (RH) in the boundary layer.

Based on (1.1), a functional form of MPI can be written as

$$V_{max} = V_{max}(T_s, T_0, RH). \quad (1.2)$$

Equation (1.2) shows that according to the MPI theory, the TC intensity is a function of SST, outflow temperature, and relative humidity in the boundary layer. The boundary layer is therefore a key component of MPI theory, serving as the energy reservoir that supplies energy to the system. A moist boundary layer is required to maintain the deep convection and thus TC intensity.

A key principle in treating a TC as a thermal heat engine lies in the application

of thermal maximum efficiency, η , where

$$\eta = \frac{T_s - T_0}{T_0}. \quad (1.3)$$

This efficiency depends on the temperature difference between the warm ocean surface and the cold outflow layer. It reflects how efficient the storm is at converting potential energy from the sea surface into kinetic energy. The thermodynamic efficiency is therefore crucial in determining the relative intensity of a TC with respect to its MPI.

Observational comparisons show that MPI theory provides a reasonable estimate of the intensity of steady-state hurricanes in a given environment. However, exceptions exist in both numerical simulations and observations. A notable example is Hurricane Isabel (2002), in which the TC intensity substantially exceeded the MPI limit based on dropsonde data.

The MPI theory also offers a framework for understanding changes in TC intensity from an energetic perspective. In steady state, a TC near LMI is close to a balance between surface enthalpy input and frictional dissipation at the surface (Emanuel, 1997). Thus, subsequent unfavourable environmental perturbations that reduce power generation or increase surface friction will disrupt this balance and lead to intensity decay dominated by surface friction (Wang and Toumi, 2022c).

The role of deep convection

Deep convection in the eyewall and rainbands plays an important role in maintaining TC intensity. It supports strong updrafts that lift warm, moist air and release latent heat through condensation. This latent heat release helps lower the central

pressure and maintain the storm's circulation. Convection also contributes to a deeper secondary circulation, with weak inflow through much of the troposphere. Ooyama (1982) argues that buoyant energy release is necessary because it enables mid-tropospheric entrainment in the cloud bands and therefore causes deep inflow, which acts to cancel the outflow component of the frictionally forced circulation and import angular momentum to spin up the vortex.

Downdrafts

Downdrafts act to partially oppose the updrafts. Barnes et al. (1983) and Powell (1990a,b) indicate that convectively active rainbands can tap the energy-rich inflow and replace it with low- θ_e downdraft air. The convective downdrafts associated with the convective core (bold downward arrows in Figure 1.2) are responsible for the decrease of θ_e in the boundary layer (Barnes et al., 1983). The recovery of θ_e depends on enthalpy fluxes from the ocean. Without such surface fluxes, low-level θ_e air would enter the eyewall convection and suppress deep convection, leading to the weakening of TC. Additionally, Powell (1990a) argues that entrainment of dry air above the boundary layer could reduce the recovery of θ_e .

TC dynamics

Apart from the thermodynamics in TCs that are associated with the relations between heat and other forms of energy, the balanced and unbalanced dynamics that describe the forces involved in the movement of TC air flow are also important for understanding storm structure and intensity change.

The gradient wind balance is useful in describing the balance in and above the boundary layer in TCs. It describes a balance in which the inward pressure gradient

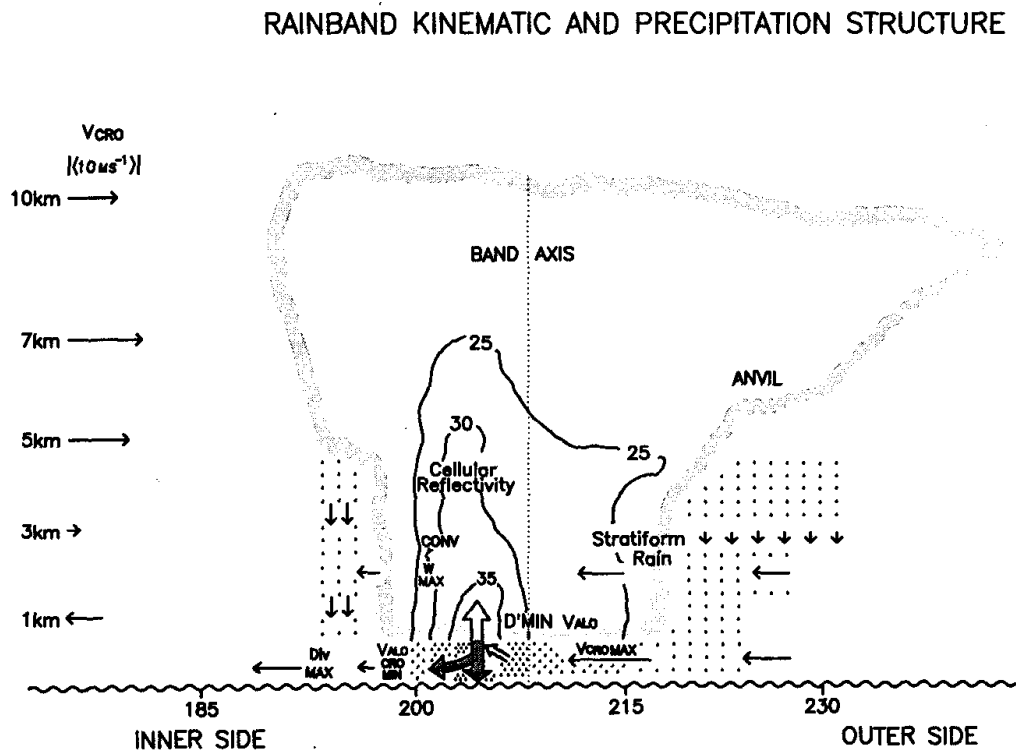


Figure 1.2: Schematic cross section of an example rainband from Hurricane Earl (1986). The bold vertical arrows indicate convective core updrafts and downdrafts, small downward arrows indicate mesoscale subsidence regions, and larger downward arrows indicate penetrative downdrafts originating in the inner anvil region. From Powell (1990b).

force is balanced by the combined effects of the Coriolis force and the outward centrifugal force, allowing air to circulate around the storm center in curved flow. The gradient wind balance is considered a fair assumption in TCs and is a common constraint of TC dynamics, particularly above the boundary layer.

García-Franco and Schwendike (2020) examined the degree of gradient wind balance using dropsonde composites. Their analysis confirms that

- the flow above the boundary layer is approximately balanced, while the supergradient winds occur near the radius of maximum wind (RMW) in the upper boundary layer;
- the degree of gradient wind balance does not differ significantly among intensifying, steady-state, and weakening storms;
- the supergradient flow is more common in strong storms than in weak storms;
- storms with a peaked wind profile are more likely to exhibit supergradient winds than those with a flat wind profile, consistent with previous case studies (Kepert, 2006a,b; Schwendike and Kepert, 2008).

Theoretical studies about boundary layer dynamics by Kepert (2001) and Kepert and Wang (2001) link the supergradient winds to the inward advection of angular momentum, thereby linking the presence of supergradient winds to the radial distribution of angular momentum.

The existence of supergradient winds in the upper boundary layer has been widely confirmed in dropsonde observations (Kepert, 2006a,b). It is also argued that supergradient winds are an essential component of TC intensification, which allows air parcels within the boundary layer to gain enough absolute angular momentum

(AAM) through rapid reduction of radial distance and thus to offset the AAM loss to the surface friction (Smith et al., 2009). In contrast, if the boundary layer does not gain enough AAM to offset frictional losses, the TC is more likely to decay (Montgomery et al., 2001a).

1.2.2 Environmental factors causing decay

After a TC reaches LMI, hostile environmental conditions can often initiate decay. These conditions can reduce the energy supply, suppress convection, and lead to weakening or rapid weakening. Key environmental factors contributing to TC weakening include landfall, low SST, ocean cooling associated with slow translation speed, strong environmental vertical wind shear, entrainment of dry air, and reduced water vapour transport (Fei et al., 2020a; Ma et al., 2019; Qian and Zhang, 2013; Walker et al., 2014a; Wood and Ritchie, 2015; Zhou et al., 2022; Chang et al., 2023a; Liang et al., 2016, 2018; Park et al., 2019; Qian and Zhang, 2013; Colomb et al., 2019; Ma, 2020).

- Landfall

Landfall is one of the most significant causes of TC intensity decay, through reduced surface moisture fluxes and increased frictional dissipation over rough land. The response of TCs to surface drying and roughness was tested in simplified numerical modelling by Chen and Chavas (2020). Surface drying stabilizes the eyewall and weakens the overturning circulation, leading to a gradual decay of the wind field that is largely confined to the inner core. In contrast, surface roughening induces rapid weakening of low-level winds across the storm, with a transient enhancement of the overturning circulation; thereafter the storm gradually decays. In addition, total

precipitation was found to temporarily increase with roughening but to decrease uniformly with drying during this decay period.

- Ocean cooling

Ocean cooling associated with slow translation speed is an important factor in rapid TC weakening. Chang et al. (2023b) investigated the rapid weakening of Typhoon Trami (2018) by examining SST cooling in an air–sea coupled simulation. They found that strong SST cooling induced a dramatic decrease in surface enthalpy flux, which led to the collapse of convective clouds and convective bursts in the inner core, accompanied by stabilization of the boundary layer. The suppressed convection further reduced diabatic heating and contributed to storm weakening. Similarly, Walker et al. (2014b) concluded that intense SST cooling associated with slow translation speed was the main cause of the rapid weakening of Hurricane Kenneth (2005). Park et al. (2019) also found that the slowly moving Typhoon Soulik (2018) decayed rapidly by losing energy to the ocean while remaining over a cold wake. These results emphasize the importance of negative air–sea interaction for TC weakening.

- Vertical wind shear

Vertical wind shear (VWS), which is conventionally defined as the difference in wind speed or direction between 850 and 200 hPa, is one of the most influential environmental factors contributing to TC weakening. Two main approaches have been proposed to explain how vertical wind shear influences TC intensity. The first is a dynamical mechanism proposed by Tang and Emanuel (2010), known as ventilation of the mid-level warm core. It describes how the inward transport of low-entropy air

across the eyewall reduces the entropy in the eye region, thereby constraining the TC intensity.

The second approach is thermodynamic, described by Riemer et al. (2010), which views intense TCs in shear as a Carnot-cycle heat engine. They argue that the shear-induced downward transport of low- θ_e air can significantly decrease θ_e in the inflow layer and reduce θ_e near the core as air parcels flow into eyewall updrafts. This process can disrupt the Carnot-cycle heat engine and decrease TC intensity. Downdrafts in TCs under vertical wind shear have been linked to convective asymmetry outside the eyewall (out to about 150 km). These downdrafts are on the vortex scale and form through evaporative cooling as precipitation falls from sloping updrafts into unsaturated air below.

Alland et al. (2021a,b) examined how midlevel dry air and vertical wind shear modulate TC development via both downdraft and radial ventilation. The downdraft ventilation associated with the vortex tilt reduces the vertical mass flux by reducing the areal extent of strong upward motions, and thus hinders the TC development. Two types of radial ventilation, one between heights 0-3 km and another between 5-9 km, have been shown to transport low- θ_e air inward, which suppresses convection and hinders the TC development.

• TC structure

The response of TCs to external forcing largely depends on their internal structure, particularly their inertial stability. Inertial stability measures a TC's resistance to external influences. A storm that is intense, or whose strong winds extend farther from its center (i.e., a larger TC), tends to be more resilient to adverse environmental forcing (Merrill, 1984). DeMaria (1996a) concluded that high-latitude, large, and

intense TCs tend to be more resilient to the adverse effects of vertical wind shear than low-latitude, small, and weak storms. However, inertial stability decreases dramatically at upper levels, making TCs more sensitive to environmental forcing in the upper troposphere. In addition, inertial stability cannot protect a TC from adverse forcing from below, such as ocean cooling and surface roughening or drying.

1.2.3 Spin-down theory

The well-known boundary-layer spin-down describes the decay of a vortex in a rotating flow due to frictional effects in the boundary layer (Montgomery et al., 2001a). This process can be understood as follows. Above the boundary layer, the circulation is approximately in gradient-wind balance, whereas near the surface, friction reduces the wind speed. This reduction weakens the Coriolis and centrifugal forces while the pressure-gradient force remains largely unchanged, leading to radial inflow toward the center and compensating divergent flow above the boundary layer. By conservation of angular momentum, the divergent flow spins more slowly as it moves to larger radii, and the tangential wind of the vortex gradually decreases. Spin-down theory therefore explains TC intensity decay in the absence of strong diabatic heating, such as when a TC moves over land or cooler ocean surfaces, where decay is largely controlled by friction.

1.3 Decay models

Estimating the evolution of TC intensity decay with time using simple parametric models is desirable for both theoretical understanding and practical applications. Several decay models have been developed to describe the temporal decay of TC

intensity based on empirical relationships or physical laws.

1.3.1 Exponential model

Theoretical studies by Greenspan and Howard (1963) and Eliassen (1971a) have shown that, for a laminar boundary layer, the temporal decay of tangential winds is exponential. Observations also confirm that the post-landfall wind-speed decay rate is approximately proportional to wind speed. Based on these assumptions, a widely used empirical exponential decay model (EXP) was proposed for post-landfall decay by Kaplan and DeMaria (1995a):

$$\frac{dv}{dt} = -\alpha v, \quad (1.4)$$

with the solution of

$$v(t) = v_0 e^{-\alpha t}, \quad (1.5)$$

where v is the maximum surface wind, t is the time of decay, v_0 is the maximum surface wind at $t = 0$, and α is the decay constant.

In the EXP model, the decay rate ($\frac{dv}{dt}$) is proportional to wind speed, with a linear rate coefficient $-\alpha$. However, this exponential decay of tangential winds is exclusively applicable in a laminar boundary layer (i.e., in the absence of turbulent mixing). Therefore, the assumption of simple exponential decay is questionable for TC environments with shear-driven turbulent flow (Montgomery et al., 2001b).

1.3.2 Algebraic model

An algebraic temporal decay (ALG) is then proposed for the case of a turbulent boundary layer (Eliassen, 1971a; Eliassen and Lystad, 1977a). The ALG model is based on a quadratic form of the turbulent drag

$$\frac{dv}{dt} = -\kappa v^2, \quad (1.6)$$

where κ is the decay parameter defined as

$$\kappa = \frac{C_D \chi}{H}, \quad (1.7)$$

where C_D is the surface drag coefficient, χ is the ratio of tangential winds at the surface to the top of the boundary layer, and H is the effective height of the vortex with regard to the depth over which the friction acts to spin down the vortex. The solution to Eq.1.6 is

$$\frac{1}{v(t)} = \frac{1}{v_0} + \kappa t. \quad (1.8)$$

The ALG model has been validated both for the decay of hurricane-strength vortices over the open ocean (Montgomery et al., 2001b) and for the post-landfall decay of TCs (Phillipson and Toumi, 2021).

In contrast to the EXP model, where decay is governed by a linear drag ($-\alpha v$), the ALG model describes that changes in TC intensity during decay are dominated by the quadratic form of turbulent drag ($-\kappa v^2$). Despite their different formulations, both the EXP and ALG models reflect the same principle: the decay rate decreases as intensity decreases.

1.3.3 Logistic model

Both the EXP and ALG models are fundamentally based on the spin-down theory, in which decay is primarily controlled by surface friction. A further elaboration, the logistic model (LGT), is then proposed for the decay before landfall by considering the intensity decay as the residual between energy production by heat fluxes and frictional dissipation from surface drag (Wang and Toumi, 2022b). The LGT model can be written as

$$\frac{\partial v}{\partial t} = -\kappa v^2 + \kappa b v, \quad (1.9)$$

The solution to the LGT model is

$$\frac{1}{v(t)} = \frac{1}{v_0} e^{-\kappa b t} - \frac{1}{b} (e^{-\kappa b t} - 1), \quad (1.10)$$

where $\kappa = \frac{C_D}{H}$ is a constant decay coefficient, and b is a non-zero constant background wind speed towards which v_{max} decays. The term $-\kappa v^2$ represents frictional dissipation, while $\kappa b v$ represents energy production. By definition, frictional dissipation should exceed energy production during decay. In particular, when the energy production is negligible ($\kappa b v \ll |-\kappa v^2|$), intensity decay is dominated by frictional dissipation, and the LGT model in Eq. 1.9 reduces to the ALG model in Eq. 1.6.

In summary, the existing decay models suggest that the decay rate decreases as intensity decreases, implying a decay that slows with time and is primarily driven by surface drag that is proportional to TC intensity.

1.4 Synthetic TC models

TCs have great destructive potential and account for the highest losses of all natural disasters over time. Typhoon Haiyan (2013), also known as Yolanda in the Philippines, was one of the strongest TCs ever recorded at landfall. It reached Category 5 intensity, with estimated 1-minute sustained winds of about 87.5 m s^{-1} , before striking the central Philippines on 8 November 2013. Haiyan caused catastrophic storm surge, widespread destruction, and significant loss of life, leading to thousands of fatalities, large-scale displacement, and severe damage to infrastructure and livelihoods. Economic losses reached tens of billions of US dollars (Lagmay et al., 2015). Haiyan highlights the severe societal consequences of extreme TCs, emphasizing the need for reliable TC risk assessments to support mitigation efforts.

However, assessing TC risk remains challenging. This is firstly because of the infrequency of landfalling events. There are about 90 (± 10) TCs form each year globally (Emanuel, 2008), of which only 16 TCs on average make landfall with intensity greater than 33 m s^{-1} (Weinkle et al., 2012). Moreover, the number of storms impacting certain areas is even more rare. The period of reliable observations is also short with the application of satellite data from 1980 onwards. The infrequency and short period of reliable observations mean that for many coastal regions, there may not even be a single landfalling TC event in available datasets, especially for extreme TCs with long return periods. Reliable TC risk assessments and corresponding risk management have thus been difficult due to the lack of information about landfalling TCs.

To overcome the data scarcity for infrequent TCs, one popular approach is to

generate a large number of synthetic TCs using synthetic models. In this approach, TC tracks and intensities are resampled and modelled from historical tracks and meteorological datasets from reanalysis data or climate models. The generated synthetic TCs share similar characteristics with the underlying datasets. It can be repeated for a large number of years, thereby creating a long enough synthetic TC dataset for reliable TC risk assessments.

This synthetic approach has been widely explored over the past decades, including:

- Purely statistical models (Vickery et al., 2000; James and Mason, 2005)
- A coupled statistical–dynamical TC downscaling model (Emanuel et al., 2006, 2008)
- The Columbia Hazard model (CHAZ) (Lee et al., 2018)
- The Princeton environment-dependent probabilistic tropical cyclone model (PepC) (Jing and Lin, 2020)
- The Synthetic Tropical cyclOne geneRation Model (STORM) (Bloemendaal et al., 2020)
- A physics-based downscaling model with intensity-dependent steering (Lin et al., 2023b)
- The ImpeRIal College Storm Model (IRIS) (Sparks and Toumi, 2024)

The methodologies used in these synthetic models are broadly similar, with major differences in how individual components are represented. While all of the synthetic models listed above simulate the full life cycle (track and intensity evolution), IRIS is

a novel stochastic TC model that focuses on the post-LMI decay process. The design of IRIS reduces biases associated with genesis and intensification by focusing on the decay stage before landfall (Sparks and Toumi, 2024), recognizing that landfall information can be effectively captured from LMI and the subsequent decay process (Wang and Toumi, 2022b). IRIS has been applied to climate-change attribution of Typhoon Haiyan (Sparks and Toumi, 2025a), current hurricane risk assessments (Toumi and Sparks, 2025), and future projections of U.S. landfalling hurricanes (Sparks and Toumi, 2025b).

IRIS relies critically on how TC decay is represented. This motivates integrating the modified empirical decay model developed in this study into IRIS, which is undertaken in Chapter 5 to assess simulated landfall intensities.

1.5 Research challenges

Previous sections establish the importance of TC decay for TC risk management and provide a systematic overview of TC decay, including the underlying physical mechanisms, existing parametric decay models, potential factors driving decay, and synthetic TC models, particularly IRIS, which focuses on the post-LMI decay process. Several research challenges remain in the following areas.

Existing decay models suggest that the decay rate decreases as intensity decreases, implying a decay that slows with time and is primarily driven by surface drag that scales with TC intensity. While the post-landfall decay is dominated by surface drag that is proportional to TC intensity, it is questionable whether these friction-dominated decay models can fully account for temporal decay over the ocean.

Factors affecting TC decay, including storm characteristics and environmental

conditions, have been widely investigated in statistical and numerical studies, e.g., Fei et al. (2020b) and Chang et al. (2023b). However, although the Coriolis effect is a fundamental factor influencing TC formation, intensification, and structure, its role in TC decay remains unclear.

The infrequency of landfalling TCs and the short period of reliable observations introduce substantial uncertainty in attribution studies and TC risk assessments under climate change. The stochastic model IRIS has been shown to have great potential in supporting reliable TC risk assessments (Sparks and Toumi, 2025b). In particular, the IRIS model relies critically on the representation of TC decay, making it important to test the sensitivity of simulated landfall properties to different decay models. IRIS also provides an opportunity to investigate the drivers of increased intensity of North Atlantic hurricanes.

1.6 Main goal and research questions

The main goal of this thesis is to advance understanding of TC decay and to support effective TC risk management at landfall. This research goal is addressed through the following research questions:

1. How can over-ocean decay be represented using an empirical framework, and how do environmental conditions affect TC decay?
2. What is the role of the Coriolis effect in the TC decay process?
3. How sensitive is IRIS to different decay models, and how can it be used to attribute the causes of increased North Atlantic hurricane intensity?

1.7 Thesis layout

This thesis is structured as follows. Chapter 2 describes the datasets used, the numerical simulation model (WRF), the idealized model set-up, and the stochastic TC wind model (IRIS). Chapter 3 introduces a new modified decay model with two free parameters. The dependence of decay parameters on potential factors at the global scale and across basins is also investigated. Chapter 4 examines the impact of the Coriolis parameter (f) on a well-developed TC vortex in idealized simulations by reducing f from 20°N to 0, both gradually and abruptly. The underlying mechanisms driving the resulting decay are explored. Chapter 5 focuses on simulating decay from the point of LMI in the stochastic TC wind model (IRIS) and attributing the increased intensity of North Atlantic hurricanes from 1979 to 2024. Chapter 6 summarizes the key findings and implications of the thesis.

Chapter 2

Data and Models

2.1 Data

2.1.1 The best-track data

Datasets consisting of best estimates of storm position and intensity at 6-hourly intervals are termed best-track data. They are produced through postseason reanalysis of a storm's position and intensity using all available information, such as ship reports, satellite observations, and weather-station data.

Different best-track datasets are compiled and archived by World Meteorological Organization (WMO) Regional Specialized Meteorological Centers (RSMCs), Tropical Cyclone Warning Centres (TCWCs), and other national agencies. The common sources of best track data are summarized in Knapp et al. (2010) as follows:

- RSMC Miami – NOAA's National Hurricane Center (NHC)
- RSMC Honolulu – U.S. National Oceanic and Atmospheric Administration (NOAA) Central Pacific Hurricane Center

- RSMC Nadi – Fiji Meteorological Service
- RSMC Tokyo – Japan Meteorological Agency
- RSMC New Delhi – India Meteorological Department
- RSMC La Réunion – Météo-France
- TCWC Perth, Darwin, Brisbane – Australian Bureau of Meteorology
- TCWC Wellington – Meteorological Service of New Zealand, Ltd.
- China Meteorological Administration’s Shanghai Typhoon Institute (CMA/STI)
- Hong Kong Observatory (HKO)
- US Department of Defense Joint Typhoon Warning Center (JTWC)

. To create a complete global best-track dataset, different best-track datasets are collected and archived in the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010). IBTrACS provides a comprehensive and unified record of historical TC activity by compiling best-track data from multiple meteorological agencies worldwide.

Different meteorological agencies use different averaging periods when reporting the maximum sustained wind speed. U.S. agencies, including NHC and JTWC, use a 1-minute averaging period. The China Meteorological Administration (CMA) uses a 2-minute averaging period, while the India Meteorological Department (IMD) uses a 3-minute averaging period. A 10-minute averaging period is adopted by several other agencies, including the Japan Meteorological Agency (JMA), the Australian Bureau

of Meteorology (BoM), Météo-France La Réunion, the Fiji Meteorological Service in Nadi, MetService in Wellington (New Zealand), the Hong Kong Observatory (HKO), and the Korea Meteorological Administration (KMA). The wind speeds based on shorter averaging periods are generally higher than those based on longer periods for the same storm.

For consistency, the variables used in this study are provided by the US agencies, such as NHC and JTWC. The NHC and JTWC are two well-known centres. The NHC provides hurricane database for the Atlantic (1851-present) and North Central Pacific (1949-present), known as HURDAT2 (Landsea and Franklin, 2013; Landsea et al., 2015). The JTWC is responsible for the warnings of TCs over the Western North Pacific, North Indian Ocean, and South Hemisphere from 1945 to the present.

While no validation of best-track data is provided—as the best-track data are supposed to be the best estimates using all available storm information—uncertainties from the observational techniques and algorithms can still be added to TC position, count, and intensity (Gahtan et al., 2024). For example, TC intensity estimates depend highly on the available observations and methods, both of which have changed over time and differ among agencies. Older data, particularly before the satellite era (1980), are less reliable due to sparse observations and potential under-reporting of storms. Differences in wind averaging periods, analysis techniques, and estimation methods among contributing agencies also introduce inconsistencies in intensity measurements, necessitating caution when comparing storms across basins or examining long-term trends.

2.1.2 ADT-HURSAT

While best-track data provide the most complete record of TCs, they have issues with temporal consistency. To address heterogeneities in best-track data, a satellite-based TC intensity dataset was constructed by applying the Advanced Dvorak Technique (ADT) to a globally homogenized record of geostationary satellite imagery (the Hurricane Satellite record, HURSAT), known as ADT-HURSAT (Kossin et al., 2013, 2020). It covers 4,180 global TCs over the period 1978–2017. The ADT-HURSAT record is homogeneous in time and across regions. It provides estimates of TC center location and surface wind speed every 6 hours along each storm track.

ADT-HURSAT is not designed for accurate TC intensity measurements, as it relies on relatively coarse-resolution (8 km) satellite data. In fact, the ADT-HURSAT is a record that sacrifices some measure of absolute accuracy for homogeneity, which allows more consistent estimates of TC intensity (Kossin et al., 2020).

2.1.3 SHIPS dataset

The Statistical Hurricane Intensity Prediction Scheme (SHIPS) aims to provide statistical forecasts of TC intensity change. The scheme is designed to support operational forecasting using statistical-dynamical model combined with key environmental and storm-related factors that influence intensity evolution, including rapid intensification and decay (DeMaria and Kaplan, 1999; DeMaria et al., 2005).

Closely associated with the development of SHIPS, the SHIPS predictor file provides a comprehensive set of environmental and storm-related variables used for statistical intensity forecasting. The environmental factors in the SHIPS predictor

file are derived from atmospheric forecast analyses. These factors include SST, vertical wind shear, relative humidity, and ocean heat content. The storm-related metrics include latitude, longitude, and LMI. The SHIPS predictor file provides environmental and storm-related variables for global TCs. The dataset covers storms from 1982 to the present, with predictors available at 6-hourly intervals along each storm track (DeMaria et al., 2023).

In this study, the SHIPS predictor file was used to extract the environmental conditions corresponding to each decay event, enabling the investigation of potential relationships between environmental factors and decay parameters.

2.2 The Weather Research and Forecasting Model

2.2.1 Model overview

The Weather Research and Forecasting Model (WRF) is used in this study. WRF is a collaborative effort primarily developed by the National Center for Atmospheric Research (NCAR) and the National Centres for Environmental Prediction (NCEP). It is a sophisticated numerical weather prediction system designed to serve both atmospheric research and operational forecasting needs.

WRF supports multiple nested grids, allowing high-resolution simulations (even down to hundreds of meters) within larger-scale domains. It can be run at very fine horizontal resolutions (e.g., < 1 km), capturing small-scale phenomena such as convection, mountain-induced flows, and TC structure. This makes it particularly useful for studying mesoscale weather systems and extreme events, such as TCs.

The WRF model provides two main dynamical cores, i.e., ARW (Advanced

Research WRF) widely used in research applications and NMM (Non-hydrostatic Mesoscale Model) primarily used for operational forecasting. The ARW core is based on a fully compressible, non-hydrostatic Euler equation system. The non-hydrostatic nature and high-order numerical accuracy of the ARW core make it particularly suitable for TC studies. The ARW model features ARW dynamics solver together with other compatible components to produce a simulation, including physics schemes, numerics/dynamics options, initialization routines, and a data assimilation package.

A complete TC simulation in WRF requires an initialization setup for the first-guess field and boundary conditions. Specific physical parameterization schemes are also needed for simulating certain physical processes such as radiation, microphysics, cumulus convection, surface-atmosphere exchange, and boundary layer turbulence. The idealized model set-up and the selected parameterization schemes are described in the following section.

2.2.2 Idealized model set-up

The WRF Model (version 4.2.2) (Skamarock et al., 2019) is used in Chapter 4 to simulate TCs on an idealized aqua planet with a full-physics parameterization setup. Two nested square domains are used. The side of the outer domain is 5400 km (450 $\times$ 450 grid cells, 12 km grid spacing). The inner domain has a side length of 1800 km (450 $\times$ 450 grid cells, 4 km grid spacing). The model consists of 41 layers in the vertical from $\sigma = 0$ to $\sigma = 1$ with 8 levels under 2 km and 18 levels under 5 km.

A full suite of physics schemes is used and includes the WRF single-moment 6-class microphysics (WSM6) scheme (Hong and Lim, 2006), the Rapid Radiative Transfer Model for general circulation models (RRTMG) scheme (Iacono et al., 2008)

for shortwave and longwave radiation, the Yonsei University (YSU) scheme (Hong et al., 2006) for planetary boundary layer processes, the revised MM5 scheme for surface-layer physics (Fairall et al., 2003; Jiménez et al., 2012), and the New Tiedtke scheme (Zhang and Wang, 2017) for cumulus parameterization in the outer domain.

The SST is fixed at 27°C . The initial environmental condition is specified with the moist tropical soundings from Dunion (2011). All the simulations are performed in an idealised environment with no environmental flow or shear imposed.

The simulations are also initialized with an axisymmetric vortex with a tangential velocity ($v(r, z, 0)$) following Rotunno and Emanuel (1987):

$$v(r, z, 0) = \frac{z_* - z}{z_*} \left\langle \left\{ v_m^2 \left(\frac{r}{r_m} \right)^2 \left[\left(\frac{2r_m}{r + r_m} \right)^3 - \left(\frac{2r_m}{r_0 + r_m} \right)^3 \right] + \frac{f^2 r^2}{4} \right\}^{1/2} - \frac{fr}{2} \right\rangle,$$

where r_0 is the outer radius of the vortex beyond which $v = 0$, v_m the maximum wind, r_m the radius of maximum wind. The intensity decays linearly with height, so that $v = 0$ at $z = z_*$. We also let $v = 0$ for $z > z_*$ and set z_* as 20 km. We choose $r_0 = 412.5$ km, $r_m = 82.5$ km, and $v_m = 15 \text{ m s}^{-1}$.

2.3 Overview of the IRIS model

The ImperIal College Storm model (IRIS) is employed in Chapter 5 to attribute the recent increase in North Atlantic hurricane intensity. IRIS is a synthetic TC model designed to simulate the decay process from the point of LMI (i.e., post-LMI decay) (Sparks and Toumi, 2024). It is a stochastic TC wind-speed model featuring parametric formulations and stochastic parameters, where parameters are drawn from probability distributions fitted to observations. The key elements of the IRIS

model consist of a basin-count model, a track model, an LMI model, and an algebraic decay model. Using historical observed TC data (including LMI, counts, and tracks), the goal of IRIS is to generate synthetic wind and size information of decay, thereby estimating potential damage at landfall across global coastal regions.

The synthetic tracks are generated by perturbing the parent track in space through the addition of small random deviations. Specifically,

$$\text{synthetic longitude} = \text{original longitude} + \text{random deviation}, \quad (2.1)$$

$$\text{synthetic latitude} = \text{original latitude} + \text{random deviation}. \quad (2.2)$$

The random deviation is drawn from a normal distribution,

$$\text{dev} \sim \mathcal{N}(0, \sigma^2), \quad (2.3)$$

where $\sigma = 1$.

A constant deviation is applied at all time steps, resulting in a uniform spatial shift of the entire track. Consequently, the shape of the track is preserved. In other words, each synthetic track is a spatially shifted version of the original, with a slightly displaced starting point but an otherwise identical trajectory. An example of track perturbations in IRIS is shown in Figure 2.1.

A schematic flow chart of creating a synthetic year of TC events in IRIS is given in Figure 2.2:

- The annual basin count is drawn from a Poisson distribution, which controls how many synthetic TC events are simulated for each year.

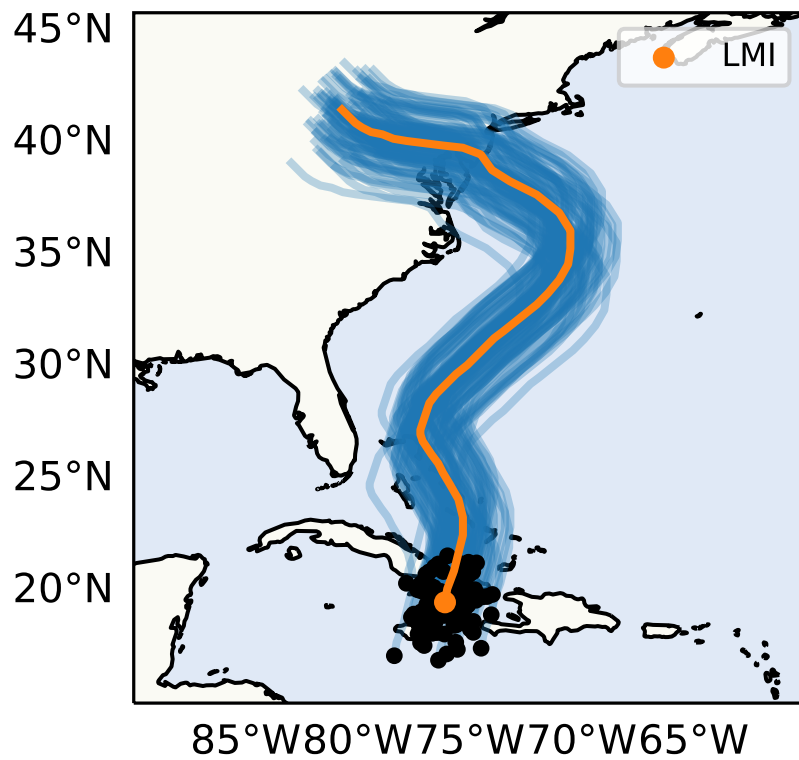


Figure 2.1: Track perturbations for Hurricane Sandy (2012): the original track (orange) and 100 simulated post-LMI tracks (blue). The orange dot marks the original LMI position, and the black dots show the LMI positions of the perturbed tracks.

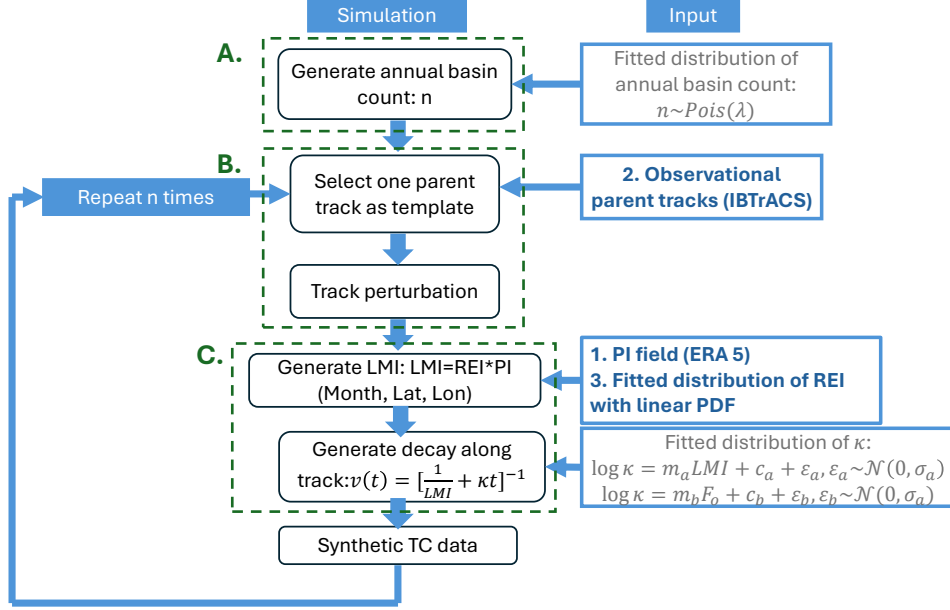


Figure 2.2: Schematic flow chart of the IRIS simulation for each year's synthetic TC data, with essential inputs and three main components: annual basin count, tracks, and wind speed.

- The track is simulated by perturbing the observational parent track in space.
- The LMI is physically constrained by the MPI (Emanuel, 1987), with a scaling parameter REI. MPI acts as a physical constraint on LMI through thermodynamic state, which is calculated from the SST and vertical profiles of temperature and humidity using ERA5. REI is drawn from the fitted linear PDF based on the observed REI distribution.
- The physically informed algebraic decay model (Eq. 1.8) is used to characterize the decay process of TC, and the distribution of decay parameter is fitted separately over the ocean and over land, with dependence on LMI and ocean fraction, respectively.

The key inputs to the IRIS model include the historical parent tracks from

observed best-track data, MPI fields derived from ERA5, and parameters randomly drawn from fitted distributions. Simulations are run using the Monte Carlo method with stochastically sampled inputs, such that every simulated year is independent from each other. The detailed descriptions of data preparation, parameter fitting, and simulation procedures are provided in Sparks and Toumi (2024) and Sparks and Toumi (2025b).

Chapter 3

A Modified Empirical Decay Model of TC Wind Speed Over the Ocean

3.1 Introduction

While post-landfall decay is well understood as a process driven by frictional dissipation and a lack of energy supply, the decay stage over the ocean remains unclear. Yet this phase can significantly affect subsequent landfall intensity, making it essential for effective TC risk assessments.

This chapter presents a modified exponential model (the β model) describing the decay of TC wind speed over the ocean. Building on the widely used exponential decay model by Kaplan and DeMaria (1995b), the β model is developed by introducing an additional shape parameter as a time exponent to better represent the temporal decay over the ocean. The analysis further examines the dependence of decay parameters on potential environmental and storm-related factors, providing physical context for their variability. Finally, regional variability in the estimated decay characteristics is

investigated to assess the extent to which TC decay behaviour differs across ocean basins. Together, these results aim to improve the empirical representation of TC wind decay and its applicability to regional and global TC risk assessments.

3.2 Data and Methods

3.2.1 Data and preprocessing

Global TC data are analysed in this study. Time series of TC data, including v_{max} , TC position (latitude and longitude), TC inner-core size (radius of maximum wind, RMW), and TC outer-core size (radius of 17 m s^{-1} wind, R17) are extracted from the IBTrACS dataset (Knapp et al., 2010). Here we use the global TC data collected by the US agencies, such as NOAA and JTWC. The US agencies use 1-min mean sustained wind as TC intensity. The Coriolis parameter and translation velocity are calculated based on the TC position. We use data at standard 6-hour intervals (00, 06, 12, 18 UTC) from the period 2001 to 2020 for both datasets. The RMW has been available since 2001.

Corresponding environmental conditions, including MPI and vertical wind shear (VWS), are extracted from the SHIPS (Statistical Hurricane Intensity Prediction Scheme) dataset (DeMaria and Kaplan, 1999; DeMaria et al., 2005). The VWS is defined as the wind difference between the 200-hPa wind and 850-hPa wind within the area between 200 and 800 km annulus around the TC centre.

Additional constraints are applied to minimize uncertainties in modelling and analysing the decay:

1. TCs from the South Atlantic are excluded.

2. Only the TCs with the LMI at least of Category 1 (CAT 1, $33 \text{ m s}^{-1} \leq v_{max} < 42 \text{ m s}^{-1}$) based on the Saffir-Simpson Hurricane Wind Scale (Simpson and Saffir, 1974) are considered.
3. Only the TCs with a decay stage lasting at least 24 hours over the ocean are considered to ensure sufficient data for analysing the temporal decay.
4. Only the TCs that have the entire decay period fully within the latitude range of 40°N to 40°S are retained.
5. Only TCs with the final reported intensity over water at least of tropical storm strength (17 m s^{-1}) are kept.
6. For each case, no landfall is permitted for each point within the next 3 hours during the decay period, following the definition of landfall in IBTrACS. The distance to land from the current position is calculated based on the TC centre.

Both landfall and non-landfall TCs are included in this study. After the data filtering, there are 551 cases left for global TCs from 2001 to 2020.

3.2.2 Definition of decay over the ocean

In this study, the decay of TC intensity over the ocean is defined as the period during which the cyclone undergoes a sustained decrease in maximum sustained wind speed (v_{max}). Practically, the decay stage is defined here as the period from the last recorded LMI to the last reported value over the ocean.

While some TCs may reach their peak intensity multiple times or maintain it for an extended period before beginning to decay, the last recorded LMI marks the last

peak intensity of a TC before it enters the decay phase. The last recorded LMI also sets the initial intensity (v_0) at which decay begins, with the timing of this point referred to as the initial time. The environmental conditions at this initial time are then regarded as the initial conditions for decay.

3.2.3 Model development

The widely used empirical exponential decay model proposed by Kaplan and DeMaria (1995b) is recalled here:

$$\frac{dv}{dt} = -\lambda v, \quad (3.1)$$

where v is the current intensity at which TC decays, $\frac{dv}{dt}$ is the decay rate, and λ represents the decay scale that determines the final intensity to which TCs decay. Specifically, at the end of the decay process, when $t = 1$ (with the decay time normalised between 0 and 1), the intensity v decreases to v_0/e^λ .

This model describes decay controlled by linear drag, with a decay rate that decreases as intensity decreases. The solution for v to Eq. 3.1 is

$$v(t) = v_0 e^{-\lambda t}, \quad (3.2)$$

where v_0 is the initial intensity where the TC starts to decay, and t denotes the decay duration.

While Eq. 3.2 depicts decay following a simple exponential function in which the decay rate slows with time, a fractional power law is inserted into Eq. 3.2 to obtain

a more general decay model (the β model):

$$v(t) = v_0 e^{-\alpha t^\beta}, \quad (3.3)$$

where β is the shape parameter, which determines whether the decay slows down or speeds up over time. This parameter is typically greater than 0. When $0 < \beta \leq 1$, the decay process slows down over time, leading to a decelerating decay. When $\beta = 1$, the function Eq.3.3 reduces to a simple exponential decay [Eq.3.2]. When $\beta > 1$, the decay process speeds up over time, leading to an accelerating decay. The α here acts as the new decay scale that determines the final intensity to which TCs decay (v_0/e^α). While β as a shape parameter primarily affects how the decay rate changes over time, it does not alter α 's role as a scale parameter as λ . Figure A.1c confirms that λ and α are closely correlated, with a strong positive correlation of $r = 0.89$. This β model allows for a versatile description of different decay behaviours by introducing a relaxation exponent β .

3.2.4 Model fitting

The β model (Eq. 3.3) is used to fit the decay data and describe the underlying patterns of temporal decay. The α and β values for each case are obtained by fitting Eq. 3.3 to the time series of v_{max} . They are determined by minimizing the error between predicted and observed values of v_{max} using least squares. To enable meaningful comparisons across cases, the time series of v_{max} is normalized by dividing by the initial intensity v_0 , and time t is normalized by dividing by the total duration of the decay period. This results in a normalized range of $[0,1]$ for both TC intensity and decay duration. For comparison, the exponential model (Eq. 3.2), algebraic

model (Eq. 1.8), and logistic model (Eq. 1.10) were also fitted to the decay data.

3.2.5 Correlation analysis

Correlation analysis was conducted between the fitted model parameters (α and β ; Eq. 3.3) and potential factors at the initial time of decay. The factors include the initial intensity (v_0), initial radius of maximum wind (RMW_0), initial Coriolis parameter at the TC centre (f_0), initial maximum potential intensity ($MP I_0$), initial vertical wind shear ($VW S_0$), initial planetary angular momentum at the radius of 17 m s⁻¹ wind ($(fR_{17}^2)_0$), and the meridional component of the initial translation velocity (u_0), where poleward motion is defined as positive and equatorward motion as negative. These initial factors are intended to capture the most relevant conditions influencing subsequent decay. The variables used in this chapter are summarized in Table 3.1.

To reduce the noise level, the correlation analysis was conducted after dividing global TCs into ten groups based on the deciles of the potential factors. The mean values of each factor and the corresponding mean α and mean β in each group are then used for analysis. For example, to explore how the initial Coriolis parameter (f_0) could influence α , the data are grouped into 10 groups based on the deciles of f_0 . The mean f_0 and mean α in each group are then used for analysis. The same procedures were applied to analyse other potential factors. This decile analysis is similar to that used in Wang and Toumi (2021).

Table 3.1: Description of variables.

Variables	Descriptions	Units	Source
v_0	Initial v_{max}	m s^{-1}	IBTrACS
RMW_0	Initial radius of the maximum wind (RMW)	km	IBTrACS
f_0	Initial Coriolis parameter at TC centre	s^{-1}	IBTrACS
MPI_0	Initial maximum potential intensity in terms of v_{max}	m s^{-1}	SHIPS
VWS_0	Initial vertical wind shear (200-850 hPa)	m s^{-1}	SHIPS
$(f * R17^2)_0$	2*Initial planetary angular momentum at R17	$\text{m}^2 \text{s}^{-1}$	IBTrACS
u_0	Meridional component of the initial translation velocity	m s^{-1}	IBTrACS

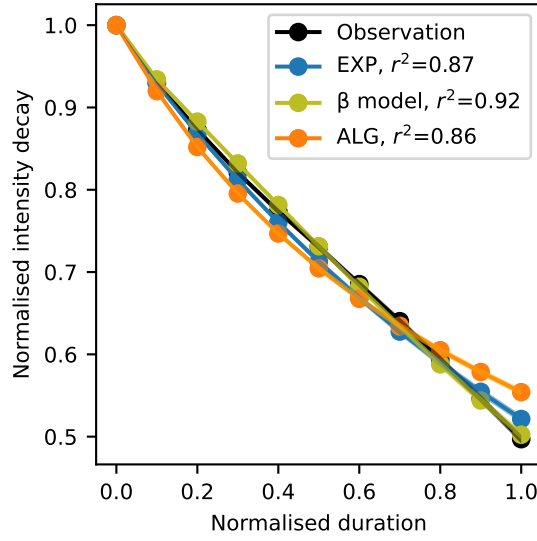


Figure 3.1: Composite of observed and fitted intensity decay over the ocean from the EXP model, the β model, and the ALG model. Prior to compositing, time series are normalised by initial intensity and interpolated onto the deciles of duration. The shadings show one standard error of the mean at each decile. The mean coefficient of determination, r^2 , is given in the legend.

3.3 Results

The mean fitted curve of v_{max} from the β model shows the best agreement with the observations (Figure 3.1). The comparison of the four decay models across several statistical metrics is shown in Table 3.2. The β model has the highest r^2 value (0.92) compared to the other models, indicating it explains more variance in TC intensity. It also has the lowest RMSE (0.03) and MAE (0.03), demonstrating better predictive accuracy. The lowest bias value of the β model (0.001) also indicates minimal systematic error in predictions. Overall, the β model outperforms the other three models in terms of explained variance (r^2), predictive accuracy (RMSE and MAE), and systematic error in predictions (bias).

The distribution of the fitted parameters from the β model is shown in Figure

Table 3.2: Error metrics for the fitting results of the simple exponential model (EXP), algebraic model (ALG), logistic model (LGT), and β model. The coefficient of determination (r^2), p-value, root-mean-square error (RMSE), mean absolute error (MAE), and bias are the mean values of the fittings for each case.

Models	r^2	p-value	RMSE	MAE	bias
EXP	0.87	0.01	0.06	0.05	-0.004
ALG	0.86	0.01	0.06	0.05	-0.003
LGT	0.86	0.01	0.06	0.05	-0.003
β model	0.92	0.0	0.03	0.03	0.001

3.2a and 3.2b. The distribution of the decay scale, α , fits a beta distribution with most values concentrated between 0.3 and 1.0 (Figure 3.1a). The PDF of β fits a log-normal distribution (Figure 3.1b). There are 213 cases with $\beta \leq 1$ (decelerating decay) and 338 cases with $\beta > 1$ (accelerating decay). Those decelerating decays account for about 40% of the total cases, while the accelerating decays account for the majority of the total cases of about 60%. Figure 3.2c shows that α is positively correlated with β ($r = 0.35, p < 0.01$), indicating that the accelerating decay tends to have a larger decay scale compared to the decelerating decay. Meanwhile, the distance to land has marginal effect on α and β (Figure A.1a and A.1b).

The dependence of decay scale α on potential environmental and TC-related factors is given in Figure 3.3 and Figure 3.4. Among all the potential factors, strong and significantly negative correlations have been found between α and f_0 ($r = -0.96$), $(fR17^2)_0$ ($r = -0.89$), and u_0 ($r = -0.73$) (Figure 3.3a-c), indicating that decay happens faster at lower latitudes. Despite the high coefficient between α and RMW ($r = -0.97$), the correlation between them remains unclear, as only four groups are available due to the limited range of RMW (Figure 3.3d). However, there are only moderate correlations between α and v_0 as well as MPI_0 , with an insignificant correlation with VWS_0 (Figure 3.4).

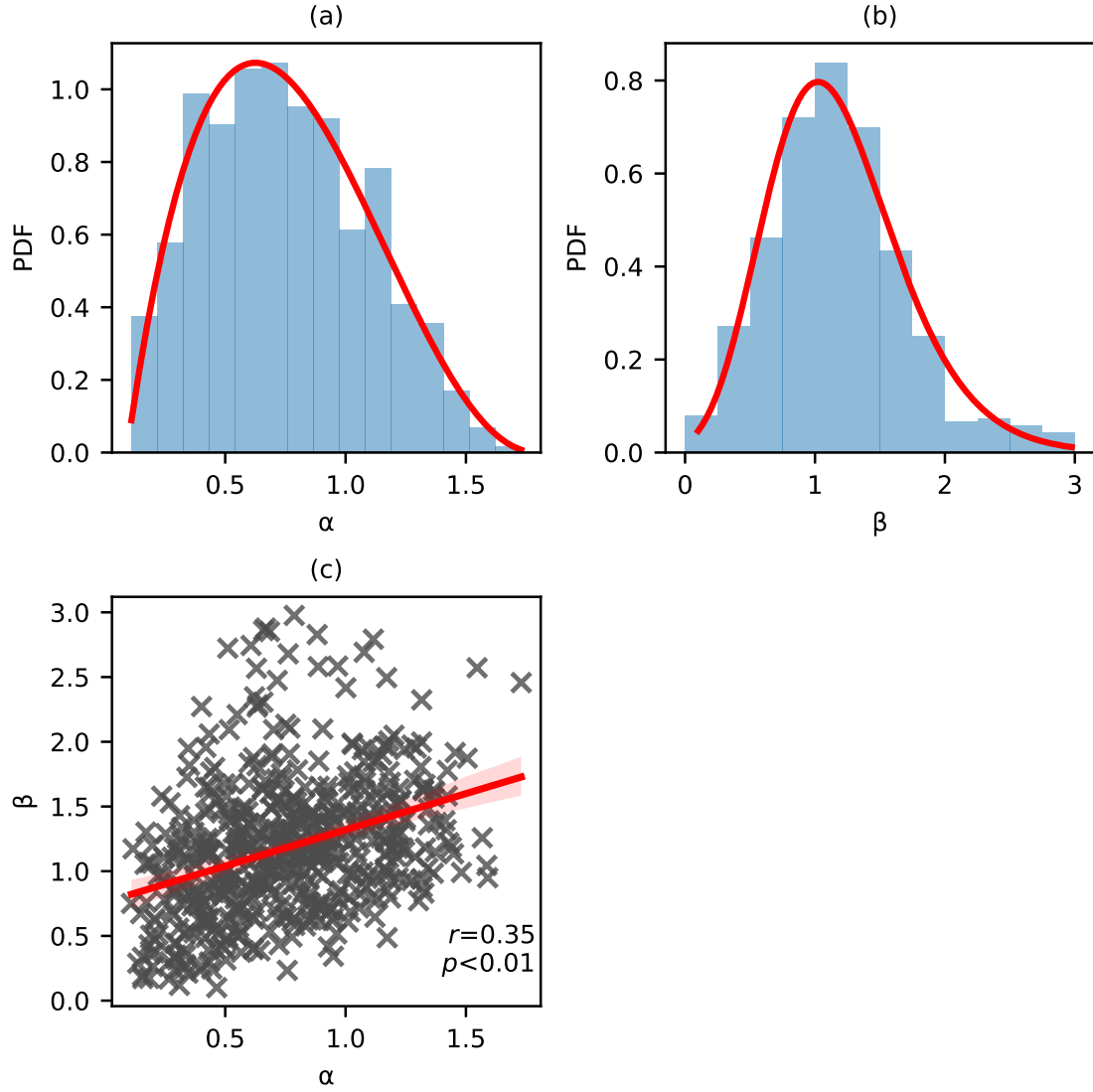


Figure 3.2: (a) Distribution of the fitted parameter α with the PDF fitted to a beta distribution (red curve). (b) Distribution of the fitted parameter β with the PDF fitted to a log-normal distribution (red curve). (c) Scatter plots between α and β . The shaded region around the regression line represents the 99% confidence interval.

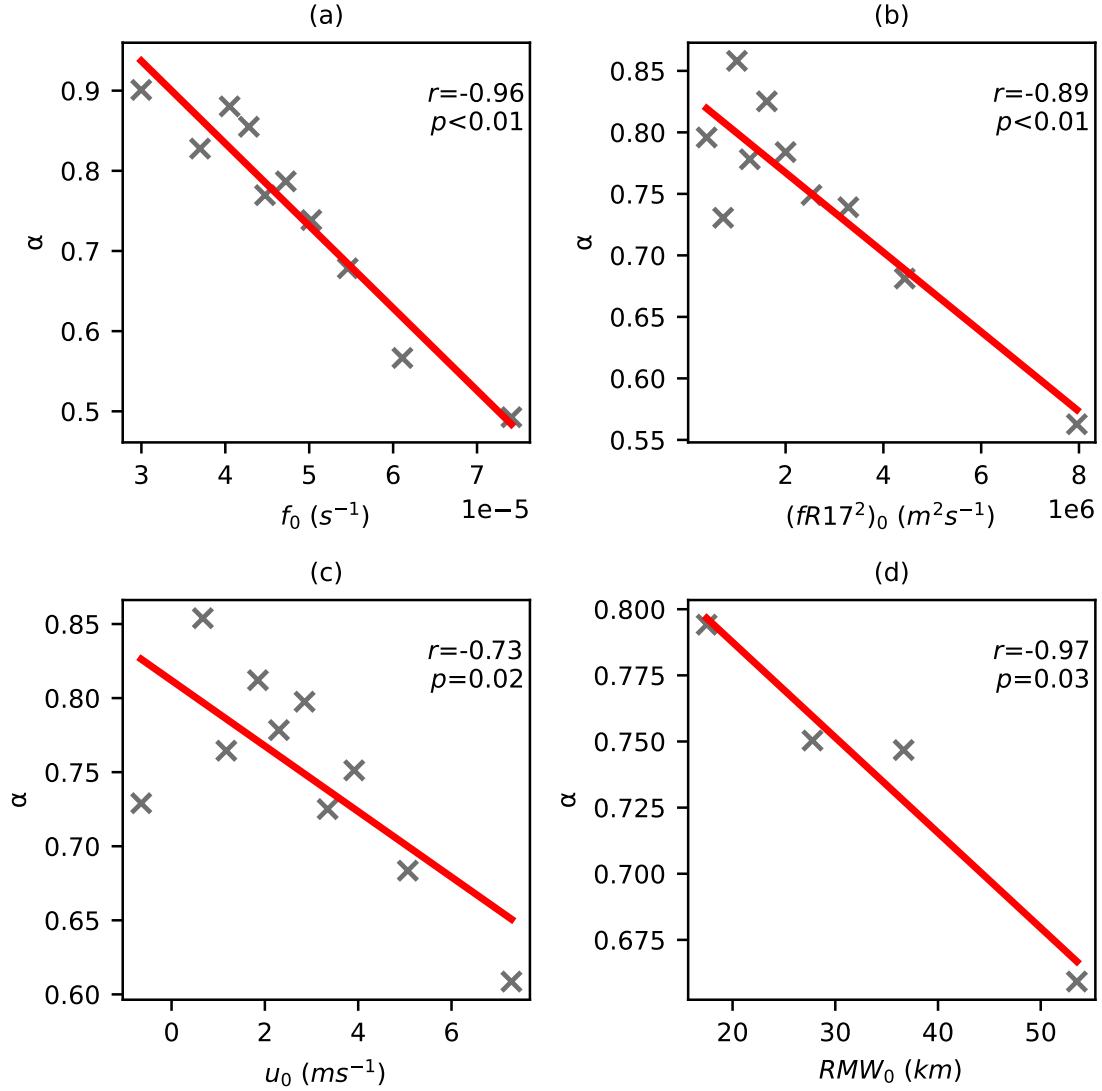


Figure 3.3: Correlation analysis between mean α and deciles of (a) initial Coriolis parameter (f_0), (b) initial planetary angular momentum at R17 ($(fR17^2)_0$), (c) meridional component of the initial translation velocity (u_0), and (d) initial RMW (RMW_0). The linear regression model of α on f_0 for the global TCs is estimated as $\alpha = -1.03 \times 10^4 \cdot f_0 + 1.25$ ($p < 0.01$, $R^2 = 0.93$).

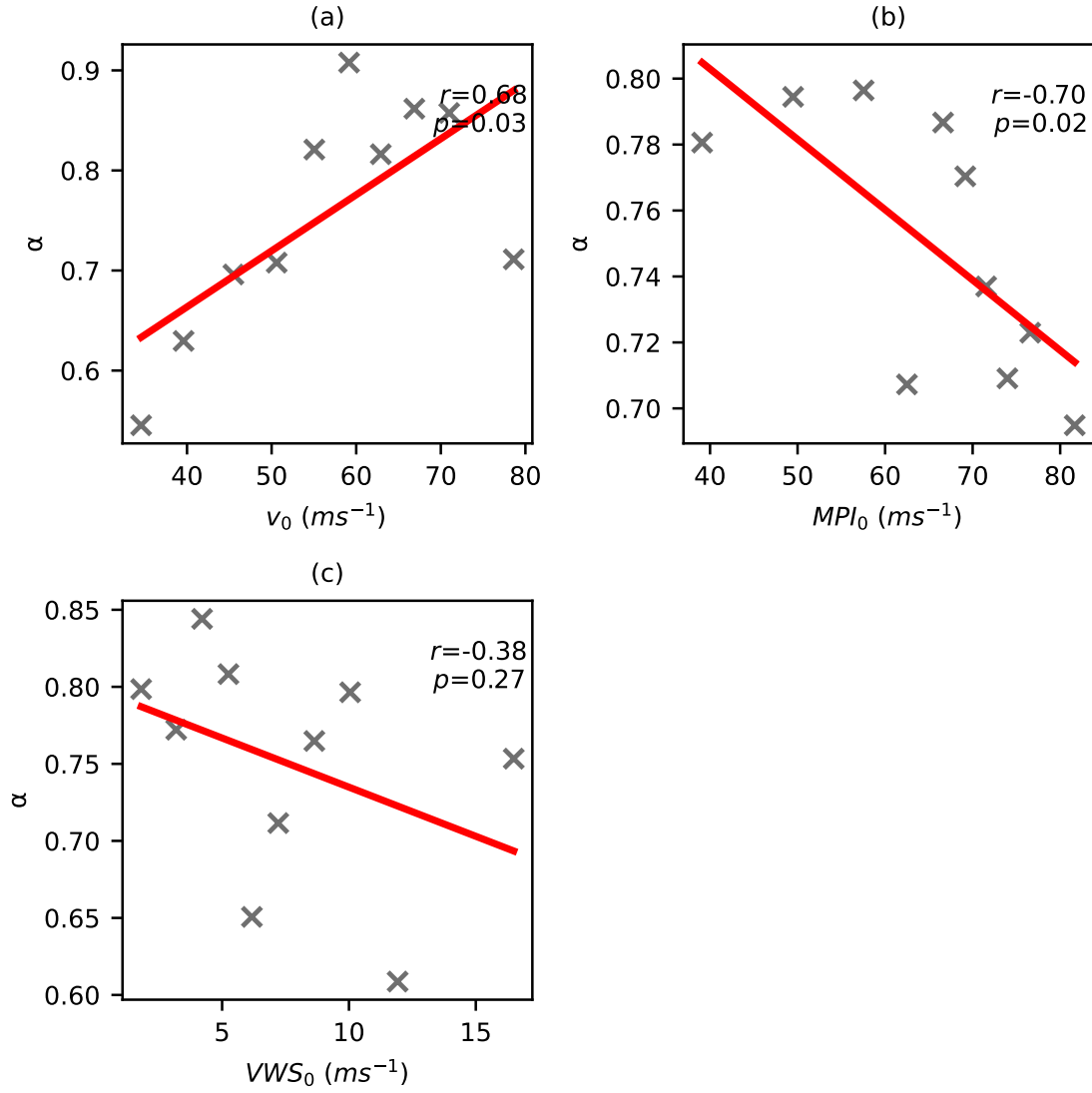


Figure 3.4: Correlation analysis between mean α and deciles of (a) initial intensity (v_0), (b) initial MPI (MPI_0), and (c) initial VWS (VWS_0).

Table 3.3: Linear fit of α to f_0 across different basins.

Basin	Intercept	Slope	R^2
NA	0.76	-3958.60	0.36
EP	1.54	-16454.71	0.67
NI	0.53	7987.18	0.03
SP	1.11	-6407.73	0.19
SI	1.23	-7933.01	0.19
WP	0.95	-5858.21	0.87

Given the strong dependence of the decay scale α on grouped f_0 , α was further fitted using a linear regression with f_0 for global TCs. The linear regression models of α on f_0 for different basins are provided in Table 3.3. The fitted slopes are predominantly negative across basins, with the exception of the North Indian (NI) basin, which exhibits a positive slope. The strength of the linear relationship varies among basins, as reflected by the R^2 values, ranging from weak in the NI basin to relatively strong in the Eastern Pacific (EP) and Western Pacific (WP) basins.

Figure 3.5a compares the temporal evolution of $v_{\max}$ between the lower 25% and upper 75% quantile groups of the shape parameter β . The low β group exhibits a decelerating decay where the decay slows down over time. The high β group shows an accelerating decay where the decay speeds up over time. Further correlation analysis shows that β exhibits the strongest dependence on u_0 with $r = 0.75$ (Figure 3.5b), in comparison to other potential factors (Figure 3.6).

To eliminate potential compensatory effects from α , a partial correlation between u_0 and β was conducted with α held constant. The stronger partial correlation ($r = 0.81, p = 0.008$) confirms that the dependence of β on u_0 is robust. The PDF of u_0 for each β group is shown in Figure 3.5c; a p-value of 0.01 indicates that the difference in u_0 between the two groups is statistically significant. The low β group has more low- u_0 cases, with a peak density around 1.4 m s^{-1} , while the high β group

Table 3.4: Linear fit of β to u_0 across different basins.

Basin	Intercept	Slope/100	R^2
NA	0.85	-1.77	0.23
EP	1.10	6.29	0.37
NI	1.35	-0.79	0.00
SP	1.28	2.09	0.05
SI	1.14	4.78	0.54
WP	0.93	7.66	0.56

has more high- u_0 cases, peaking around 2.8 m s^{-1} . This further supports the robust correlation between β and u_0 .

Given the dependence of the shape parameter β on grouped u_0 , β was further fitted using a linear regression with u_0 for global TCs. The linear regression models of β on u_0 for different basins are provided in Table 3.4. The fitted slopes vary in both magnitude and sign across basins, with negative slopes in the North Atlantic (NA) and North Indian (NI) basins and positive slopes in the remaining basins. The strength of the linear relationship also differs among basins, as indicated by the R^2 values, which range from near zero in the NI basin to above 0.5 in the South Indian (SI) and Western Pacific (WP) basins.

Median values of the fitted α and β , along with the corresponding f_0 and u_0 for TCs over each basin, are given in Table 3.5. The median values of α and f_0 for each basin are consistent with the derived linear correlation between them: the lower α is aligned perfectly with higher f_0 (Figure 3.3a). However, the β is not always consistent with u_0 , likely due to β 's varying sensitivity to u_0 across different basins (Table 3.4). Among all basins, the North Atlantic (NA) stands out with the lowest α and β , alongside the highest f_0 . This indicates that TCs in the NA are more likely to decay at higher latitudes, with a smaller decay scale and a tendency for decelerating decay.

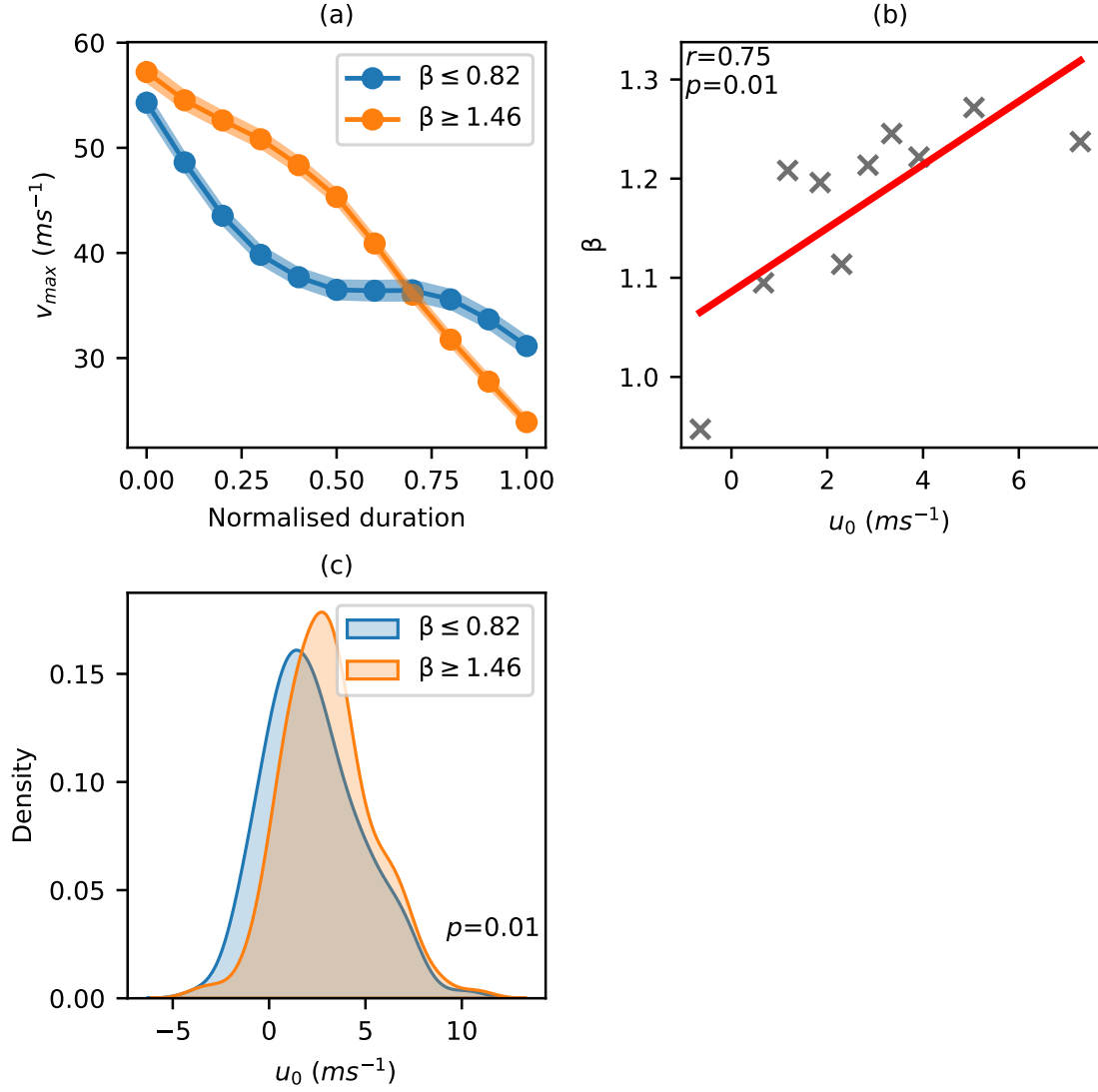


Figure 3.5: (a) Composite of the temporal evolution of v_{max} based on β : below the 25th percentile of β ($\beta \leq 0.82$, blue) and above the 75th percentile of β ($\beta \geq 1.46$, orange). The shadings represent one standard error of the mean at each decile point. (b) Correlation analysis between mean β and deciles of u_0 . The linear regression model of β on u_0 for the global TCs is estimated as $\beta = 0.03 \cdot u_0 + 1.09$ ($p=0.01$, $R^2 = 0.56$). (c) PDF of u_0 for the same two groups in (a). The p-value of 0.01 is derived from the KS test.

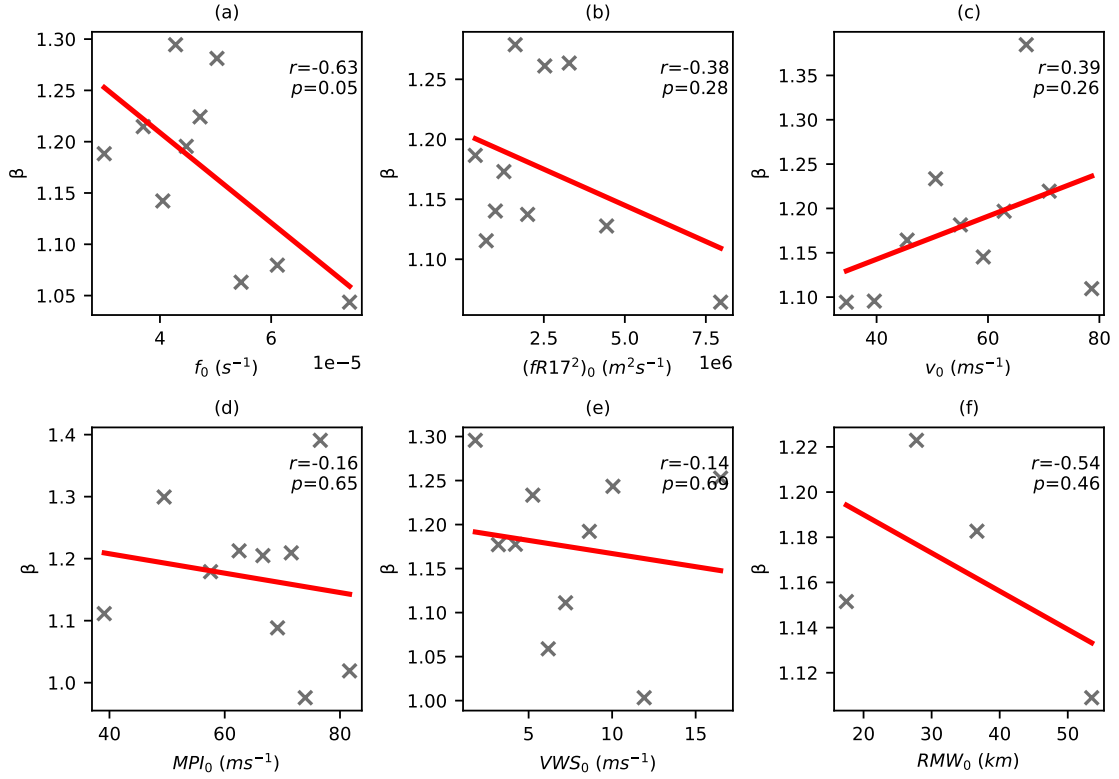


Figure 3.6: Correlation analysis between mean β and deciles of (a) initial intensity (v_0), (b) initial RMW (RMW_0), (c) initial Coriolis parameter (f_0), (d) initial planetary angular momentum at R17 ($(fR17^2)_0$), (e) initial MPI (MPI_0), and (f) initial VWS (VWS_0).

Table 3.5: Median values of α , β , initial Coriolis parameter (f_0), meridional component of the initial translation velocity (u_0) for TCs across different basins. Basin abbreviations used in the table include the following: EP (Eastern Pacific), NA (North Atlantic), NI (North Indian Ocean), SI (South Indian Ocean), SP (South Pacific), and WP (Western Pacific). The total number of decay cases in each basin is shown in the last row.

	EP	NA	NI	SI	SP	WP	Global
α	0.81	0.51	0.92	0.89	0.77	0.59	0.73
β	1.18	0.76	1.25	1.26	1.24	1.13	1.14
$f_0(\times 10^{-5}s^{-1})$	4.2	6.1	3.9	4.4	4.7	5.2	4.6
$u_0(m s^{-1})$	2.05	3.07	1.02	2.56	3.07	3.33	2.56
Total TCs	132	75	14	113	55	162	551

3.4 Discussion

Previous studies on theoretical decay models are typically based on spin-down theory, which assumes weak convection and attributes intensity decay primarily to frictional dissipation. In the friction-dominated framework, the temporal decay follows a linear or quadratic relationship with surface drag, which is proportional to the TC intensity. As a result, the decay rate slows down as the intensity decreases, leading to a decelerating decay pattern; stronger storms are also expected to decay more rapidly than weaker ones. However, it is not clear whether the friction-dominated decay models can account for the temporal decay over the ocean.

To help understand the decay over the ocean, a modified exponential model (β model) is proposed. The β model captures the temporal decay well by encompassing the scale parameter α and the shape parameter β . While α characterises the overall decay scale, β describes how the decay rate changes over time, either speeding up or slowing down. Furthermore, the global fitting gives that the scale parameter α can be estimated as a linear function of f_0 , and the shape parameter β as a linear function of u_0 . Specifically, the β model for global decay can be given as $v(t) = v_0 e^{-\alpha t^\beta}$, with $\alpha = -1.03 \times 10^4 \cdot f_0 + 1.25$ and $\beta = 0.03 \cdot u_0 + 1.09$. The β model offers an accurate representation of the decay process in oceanic conditions. Notably, this model is the first to distinguish between decelerating and accelerating decay by introducing a shape parameter. While numerical simulations encompass full physics, a parametric model remains valuable for testing against observational data and facilitates the analysis of potential factors affecting decay.

The global fit to the β model shows that the majority of TCs (60%) exhibit an

accelerating decay over the ocean. This indicates that the decelerating decay is not a typical pattern over the ocean, and stronger storms do not necessarily decay faster. However, this accelerating decay can not be explained by spin-down models, which predict a decelerating decay. This suggests that the surface drag is not the sole factor behind decay, at least over the ocean. Energy production could play a significant role in allowing intense storms to sustain relatively high wind speeds and decay more slowly.

Further analysis of model parameters indicates that TCs exhibit larger decay scales at lower latitudes. Why do TCs decay faster at lower latitudes? First, f_0 can be understood as an independent factor. It has been suggested that low-latitude hurricanes are more vulnerable to vertical wind shear (DeMaria, 1996b), as the smaller Rossby penetration depth at lower latitudes leads to weaker resistance to vortex tilt. Lower latitudes may also contribute less planetary angular momentum at the outer radius to offset frictional losses, and thus lead to a faster decay.

Latitudes may influence TC intensity decay via u_0 . Figure 3.7 shows a strong positive correlation between f_0 and u_0 . The slower meridional translation velocities at lower latitudes mean smaller background winds and more time for negative cooling feedback, both of which may lead to a faster decay (Chang et al., 2023a; Walker et al., 2014a; Park et al., 2019; Kaplan and DeMaria, 1995b).

The shape parameter β is found to be positively correlated with u_0 ($r = 0.75$), which means a larger u_0 facilitates an accelerating decay. A larger translation velocity will reduce the negative intensity feedback from the cold wake, which could help TCs maintain their intensity initially. However, as TCs move into high latitudes more quickly, the hostile environment of colder water and stronger wind shear would cause

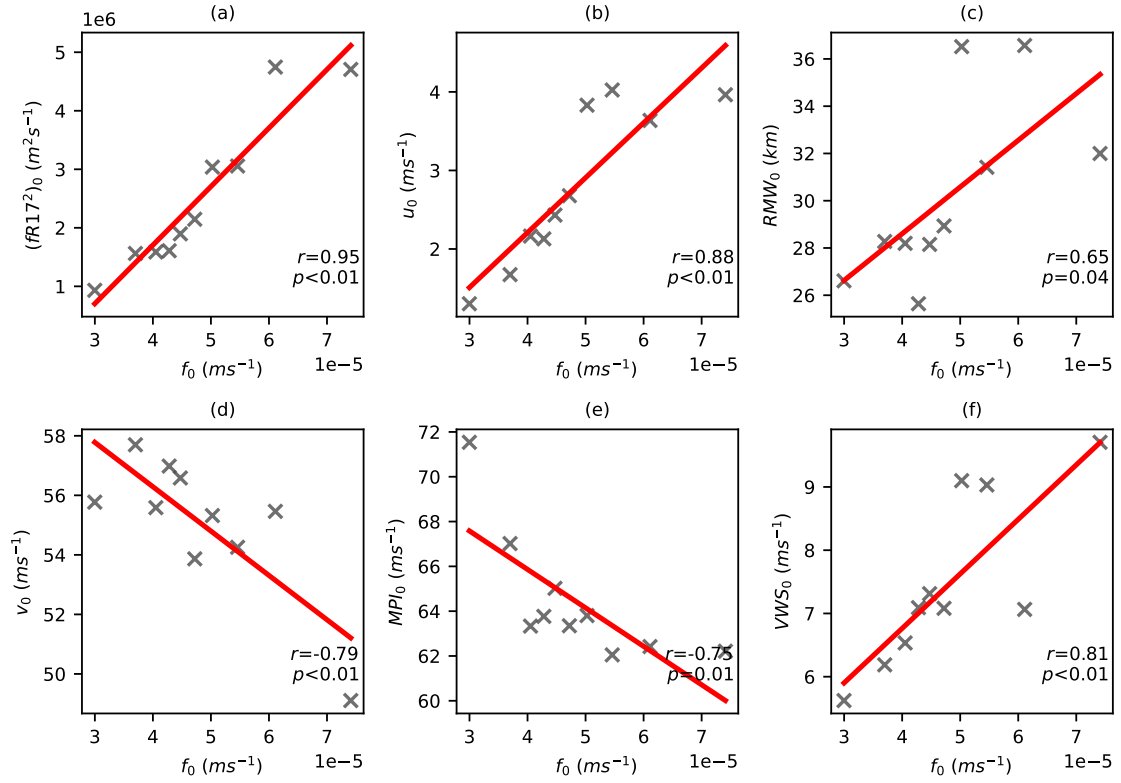


Figure 3.7: Correlation analysis between deciles of f_0 and mean (a) initial planetary angular momentum at R17 ($(fR17^2)_0$), (b) meridional component of the initial translation velocity (u_0), (c) initial RMW (RMW_0), (d) initial intensity (v_0), (e) initial MPI (MPI_0), and (f) initial VWS (VWS_0).

TCs to decay increasingly faster. In that case, the decay will show the feature of accelerating decay. While α is more sensitive to the initial latitude position, β is more likely influenced by the time-varying properties during the decay evolution.

3.5 Conclusions

A modified exponential decay model (β model) with two parameters α and β has been derived. The scale parameter α defines the decay scale, while the shape parameter β determines whether the decay rate decelerates or accelerates over time. Global fittings indicate that around 40% of TCs exhibit decelerating decay ($\beta \leq 1$), while the majority (about 60%) show accelerating decay ($\beta > 1$). Further correlation analysis shows that the scale parameter α increases with initial latitude, indicating a larger decay scale at lower latitudes. The shape parameter β is found to be associated with translation speed, with TCs exhibiting more accelerated decay when moving rapidly poleward. The β model provides a comprehensive understanding of how TCs decay with time and how environmental conditions affect the decay scale and evolution.

Chapter 4

On the Simulated Decay of Tropical Cyclones Moving to the Equator

4.1 Introduction

While the previous chapter employed an empirical decay model to characterize the temporal decay of TCs over the ocean, this chapter examines the impact of the Coriolis parameter (f) on well-developed TCs moving toward the Equator and investigates the mechanisms driving the resulting decay using idealized numerical simulations.

The Coriolis parameter f , a fundamental aspect of geophysical flow, plays a pivotal role in TC genesis and in governing TC circulation. The Coriolis effect is a consequence of Earth's rotation. It initiates cyclonic rotation by deflecting moving air—counter-clockwise in the Northern Hemisphere and clockwise in the Southern

Hemisphere. It is widely accepted that cyclones rarely form within about 5 degrees of the Equator due to the weak Coriolis effect there (Gray, 1968, 1979, 1985, 1998; Briegel and Frank, 1997).

However, there are exceptions. One noteworthy example is Typhoon Vamei, which was first classified as a tropical depression at about 1.5°N latitude on 26 December 2001 over the South China Sea. Its formation was associated with a persistent low-level cyclonic Borneo vortex and the enhancement of background cyclonic vorticity by a cold surge (Chang et al., 2003). Studies of TC formation near the Equator have used idealized simulations with a weak prescribed vortex and have examined events such as Typhoon Vamei and Hurricane Pali (Steenkamp et al., 2019; Kilroy et al., 2020). These results suggest that cyclogenesis processes near the Equator are similar to those at higher latitudes, indicating that Earth’s background rotation is not essential for TC genesis if an initial vortex is present and can be intensified by other systems.

Because the Coriolis parameter f is directly related to planetary vorticity, it influences TC size by contributing planetary angular momentum to the TC system. Climatology studies have shown that TCs develop a larger outer size at higher latitudes with more sufficient import of planetary angular momentum in the lower troposphere (Merrill, 1984; Chan and Chan, 2013). An analytic growth model shows that the mean latitude during growth is one of the four factors dominating the growth of the outer size, with TCs tending to grow faster at higher latitudes (Wang and Toumi, 2022a). Simulation work by Li et al. (2012) confirms that not only is the outer size larger at higher latitudes, but the radius of maximum wind (RMW) is also larger. Whereas the larger RMW is attributed to higher inertial stability at

higher latitudes, the outer size is primarily determined by environmental angular momentum import.

The Coriolis effect affects the intensification rate of TCs. Model simulations have shown that TCs intensify more rapidly at lower latitudes (DeMaria and Pickle, 1988; Smith et al., 2011; Rappin et al., 2011; Li et al., 2012). Li et al. (2012) attributed this to stronger and deeper subgradient inflow under lower planetary vorticity environment, which enhances boundary layer moisture convergence and condensational heating, thereby facilitating faster TC development compared to higher planetary vorticity conditions. Smith et al. (2015) similarly explained that TCs at lower latitudes possess stronger inflow in the boundary layer, which induces stronger convergence of absolute angular momentum and thus more rapid intensification. Li et al. (2023b) revisited the low-latitude problem and highlighted that lower latitude enhances convergent inflow in the boundary layer and deepens eyewall convection by reducing inertial stability in the boundary layer rather than in the outflow layer. Beyond the intensification phase, Li and Toumi (2024) found that TCs at lower latitudes decay more quickly after reaching their LMI, which has not been fully understood.

In summary, while sufficient f may not be necessary for TC formation, it remains an important factor influencing TC development through boundary-layer dynamics. However, it is not clear how a reduced f would affect the evolution of a pre-existing TC, or through which mechanisms. In particular, this study aims to investigate whether a TC vortex can exist near the Equator under the hypothetical circumstance of $f = 0$, focusing on the response of pre-existing TC intensity to the removal of the Coriolis effect.

4.2 Methods

4.2.1 Experimental design

The WRF Model (version 4.2.2) (Skamarock et al., 2019) is used to simulate TCs on an idealized aqua planet with a full-physics parameterization setup. To investigate the impact of a reduced Coriolis parameter f on a developed TC vortex, a series of reduced- f experiments was designed. The control run is conducted on an f -plane at 20°N and lasts for 10 days (f20). Sensitivity experiments involved shifting the f -plane from 20°N to the Equator (0°) at different rates, both abrupt and gradual. The shift was imposed at simulation time 144 h (T_{144}). These were identified as f20-0@144h and f-varying@144h, respectively. In the f20-0@144h experiment, f was instantaneously decreased to zero at T_{144} . Unlike the instantaneous f -plane reductions, the f-varying@144h experiment gradually decreased f by 0.625° every 3 hours from T_{144} , reaching zero by T_{240} . Note that we use T to denote absolute simulation time and t to represent the relative time since the restart.

Additional experiments with the same instantaneous change to $f = 0$ were performed at T_{72} , T_{96} , T_{120} , and T_{168} to test the sensitivity to initial TC intensity when f was decreased to zero. An experiment with a constant $f = 0$ throughout (f0) was also conducted for comparison. All experiments and the corresponding changes in f are summarized in Table 4.1. Here we focus on f20, f20-0@144h, and f-varying@144h to investigate the physical mechanisms underlying the TC intensity response to reduced f (highlighted in Table 4.1). Results from another group at T_{96} (f20 and f20-0@96h) show consistent responses to those at T_{144} . Relevant figures are provided in Appendix A.

Table 4.1: List of simulations. Changes are reported relative to the control run.

Simulations	Changes in f	Restart time	Run time
f20 (Control)	$f = 20^\circ$		240 h
f0	$f = 0^\circ$		216 h
f20-0@72h	$\Delta f = -20^\circ$	$T = 72h$	120 h
f20-0@96h	$\Delta f = -20^\circ$	$T = 96h$	120 h
f20-0@120h	$\Delta f = -20^\circ$	$T = 120h$	120 h
f20-0@144h	$\Delta f = -20^\circ$	$T = 144h$	120 h
f20-0@168h	$\Delta f = -20^\circ$	$T = 168h$	120 h
f-varying@144h	$\Delta f = -0.625^\circ$ every 3 hrs	$T = 144h$	144 h

4.2.2 Gradient wind balance

Except in the surface frictional boundary layer and the outflow layer, where friction and radial acceleration are not negligible, gradient wind balance is essential to controlling the primary circulation in intense storms. The gradient balance describes the balance between three key forces that govern the motion of air parcels around the cyclone: the centrifugal force, the pressure gradient force, and the Coriolis force. The impact of zero f on the gradient wind balance and TC circulation will be one focus of this study. The gradient wind equation can be expressed as

$$\frac{V_{gr}^2}{r} + fV_{gr} = \frac{1}{\rho} \frac{\partial p}{\partial r}, \quad (4.1)$$

where V_{gr} is the gradient wind (which approximates the tangential wind), r is the radial distance from the TC centre, f is the Coriolis parameter, ρ is the air density, and $\frac{\partial p}{\partial r}$ is the radial pressure gradient.

4.3 Results

4.3.1 Simulations

Figure 4.1a illustrates the intensity evolution of simulated TCs listed in Table 4.1. In the control experiment (f20), the TC remains in a stable mature phase following its developmental stage. In contrast, in the case of constant $f = 0$ (f0), the hurricane-strength threshold cannot be maintained after the initial spin-up. In the reduced- f experiments, TC intensity decreases after a temporary intensification as f is decreased. While the weakest storm (f20-0@72h) and the storm under varying f (f-varying@144h) maintain Saffir–Simpson Category 1 intensity (Simpson and Saffir, 1974) as f decreases, the other simulated TCs dissipate completely. Stronger storms decay faster than weaker storms. The weakening rates over the first 24 hours are 12.1, 12.7, 17.4, 20.7, and 30.5 m s^{-1} in f20-0@72h, 96h, 120h, 144h, and 168h, respectively.

The set of comparable experiments restarted at T_{144} is shown in Figure 4.1b. In f20-0@144h, a rapid weakening occurs post a temporary intensification, followed by another rapid weakening starting at t_{60} . In f-varying@144h, TC intensity decreases followed by a 26-hour stable period. The weakening mechanisms under the zero f are examined at $t_6 \rightarrow t_{36}$ for f20-0@144h, and at $t_6 \rightarrow t_{48}$ for f-varying@144h.

Comparisons of axisymmetric TC wind structure between f20 and reduced- f experiments are shown in Figure 4.2 and Figure 4.3. At t_6 , the reduced- f experiments showed a temporary strengthening of both inflow and outflow throughout the entire cyclone depth (Figure 4.2d, and 4.2f). The strengthening of inflow at the low and mid-levels is associated with an increase in the inflow layer height (Figure 4.2d), which is defined by 5% of the maximum radial inflow (Zhang et al., 2011). During

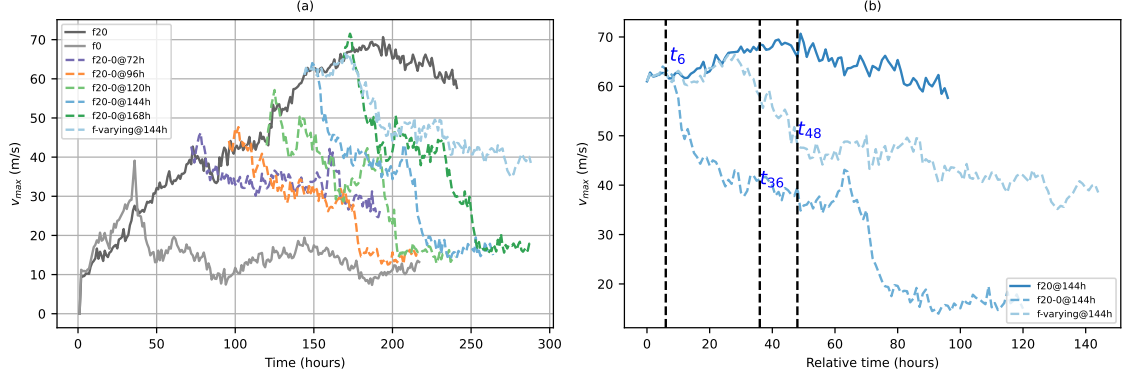


Figure 4.1: (a) Time evolution of the maximum surface wind (v_{max}) from the control experiment and seven reduced- f experiments. (b) Time evolution of v_{max} from three comparable experiments: f20, f20-0@144h, and f-varying@144h, relative to the restart time at T_{144} . The vertical dashed lines (t_6 , t_{36} and t_{48}) mark the key points for subsequent analysis.

the weakening stage, f20-0@144h showed a significant decline of both inflow and outflow at t_{36} (Figure 4.2e); f-varying@144h showed a limited change in the strength of upper-level outflow but an outward shift at t_{48} (Figure 4.2g). The reduced- f experiments both showed a deeper inflow layer height.

Regarding vertical motion, f20-0@144h showed that the sloping updrafts extended outward above 5 km at t_6 (Figure 4.3d) and declined by t_{36} (Figure 4.3e). In the f-varying@144h, the sloping updrafts broadened outward above 5 km and were significantly reduced at t_{48} (Figure 4.3g). The expansion of updrafts above 5 km relates to the expansion of deep convection (Figure 4.4b and 4.4c), which is evidenced by radar reflectivity greater than 20 dBZ at 10 km in altitude in Figure 4.4 (Rogers et al., 2020; Stone et al., 2023; Wadler et al., 2023). The expansion of deep convection is attributed to strengthened low-level inflow, which enhances convergence outside the eyewall (Figure 4.2). While the low-level updrafts outside the eyewall can be offset by downdrafts from evaporative cooling, the expansion of updrafts persists above 5 km.

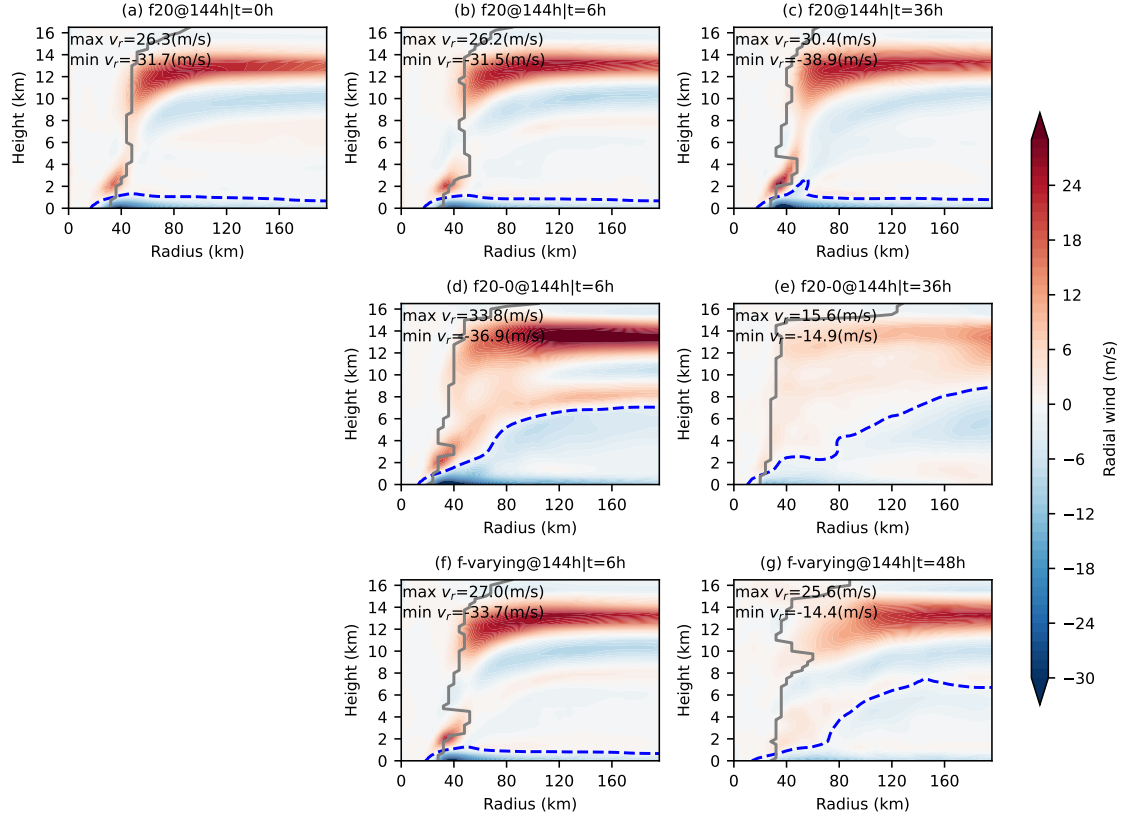


Figure 4.2: Height-radius plots of the azimuthally-averaged tangential wind (contours) and radial wind (shading) from experiments f20 (first row), f20-0@144h (second row), and f-varying@144h (third row) at $t = 0h$ (first column), $t = 6h$ (second column), and $t = 36/48h$ (third column). The annotations on the top-left corner of each panel give the maximum and minimum radial wind. The blue contours defined as 5% of the maximum radial inflow represent the inflow layer height. The grey dashed lines indicate the radius of maximum wind at each level for each snapshot.

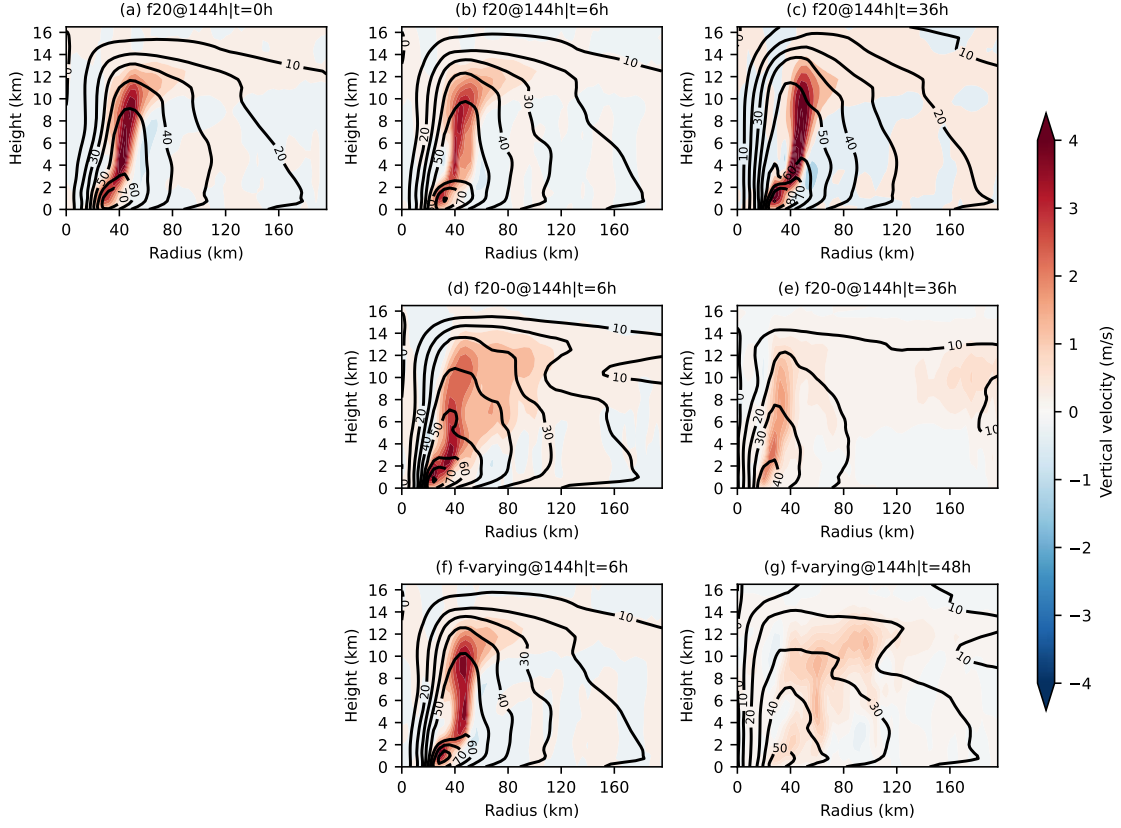


Figure 4.3: Height-radius plots of the azimuthally-averaged vertical velocity (shading) and tangential wind (contours) from experiments f20 (first row), f20-0@144h (second row), and f-varying@144h (third row) at $t = 0h$ (first column), $t = 6h$ (second column), and $t = 36/48h$ (third column).

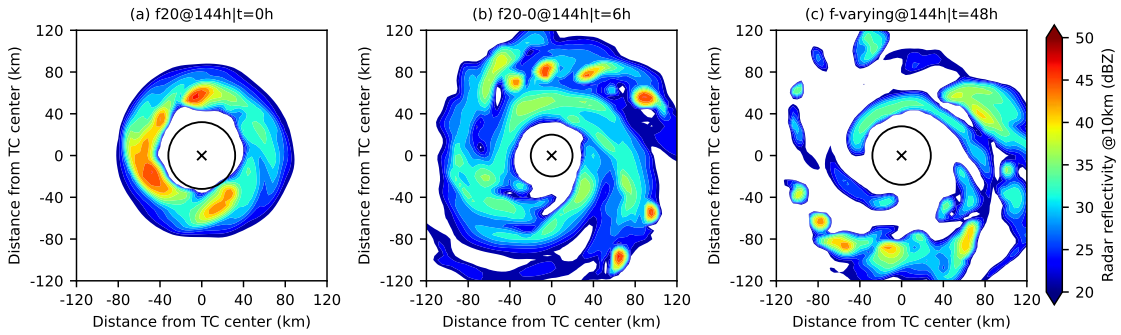


Figure 4.4: Horizontal cross-sections of radar reflectivity greater than 20 dBZ at a height of 10 km around the TC centre for (a) the initial state, (b) f20-0@144h at $t = 6h$, and (c) f-varying@144h at $t = 48h$. The circles indicate the radius of maximum wind at each snapshot.

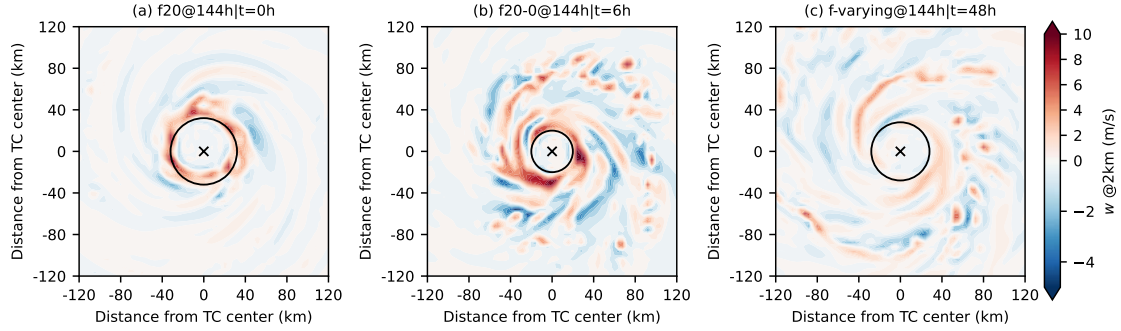


Figure 4.5: Horizontal cross-sections of vertical velocity (w) at a height of 2 km around the TC centre for (a) the initial state, (b) f20-0@144h at $t = 6$ h, and (c) f-varying@144h at $t = 48$ h. The circles indicate the radius of maximum wind at each snapshot.

Alongside the more active deep convection in the outer rainbands (Figure 4.4b and 4.4c), there are more pronounced convective updrafts and downdrafts (Figure 4.5b and 4.5c). The downdrafts occur on the convective scale and typically form due to evaporative cooling of precipitation in mid-levels in the outer rainbands. The convective downdrafts play an important vertical mixing role in bringing low θ_e mid-tropospheric air to the surface (Barnes et al., 1983; Powell, 1990a,b).

4.3.2 Reduction in equivalent potential temperature in the boundary layer

To investigate the decay under the zero f , we examine the changes in equivalent potential temperature (θ_e) below 1.5 km, which is the typical height of the boundary layer in TCs (approximately 1 to 1.5 km) (Kepert, 2001). Figure 4.6 shows the time evolution of θ_e within the boundary layer. A pronounced decrease in θ_e , approximately 12 K near the eyewall region, is observed from t_6 in f20-0@144h. In the f-varying@144h scenario, a minor decrease in θ_e occurred until a noticeable

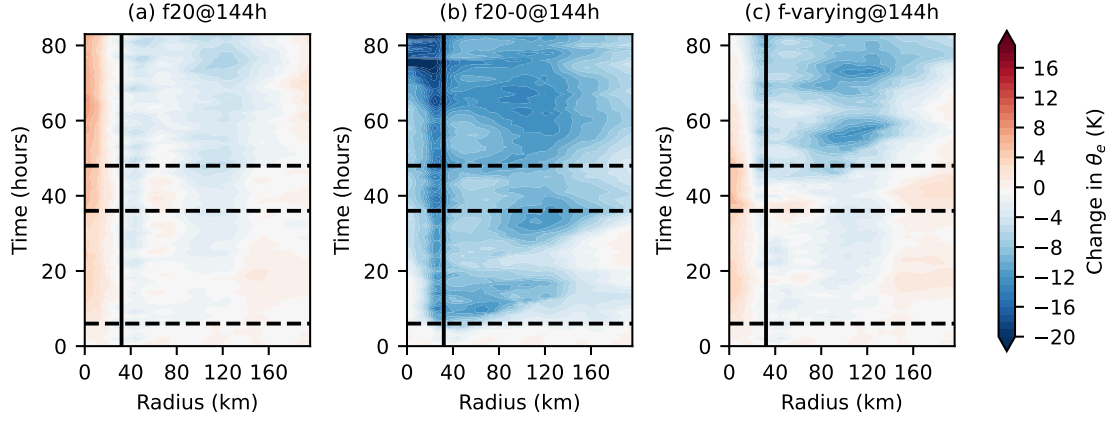


Figure 4.6: Time-radius plots of changes in azimuthally averaged equivalent potential temperature (θ_e) under 1.5 km relative to its initial restart value. Black dashed lines indicate $t = 6\text{h}$, $t = 36\text{h}$ and $t = 48\text{h}$ after reduction f . Vertical lines mark the radius of maximum wind at t_0 for each case.

decline was observed starting at t_{48} . If the θ_e reduction in the boundary layer can't be recovered by the surface flux, the low- θ_e air feeding into the eyewall would suppress the eyewall convection and cause a weakening of the TC (Riemer et al., 2010; Alland et al., 2021a).

Why does the θ_e in the boundary layer decrease for smaller f ? The deepening of the inflow layer (e.g., Figure 4.2d) and increasing downdrafts (e.g., Figure 4.5b) come into our consideration.

The inflow layer height in the reduced- f experiments has significantly increased due to the enhancement of radial inflow at the low and mid-levels (e.g., Figure 4.2d). Meanwhile, the distribution of θ_e shows high values in the boundary layer and low values in the mid-levels (approximately 3–8 km altitude) (Figure 4.7b and 4.7c), confirming that the free troposphere is the source of low θ_e (Simpson and Riehl, 1958). Therefore, a deeper inflow layer would enhance the entrainment of dry air from the mid-levels, leading to a reduction in θ_e within the boundary layer.

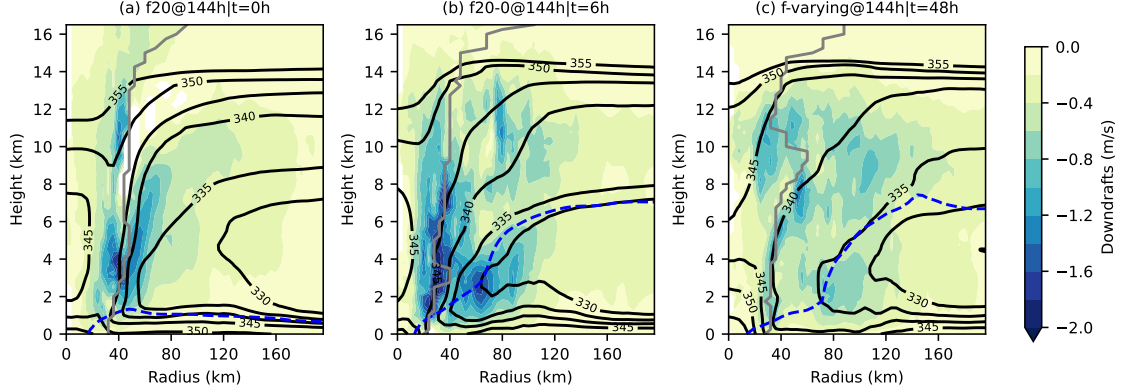


Figure 4.7: Height-radius plot of the azimuthally-averaged negative vertical velocity (shading) and θ_e (contours) for (a) the initial state, (b) f20-0@144h at $t = 6$ h, and (c) f-varying@144h at $t = 48$ h. The blue dashed contours represent 5% of the maximum radial inflow. The grey solid lines indicate the radius of maximum wind at each snapshot.

Moreover, the reduced- f experiments have stronger downdrafts in the outer rainbands (Figure 4.5 and Figure 4.7). The strengthened downdrafts would also carry low- θ_e air from the mid-troposphere to the boundary layer. Collectively, the combined effects of the highly elevated inflow layer and the enhanced downdrafts outside the eyewall will enhance the entrainment of low- θ_e air into the inflow layer and lower the θ_e in the boundary layer, thereby disrupting the energy production necessary for sustaining deep convection.

4.3.3 Gradient imbalance analysis

A gradient force (AGF) is a key force in driving the radial wind. It arises when the gradient wind balance is unbalanced, which can be given as

$$AGF = \frac{V_{gr}^2}{r} + fV_{gr} - \frac{1}{\rho} \frac{\partial p}{\partial r}. \quad (4.2)$$

An outward agradiant force (supergradient force) accelerates radial outflow, while an inward agradiant force (subgradient force) accelerates radial inflow. The comparison of the agradiant force for the three experiments outside the eyewall region (> 40 km) is shown in Figure 4.8(a–c). Figure 4.8(d–f) shows the pressure gradient force, while Figure 4.8(g–i) shows the combined centrifugal and Coriolis forces, illustrating the components of the gradient imbalance.

In the outer-core region (40–160 km) and lower to mid-troposphere (0–10 km), the reduced- f experiments show an enhanced subgradient force (Figure 4.8b and 4.8c), which can accelerate the radial inflow. They also show a decrease in centrifugal and Coriolis forces (Figure 4.8h and 4.8i), consistent with the enhanced subgradient force, while the low-level pressure gradient force remains largely unchanged (Figure 4.8e and Figure 4.8f). This indicates that the reduced centrifugal and Coriolis forces under the smaller f are responsible for the enhanced subgradient force at low to mid-levels at t_6 . The enhanced subgradient force could drive a stronger inflow in the lower troposphere.

In the mid- to upper troposphere (above 6 km) near the eyewall (40–80 km radius), the reduced- f experiments show a much stronger supergradient force than the control run (e.g., Figure 4.8d), contributing to a stronger upper-level outflow. Figure 4.8e shows an increased outward pressure gradient force, aligning with the enhanced supergradient force. In contrast, changes in centrifugal and Coriolis forces oppose the agradiant change (Figure 4.8h). These results suggest that the increased pressure gradient force is responsible for the stronger upper-level supergradient flow, leading to stronger upper-level outflow.

Inertial stability describes how resistant the TC circulation is to changes or

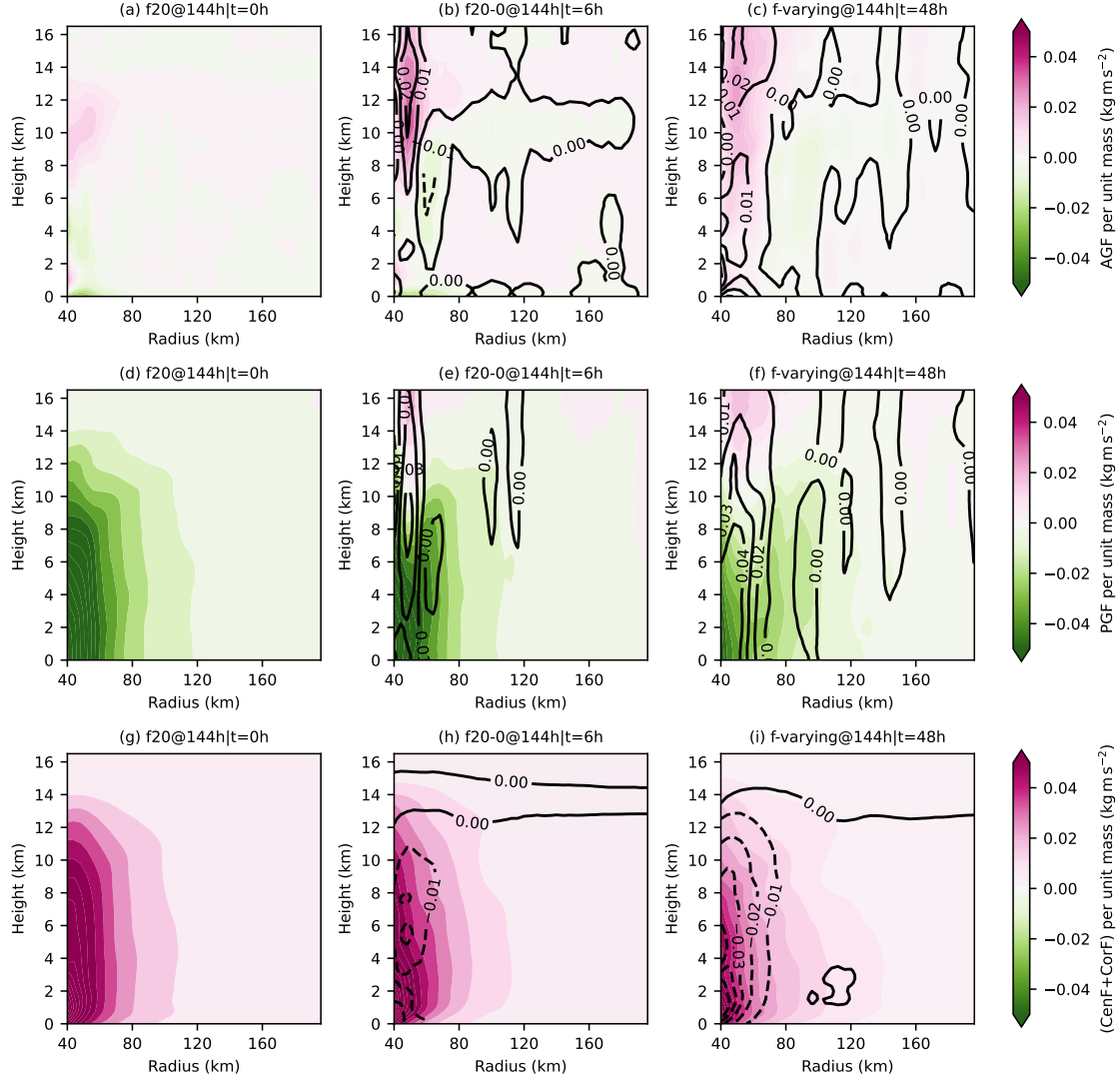


Figure 4.8: Height-radius plots of the azimuthally-averaged forces: agradiant force (AGF, shading, first row), pressure gradient force (PGF, shading, second row), and the sum of centrifugal and Coriolis forces (CenF+CorF, shading, third row), shown for the initial state (first column), f20-0@144h at $t = 6h$ (second column), and f-varying@144h at $t = 48h$ (third column). Contours indicate changes from the initial state with a 0.01 interval $\text{kg} \cdot \text{m} \cdot \text{s}^{-2}$.

perturbations in the radial direction. High inertial stability means that the system strongly resists such changes, maintaining a stable and tightly wound circulation. Inertial stability can be expressed as

$$I^2 = \left(\frac{\partial r v_t}{r \partial r} + f_0 \right) \left(f_0 + \frac{2v_t}{r} \right), \quad (4.3)$$

where I^2 is inertial stability, r is the radial distance from TC center, v_t is the tangential wind, and f_0 is the Coriolis parameter at TC center.

Figure 4.9 illustrates the distribution of I^2 . Due to a substantial decrease of f in f20-0@144h, there is a significant decrease in I^2 near the eyewall caused by the shrinkage of maximum wind speed during intensification at t_6 , with relatively smaller changes observed in the outer-core region (Figure 4.9b). While the quantity of I^2 is directly related to both the storm's intensity and the change in f , the net effect from f was evaluated by computing the changes in the I^2 field before and after the reduction of f_0 to zero at t_6 . We find a median decrease of approximately $1.26 \times 10^{-8} s^{-2}$ in I^2 , compared to the actual decrease of $1.46 \times 10^{-8} s^{-2}$ in I^2 outside the radius of 80 km. This confirms the relatively significant role of f in the outer-core region. Collectively, the decline in I^2 in the outer-core region, along with enhanced agradient force (Figure 4.8b and 4.8c), can thus drive stronger radial inflow at low to mid-levels and stronger radial outflow aloft.

The changes in radial wind driven by agradient force can change the TC intensity by transporting absolute angular momentum. The absolute angular momentum (AAM) per unit mass of an air parcel about the rotation axis is denoted as

$$AAM = r v_t + \frac{1}{2} f r^2$$

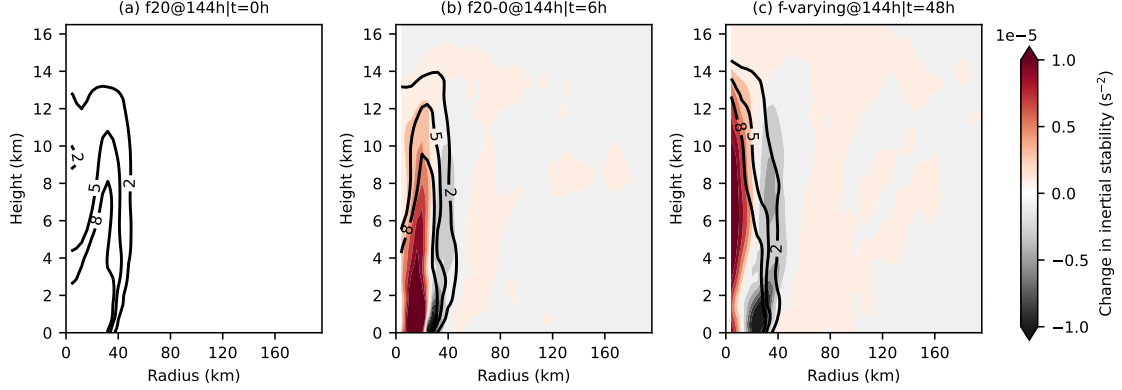


Figure 4.9: Height-radius plots of the azimuthally-averaged inertial stability (I^2 , contours) and changes in I^2 (shading) relative to restart time for (a) the initial state, (b) f20-0@144h at $t = 6\text{h}$, and (c) f-varying@144h at $t = 48\text{h}$. The contours have an interval of $3e - 06\text{s}^{-2}$.

, where v_t is the tangential wind, rv_t is the relative angular momentum, and $\frac{1}{2}fr^2$ is the planetary angular momentum. The radial transport of AAM (AAMF) towards the TC centre at each point is given by

$$AAMF = v_r \cdot AAM.$$

Radial inflow contributes to vortex spin-up by transporting angular momentum inward, partially offsetting losses due to frictional dissipation near the surface. Figure 4.10 shows the radial transport of absolute angular momentum (AAM) in the three experiments. AAM generally increases with radius due to its radial dependence, but under reduced- f , it decreases notably in the outer region (Figure 4.10b and 4.10c). Despite radial inflow strengthening at low and mid-levels, it may bring less AAM into the inner core if the overall AAM reservoir is reduced. Previous research has also shown that the changes in TC intensity are positively related to the changes in upper-level AAM export (Chan and Chan, 2013).

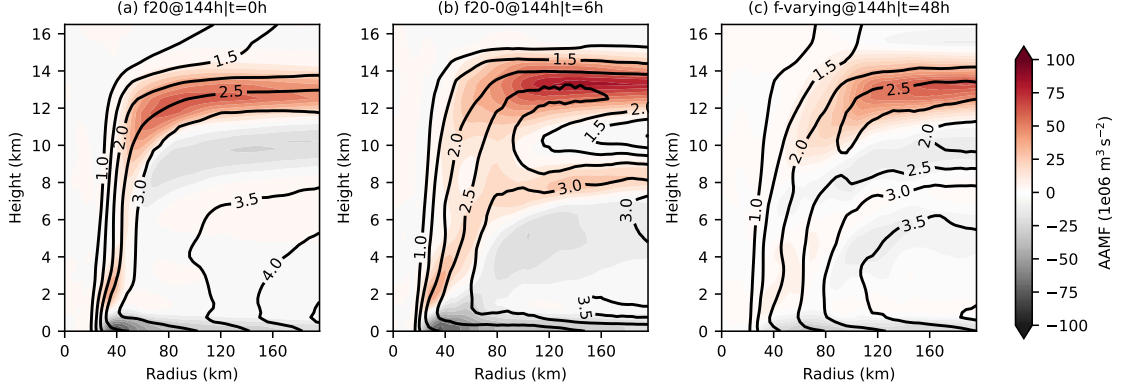


Figure 4.10: Height-radius plots of the azimuthally-averaged radial flux of absolute angular momentum (AAMF, shading) for (a) the initial state, (b) f20-0@144h at $t = 6$ h, and (c) f-varying@144h at $t = 48$ h. The contours show the value of absolute angular momentum with an interval of $5 \times 10^5 \text{ m}^2 \cdot \text{s}^{-2}$.

4.3.4 Summary

Figure 4.11 presents a schematic illustrating the potential mechanisms by which a developed TC responds to a reduced Coriolis parameter (f). Based on our analysis, the direct effect of zero- f on TCs is the reduction of inertial stability and an increased agradient force in the outer-core region, which can strengthen both the radial inflow and outflow throughout the storm's depth. The enhanced radial inflow will not only deepen the inflow layer but also facilitate convergence, thereby intensifying deep convection and strengthening downdrafts in the outer rainbands. However, the deepened inflow layer combined with enhanced downdrafts could promote greater entrainment of dry air from the free troposphere, which in turn would lower the boundary layer θ_e and cause decay. The lowering boundary layer θ_e will then suppress the deep convection in the eyewall and lead to the weakening of TC.

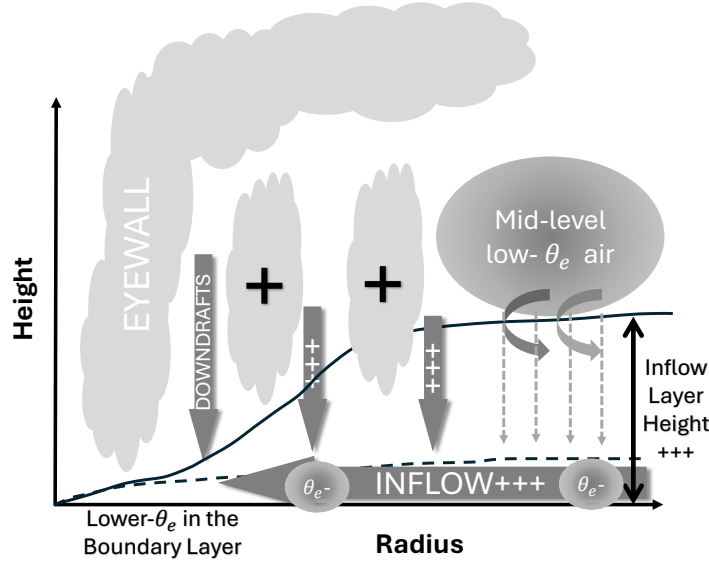


Figure 4.11: Schematic diagram indicating the decay mechanism under the reduced f : the deepening of the inflow layer height, accompanied by strengthened downdrafts, enhances the entrainment of low- θ_e air from mid-levels, which leads to the reduction of θ_e in the boundary layer.

4.4 Discussion

A sufficient Coriolis effect is one of the key factors influencing the formation and development of TCs. However, it is not clear how a lower latitude would affect an already developed TC vortex. This study investigates the response of TC intensity to the reduction of f and reveals that TCs gradually weaken as f is removed. The key effect of reduced- f on this decay process lies in the deepening of the inflow layer and the enhancement of downdrafts in the outer rainbands, which is associated with the strengthening of radial inflow in the absence of f . The deeper inflow layer depth and enhanced downdrafts introduce low- θ_e air into the boundary layer, leading to the weakening of convection and TCs to decay. However, it is acknowledged that

both the inflow and outflow are amplified due to the reduction of f , with in/outflow patterns strengthening throughout the cyclone depth.

The impact of low latitude (f) on developed TC vortex differs from that on TC formation and intensification. During TC formation, sufficient f facilitates spin-up by rotating convergent flow and creating angular momentum (Briegel and Frank, 1997; Gray, 1968, 1979, 1985, 1998). For TC intensification, the stronger boundary layer inflow associated with lower latitudes will bring more angular momentum into the system, promoting faster intensification (Li et al., 2012; Smith et al., 2015; Li et al., 2023b). However, in the case of an already developed TC vortex, the enhancement of the low-level inflow combined with enhanced downdrafts disrupts the boundary layer by entraining more low- θ_e air from mid-levels. Li and Toumi (2024) shows that TCs decay more quickly with a smaller initial f . Although the phenomenon might not be fully linked to the decreasing f scenario in this study, stronger radial inflow at lower latitudes likely leads to faster decay.

The weakening rate of the first 24-hour decay is proportional to TC intensity, with the strongest storm showing the largest weakening rate (Figure 4.1a). Sensitivity experiments with zero- f initiated earlier at T_{96} are presented in Appendix B. The same mechanism is discernible in this analysis, characterized by enhanced radial inflow and outflow, the presence of downdrafts external to the eyewall, and a marked reduction in θ_e within the boundary layer. However, it has a lower weakening rate of 12.7 m s^{-1} compared to 20.7 m s^{-1} at T_{144} . This is consistent with existing observations that suggest stronger storms usually decay faster than weaker storms (Wang et al., 2020). Notably, the stronger storm shows more intense downdrafts near the eyewall (comparing Figure 4.7b and Figure B.7b), resulting in a more substantial

decrease in θ_e in that region (comparing Figure 4.6b and Figure B.6b). This result suggests that the influence of zero- f on weakening rate may depend on the strength of downdrafts, which is expected to increase with TC intensity.

The deeper inflow layer height under lower- f in this study also aligns with theoretical studies. The inflow layer height is commonly used as a dynamical definition for the boundary layer height in TCs (Zhang et al., 2011, 2023). Theoretical studies indicate that the boundary layer height is inversely proportional to the square root of inertial stability (I) at the top of the boundary layer, expressed as $D_e = (2K/I)^{1/2}$, where K is the turbulent diffusivity (Kepert and Wang, 2001). As I is typically proportional to the Coriolis parameter f , this relationship implies that boundary layer height increases when f (and thus I) decreases. This is consistent with the increased inflow layer height observed under reduced f conditions in our results. Outside the core region, where inertial stability is lower, and the Coriolis parameter f plays a relatively greater role, the boundary layer height is more sensitive to reductions in f . This is consistent with our findings that the inflow layer deepens more significantly in the outer-core region under reduced f conditions.

The mechanisms identified in this study share notable similarities with those previously proposed for TC weakening under vertical wind shear (Riemer et al., 2010; Alland et al., 2021a,b). Shear-induced downward transport of low-equivalent potential temperature (θ_e) air into the boundary layer has been shown to reduce TC intensity from the view of Carnot-cycle heat engine for intense TCs in shear (Riemer et al., 2010). Radial and downdraft ventilation associated with vortex tilt under shear were shown to contribute to this weakening by transporting low- θ_e air inward and downward, respectively, which suppresses inner-core upward mass flux and limits

the spatial extent of strong convection (Alland et al., 2021b,a). Interestingly, the dynamic response observed in the reduced- f experiments exhibits comparable effects with shear. However, unlike shear-induced cases, no vertical wind shear is imposed in this study, and no significant vortex tilt develops, with maximum changes of 4.2 km and 2.4 km in f20-0@144h (mean tilt= 6.3 km) and f-varying@144h (mean tilt = 6.5 km), respectively, compared to the control (mean tilt = 5.4 km) during the first 24 hours after restart; thereby validating the thermodynamic decay method irrespective of shear or zero- f . Other dynamical processes, such as outflow layer dynamics, increased frictional dissipation, and potential eyewall replacement cycles, may also influence TC weakening, however, are not explored and out of the scope of this study. Regardless of that, we find that the combined effect of increasing inflow layer depth and downdrafts is the main cause of decay under the pure modification of f .

4.5 Conclusions

This study investigated the response of a pre-existing TC vortex to the removal of the Coriolis effect. The simulated cyclones are found to decay gradually under extremely reduced f . During this process, both radial inflow and outflow strengthened throughout the cyclone depth due to decreased inertial stability and increased agradient force. This further causes a deeper inflow layer and stronger downdrafts, which are associated with intensified convection in the outer rainbands. The downdrafts entrainment of mid-level dry air into the deeper inflow layer stabilises the boundary layer and suppresses deep convection, ultimately resulting in the weakening of TCs.

These findings provide a deeper understanding of how the Coriolis effect affects the

intensity evolution, particularly in the declining phase of the TC life-cycle. This study implies that while TCs may not form near the equator, a TC steered equatorward could persist for several days despite gradual weakening, posing a potential threat to vulnerable and unprepared communities in equatorial regions.

Chapter 5

Stochastic Modelling of the Decay of North Atlantic Hurricanes

5.1 Introduction

In this chapter, we apply existing decay models within IRIS and assess their performance in simulating the landfall risk of North Atlantic hurricanes. We then use this framework to attribute the underlying causes of the increased intensity of North Atlantic hurricanes from 1979 to 2024.

As environmental and climatic conditions continue to change, understanding long-term variations in TC intensity is important for effective disaster risk management and mitigation. Theoretically, TC maximum intensity is largely modulated by the storm-local potential intensity (PI) as a thermodynamic control (Emanuel, 1987; Sobel et al., 2016; Knutson et al., 2019; Kossin and Camargo, 2009). A rising PI related to an increase in SST over NATL and elsewhere is expected to cause an increasing trend in TC intensity (Emanuel, 1987; Elsner et al., 2008; Emanuel, 2000;

Kossin et al., 2013).

While PI is clearly increasing at the basin scale, the storm-local PI may also be modulated by shifts in TC tracks. A recent study using best-track data indicates a robust southward shift in LMI locations to higher-PI regions in the North Atlantic during the satellite era (Cao et al., 2025). This could increase the storm-local PI and lead to larger LMIs. Finally, the relative intensity (REI, defined as LMI/PI) may have changed. Rapid intensification has been reported to increase (Balaguru et al., 2018; Bhatia et al., 2019; Wang et al., 2020; Balaguru et al., 2022; Garner, 2023), including its coastal migration (Li et al., 2023a). One implication is that more TCs may reach a larger REI, which alone could also drive trends in LMI.

We therefore have three factors that each could cause the trends in LMI: the basin-scale increase in PI, a shift of LMI towards higher PI regions, and a larger REI. IRIS will then be applied to simulate the North Atlantic hurricanes from 1979 to 2024 and assess the influence of the above three factors on TC intensity.

5.2 Data and Methods

5.2.1 Data

The best-track data are used both to evaluate the simulated results and to conceptualize the simulations. TCs with an LMI of at least 33 m s^{-1} (Category 1 or higher) are included. For the landfall analysis, only TCs with landfall intensities exceeding 17 m s^{-1} (tropical storm strength) are considered. ADT-HURSAT data are also used as supplementary data for the trend analysis.

5.2.2 The LMI in IRIS

The LMI of a synthetic TC in IRIS is constrained by the PI via an LMI model:

$$LMI = REI \cdot (PI_{loc} - 33) + 33, \quad (5.1)$$

where

$$PI_{loc} \equiv PI(\text{Month}, \text{Lat}, \text{Lon}). \quad (5.2)$$

PI_{loc} is in m s^{-1} and is derived from the monthly-mean PI field given the month, latitude, and longitude at LMI. Therefore, PI_{loc} is determined by both the climatological PI and shifts in the LMI location.

REI is the relative intensity, defined as the ratio between maximum wind speed ($v_{\max}$) and PI using a lower bound of hurricane strength of 33 m s^{-1} ($REI = \frac{v_{\max} - 33}{PI_{loc} - 33}$). REI is a scaling factor between 0 and 1.1 that controls the actual wind speed the storm can achieve.

The distribution of the observed REI for LMI is based on best-track data. REI has been suggested to follow a uniform PDF within the range of $[0, 1]$, implying that a TC has an equal likelihood of reaching any intensity up to its PI (Emanuel, 2000). However, observations (not shown) and the presence of supergradient winds in the boundary layer indicate that super-intensity is possible. Therefore, we adopt 1.1 as the upper limit of REI, with any values exceeding 1.1 clipped to 1.1. The 1.1 value is the median value of REI greater than 1.0. A linear probability density function (PDF), which adds one degree of freedom to a uniform distribution, was then fitted directly to the observed REI values using maximum likelihood estimation.

5.2.3 Experimental design

The basin-scale PI, track shifts, and REI are treated as separate inputs to IRIS (Figure 2.2). To evaluate their effects on long-term trends in LMI, we designed three experiments in which each factor was incorporated sequentially by varying the corresponding inputs in IRIS:

- **PI-Clim** uses the monthly-mean PI of each year at the LMI location. Tracks are randomly selected from the climatology, which is assumed to show no trend in track shifts. REI follows a linear distribution with a slope of -0.63 over the range $[0, 1.1]$ (Figure 5.6a).
- **PI-Track** is based on PI-Clim, but uses the observed parent track in the corresponding years as templates for stochastic perturbations. These annual tracks exhibit southward shifts, as established in Cao et al. (2025). PI-Track uses the same default linear REI distribution as PI-Clim.
- **PI-Track-REI** is based on PI-Track but uses an REI distribution that is linearly decreasing over $[0, 1.1]$, with a slope of -0.69 for 1979–2001 (Figure 5.6b) and -0.58 for 2002–2024 (Figure 5.6c). This incorporates the influence of the increase in REI over the two epochs.

While the experiments are designed to assess the additive contributions of the three factors to overall intensity trends, potential interactions or nonlinearities may exist among these drivers. A summary of the model setup is given in Table 5.1. The model period spans 1979–2024, with an ensemble size of 1000 for each synthetic year. Sensitivity tests of simulated TC intensity trends to the PI calculation and

Table 5.1: Setup of the IRIS model simulations.

Experiments	PI	Tracks	Linear PDF of REI $\sim[0,1.1]$
PI-Clim	Monthly mean	Climatology	Slope=-0.63
PI-Track	Monthly mean	Annually	Slope=-0.63
PI-Track-REI	Monthly mean	Annually	1979–2001: Slope=-0.69 2002–2024: Slope=-0.58

to alternative REI PDFs (uniform and beta distributions with two free parameters; Figure 5.6) were also conducted.

5.2.4 Statistical analysis

The ordinary least-squares linear regression was used to estimate the linear trend. The significance of the estimated linear trend is evaluated using both 95% confidence intervals (CIs) and p-values. The CIs are calculated from the standard error of the linear fit and the corresponding Student’s t critical value, while the p-values of the trend slopes are obtained from the non-parametric Mann-Kendall test. The non-parametric Kolmogorov–Smirnov (K-S) test was applied to assess if REI comes from a linear distribution. The non-parametric Mann–Whitney U test (MWU) was applied to assess the significance of differences in REI between 1979–2001 and 2002–2024.

5.3 Results

5.3.1 North Atlantic hurricanes

Landfalling TCs over the North Atlantic are relatively infrequent. From 1950 to 2024, 154 North Atlantic TCs made landfall with an intensity of at least 33 m s^{-1} ,

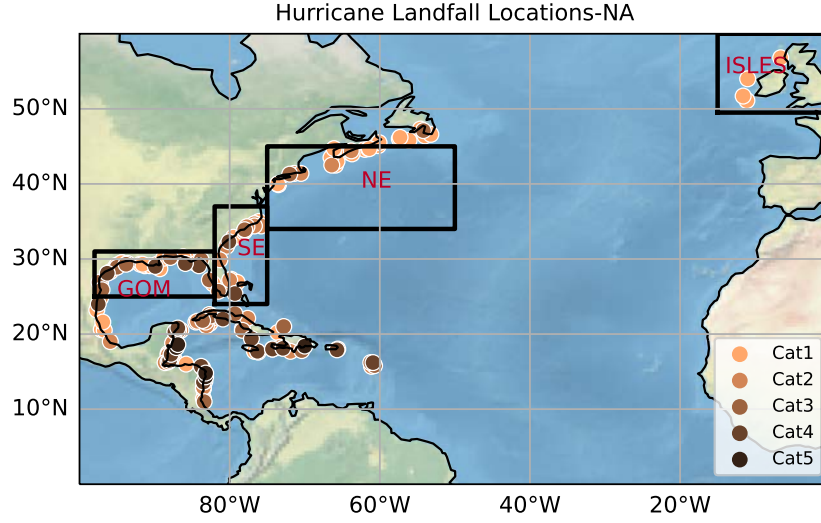


Figure 5.1: Map of landfall locations and categorical intensities of North Atlantic hurricanes (154 cases), highlighting four major coastal regions affecting the US and UK: Gulf of Mexico (GOM, 30 cases), southeastern coast of the US (SE, 22 cases), northeastern coast of the US (NE, 17 cases), and the British Isles (ISLES, 4 cases).

including 30 cases in the Gulf of Mexico (GOM), 22 cases along the southeastern coast of the US (SE), 17 cases along the northeastern coast of the US (NE), and 4 cases in the British Isles (ISLES), as shown in Figure 5.1.

Figures 5.2 and 5.3 together indicate a systematic shift in North Atlantic hurricane tracks in recent decades. The spatial distribution of normalised track density shows increased activity in the western subtropical North Atlantic and reduced density in parts of the central and eastern tropical Atlantic during 2002–2024 compared with 1979–2001. Consistent with this, the annual mean latitude of LMI locations exhibits a significant decreasing trend of approximately 0.12° per year ($p < 0.01$), indicating that hurricanes have, on average, reached their peak intensity at progressively lower latitudes. Together, these results suggest a basin-scale redistribution of hurricane tracks, with a tendency for more recent storms to concentrate farther west and to achieve maximum intensity at lower latitudes.

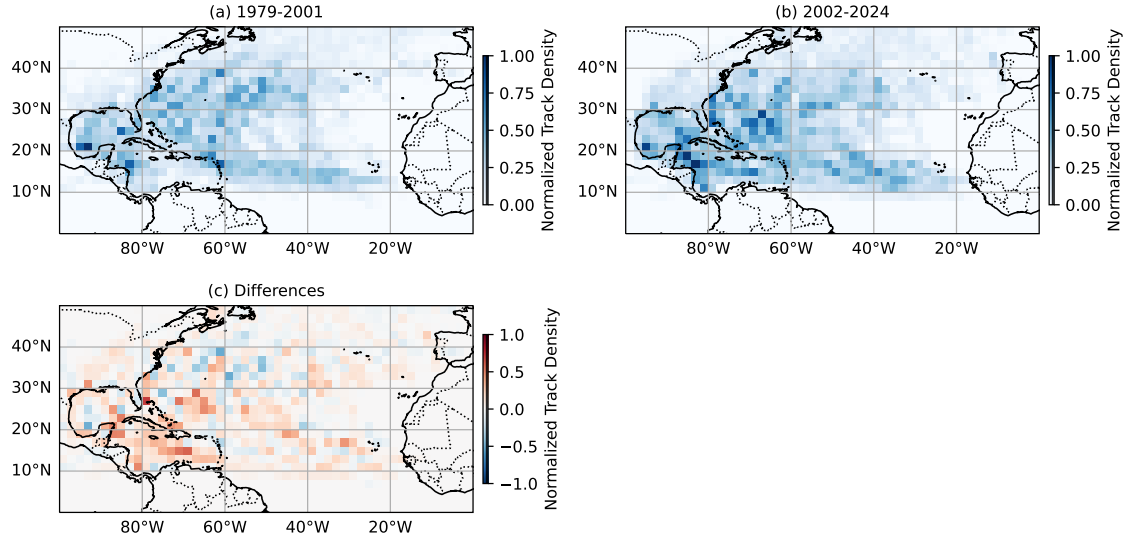


Figure 5.2: Normalised track density of North Atlantic hurricanes during (a) the first epoch (1979–2001), (b) the second epoch (2002–2024), and (c) the difference between the two periods.

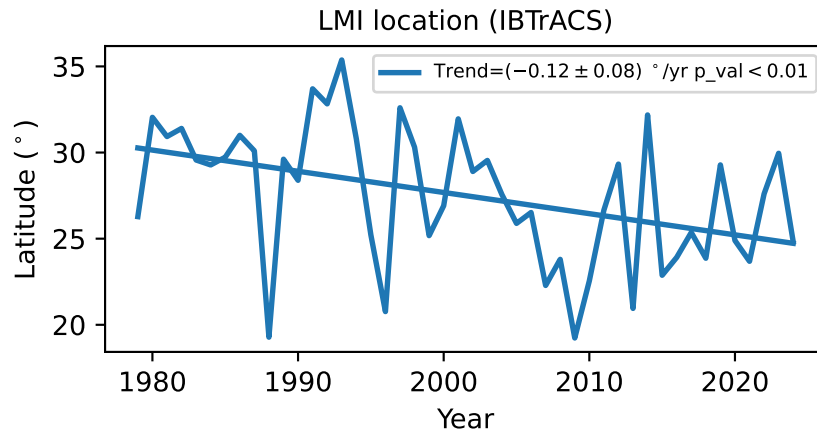


Figure 5.3: Long-term trends in the annual mean latitude of LMI locations for North Atlantic hurricanes from 1979 to 2024.

5.3.2 Evaluation of decay models in IRIS over the North Atlantic

For facilitating the risk assessments of landfalling TCs, IRIS is designed to generate a large ensemble of synthetic TC data by simulating the decay of TC wind speed from the point of LMI. Our first step is thus to compare the landfall intensity simulated from IRIS with 10,000 ensembles for each year to the observations. Three decay models, the modified β model derived in Chapter 3 (Eq. 3.3), the empirical exponential model (Eq. 1.5), and the algebraic model (Eq. 1.8), were tested and compared within IRIS.

To apply the parametric decay model in IRIS, first we need to fit each decay model to the observations to get the samples of decay parameters, which will then be used to fit parametric probability distributions for subsequent stochastic modelling in IRIS. Here, we only focus on the over-ocean decay to get the landfall intensity. The used observation is from 1979 to 2024, and for Atlantic hurricanes only. The used decay models are listed in Table 5.2.

For the exponential (EXP) model, the decay parameter λ was estimated by fitting the exponential decay function to the wind speed time series of each event. The empirical distribution of λ was subsequently fitted using a lognormal distribution, characterised by its variance parameter ($\sigma=0.45$). For the ALG model, the $\log \kappa$ for the over-ocean decay was found to be distributed approximately normally with a dependence on LMI. It is then fitted to a linear regression against LMI with a noise term assumed to follow a Gaussian distribution (Sparks and Toumi, 2024). For the β model, two decay parameters, α and β , are correlated with each other with

Table 5.2: Summary of decay models, parameters, and fitted distributions.

Decay model	Expression	Decay parameters	Fitted distribution
EXP	$v(t) = v_0 e^{-\lambda t}$	λ	$\log \lambda \sim \mathcal{N}(0, \sigma^2)$ $\sigma = 0.45$
ALG	$\frac{1}{v} = \frac{1}{v_0} + \kappa t$	κ	$\log \kappa = m_a \text{ LMI} + c_a + \varepsilon_a, \varepsilon_a \sim \mathcal{N}(0, \sigma_a^2)$ $m_a = -0.03, c_a = -6.84, \sigma_a = 0.67$
β	$v(t) = v_0 e^{-\alpha t^\beta}$	α, β	$\log \alpha \sim \mathcal{N}(0, \sigma_\alpha^2), \sigma_\alpha = 0.45$ $\log \beta \sim \mathcal{N}(0, \sigma_\beta^2), \sigma_\beta = 0.29$

$r = 0.33$, and $\log \alpha$ and $\log \beta$ were each fitted using normal distributions. These fitted distributions provide the statistical inputs required for sampling decay parameters in the stochastic model IRIS described in section 2.3. 10,000 years of synthetic datasets of TC wind speed during decay were created over the North Atlantic for each experiment and will be validated against the best-track data.

From the perspective of risk, the mean landfall intensity (Table 5.3), distribution of landfall intensity (Figure 5.4), and the landfall rate (average number of landfalls per year) with respect to each category (Table 5.4) are compared between simulations and observations among each run with different decay models. Overall, the differences among the decay models are small.

All models capture the distribution for landfall intensity well over the whole North Atlantic and in the NE and SE regions, but performance is poorer in the Gulf of Mexico (GOM). The β model performs relatively well in the ISLES region, which is not surprising given its two free parameters. The reduced skill in the GOM mainly reflects difficulties of IRIS in reproducing the first peak of the intensity distribution for Category 1 storms. In addition, IRIS tends to overestimate the mean landfall intensity in the SE. In summary, the models show good agreement at the basin scale, while larger regional biases likely arise from the low frequency of landfalling events in certain areas. For simplicity of use, the default algebraic model will be used for the following analyses.

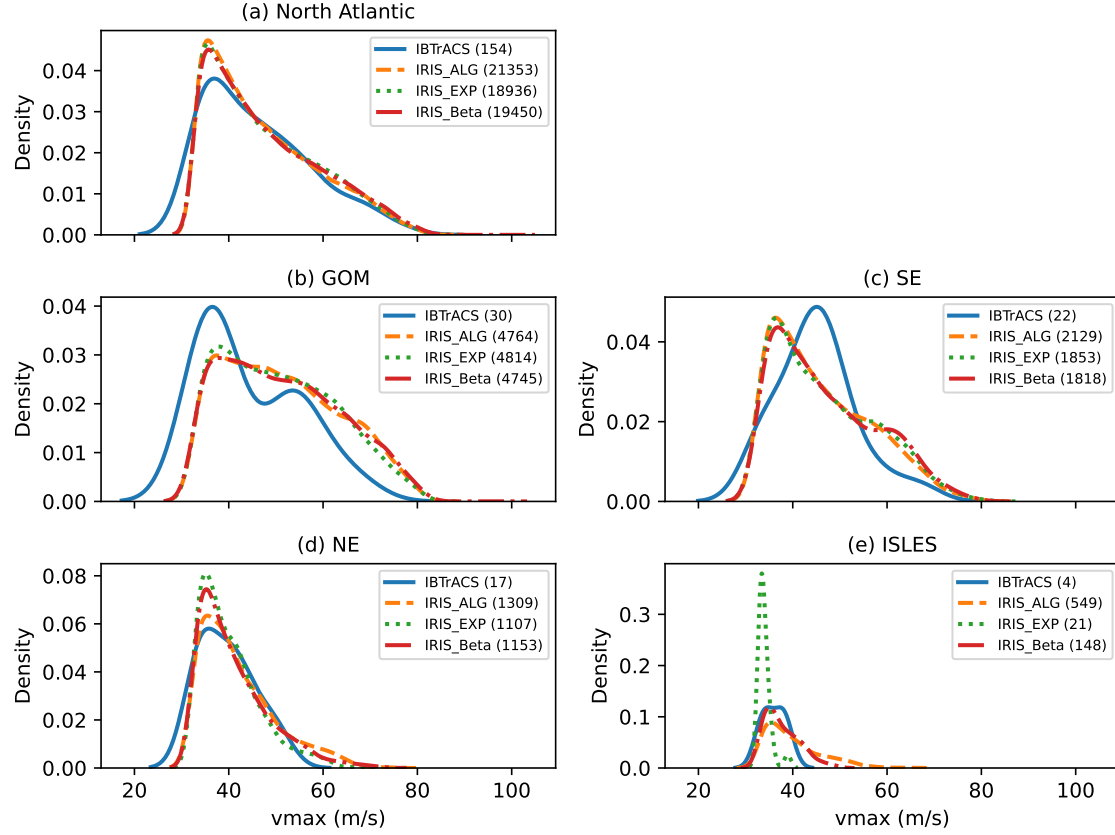


Figure 5.4: Distribution of landfall intensities with kernel density estimates for hurricanes in (a) North Atlantic, (b) GOM, (c) SE, (d) NE, and (e) ISLES. Each simulation was run for 10000 years of synthetic hurricane events. Sample sizes for each dataset are indicated in the legend.

Table 5.3: Mean landfall intensities. Numbers in parentheses indicate the 95% bootstrap confidence interval (CI) for the mean based on 75 years of observations (1950–2024). Values in bold lie within the 95% CI of the mean derived from observations.

(Sub-)Basin	IBTrACS	IRIS_ALG	IRIS_EXP	IRIS_Beta
NATL	46.22 (44.5, 48.08)	47.26	47.54	47.80
GOM	44.38 (40.86, 48.03)	51.35	50.85	51.47
NE	45.09 (41.77, 48.48)	46.30	46.73	47.05
SE	39.63 (37.04, 42.39)	41.89	40.22	41.05
ISLES	35.99 (33.92, 38.04)	39.75	33.97	37.65

Table 5.4: Landfall rate (average number of landfalls per year) of North Atlantic hurricanes by intensity category. Numbers in parentheses indicate the 95% bootstrap confidence interval (CI) for the mean based on 75 years of observations (1950–2024). Values in bold lie within the 95% CI of the mean derived from observations.

Category	Obs	Sub_basin	ALG	EXP	Beta
Cat1	0.93 (0.77, 1.09)	NATL	0.97	0.84	0.85
Cat2	0.43 (0.29, 0.56)	NATL	0.36	0.31	0.33
Cat3	0.34 (0.23, 0.47)	NATL	0.39	0.35	0.35
Cat4	0.28 (0.17, 0.40)	NATL	0.32	0.30	0.31
Cat5	0.07 (0.01, 0.12)	NATL	0.10	0.09	0.11
Cat1	0.24 (0.13, 0.35)	GOM	0.15	0.16	0.15
Cat2	0.00 (0.00, 0.00)	GOM	0.08	0.08	0.08
Cat3	0.11 (0.04, 0.17)	GOM	0.11	0.11	0.11
Cat4	0.05 (0.01, 0.11)	GOM	0.10	0.11	0.10
Cat5	0.00 (0.00, 0.00)	GOM	0.04	0.03	0.04
Cat1	0.11 (0.04, 0.17)	SE	0.10	0.08	0.08
Cat2	0.13 (0.05, 0.21)	SE	0.04	0.03	0.03
Cat3	0.03 (0.00, 0.07)	SE	0.04	0.04	0.03
Cat4	0.03 (0.00, 0.07)	SE	0.03	0.03	0.03
Cat5	0.00 (0.00, 0.00)	SE	0.00	0.00	0.00
Cat1	0.16 (0.08, 0.25)	NE	0.09	0.08	0.08
Cat2	0.05 (0.01, 0.11)	NE	0.02	0.02	0.02
Cat3	0.01 (0.00, 0.04)	NE	0.02	0.01	0.01
Cat4	0.00 (0.00, 0.00)	NE	0.01	0.00	0.00
Cat5	0.00 (0.00, 0.00)	NE	0.00	0.00	0.00
Cat1	0.05 (0.01, 0.11)	ISLES	0.04	0.00	0.01
Cat2	0.00 (0.00, 0.00)	ISLES	0.01	0.00	0.00
Cat3	0.00 (0.00, 0.00)	ISLES	0.00	0.00	0.00
Cat4	0.00 (0.00, 0.00)	ISLES	0.00	0.00	0.00
Cat5	0.00 (0.00, 0.00)	ISLES	0.00	0.00	0.00

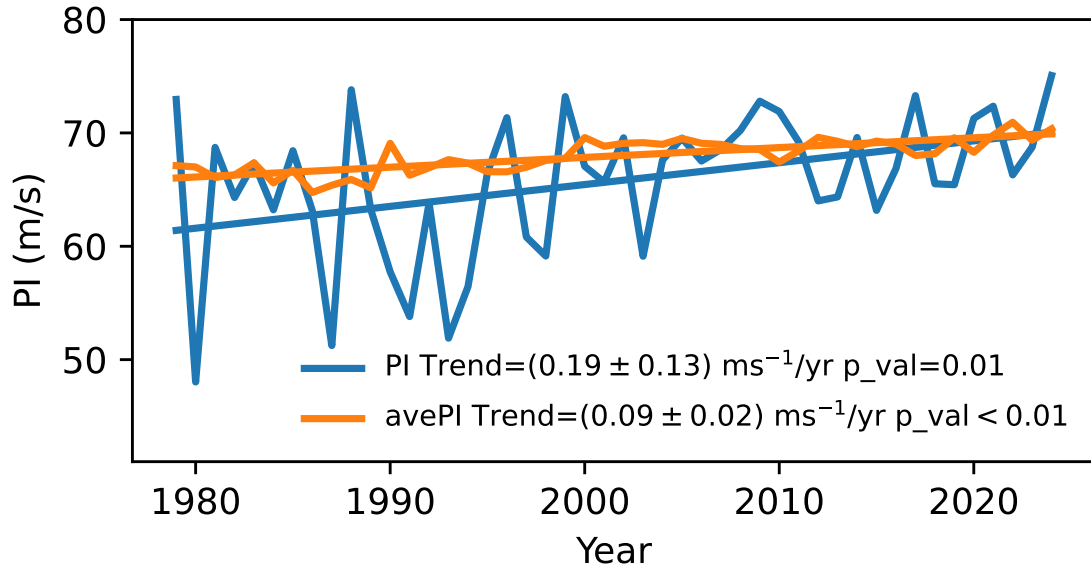


Figure 5.5: Observed trends in regional average PI (orange) and storm-local PI (blue) over the North Atlantic, showing the slope with 95% confidence intervals and p-value in the legend.

5.3.3 Attributing increased intensity of North Atlantic hurricanes

Our next step is to apply the established framework for attribution. Figure 5.5 shows the time series of the annual mean regional-average PI (orange), which averages out the changes in LMI position, and the storm-local PI (blue), which includes the effects of LMI shifts on PI changes. The regional average PI has a trend of 0.09 m s^{-1} per year, whereas the storm-local PI has a much larger trend of 0.19 m s^{-1} . PI trends are nearly doubled when the effect of LMI shifts is included. This regional average PI reflects the basin-scale increase in PI with a random selection of LMI position in the PI-Clim run, while the storm-local PI reflects the basin-scale increase and the effect of LMI shifts on PI changes in the PI-Track run.

The linear decreasing PDFs were fitted to observed REI on $[0, 1.1]$ (Figure 5.6). The slope for the climatology during 1979–2024 is -0.63 (Figure 5.6a). The changes in the REI distribution between two epochs, 1979–2001 and 2002–2024, were considered. These two epochs of data were fitted to linearly decreasing PDFs with different slopes of -0.69 and -0.58 , respectively (Figure 5.6b-c). All fits passed the Kolmogorov–Smirnov test at the 95% significance, with statistics of 0.06 ($p=0.19$), 0.07 ($p=0.51$), and 0.06 ($p=0.61$). A shallower negative slope in the linear PDF during the second epoch indicates an increased likelihood of higher REI values compared to the first epoch. However, this epochal change is marginal according to the MWU test; nevertheless, its influence on long-term trends in LMI is incorporated and evaluated in the PI–Track–REI simulation.

Figure 5.7 shows the time series of annual mean LMI and landfall intensity from observations and simulations. The best-track data shows a significant increasing trend in the annual mean LMI of 0.14 m s^{-1} per year, whereas ADT-HURSAT indicates an insignificant trend of 0.14 m s^{-1} per year ($p = 0.17$), likely due to the shorter analysis period (Figure 5.7a–b). In comparison, the simulated annual mean LMI shows significant increasing trends of 0.04, 0.08, and 0.09 m s^{-1} per year by sequentially including the effect from increasing PI, southward track shifts, and epochal increase in REI (Figure 5.7c–e). Regional PI and southward shift of TC tracks show comparable effects on the increasing trend in LMI, whereas the epochal increase in REI shows only a limited positive influence. The annual mean landfall intensity shows only a weak increasing trend of 0.02 m s^{-1} per year when the increasing PI is considered (Figure 5.7c).

Percentile regression was applied to the trend analysis in LMI (Table 5.5). It

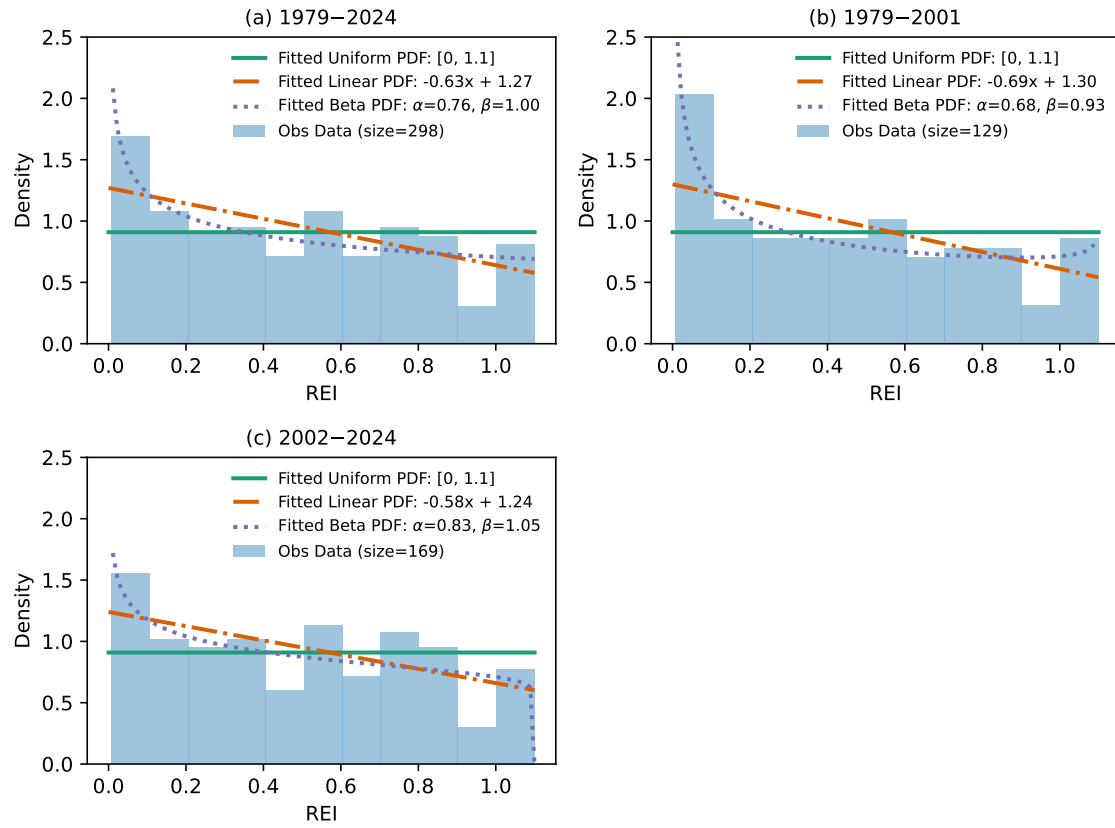


Figure 5.6: Distribution of observed relative intensity (REI) within the range $[0, 1.1]$ and the corresponding fitted uniform, linear, and beta probability density functions (PDFs) for (a) 1979–2024, (b) 1979–2001, and (c) 2002–2024. The fitted PDFs and corresponding sample sizes are shown in the legend.



Figure 5.7: Time series of annual mean lifetime maximum intensity (LMI; blue) and landfall intensity (LF; orange) from 1979–2024 (1979–2017 for ADT-HURSAT) based on different datasets: (a) IBTrACS, (b) ADT-HURSAT, (c) PI-Clim, (d) PI-Track, and (e) PI-Track-REI. Linear trend estimates ($\pm 95\%$ confidence interval) and associated p-values are provided in the legend.

reveals that positive trends in LMI systematically increase with percentile across all datasets. Both observations and model experiments show larger trends at high percentiles, indicating that the increasing intensity is concentrated in the strongest storms, consistent with (Elsner et al., 2008). However, the simulations struggle to capture the observed trends in the higher-intensity quantiles.

Sensitivity experiments using alternative REI PDFs show that the simulated trends in TC intensity are not sensitive to the assumed REI distribution (Table 5.6). For the PI-Track experiments, replacing the default linear REI PDF with either a uniform or Beta distribution produces nearly identical trends in both LMI ($0.08\text{--}0.09\text{ m s}^{-1}\text{ yr}^{-1}$) and LF intensity ($0.03\text{--}0.04\text{ m s}^{-1}\text{ yr}^{-1}$). Similarly, the simulated trends remain unchanged in the PI-Track-REI experiments within uncertainty, with LMI trends of $0.09\text{--}0.10\text{ m s}^{-1}\text{ yr}^{-1}$ and LF intensity trends consistently at $0.04\text{ m s}^{-1}\text{ yr}^{-1}$.

Figure 5.8 gives the trend analysis of LMI and landfall latitudes. There is a significant southward shift of LMI location in both the best track data ($-0.12\text{ }^{\circ}/\text{yr}$) and ADT-HURSAT ($-0.10\text{ }^{\circ}/\text{yr}$) (Figure 5.8a–b). Since the PI-Clim experiment uses all historical tracks for each year, trends in the locations are not expected (Figure 5.8c). The simulated tracks in PI-Track and PI-Track-REI are constrained by the observed parent tracks in the observations and show consistent decreasing trends of $-0.12\text{ }^{\circ}/\text{yr}$ in LMI location. While no trend is observed for the landfall location, likely due to noise and small sample size, the IRIS model predicts a small southward shift of landfall location ($-0.10\text{ }^{\circ}/\text{yr}$). This landfall shift follows the shift of LMI in the parent tracks.

Figures 5.9 and 5.10 show the distribution of simulated trends across the 1000-

Table 5.5: Percentile regression for the linear trend analysis of LMI. Slope $\pm$ 95% t-based error (units: $\text{m s}^{-1} \text{yr}^{-1}$); values in regular font indicates $p \leq 0.05$ based on the Mann-Kendall test.

Dataset	mean	p50	p60	p70	p80	p90
IBTrACS	0.14 ± 0.10	0.14 ± 0.15	0.18 ± 0.14	0.25 ± 0.15	0.29 ± 0.18	0.27 ± 0.20
ADT-HURSAT	<i>0.14 ± 0.21</i>	<i>0.15 ± 0.26</i>	<i>0.19 ± 0.26</i>	<i>0.25 ± 0.27</i>	<i>0.28 ± 0.27</i>	0.31 ± 0.29
PI-Clim	0.04 ± 0.01	0.04 ± 0.01	0.05 ± 0.01	0.06 ± 0.01	0.07 ± 0.02	0.08 ± 0.02
PI-Track	0.08 ± 0.05	0.09 ± 0.06	0.10 ± 0.07	0.11 ± 0.07	0.11 ± 0.07	0.13 ± 0.07
PI-Track-REI	0.09 ± 0.05	0.10 ± 0.06	0.12 ± 0.07	0.13 ± 0.07	0.14 ± 0.07	0.15 ± 0.07

Table 5.6: Sensitivity of simulated trends in TC intensity to alternative REI PDFs.

Experiments	PDF of REI $\sim[0, 1.1]$	Trends in LMI ($\text{m s}^{-1}/\text{yr}$)	Trends in LF intensity ($\text{m s}^{-1}/\text{yr}$)
PI-Track (Default)	Linear: Slope=-0.63	0.08 $\pm$ 0.05	0.03 $\pm$ 0.10
PI-Track (Uni)	Uniform	0.09 $\pm$ 0.05	0.04 $\pm$ 0.10
PI-Track (Beta)	Beta: $\alpha = 0.76, \beta = 1.0$	0.08 $\pm$ 0.05	0.04 $\pm$ 0.10
PI-Track-REI (Default)	1979-2001: Slope=-0.69 2002-2024: Slope=-0.58	0.09 $\pm$ 0.05	0.04 $\pm$ 0.10
PI-Track-REI (Beta+Beta)	1979-2001: $\alpha = 0.68, \beta = 0.93$ 2002-2024: $\alpha = 0.83, \beta = 1.05$	0.10 $\pm$ 0.05	0.04 $\pm$ 0.10

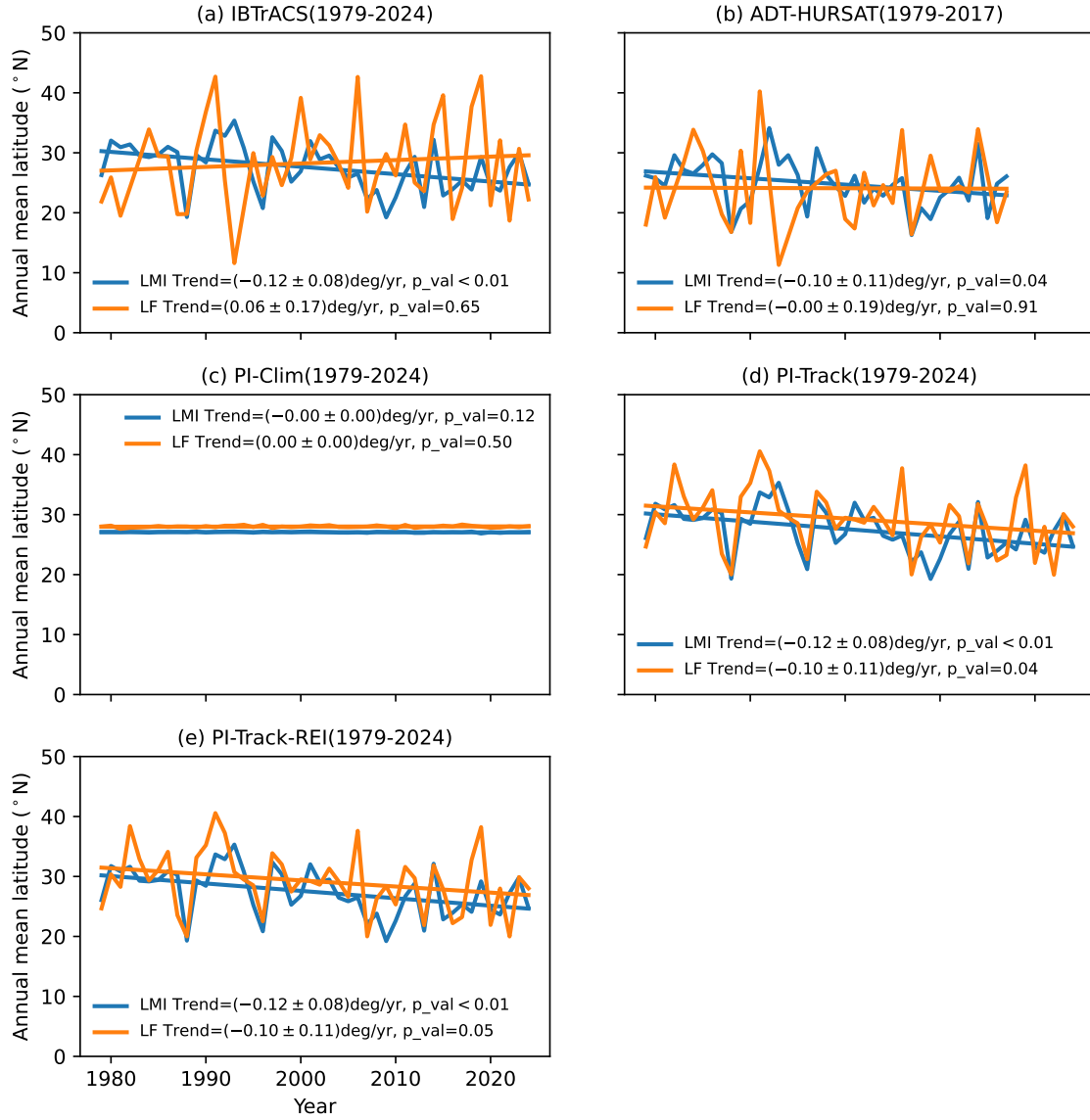


Figure 5.8: As in Figure 5.7, but for the annual mean latitudes of lifetime maximum intensity (LMI; blue) and landfall (LF; orange) locations.

member ensembles for each experiment. The spread illustrates the range of possible trends, helping to distinguish systematic changes in simulations from internal variability and to quantify uncertainty in the model results.

LMI (first column in Figure 5.9) is more likely to exhibit positive trends across ensemble members, and this tendency strengthens when track and REI effects are included, with mean trends increasing from PI-Clim ($0.04 \text{ m s}^{-1} \text{ yr}^{-1}$) to PI-Track ($0.07 \text{ m s}^{-1} \text{ yr}^{-1}$) and PI-Track-REI ($0.09 \text{ m s}^{-1} \text{ yr}^{-1}$). The trends in LMI latitudes (second column in Figure 5.9) are consistently negative for the track-including experiments (PI-Track and PI-Track-REI), following the observed trend in parent tracks.

The trends in landfall intensity (first column in Figure 5.10) across the ensemble are approximately evenly split between positive and negative values, indicating no consistent trend in landfall intensity. The trends in landfall latitude (second column in Figure 5.10) are mostly negative for the track-including experiments (PI-Track and PI-Track-REI), indicating a robust southward shift in the model simulations.

A summary of observed and simulated trends in LMI and landfall latitude, including the model spread of simulated trends across the ensemble in each experiment, is given in Table 5.7. For the simulated trends in LMI, PI alone drives an increasing LMI (mean trend = 0.04), but with large model variability in negative values (ranging from -0.09 to 0.19). Including both PI and track effects increases confidence in driving an increasing trend (ranging from -0.04 to 0.19). The increase in REI makes only a small contribution to the increasing trend (ranging from -0.03 to 0.21). For trends in landfall latitude, the 95% model spread for PI-Clim ranges from -0.25 to 0.03 , compared to -0.16 to 0.15 when track shifts are excluded, with trend values

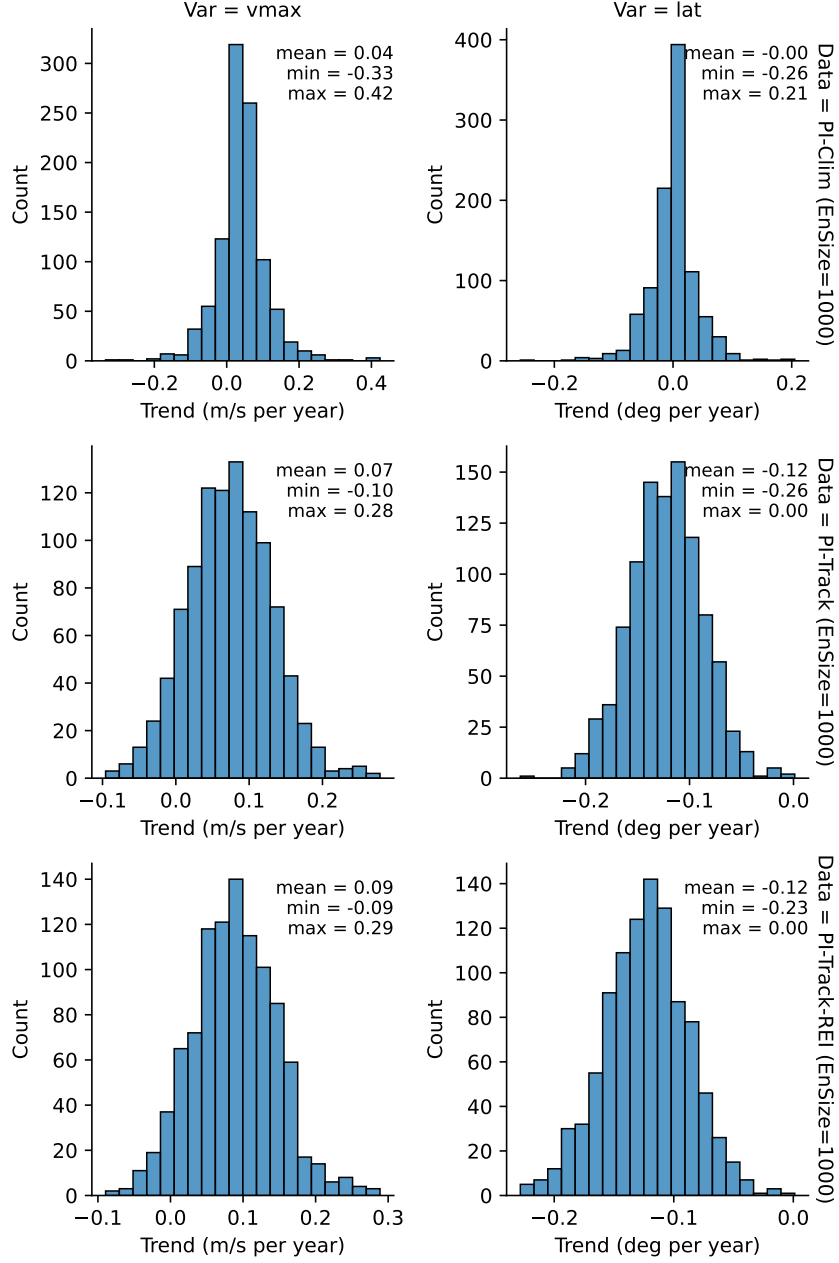


Figure 5.9: Distribution of simulated trends in lifetime maximum intensity (LMI; first column) and LMI latitude (second column) for each ensemble experiment (ensemble size = 1000): PI-Clim (first row), PI-Track (second row), and PI-Track-REI (third row). The mean, minimum, and maximum trend values are indicated in each panel.

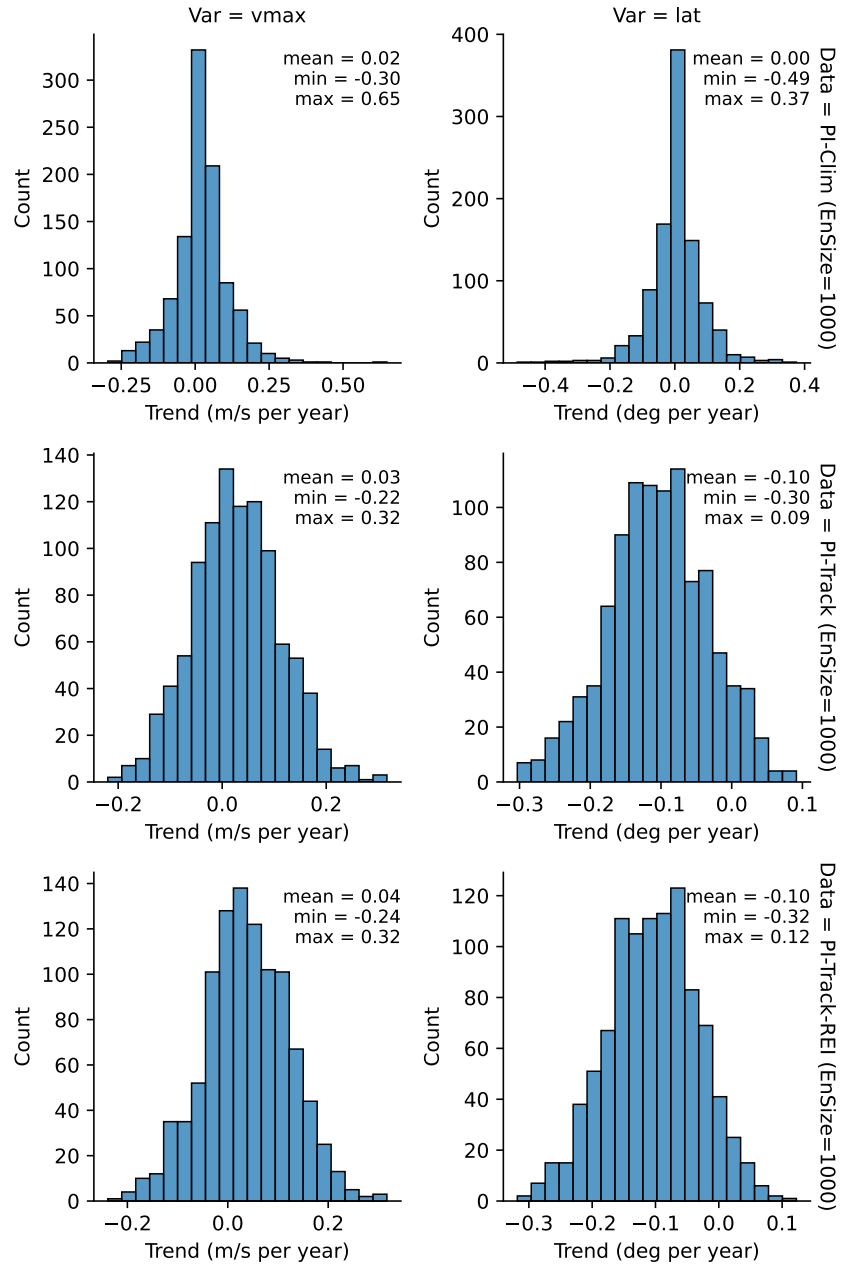


Figure 5.10: As in Figure 5.9, but for the simulated trends in landfall intensity (first column) and landfall latitudes (second column).

predominantly on the negative side. It is safe to say that the track effect results in a systematic southward shift in landfall latitudes.

5.4 Discussion

Our analysis with IRIS highlights how multiple factors influence long-term changes in LMI. In the model, TC intensity is constrained by PI, and the increasing trend in PI provides a clear thermodynamic basis for stronger TCs. This is consistent with the theoretical expectation that warming SSTs raise the upper bound of TC intensity. The increasing SST can be driven by external forcing, such as enhanced greenhouse gases, as well as by natural variability such as the Atlantic multidecadal oscillation (AMO) (Goldenberg et al., 2001; Wang et al., 2016).

However, the change in regional PI alone does not seem sufficient to fully explain the trend. Previous work has shown that regional PI may explain only up to half the trend (Sparks and Toumi, 2025b). Our results highlight the southward shift of LMI to high PI regions as an important additional factor contributing to the trend. This finding is consistent with studies in the Western North Pacific, where track shifts were found to either enhance or offset regional climatic PI trends (Kossin and Camargo, 2009; Kossin, 2015; Lin et al., 2023a). In addition, a southward shift in TC tracks may influence landfall intensity through its effect on the decay process. Li and Toumi (2024) showed that TCs reaching LMI at lower latitudes tend to have a larger decay scale. Although this effect is not included in this study, it may influence landfall intensity and warrants further investigation.

Our results also suggest that much of the variability in observed and simulated intensity trends arises from track shifts. For example, the increasing trend of PI

Table 5.7: Summary of observed and simulated trends in lifetime maximum intensity (LMI; Figure 5.7, blue) and landfall latitude (Figure 5.8, orange). Trends are reported with 95% confidence intervals and p-values. Model variability is measured by the ensemble mean and the 95% range of trend slopes across the 1000 ensemble members for each experiment.

	IBTrACS	ADT-HURSAT	PI-Clim	PI-Track	PI-Track-REI
Trends in LMI ($\text{m s}^{-1} \text{ yr}^{-1}$)	0.14 ± 0.10	0.14 ± 0.21	0.04 ± 0.01	0.08 ± 0.05	0.09 ± 0.05
p-value	0.01	0.17	0.01	0.01	0.01
Ensemble mean			0.04	0.07	0.09
95% Model spread			(-0.09, 0.19)	(-0.04, 0.19)	(-0.03, 0.21)
Trends in LF latitude ($^{\circ} \text{ yr}^{-1}$)	0.06 ± 0.17	-0.00 ± 0.19	0.00 ± 0.0	-0.10 ± 0.11	-0.10 ± 0.11
p-value	0.65	0.91	0.50	0.04	0.05
Ensemble mean			0.00	-0.10	-0.10
95% Model spread			(-0.16, 0.15)	(-0.25, 0.03)	(-0.25, 0.03)

leads to significant long-term increases in landfall intensity when considered in isolation (Figure 5.7c); however, the introduction of the effect of track shifts adds large variability to the long-term trend (Figure 5.7d).

Another potential factor is the distribution of REI, which controls how closely storms approach their local PI. A linearly decreasing PDF with different slopes was applied at different epochs (-0.69 for 1979–2001, Figure 5.6b; -0.58 for 2002–2024, Figure 5.6c), indicating a slight increase in REI where more storms reach the maximum potential. However, the fitted slopes indicate that the change in REI between 1979–2001 and 2002–2024 is moderate, likely insufficient to drive a pronounced trend in TC intensity (Figure 5.7). It is acknowledged that uncertainties in estimating the slope of the REI PDF may strongly influence the simulated trends, and changes in the REI distribution are difficult to detect using only a few decades of data. The mechanisms responsible for the potential increase in REI have not yet been fully understood and may be related to increased rapid intensification (Bhatia et al., 2019; Balaguru et al., 2018, 2022; Garner, 2023).

Our examination of observed landfall latitudes shows that the record remains too short and noisy to detect any robust long-term trends (Figure 5.8a). However, IRIS simulations suggest that the southward shift of TC tracks should be mirrored in landfall locations, with a mean rate of 0.10° per year (Table 5.7). Although observational sparseness constrains the detection and verification of this phenomenon, the simulation results suggest that track effects act as one contributing factor that tends to shift landfall locations southward. A continued southward shift in LMI could potentially increase future risks to southern coastal regions.

Other important factors influencing TC intensity, such as vertical wind shear,

ocean heat content, and the duration of travel over warm water, are not explicitly modelled or taken as inputs in IRIS. However, their effects may be indirectly captured in the three variables examined here. For example, the southward track shifts in the North Atlantic have been shown to be associated with a decrease in the vertical shear of zonal wind in the southern part (10° – 20° N) of the North Atlantic (Cao et al., 2025). Therefore, the effect of vertical shear on TC intensity is likely captured, at least in part, by these southward track shifts. In addition, this decrease in shear may also be partly reflected in the increase in REI, as it enables higher actual storm intensities, which in turn raise REI values (Sparks and Toumi, 2024, 2025b).

While this study demonstrates the significant role of southward track shifts in shaping long-term trends in TC intensity during the recent period (1979–2024), climate simulations suggest a pronounced poleward shift of peak TC genesis location over the NATL in future projections under intensified global warming (Cao et al., 2024). Because the increased intensity of North Atlantic hurricanes depends strongly on both the warming state and track shifts, as demonstrated in this study, the future projections of TC intensity remain unclear.

5.5 Conclusions

Decay models were employed and evaluated within IRIS for North Atlantic hurricanes. With the combination of decay formulations and stochastic parameterization, IRIS can efficiently generate large ensembles of synthetic TCs suitable for landfall risk assessments. Despite systematic biases in specific sub-basins, all decay models reproduce the landfall intensity distributions and landfall rate of North Atlantic hurricanes with comparable accuracy at the basin scale, showing only minimal

differences between them. For this reason, the default algebraic decay model was adopted in this study for simplicity.

While long-term trends in TC intensity are difficult to detect and explain due to limited observations and the rarity of events, the IRIS stochastic model provides a framework to attribute various factors to these trends. This study then applies the IRIS model to attribute the causes of the increased North Atlantic hurricane intensity from 1979 to 2024. In the model, increased potential intensity and southward track shifts toward regions of higher PI contribute comparably to an increasing trend of $0.08 \text{ m s}^{-1} \text{ yr}^{-1}$ in LMI. However, the simulated trends were not sensitive to epochal changes in relative intensity to date. The model also predicts a southward shift in landfall ($-0.10^\circ \text{ yr}^{-1}$), which is difficult to detect. Our findings emphasize increasing recent TC risk, particularly at low latitudes.

Chapter 6

Conclusions

TC decay plays a critical role in determining landfall intensity and associated impacts, yet remains less understood. This thesis aimed to investigate TC decay by improving the representation of over-ocean decay, examining the role of the Coriolis effect in the decay process, and, more importantly, exploiting the potential of parametric decay models in stochastic TC modelling for climate analysis. The ultimate goal of this thesis was to support more effective landfall risk assessments with a better understanding of decay.

This goal was addressed through the three research questions defined in Chapter 1. This final chapter revisits these research topics and summarizes the key findings (Section 6.1). It then discusses the remaining challenges in improving our understanding of TC risk assessments using stochastic modelling and outlines directions for future research (6.2). The concluding remarks of this thesis are given in Section 6.3.

6.1 Summary of key findings

6.1.1 Characteristics of over-ocean decay

To help understand the decay over the ocean, a modified exponential model (β model) was proposed. The β model captures the temporal decay well by encompassing the scale parameter α and the shape parameter β . While α characterises the overall decay rate, β describes how the decay rate evolves over time, either speeding up or slowing down.

The β model offers an accurate representation of over-ocean decay. It is the first model to distinguish between decelerating and accelerating decay by introducing the shape parameter β . The fitting results indicate that the majority of global TCs (about 60%) show accelerating decay ($\beta > 1$) over the ocean, which cannot be explained by post-landfall decay models or traditional spin-down models (Eliassen, 1971b; Eliassen and Lystad, 1977b; Kaplan and DeMaria, 1995b). This suggests that the surface drag is not the sole factor behind decay, at least over the ocean. Energy production could play a significant role in allowing intense storms to sustain relatively high wind speeds and decay more slowly.

Furthermore, the global fitting indicates that α can be estimated as a linear function of f_0 , and β as a linear function of u_0 . Specifically, the global-decay form of the β model is $v(t) = v_0 e^{-\alpha t^\beta}$, with $\alpha = -1.03 \times 10^4 \cdot f_0 + 1.25$ and $\beta = 0.03 \cdot u_0 + 1.09$. By representing the decay of TC intensity over time using a simple mathematical formulation with environment-based decay parameters, the β model also has potential applications in climate-change analysis and synthetic TC modelling.

The physical basis for the latitude dependence of the decay scale remains unclear

and warrants further investigation. Idealised numerical simulations on different f -planes, with controlled decay forcing, may help diagnose the underlying mechanisms.

6.1.2 Coriolis effect on decay

Chapter 4 investigated the impact of the Coriolis parameter (f) on well-developed TCs moving to the equator, and the mechanisms driving the resulting decay, using idealised numerical simulations. A set of f -sensitivity experiments was applied to a well-developed TC vortex by decreasing f to zero, both abruptly and gradually.

The simulated results show that TCs gradually weaken as f is reduced, with in/outflow patterns strengthening throughout the cyclone depth. The key mechanism for TC weakening is the deepening of the inflow layer and the reduction in boundary-layer θ_e . Specifically, the deeper inflow layer and strengthened downdrafts in the outer rainbands under reduced- f enhance the entrainment of mid-level dry air into the boundary layer. This reduces boundary-layer θ_e and suppresses deep convection in the eyewall, thereby weakening the TC. These findings provide a deeper understanding of how the Coriolis effect influences intensity evolution, particularly during the declining phase of the TC life cycle.

These results also suggest that the effect of f on TC depends on its developmental stage. During TC formation, sufficient f facilitates spin-up by rotating convergent flow and creating angular momentum (Briegel and Frank, 1997; Gray, 1968, 1979, 1985, 1998). For TC intensification, the stronger boundary layer inflow associated with lower latitudes will bring more angular momentum into the system, promoting faster intensification (Li et al., 2012; Smith et al., 2015; Li et al., 2023b). However, in the case of an already developed TC vortex, the loss of f unbalances the TC dynamics

and leads to excessive inflow, which disrupts the boundary layer by entraining more low- θ_e air from mid-levels.

Chapter 3 shows that TCs decay more quickly with a smaller initial f . Although the phenomenon might not be fully linked to the decreasing f scenario in this study, stronger radial inflow or reduced dynamic balance at lower latitudes is likely to facilitate decay, as suggested here. While the experiments focused on reduced f , expanding the analysis to increased f would provide a useful counterfactual for understanding the sensitivity of TC to planetary rotation.

6.1.3 Application of decay in TC risk assessments

The ultimate goal is to facilitate TC risk assessments at landfall. While long-term trends in TC intensity are often difficult to detect and explain due to the rarity of events and the short period of reliable observations, the stochastic model IRIS, which focuses on the post-LMI decay process, provides a robust framework for attribution. In this study, we employed decay models within IRIS and then used IRIS to attribute the causes of increased intensity of North Atlantic hurricanes from 1979 to 2024 by generating large ensembles of synthetic TC data.

The model attributes the increasing trend in LMI ($0.08 \text{ m s}^{-1} \text{ yr}^{-1}$) to comparable contributions from rising potential intensity and a southward shift in TC tracks. However, the simulated trends were not sensitive to epochal changes in relative intensity to date. This result suggests that changes in regional PI alone are insufficient to explain the observed trend, consistent with previous studies (Sparks and Toumi, 2025b). The contribution of the observed southward shift in LMI locations (Cao et al., 2025) is shown here to be of a similar magnitude to that of PI changes.

The model also predicts a southward shift in landfall ($-0.10^\circ \text{ yr}^{-1}$), which is difficult to detect in observations. Although observational sparseness constrains the detection and verification of this phenomenon, the simulation results suggest that track effects act as one contributing factor that tends to shift landfall locations southward. A continued southward shift in LMI could potentially increase future risks to southern coastal regions.

An extension of this work will be to apply IRIS to the Western North Pacific. The larger sample sizes and documented poleward track shifts provide an opportunity to attribute long-term intensity variability. This framework also enables quantification of how track shifts, such as a southward shift of LMI, modify decay scales based on the findings in Chapter 3, and thereby influence TC landfall risk.

6.2 Future work

The application of TC decay in IRIS has shown great potential for TC risk assessments and climate attribution (Chapter 5). IRIS has previously been applied to the climate-change attribution of Typhoon Haiyan (Sparks and Toumi, 2025a), current hurricane risk assessments (Toumi and Sparks, 2025), and future projections of U.S. landfalling hurricanes (Sparks and Toumi, 2025b). By advancing the robust analysis of extreme TC events and facilitating accessible climate analysis, IRIS is increasingly being adopted for risk assessments across both academia and industry. There are opportunities for future research to further improve our understanding of TC risk via the IRIS framework.

6.2.1 Extending the hurricane model to include tropical storms

Currently, IRIS only includes TCs that reach at least 33 m s^{-1} (hurricane strength). However, weaker storms represent a significant portion of TC activity; of the 596 TCs in the North Atlantic, 285 (48%) never reach hurricane strength. These weaker storms exhibit distinct characteristics compared to hurricanes; for instance, a uniform REI does not apply to them, and they typically decay much more slowly than their stronger counterparts. While weaker storms may not cause the catastrophic damage associated with extreme events, they remain a socio-economic concern. Observations indicate an increasing frequency of weak storms under climate change, and more frequent storms may increase the statistical likelihood of intensification into hurricanes. Therefore, developing a specialized model for weak storms would benefit both scientific understanding and risk management.

6.2.2 Integrating reanalysis data and CMIP6 Projections

IRIS currently relies on best-track inputs. While best-track data is available from 1950, utilizing extended global best-track data derived from reanalysis would be invaluable for analysing long-term climate trends and multi-decadal variability in TC activity. A prominent example is the Reanalysis-Based Global Tropical Cyclone Tracks Dataset for the Twentieth Century (RGTracks-20C), which is reconstructed from the National Oceanic and Atmospheric Administration's Twentieth Century Reanalysis (Ye et al., 2025). Such extended historical TC data serves as a valuable reference for IRIS in future research regarding climate change and TC risk assessments.

Another promising area for future research lies in situating the IRIS framework within a broader climate context by incorporating simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6). CMIP6 can help contextualize observed trends in North Atlantic hurricanes within externally forced climate variability. By using large-scale environmental fields from CMIP6—such as Sea Surface Temperature (SST)—to drive the stochastic model, we can generate synthetic TC ensembles under various climate states. This provides a physically consistent framework to assess the extent to which observed changes are attributable to anthropogenic forcing versus internal variability.

Furthermore, CMIP6 simulations allow the analysis to extend beyond the historical period, offering a pathway to examine how the relationships identified in this study may evolve under future climate scenarios. This perspective will help evaluate the robustness of inferred mechanisms and assess their implications for long-term changes in TC activity and landfall risk. Overall, integrating CMIP6 with existing observational and stochastic modelling will provide a comprehensive understanding of TC variability across timescales, bridging the gap between historical attribution and future projections.

6.3 Concluding remarks

Overall, this thesis has thoroughly investigated the decay process prior to landfall, describing over-ocean decay features using a modified empirical model and identifying the environmental factors driving decay parameters. It further examined the impact of the Coriolis effect on developed TCs and highlighted the critical importance of boundary layer thermodynamics in TC weakening. Additionally, this work demon-

strated the effectiveness of applying decay in stochastic modelling to improve TC risk assessments by generating large-ensemble synthetic TC data. Future work should focus on expanding the utility of IRIS by incorporating a specialized weak storm model and extending its climate analysis capabilities through the integration of multi-source datasets.

Bibliography

- Alland, J. J., Tang, B. H., Corbosiero, K. L., and Bryan, G. H. (2021a). Combined effects of midlevel dry air and vertical wind shear on tropical cyclone development. part I: Downdraft ventilation. *J. Atmos. Sci.*, 78(3):763–782.
- Alland, J. J., Tang, B. H., Corbosiero, K. L., and Bryan, G. H. (2021b). Combined effects of midlevel dry air and vertical wind shear on tropical cyclone development. part II: Radial ventilation. *J. Atmos. Sci.*, 78(3):783–796.
- Balaguru, K., Foltz, G. R., Leung, L. R., Xu, W., Kim, D., Lopez, H., and West, R. (2022). Increasing hurricane intensification rate near the US atlantic coast. *Geophys. Res. Lett.*, 49(20).
- Balaguru, K., Foltz, G. R., and Ruby Leung, L. (2018). Increasing magnitude of hurricane rapid intensification in the central and eastern tropical atlantic. *Geophysical Research Letters*, 45(9):4238–4247.
- Barnes, G. M., Zipser, E. J., Jorgensen, D., and Marks, Jr, F. (1983). Mesoscale and convective structure of a hurricane rainband. *J. Atmos. Sci.*, 40(9):2125–2137.
- Bhatia, K. T., Vecchi, G. A., Knutson, T. R., Murakami, H., Kossin, J., Dixon,

- K. W., and Whitlock, C. E. (2019). Recent increases in tropical cyclone intensification rates. *Nat. Commun.*, 10(1):635.
- Bister, M. and Emanuel, K. A. (1998). Dissipative heating and hurricane intensity. *Meteorol. Atmos. Phys.*, 65(3):233–240.
- Bloemendaal, N., Haigh, I. D., de Moel, H., Muis, S., Haarsma, R. J., and Aerts, J. C. J. H. (2020). Generation of a global synthetic tropical cyclone hazard dataset using STORM. *Sci Data*, 7(1):40.
- Briegel, L. M. and Frank, W. M. (1997). Large-scale influences on tropical cyclogenesis in the western north pacific. *Mon. Weather Rev.*, 125(7):1397–1413.
- Cao, X., Watanabe, M., Wu, R., Chen, W., Sun, Y., Yan, Q., Wang, P., Deng, D., and Wu, L. (2024). The projected poleward shift of tropical cyclogenesis at a global scale under climate change in MRI-AGCM3.2H. *Geophys. Res. Lett.*, 51(3):e2023GL107189.
- Cao, X., Wu, R., Jiang, X., Dai, Y., Wang, P., Zhou, L., Wu, L., Deng, D., Sun, Y., Chen, S., Hu, K., Wang, Z., Liu, L., Lan, X., Du, Z., Zhao, J., and Xiao, X. (2025). The southward shift of hurricane genesis over the northern atlantic ocean. *Npj Clim. Atmos. Sci.*, 8(1):1–10.
- Chan, K. T. F. and Chan, J. C. L. (2013). Angular momentum transports and synoptic flow patterns associated with tropical cyclone size change. *Mon. Weather Rev.*, 141(11):3985–4007.
- Chang, C.-P., Liu, C.-H., and Kuo, H.-C. (2003). Typhoon vamei: An equatorial tropical cyclone formation. *Geophysical Research Letters*, 30(3).

- Chang, K.-F., Wu, C.-C., and Ito, K. (2023a). On the rapid weakening of typhoon trami (2018): Strong sea surface temperature cooling associated with slow translation speed. *Mon. Weather Rev.*, 151(1):227–251.
- Chang, K.-F., Wu, C.-C., and Ito, K. (2023b). On the Rapid Weakening of Typhoon Trami (2018): Strong Sea Surface Temperature Cooling Associated with Slow Translation Speed. *Monthly Weather Review*, 151(1):227–251. Publisher: American Meteorological Society Section: Monthly Weather Review.
- Chen, J. and Chavas, D. R. (2020). The Transient Responses of an Axisymmetric Tropical Cyclone to Instantaneous Surface Roughening and Drying. *Journal of the Atmospheric Sciences*, 77(8):2807–2834. Publisher: American Meteorological Society Section: Journal of the Atmospheric Sciences.
- Colomb, A., Kriat, T., and Leroux, M.-D. (2019). On the rapid weakening of very intense tropical cyclone hellen (2014). *Mon. Weather Rev.*, 147(8):2717–2737.
- DeMaria, M. (1996a). The Effect of Vertical Shear on Tropical Cyclone Intensity Change. *Journal of the Atmospheric Sciences*, 53(14):2076–2088. Publisher: American Meteorological Society Section: Journal of the Atmospheric Sciences.
- DeMaria, M. (1996b). The effect of vertical shear on tropical cyclone intensity change. *J. Atmos. Sci.*, 53(14):2076–2088.
- DeMaria, M. and Kaplan, J. (1999). An updated statistical hurricane intensity prediction scheme (SHIPS) for the atlantic and eastern north pacific basins. *Weather Forecast.*, 14(3):326–337.
- DeMaria, M., Knaff, J. A., and Sampson, C. R. (2023). *SHIPS Predictor File*.

- Cooperative Institute for Research in the Atmosphere. Technical document.
Available at: https://rammb-data.cira.colostate.edu/ships/data/ships_predictor_file.pdf.
- DeMaria, M., Mainelli, M., Shay, L. K., Knaff, J. A., and Kaplan, J. (2005). Further improvements to the statistical hurricane intensity prediction scheme (SHIPS). *Weather Forecast.*, 20(4):531–543.
- DeMaria, M. and Pickle, J. D. (1988). A simplified system of equations for simulation of tropical cyclones. *J. Atmos. Sci.*, 45(10):1542–1554.
- Dunion, J. P. (2011). Rewriting the climatology of the tropical north atlantic and caribbean sea atmosphere. *J. Clim.*, 24(3):893–908.
- Eliassen, A. (1971a). On the Ekman Layer in a circular Vortex. *Journal of the Meteorological Society of Japan. Ser. II*, 49A(0):784–789.
- Eliassen, A. (1971b). On the ekman layer in a circular vortex. *J. Meteorol. Soc. Japan*, 49A(0):784–789.
- Eliassen, A. and Lystad, M. (1977a). The Ekman layer of a circular vortex - A numerical and theoretical study. *Geophysica Norvegica*, 31:1–16. ADS Bibcode: 1977GeoNr..31....1E.
- Eliassen, A. and Lystad, M. (1977b). The ekman layer of a circular vortex - a numerical and theoretical study. *Geophysica Norvegica*, 31:1.
- Elsner, J. B., Kossin, J. P., and Jagger, T. H. (2008). The increasing intensity of the strongest tropical cyclones. *Nature*, 455(7209):92–95.

- Emanuel, K. (2000). A statistical analysis of tropical cyclone intensity. *Mon. Weather Rev.*, 128(4):1139–1152.
- Emanuel, K. (2008). The hurricane—climate connection. *Bull. Am. Meteorol. Soc.*, 89(5):ES10–ES20.
- Emanuel, K., Ravela, S., Vivant, E., and Risi, C. (2006). A statistical deterministic approach to hurricane risk assessment. *Bull. Am. Meteorol. Soc.*, 87(3):299–314.
- Emanuel, K., Sundararajan, R., and Williams, J. (2008). Hurricanes and global warming: Results from downscaling IPCC AR4 simulations. *Bull. Am. Meteorol. Soc.*, 89(3):347–368.
- Emanuel, K. A. (1986). An air-sea interaction theory for tropical cyclones. part I: Steady-state maintenance. *J. Atmos. Sci.*, 43(6):585–605.
- Emanuel, K. A. (1987). The dependence of hurricane intensity on climate. *Nature*, 326(6112):483–485.
- Emanuel, K. A. (1995). Sensitivity of tropical cyclones to surface exchange coefficients and a revised steady-state model incorporating eye dynamics. *J. Atmos. Sci.*, 52(22):3969–3976.
- Emanuel, K. A. (1997). Some aspects of hurricane inner-core dynamics and energetics. *J. Atmos. Sci.*, 54(8):1014–1026.
- Fairall, C. W., Bradley, E. F., Hare, J. E., Grachev, A. A., and Edson, J. B. (2003). Bulk parameterization of air–sea fluxes: Updates and verification for the COARE algorithm. *J. Clim.*, 16(4):571–591.

- Fei, R., Xu, J., Wang, Y., and Yang, C. (2020a). Factors affecting the weakening rate of tropical cyclones over the western north pacific. *Mon. Weather Rev.*, 148(9):3693–3712.
- Fei, R., Xu, J., Wang, Y., and Yang, C. (2020b). Factors Affecting the Weakening Rate of Tropical Cyclones over the Western North Pacific. *Monthly Weather Review*, 148(9):3693–3712. Publisher: American Meteorological Society Section: Monthly Weather Review.
- Gahtan, J., Knapp, K. R., Schreck, C. J. I., Diamond, H. J., Kossin, J. P., and Kruk, M. C. (2024). International best track archive for climate stewardship (ibtracs) project, version 4.01. Dataset.
- García-Franco, J. L. and Schwendike, J. (2020). Revisiting gradient wind balance in tropical cyclones using dropsonde observations. *Q. J. R. Meteorol. Soc.*, 147(qj.3947):801–824.
- Garner, A. J. (2023). Observed increases in north atlantic tropical cyclone peak intensification rates. *Sci. Rep.*, 13(1):16299.
- Goldenberg, S. B., Landsea, C. W., Mestas-Nunez, A. M., and Gray, W. M. (2001). The recent increase in atlantic hurricane activity: causes and implications. *Science*, 293(5529):474–479.
- Gray, W. M. (1968). GLOBAL VIEW OF THE ORIGIN OF TROPICAL DISTURBANCES AND STORMS. *Mon. Weather Rev.*, 96(10):669–700.
- Gray, W. M. (1979). *Hurricanes: Their formation, structure and likely role in the tropical circulation. Meteorology over the tropical oceans*. cir.nii.ac.jp.

- Gray, W. M. (1985). Tropical cyclone global climatology. *WMO Technical Document WMO/TD*, 72(1):3–19.
- Gray, W. M. (1998). The formation of tropical cyclones. *Meteorol. Atmos. Phys.*, 67(1-4):37–69.
- Hong, S.-Y. and Lim, J. J.-O. (2006). The WRF single-moment 6-class microphysics scheme (WSM6). *Journal of the Korean Meteorological Society*, 42:129–151.
- Hong, S.-Y., Noh, Y., and Dudhia, J. (2006). A new vertical diffusion package with an explicit treatment of entrainment processes. *Mon. Weather Rev.*, 134(9):2318–2341.
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., and Collins, W. D. (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res. D: Atmos.*, 113(D13).
- James, M. K. and Mason, L. B. (2005). Synthetic tropical cyclone database. *Journal of Waterway, Port, Coastal, and Ocean Engineering*, 131(4):181–192.
- Jiménez, P. A., Dudhia, J., González-Rouco, J. F., Navarro, J., Montávez, J. P., and García-Bustamante, E. (2012). A revised scheme for the WRF surface layer formulation. *Mon. Weather Rev.*, 140(3):898–918.
- Jing, R. and Lin, N. (2020). An environment-dependent probabilistic tropical cyclone model. *J. Adv. Model. Earth Syst.*, 12(3):e2019MS001975.
- Kaplan, J. and DeMaria, M. (1995a). A Simple Empirical Model for Predicting the Decay of Tropical Cyclone Winds after Landfall. *Journal of Applied Meteorology*

- and Climatology*, 34(11):2499–2512. Publisher: American Meteorological Society
Section: Journal of Applied Meteorology and Climatology.
- Kaplan, J. and DeMaria, M. (1995b). A simple empirical model for predicting the decay of tropical cyclone winds after landfall. *J. Appl. Meteorol. Climatol.*, 34(11):2499–2512.
- Kepert, J. (2001). The dynamics of boundary layer jets within the tropical cyclone core. part I: Linear theory. *J. Atmos. Sci.*, 58(17):2469–2484.
- Kepert, J. and Wang, Y. (2001). The dynamics of boundary layer jets within the tropical cyclone core. part II: Nonlinear enhancement. *J. Atmos. Sci.*, 58.
- Kepert, J. D. (2006a). Observed boundary layer wind structure and balance in the hurricane core. part I: Hurricane georges. *J. Atmos. Sci.*, 63(9):2169–2193.
- Kepert, J. D. (2006b). Observed boundary layer wind structure and balance in the hurricane core. part II: Hurricane mitch. *J. Atmos. Sci.*, 63(9):2194–2211.
- Kilroy, G., Smith, R. K., and Montgomery, M. T. (2020). An idealized numerical study of tropical cyclogenesis and evolution at the equator. *Q. J. R. Meteorol. Soc.*, 146(727):685–699.
- Knapp, K., Kruk, M., Levinson, D., Diamond, H., and Neumann, C. J. (2010). The international best track archive for climate stewardship (IBTrACS): unifying tropical cyclone data. *Bull. Am. Meteorol. Soc.*, 91:363–376.
- Knutson, T., Camargo, S. J., Chan, J. C. L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., and Wu, L. (2019). Tropical

- cyclones and climate change assessment: Part I: Detection and attribution. *Bull. Am. Meteorol. Soc.*, 100(10):1987–2007.
- Kossin, J. P. (2015). Validating atmospheric reanalysis data using tropical cyclones as thermometers. *Bull. Am. Meteorol. Soc.*, 96(7):1089–1096.
- Kossin, J. P. and Camargo, S. J. (2009). Hurricane track variability and secular potential intensity trends. *Clim. Change*, 97(1-2):329–337.
- Kossin, J. P., Knapp, K. R., Olander, T. L., and Velden, C. S. (2020). Global increase in major tropical cyclone exceedance probability over the past four decades. *Proc. Natl. Acad. Sci. U. S. A.*, 117(22):11975–11980.
- Kossin, J. P., Olander, T. L., and Knapp, K. R. (2013). Trend analysis with a new global record of tropical cyclone intensity. *J. Clim.*, 26(24):9960–9976.
- Lagmay, A. M. F., Agaton, R. P., Bahala, M. A. C., Briones, J. B. L. T., Cabacaba, K. M. C., Caro, C. V. C., Dasallas, L. L., Gonzalo, L. A. L., Ladiero, C. N., Lapidez, J. P., Mungcal, M. T. F., Puno, J. V. R., Ramos, M. M. A. C., Santiago, J., Suarez, J. K., and Tablazon, J. P. (2015). Devastating storm surges of typhoon haiyan. *Int. J. Disaster Risk Reduct.*, 11:1–12.
- Landsea, C., Franklin, J., and Beven, J. (2015). The revised atlantic hurricane database (hurdat2) — format documentation. Technical report, National Hurricane Center. Accessed: 2025-08-27.
- Landsea, C. W. and Franklin, J. L. (2013). Atlantic hurricane database uncertainty and presentation of a new database format. *Mon. Weather Rev.*, 141(10):3576–3592.

- Lee, C.-Y., Tippett, M. K., Sobel, A. H., and Camargo, S. J. (2018). An environmentally forced tropical cyclone hazard model. *Journal of Advances in Modeling Earth Systems*, 10(1):223–241.
- Li, M. and Toumi, R. (2024). On the temporal decay of tropical cyclones over the ocean. *Geophys. Res. Lett.*, 51(23).
- Li, T., Ge, X., Peng, M., and Wang, W. (2012). Dependence of tropical cyclone intensification on the coriolis parameter. *Tropical Cyclone Research and Review*, 1(2):242–253.
- Li, Y., Tang, Y., Wang, S., Toumi, R., Song, X., and Wang, Q. (2023a). Recent increases in tropical cyclone rapid intensification events in global offshore regions. *Nat. Commun.*, 14(1):5167.
- Li, Y., Wang, Y., and Tan, Z.-M. (2023b). Is the outflow-layer inertial stability crucial to the energy cycle and development of tropical cyclones? *J. Atmos. Sci.*, 80(6):1605–1620.
- Liang, J., Wu, L., and Gu, G. (2018). Rapid weakening of tropical cyclones in monsoon gyres over the tropical western north pacific. *J. Clim.*, 31(3):1015–1028.
- Liang, J., Wu, L., Gu, G., and Liu, Q. (2016). Rapid weakening of typhoon chan-hom (2015) in a monsoon gyre. *J. Geophys. Res. D: Atmos.*, 121(16):9508–9520.
- Lin, I.-I., Camargo, S. J., Lien, C.-C., Shi, C.-A., and Kossin, J. P. (2023a). Poleward migration as global warming’s possible self-regulator to restrain future

- western north pacific tropical cyclone’s intensification. *Npj Clim. Atmos. Sci.*, 6(1):1–9.
- Lin, J., Rousseau-Rizzi, R., Lee, C.-Y., and Sobel, A. (2023b). An open-source, physics-based, tropical cyclone downscaling model with intensity-dependent steering. *J. Adv. Model. Earth Syst.*, 15(11):e2023MS003686.
- Ma, C., Peng, M., Li, T., Sun, Y., Liu, J., and Bi, M. (2019). Effects of background state on tropical cyclone size over the western north pacific and northern atlantic. *Clim. Dyn.*, 52(7-8):4143–4156.
- Ma, Z. (2020). A study of the interaction between typhoon francisco (2013) and a cold-core eddy. part I: Rapid weakening. *J. Atmos. Sci.*, 77(1):355–377.
- Merrill, R. T. (1984). A comparison of large and small tropical cyclones. *Mon. Weather Rev.*, 112(7):1408–1418.
- Montgomery, M. T., Snell, H. D., and Yang, Z. (2001a). Axisymmetric spindown dynamics of hurricane-like vortices. *J. Atmos. Sci.*, 58(5):421–435.
- Montgomery, M. T., Snell, H. D., and Yang, Z. (2001b). Axisymmetric Spindown Dynamics of Hurricane-like Vortices. *Journal of the Atmospheric Sciences*, 58(5):421–435. Publisher: American Meteorological Society Section: Journal of the Atmospheric Sciences.
- Ooyama, K. V. (1982). Conceptual evolution of the theory and modeling of the tropical cyclone. *J. Meteorol. Soc. Japan*, 60(1):369–380.
- Park, J.-H., Yeo, D.-E., Lee, K., Lee, H., Lee, S.-W., Noh, S., Kim, S., Shin, J., Choi, Y., and Nam, S. (2019). Rapid decay of slowly moving typhoon soulik

- (2018) due to interactions with the strongly stratified northern east china sea. *Geophys. Res. Lett.*, 46(24):14595–14603.
- Phillipson, L. M. and Toumi, R. (2021). A Physical Interpretation of Recent Tropical Cyclone Post-Landfall Decay. *Geophysical Research Letters*, 48(18):e2021GL094105. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2021GL094105>.
- Powell, M. (1990a). Boundary layer structure and dynamics in outer hurricane rainbands. part II: Downdraft modification and mixed layer recovery. *Monthly Weather Review*, 118:918–938.
- Powell, M. D. (1990b). Boundary layer structure and dynamics in outer hurricane rainbands. part I: Mesoscale rainfall and kinematic structure. *Mon. Weather Rev.*, 118(4):891–917.
- Qian, Y. and Zhang, S. (2013). Cause of the rapid weakening of typhoon bebinca (0021) in the south china sea. *Tropical Cyclone Research and Review*, 2(3):159–168.
- Rappin, E. D., Morgan, M. C., and Tripoli, G. J. (2011). The impact of outflow environment on tropical cyclone intensification and structure. *J. Atmos. Sci.*, 68(2):177–194.
- Riemer, M., Montgomery, M. T., and Nicholls, M. E. (2010). A new paradigm for intensity modification of tropical cyclones: thermodynamic impact of vertical wind shear on the inflow layer. *Atmos. Chem. Phys.*, 10(7):3163–3188.
- Rogers, R. F., Reasor, P. D., Zawislak, J. A., and Nguyen, L. T. (2020).

- Precipitation processes and vortex alignment during the intensification of a weak tropical cyclone in moderate vertical shear. *Mon. Weather Rev.*, 148(5):1899–1929.
- Rotunno, R. and Emanuel, K. A. (1987). An Air–Sea interaction theory for tropical cyclones. part II: Evolutionary study using a nonhydrostatic axisymmetric numerical model. *J. Atmos. Sci.*, 44(3):542–561.
- Schwendike, J. and Kepert, J. D. (2008). The boundary layer winds in hurricanes danielle (1998) and isabel (2003). *Mon. Weather Rev.*, 136(8):3168–3192.
- Simpson, R. and Riehl, H. (1958). Mid-tropospheric ventilation as a constraint on hurricane development and maintenance. In *Preprints, Technical Conference on Hurricanes*, pages D4–1–D4–10, Miami Beach, FL. American Meteorological Society.
- Simpson, R. H. and Saffir (1974). The hurricane disaster—potential scale. *Weatherwise*, 27(4):169–186.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., and Huang, X.-Y. (2019). A description of the advanced research wrf version 4. Technical Note NCAR/TN-556+STR, National Center for Atmospheric Research (NCAR).
- Smith, R. K., Kilroy, G., and Montgomery, M. T. (2015). Why do model tropical cyclones intensify more rapidly at low latitudes? *J. Atmos. Sci.*, 72(5):1783–1804.
- Smith, R. K., Montgomery, M. T., and Van Sang, N. (2009). Tropical cyclone spin-up revisited. *Quarterly Journal of the Royal Meteorological Society: A*

- journal of the atmospheric sciences, applied meteorology and physical oceanography*, 135(642):1321–1335.
- Smith, R. K., Schmidt, C. W., and Montgomery, M. T. (2011). An investigation of rotational influences on tropical-cyclone size and intensity. *Q. J. R. Meteorol. Soc.*, 137(660):1841–1855.
- Sobel, A. H., Camargo, S. J., Hall, T. M., Lee, C.-Y., Tippett, M. K., and Wing, A. A. (2016). Human influence on tropical cyclone intensity. *Science*, 353(6296):242–246.
- Sparks, N. and Toumi, R. (2024). The ImpeRIal college storm model (IRIS) dataset. *Sci. Data*, 11(1):424.
- Sparks, N. and Toumi, R. (2025a). Climate change attribution of typhoon haiyan with the imperial college storm model. *Atmos. Sci. Lett.*, 26(1):e1285.
- Sparks, N. and Toumi, R. (2025b). The impact of global warming on U.S. hurricane landfall: A storyline approach. *Environ. Res. Lett.*
- Steenkamp, S. C., Kilroy, G., and Smith, R. K. (2019). Tropical cyclogenesis at and near the equator. *Q. J. R. Meteorol. Soc.*, 145(722):1846–1864.
- Stone, Z., Alvey, G. R., Dunion, J. P., Fischer, M. S., Raymond, D. J., Rogers, R. F., Sentić, S., and Zawislak, J. (2023). Thermodynamic contribution to vortex alignment and rapid intensification of hurricane sally (2020). *Mon. Weather Rev.*, 151(4):931–951.
- Tang, B. and Emanuel, K. (2010). Midlevel ventilation’s constraint on tropical cyclone intensity. *J. Atmos. Sci.*, 67(6):1817–1830.

- Toumi, R. and Sparks, N. (2025). The hurricane damage index (HurDI).
<https://journalofcrr.com/research/03-05-toumi-sparks/>. Accessed:
2025-10-1.
- Vickery, P. J., Skerlj, P. F., and Twisdale, L. A. (2000). Simulation of hurricane risk in the U.S. using empirical track model. *Journal of Structural Engineering*, 126(10):1222–1237.
- Wadler, J. B., Cione, J. J., Rogers, R. F., and Fischer, M. S. (2023). On the distribution of convective and stratiform precipitation in tropical cyclones from airborne doppler radar and its relationship to intensity change and environmental wind shear direction. *Mon. Weather Rev.*, 151(12):3209–3233.
- Walker, N. D., Leben, R. R., Pilley, C. T., Shannon, M., Herndon, D. C., Pun, I.-F., Lin, I.-I., and Gentemann, C. L. (2014a). Slow translation speed causes rapid collapse of northeast pacific hurricane kenneth over cold core eddy. *Geophys. Res. Lett.*, 41(21):7595–7601.
- Walker, N. D., Leben, R. R., Pilley, C. T., Shannon, M., Herndon, D. C., Pun, I.-F., Lin, I.-I., and Gentemann, C. L. (2014b). Slow translation speed causes rapid collapse of northeast Pacific Hurricane Kenneth over cold core eddy. *Geophysical Research Letters*, 41(21):7595–7601. eprint:
<https://onlinelibrary.wiley.com/doi/pdf/10.1002/2014GL061584>.
- Wang, C., Wang, L., Wang, X., Wang, D., and Wu, L. (2016). North-south variations of tropical storm genesis locations in the western hemisphere: Tropical storm genesis locations. *Geophys. Res. Lett.*, 43(21):11,367–11,374.

- Wang, S., Rashid, T., Throp, H., and others (2020). A shortening of the life cycle of major tropical cyclones. *Geophys. Res. Lett.*
- Wang, S. and Toumi, R. (2021). Recent tropical cyclone changes inferred from ocean surface temperature cold wakes. *Sci. Rep.*, 11(1):22269.
- Wang, S. and Toumi, R. (2022a). An analytic model of the tropical cyclone outer size. *npj Climate and Atmospheric Science*, 5(1):1–10.
- Wang, S. and Toumi, R. (2022b). On the intensity decay of tropical cyclones before landfall. *Scientific Reports*, 12(1):3288. Number: 1 Publisher: Nature Publishing Group.
- Wang, S. and Toumi, R. (2022c). On the intensity decay of tropical cyclones before landfall. *Sci. Rep.*, 12(1):3288.
- Weinkle, J., Maue, R., and Pielke, Jr, R. (2012). Historical global tropical cyclone landfalls. *J. Clim.*, 25(13):4729–4735.
- Wood, K. M. and Ritchie, E. A. (2015). A definition for rapid weakening of north atlantic and eastern north pacific tropical cyclones. *Geophys. Res. Lett.*, 42(22):10,091–10,097.
- Ye, G., Leung, J. C.-H., Dong, W., Xu, J., Li, W., Qian, W., Kong, H., and Zhang, B. (2025). A reanalysis-based global tropical cyclone tracks dataset for the twentieth century (rgtracks-20c). *Earth System Science Data Discussions*, 2025:1–34.
- Zhang, C. and Wang, Y. (2017). Projected future changes of tropical cyclone

activity over the western north and south pacific in a 20-km-mesh regional climate model. *J. Clim.*, 30(15):5923–5941.

Zhang, J. A., Rogers, R. F., Nolan, D. S., and Marks, F. D. (2011). On the characteristic height scales of the hurricane boundary layer. *Mon. Weather Rev.*, 139(8):2523–2535.

Zhang, J. A., Rogers, R. F., Reasor, P. D., and Gamache, J. (2023). The mean kinematic structure of the tropical cyclone boundary layer and its relationship to intensity change. *Mon. Weather Rev.*, 151(1):63–84.

Zhou, Y., Zhan, R., Wang, Y., Wu, Z., Chen, G., and Wang, L. (2022). Characteristics and controlling factors of rapid weakening of tropical cyclones after reaching their intensity peaks over the western north pacific. *J. Geophys. Res.*, 127(21):e2022JD036697.

Appendix A

Decay Parameters

This appendix collects the supplementary figures used to diagnose the decay-parameter relationships discussed in Chapter 3.

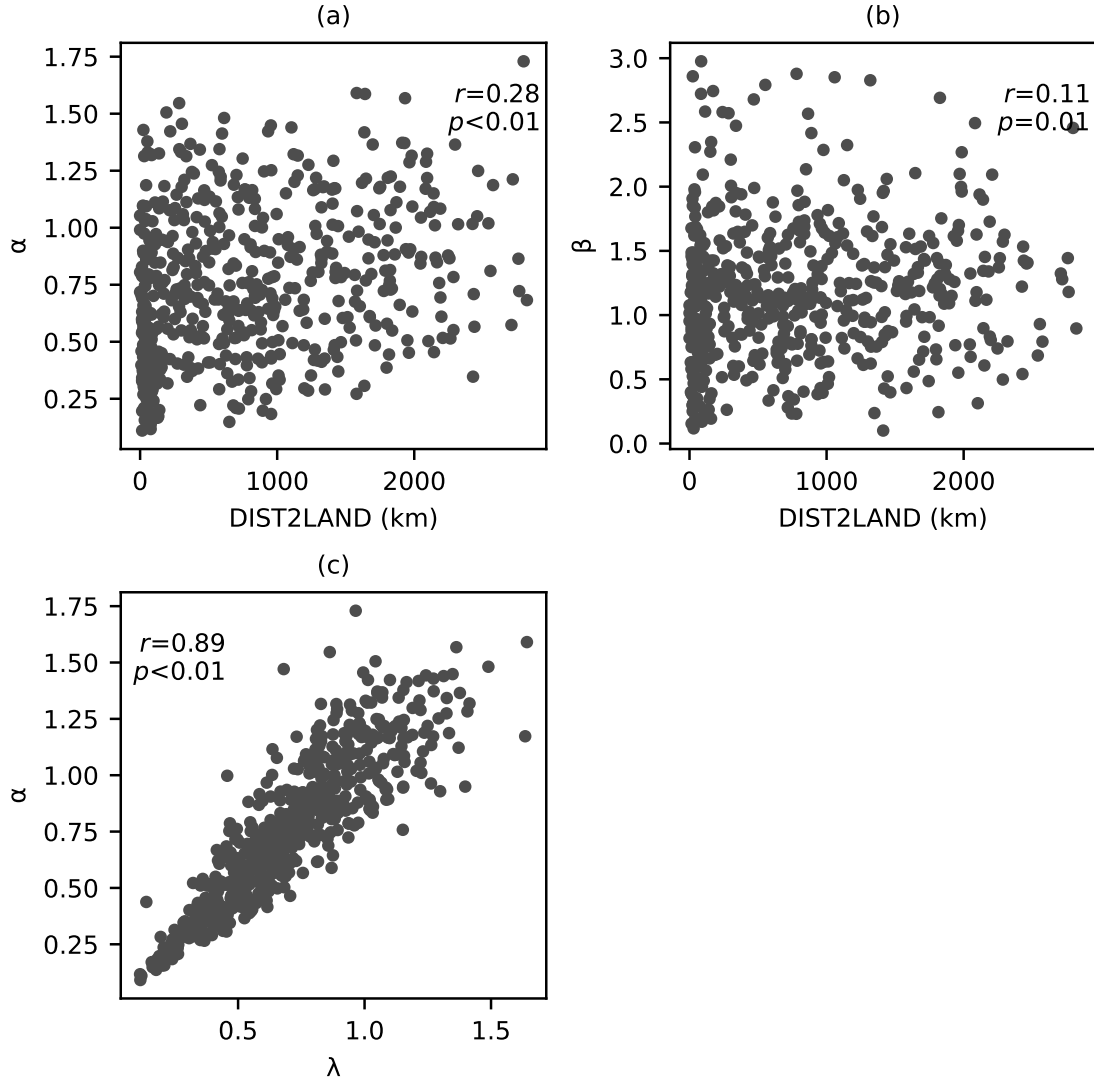


Figure A.1: Correlation analysis between (a) α and the distance to land at the end of decay (DIST2LAND), (b) β and DIST2LAND, and (c) λ from the empirical exponential model and α from the β model.

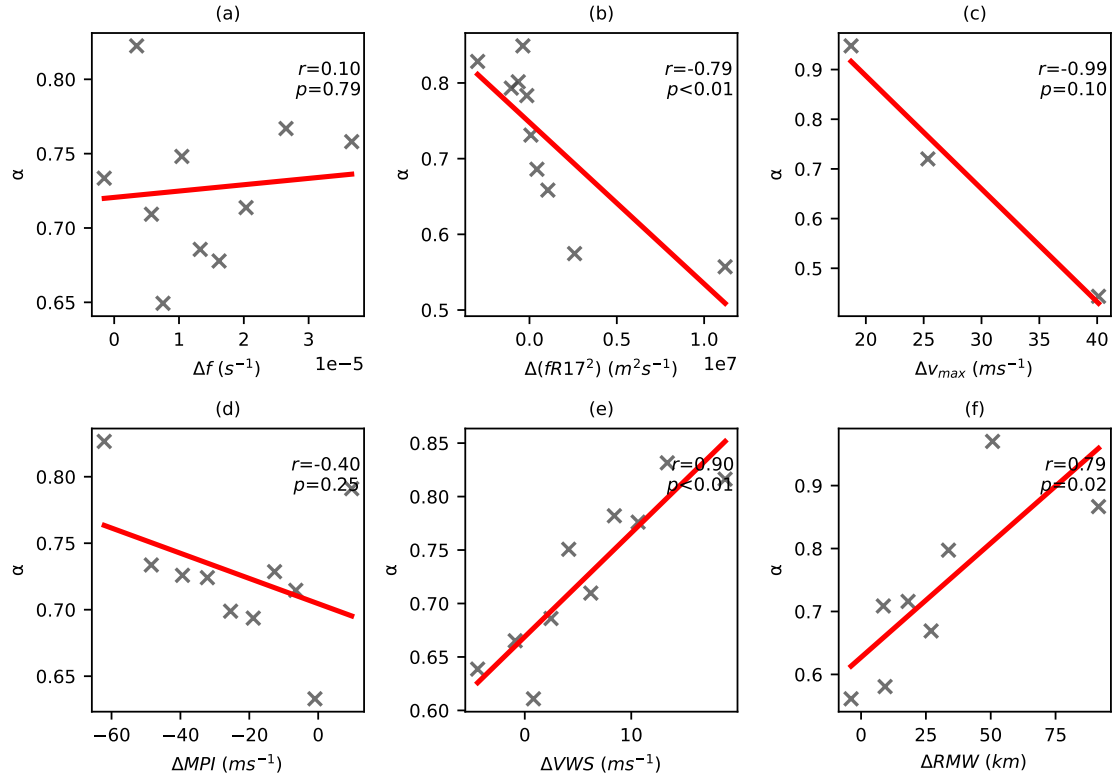


Figure A.2: Correlation analysis between mean α and deciles of changes in (a) Coriolis parameter (Δf), (b) planetary angular momentum at R17 ($\Delta(fR17^2)$), (c) intensity (Δv), (d) MPI (ΔMPI), (e) VWS (ΔVWS), and (f) RMW (ΔRMW).

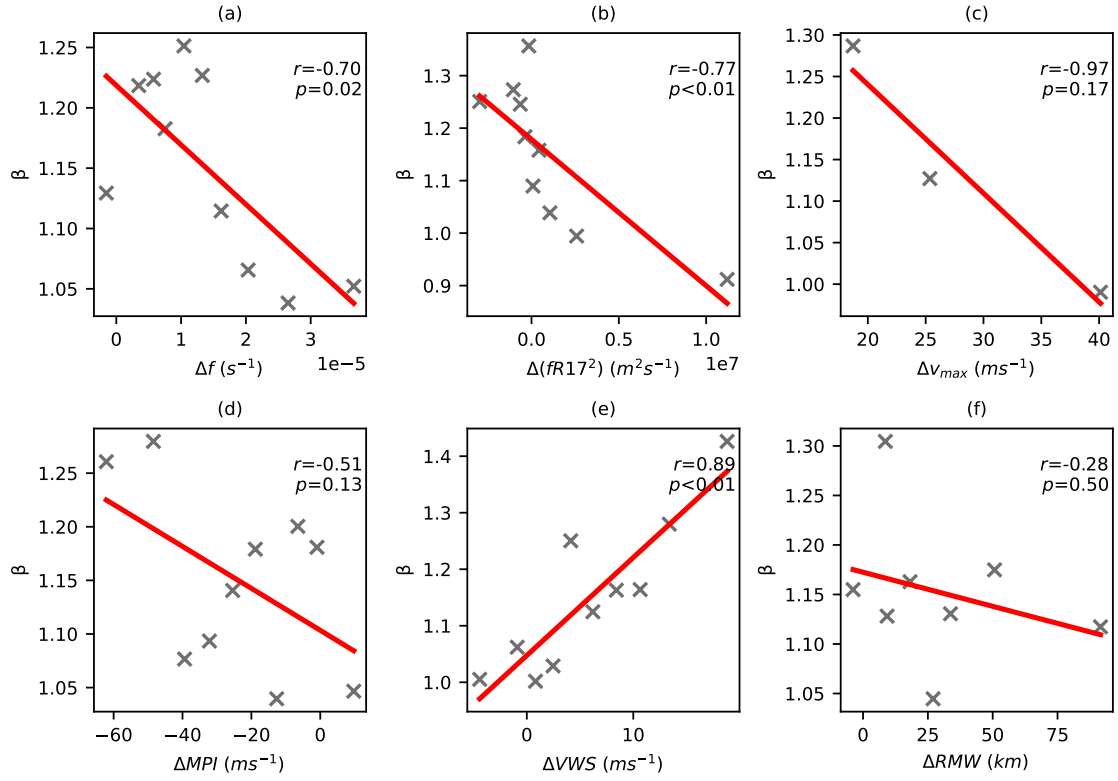


Figure A.3: Correlation analysis between mean β and deciles of changes in (a) Coriolis parameter (Δf), (b) planetary angular momentum at R17 ($\Delta(fR17^2)$), (c) intensity (Δv), (d) MPI (ΔMPI), (e) VWS (ΔVWS), and (f) RMW (ΔRMW).

Appendix B

Comparable Experiments

This appendix presents results from an earlier set of experiments (T_{96}). These cases are referred to as *weaker storms* compared with the *stronger storms* (T_{144}) analysed in the main text.

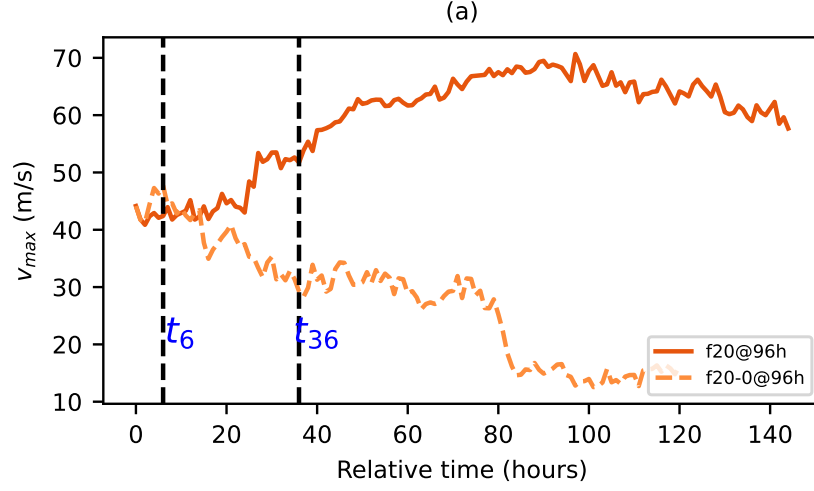


Figure B.1: Time evolution of v_{max} from two comparable experiments: f20, and f20-0@96h, relative to the restart time at T_{96} . The vertical dashes lines ($t_6h, t_{36}h$) mark the key stages of weakening.

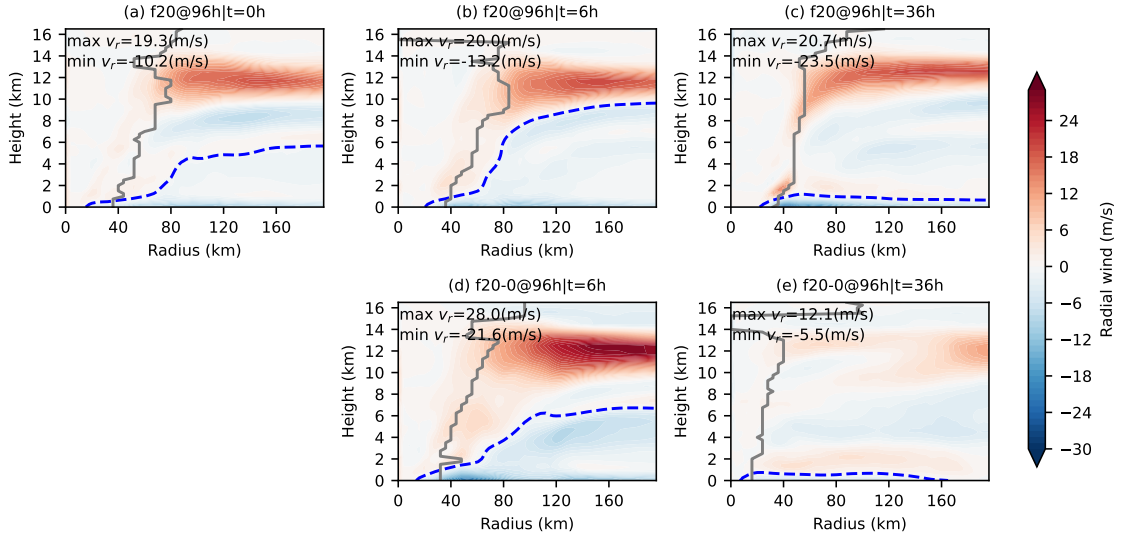


Figure B.2: Height-radius plots of the azimuthal-averaged tangential wind (contours) and radial wind (shading) from experiments f20 (first row), and f20-0@96h (second row) at $t = 0h$ (first column), $t = 6h$ (second column), and $t = 36h$ (third column). The annotations on the top-left corner of each panel give the maximum and minimum radial wind. The blue contours defined as 5% of the maximum radial inflow represent the inflow layer height. The grey dashed lines indicate the radius of maximum wind at each level for each snapshot

Appendix B. Comparable Experiments

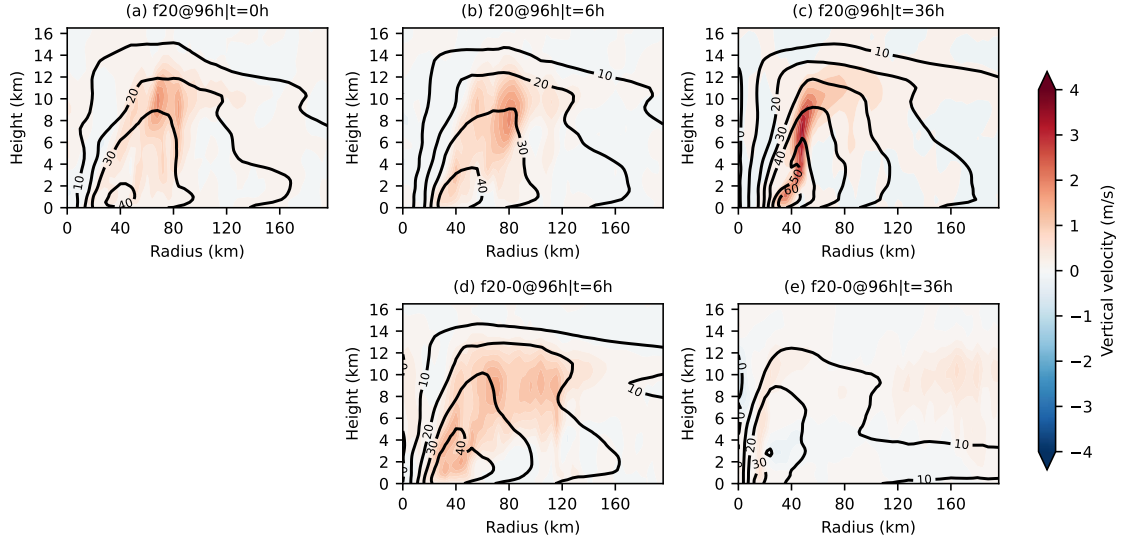


Figure B.3: Height-radius plots of the azimuthal-averaged vertical velocity (shading) and tangential wind (contours) from experiments f20 (first row), and f20-0@96h (third row) at $t = 0h$ (first column), $t = 6h$ (second column), and $t = 36h$ (third column).

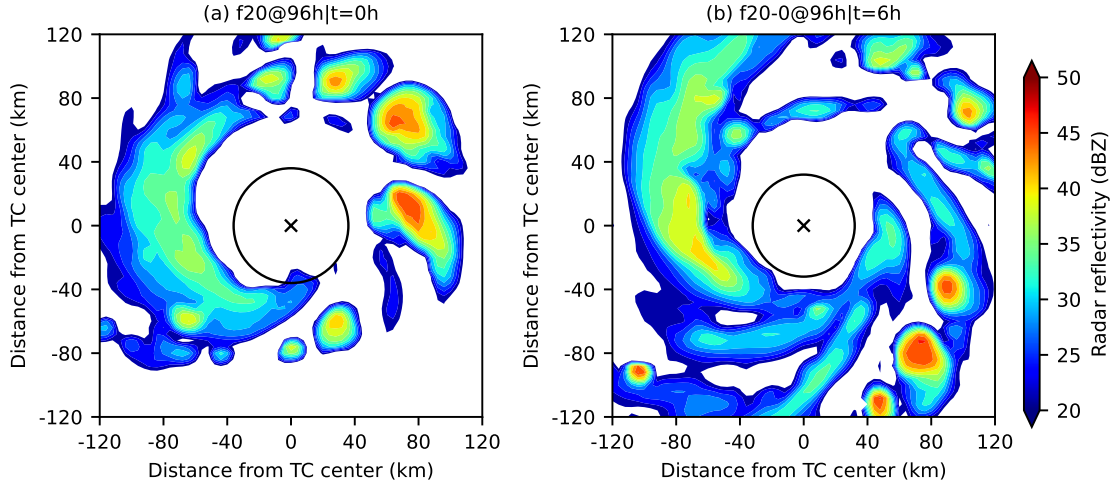


Figure B.4: Horizontal cross-sections of radar reflectivity greater than 20 dBZ at the height of 10 km around the TC centre for (a) the initial state and (b) f20-0@96h at $t = 6h$. The circles indicate the radius of maximum wind at each snapshot.

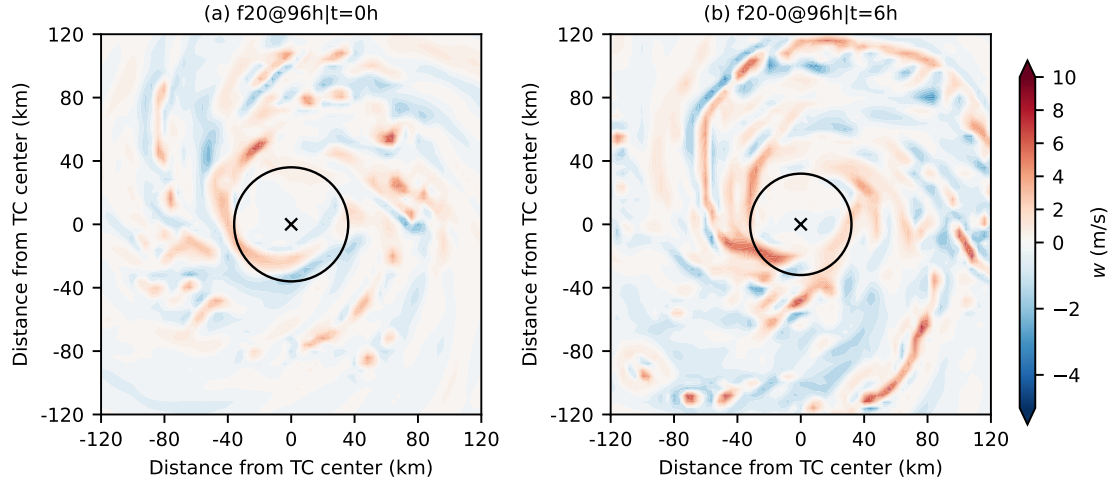


Figure B.5: Horizontal cross-sections of vertical velocity at the height of 2 km around the TC centre for (a) the initial state and (b) f20-0@96h at $t = 6$ h. The circles indicate the radius of maximum wind at each snapshot.

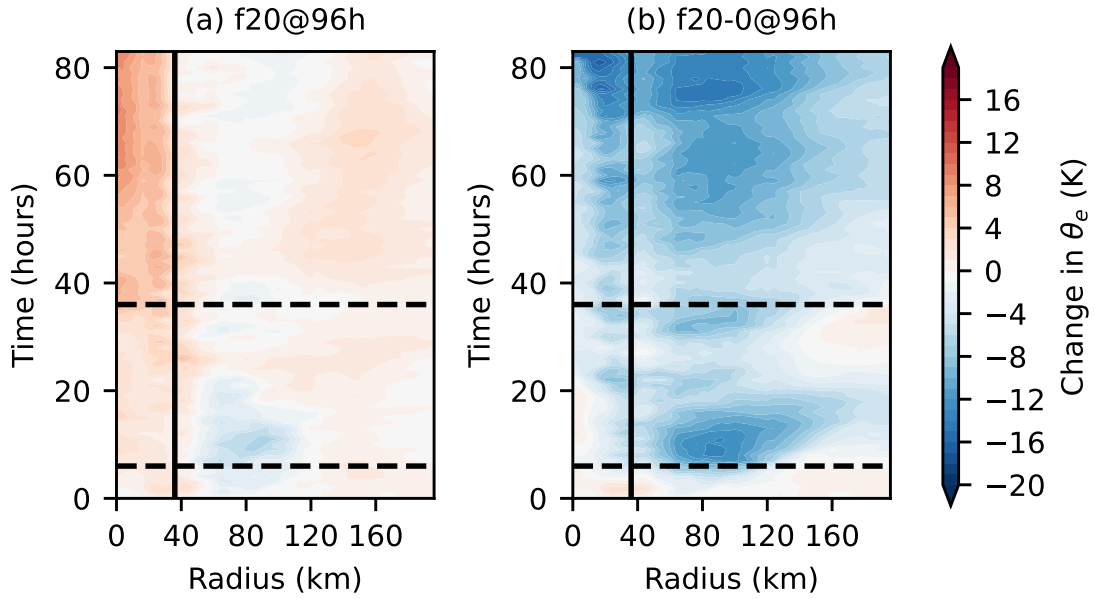


Figure B.6: Time-radius plots of changes in azimuthally averaged equivalent potential temperature (θ_e) under 1.5 km relative to its initial restart value. Black dashed lines indicate $t = 6$ h and $t = 36$ h after reduction f . Vertical lines mark the radius of maximum wind at restart for each case.

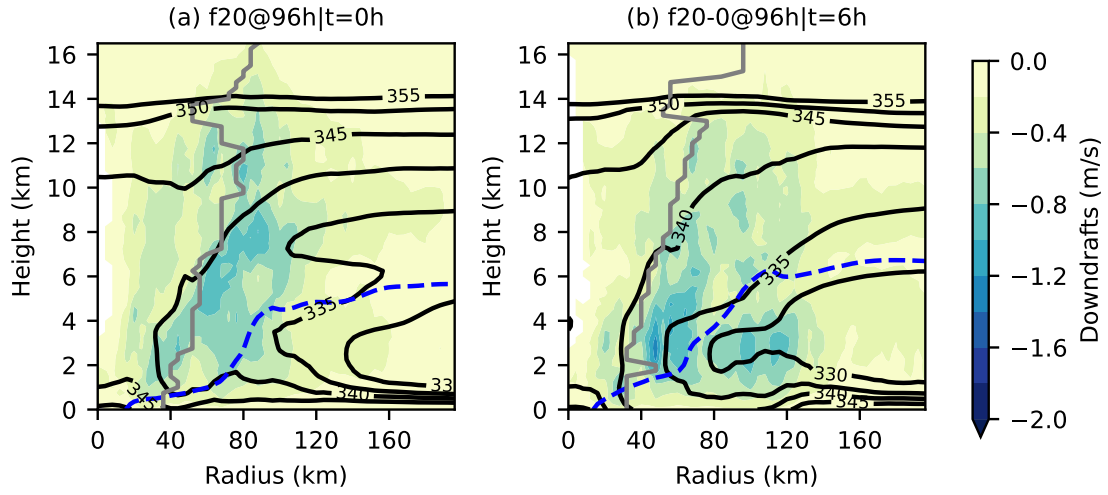


Figure B.7: Height-radius plot of the azimuthal-averaged negative vertical velocity (shading) and θ_e (contours) for (a) the initial state and (b) f20-0@96h at $t = 6$ h. The blue dashed contours represent 5% of the maximum radial inflow. The grey dashed lines indicate the radius of maximum wind at each snapshot.

Appendix C

IRIS

This appendix provides supporting sensitivity results for the IRIS experiments discussed in Chapter 5.

Table C.1: Sensitivity of simulated trends in TC intensity to the ratio of C_k/C_d .

Experiments	C_k/C_d	Trends in LMI ($m\ s^{-1}\ yr^{-1}$)	Trends in LF intensity ($m\ s^{-1}\ yr^{-1}$)
PI-Clim (default)	0.9	0.04 ± 0.01	0.02 ± 0.01
PI-Clim (1.0)	1.0	0.05 ± 0.01	0.02 ± 0.01
PI-Clim (0.8)	0.8	0.04 ± 0.01	0.02 ± 0.01