

Characteristics and Mechanisms of the Tropical Indian Ocean Warming projected by Climate models

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By

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DECLARATION

I, Gopika S, hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau

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Date:

CERTIFICATE

I hereby certify that the above Declaration of the candidate, Gopika S is true and the work was carried out under my/our supervision.

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"Fyodor Dostoevsky once wrote, 'But how could you live and have no story to tell?' "

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*To
My Achan (Suresh), Amma (Mini)
and husband (Sujish)*

Abstract

The tropical Indian Ocean has experienced significant warming over the past century, a trend expected to intensify with ongoing greenhouse gas emissions. However, climate models often struggle to capture the spatial pattern of observed sea surface temperature (SST) changes, which critically influence rainfall and atmospheric circulation. This thesis develops a robust method to detect significant climate change signals, facilitating meaningful comparisons of models with observations. It also investigates the physical mechanisms driving Indian Ocean warming, focusing on both its amplitude and spatial pattern.

This thesis introduces a novel statistical framework, the Time of Detection (ToD), to determine when climate change signals become statistically significant amid background climate variability. Applied to SST trends in CMIP5/6 climate models and observations, ToD outperforms the conventional Time of Emergence (ToE), allowing earlier and more robust detection of regional warming. In the equatorial Pacific, strong El Niño–Southern Oscillation variability obscures regional trends, suggesting that the apparent mismatch, model projections of decreasing zonal SST gradient and Walker circulation versus observed increases stems from internal variability. The Indian Ocean is one of the few regions where warming is already detectable in both models and observations, with particularly strong trends in the west, though early observational biases may overstate the magnitude.

The physical drivers of the Indian Ocean warming pattern are examined using two complementary approaches that yield consistent results: (i) a simplified upper-ocean heat budget applied to 69 CMIP5/6 models, and (ii) targeted sensitivity experiments with an ocean general circulation model (OGCM), designed to reduce coupled model biases and isolate the roles of heat-flux–driven stratification and wind-

driven circulation changes. The basin-wide warming is primarily thermodynamically driven, especially by reduced evaporative cooling linked to weaker surface winds and higher surface relative humidity. The coupled Bjerknes feedback amplifies the reduction in the equatorial zonal SST gradient, often described as an “IOD-like” pattern, triggered either by enhanced evaporative cooling in the climatologically warmer eastern equatorial Indian Ocean or by interactions with the Pacific. Evaporative cooling also plays a strong role in the strengthening of the interhemispheric SST gradient, a feature that has received less attention than the “IOD-like” pattern, despite its importance for the monsoon.

Overall, this work provides new tools and physical insights that enhance our understanding of, and confidence in, future climate projections in the Indian Ocean and beyond.

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Acronyms

CMIP Coupled Model Intercomparison Project.

CMIP5 CMIP-Phase 5.

CMIP6 CMIP-Phase 6.

DMI Dipole Mode Index.

EEIO Eastern Equatorial Indian Ocean.

EEP Eastern Equatorial Pacific.

ENSO El-Nino Southern Oscillation.

GCMs General Circulation Models.

GHG greenhouse gases.

IO Indian Ocean.

IOBM Indian Ocean Basin Mode.

IOD Indian Ocean Dipole.

IPCC Inter-governmental Panel on Climate Change.

IPO Inter-decadal Pacific Oscillation.

MGRAD interhemispheric SST gradient.

MMM Multi Model Median.

MMMe Multi Model Mean.

MOM Multi Observational Median.

N Noise.

NEMO Nucleus for European Modelling of the Ocean.

NIO Northern tropical Indian Ocean.

RCP Represented concentration pathways.

S Signal.

SEP southeastern Pacific.

SIO Southern tropical Indian Ocean.

SSP Shared Socioeconomic Pathways.

SST Sea Surface Temperature.

ToD Time of Detection.

ToE Time of Emergence.

WEIO Western Equatorial Indian Ocean.

WIO western Indian Ocean.

ZGRAD zonal SST gradient.

Chapter 1

Introduction

1.1 Climate change: General overview

Climate change refers to the long-term shift in Earth's climate, which has already begun to impact communities by affecting lives, health, and ecosystems. It is one of the most critical challenges we and future generations will face. These shifts can result from natural processes or anthropogenic influences. The Intergovernmental Panel on Climate Change (IPCC) describes the recent climate change and its anthropogenic causes as unequivocal. Understanding climate change is essential for making accurate future projections and reducing the risks through planning and implementing effective adaptation and mitigation measures.

1.1.1 An anthropogenically induced warming

Over the past two millennia, the Earth's climate has undergone natural fluctuations, however, the warming observed in recent decades since the onset of the Industrial Revolution is notable for its magnitude and rate. Since 1850, global surface temperatures have increased at a rate faster than the past 2000 years of proxy records (Fig. 1.1a). This warming, approximately 1°C globally (IPCC, 2018), is unprecedented compared to changes over the past 24,000 years (Osman et al., 2021).

This unprecedented global surface warming is primarily linked to shifts in climate change drivers. Since the Industrial Revolution, these drivers have been dominated by rising atmospheric greenhouse gas concentrations due to human activities. Over the past 60 years, atmospheric CO_2 levels have increased by over 100 ppm (Fig. 1.1b), making the recent centennial rate of CO_2 change greater than any seen in the last 800,000 years (IPCC Technical Summary Arias et al., 2021).

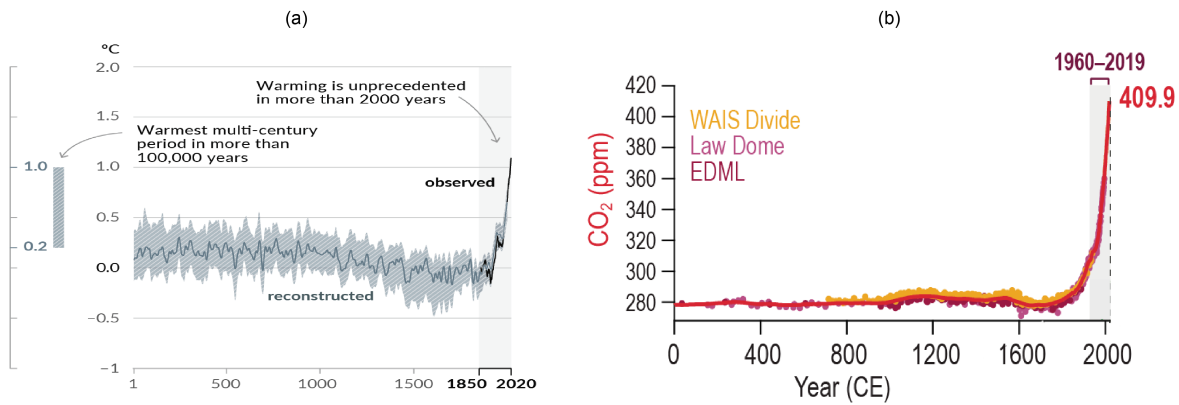


Figure 1.1: Time series of global temperature and atmospheric carbon dioxide (CO₂) levels over the last 2000 years. (a) Global surface temperature variations reconstructed from paleo-climate data (up to 2000; grey line) and from observational data (Post-1850; black line), shown as anomalies relative to the 1850–1900 baseline and averaged per decade. The vertical bar on the left indicates the warmest multi-century period within the last 100,000 years. Grey shading with diagonal white lines represents the very likely range of reconstructed temperatures. (b) Changes in atmospheric CO₂ concentrations derived from proxy data extending back 3.5 billion years. Figure adapted from IPCC, 2021, Working Group I: The Physical Science basis Technical Summary and Summary for policy makers.

1.1.2 Projected future warming and impacts

General Circulation Models (GCMs) are complex mathematical models of the climate system (atmosphere, ocean, land surfaces, cryosphere, carbon cycle) developed to understand past, present and projected future climate variations and understand underlying mechanisms (Wetherald, 2003). These models incorporate natural forcings, such as solar radiation changes at the top of the atmosphere and volcanic activity, alongside human-induced greenhouse gases, aerosols, ozone and land-use changes, both individually and in combination. These forcings have been reconstructed over the past, and several future possible scenarios based on various hypotheses, for global socioeconomics pathways, can be used to simulate future climate scenarios up to 2100.

The Coupled Model Intercomparison Project (CMIP) initiated by IPCC serves as a key platform for this purpose. CMIP provides a common protocol (in particular historical and scenario forcing) which allows historical and future projections by various Coupled General Circulation Models (CGCMs) to be compared (Meehl et al., 2007). CMIP has progressed through multiple phases, with the latest releases, CMIP-Phase5 (CMIP5; Eyring et al., 2016) and CMIP-Phase6 (CMIP6; Swart et al., 2019) serving as the main databases on which the 5th and 6th IPCC Assessment Reports have been

based. CMIP also provides a range of standardized scenarios to assess future climate system responses under different conditions (Meehl et al., 2007). These scenarios, based on Representative concentration pathways (RCP's) of CMIP5 and Shared Socioeconomic Pathways (SSP's) of CMIP6, offer forcing projections up to 2100, which reflect distinct socioeconomic narratives (Fig. 1.2a; Rogelj et al., 2018 ; Riahi et al., 2017).

Surface temperatures are expected to keep rising if greenhouse gases (GHG) continue to increase (Collins et al., 2013). The future projections from CMIP scenarios indicate that global warming is expected to rise by approximately 2 to 5°C relative to the 1850–1900 average in the coming decades, depending on the specific scenario considered (Fig. 1.2b, IPCC, 2021, Working Group I). The most optimistic emission scenario (SSP1-1.9) predicts the lowest warming, with an increase of less than ~2°C, while the highest emission scenario (SSP5-8.5) projects a globally-averaged surface temperature rise of up to ~5°C by the end of 2100.

This anthropogenic climate change has caused adverse impact to nature and people: Increasing surface temperatures contribute to heightened rainfall due to the greater amount of water vapour in the atmosphere, although this increase occurs at a rate lower than predicted by the Clausius-Clapeyron relation (Fig. 1.2c; Xie et al., 2010). The melting of ice caps and glaciers, leading to rising sea levels (Church and White, 2011), poses serious threats to coastal populations. Changes in global temperature and rainfall patterns, an increase in extreme events such as marine and terrestrial heat waves, also induce strong stresses on ecosystems. Around 3.3 to 3.6 billion people reside in areas that are highly susceptible to the effects of climate change. According to the International Union for Conservation of Nature Red List of Threatened Species (IUCN, 2024), 10,967 species are currently at risk of extinction (although climate change is not the only factor). Also, climate change affects human populations by endangering food security, favouring the emergence of infectious diseases (Liao et al., 2024), and disrupting habitats for current and future generations (Shivanna, 2022).

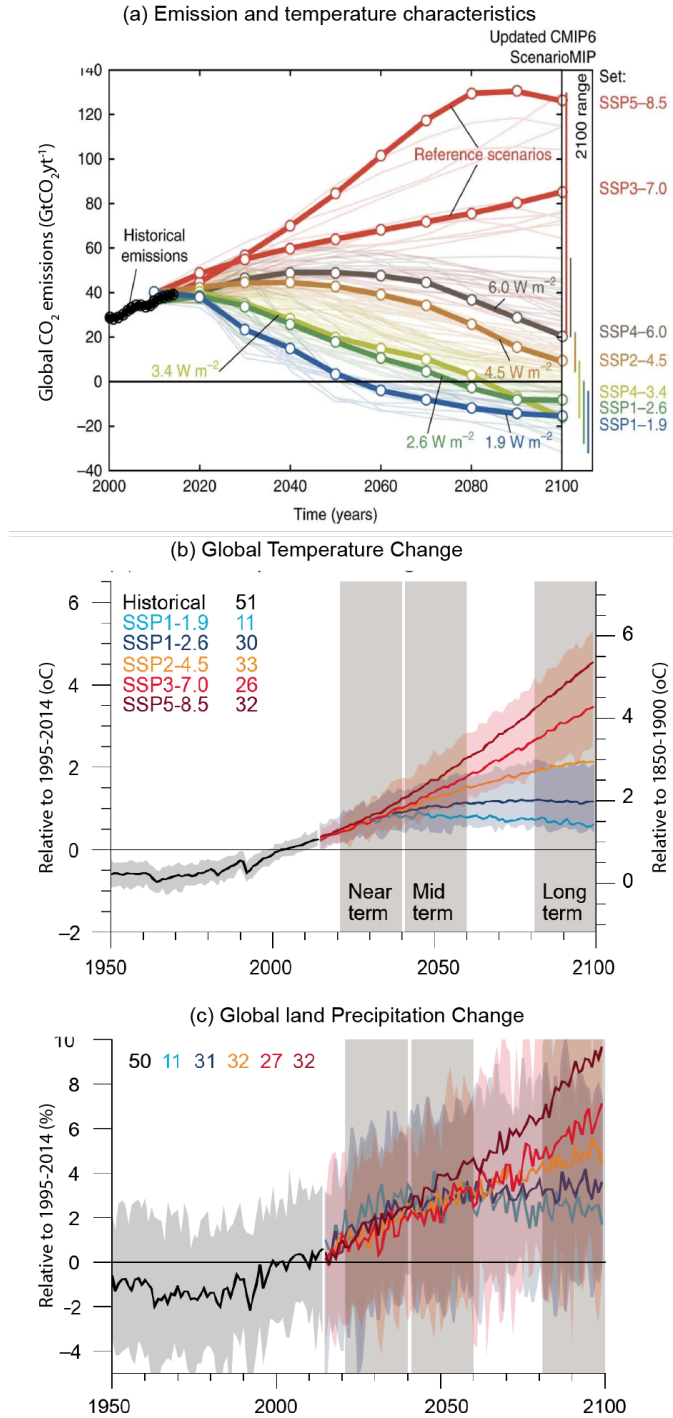


Figure 1.2: Key selected indicators of global climate change based on CMIP6 historical and scenario simulations. (a) Global CO₂ emissions under different SSP scenarios (Rogelj et al., 2018). (b) Changes in global surface air temperature relative to the 1995–2014 average (left axis) and the 1850–1900 average (right axis), with an offset of 0.82 °C representing the multimodel mean, closely aligning with observed estimates (Cross-Chapter Box 2.1, Table 1). (c) Changes in global land precipitation relative to the 1995–2014 average. Panels (b) and (c) display annual averages. In these panels, the curves represent multimodel averages from CMIP6 simulations, with shading around the SSP1-2.6 and SSP3-7.0 curves indicating the 5–95% range. The numbers at the top denote the number of model simulations used. These results are based on concentration-driven simulations. The dashed curve represents a low confidence and low likelihood scenario at the upper range of SSP5-8.5, reflecting deep uncertainties associated with potential ice sheet and ice-cliff instabilities. (Adapted from IPCC, 2021)

1.2 Tropical Ocean warming

Oceans cover more than 70% of Earth's surface. Due to their large heat capacity, they store over 90% of the excess heat into the climate system due to anthropogenic GHG emissions (Levitus et al., 2001). This thesis initially focuses on the tropical oceans, which host some of the world's most susceptible ecosystems and exert a strong climatic influence on vulnerable societies (Cai et al., 2013; IPCC, 2014), and later refines this focus to a more detailed investigation of the mechanisms driving warming in the Indian Ocean (IO).

1.2.1 Present-day mean state

In the current climate, deep atmospheric convection can only occur at Sea Surface Temperature (SST) above about 27°C (Gadgil et al., 1984). The Indo-Pacific warm pool is the largest region of warm water on the planet, maintaining deep atmospheric convection over the western Pacific and eastern IO (Fig. 1.3a). The mid-tropospheric heating due to the associated latent heat releases plays a crucial role in driving the zonal tropical atmospheric circulation (De Deckker, 2016). The ascending air over the Indo-Pacific warm pool drives low-level easterlies over the equatorial Pacific Ocean. In contrast, seasonally alternating winds over the equatorial Indian Ocean, westerlies during boreal winter to spring and southwesterlies during the summer monsoon , with opposite circulation patterns at height (Gill, 1980). Clear skies over the cooler eastern Pacific and western IO are on the other hand associated with radiative cooling and therefore subsidence (Fig. 1.3a and b). This zonal circulation cell is known as the Walker circulation (Fig. 1.3b).

In the Pacific and Atlantic Oceans, lower-tropospheric winds blow from east to west along the equator: they are known as trade winds. These trade winds blow northward along the coasts of South Africa and South America, yielding coastal upwelling. The equatorial Sverdrup balance (i.e. equilibrium between the force exerted by the wind on the upper ocean and the balancing pressure gradient) implies a shallower thermocline to the east, and therefore colder SST in response to Ekman-

driven equatorial upwelling there. Located west of the Indo-Pacific warm pool, the IO experiences predominantly westerly winds on an annual average. This leads to a

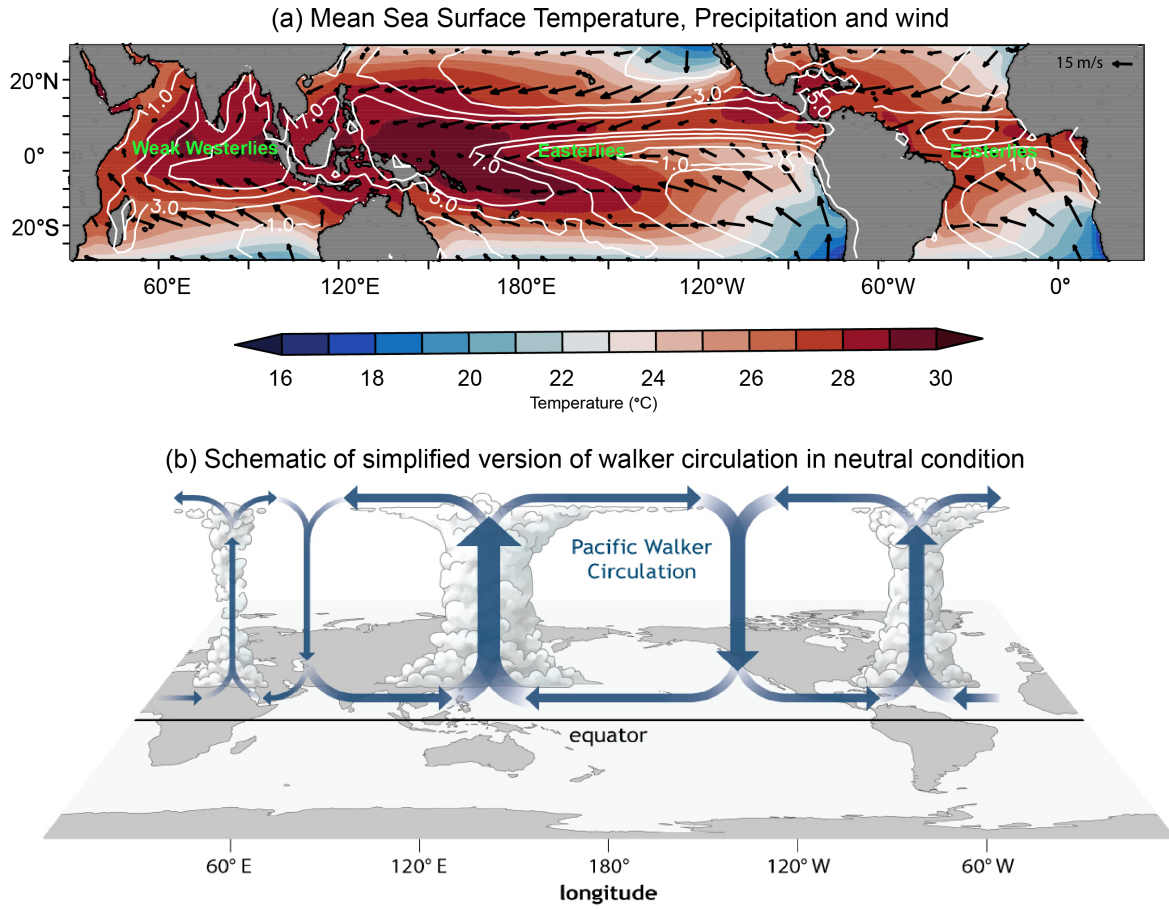


Figure 1.3: Illustrating (a) observed mean SST (HadISST; shaded), Precipitation (From CMAC; contours), and Surface wind from (From NCEP; vectors) for the period 1979-2023. (b) Generalized Walker Circulation (December-February) during El-Nino Southern Oscillation (ENSO)-neutral conditions (Picture courtesy: <https://www.climate.gov/news-features/blogs/enso/walker-circulation-ensos-atmospheric-buddy>). Note: The lower panel is a simplified conceptual illustration of walker circulation and does not represent the full details of the circulation.

shallower thermocline in the western IO, and slightly colder surface temperature there. Temperature is also colder in the western Arabian Sea due to coastal upwelling during the summer monsoon, as we will see in a later section. Because of the interconnection of the tropical circulations, shifts in one system affect the others (Eg, Luo et al., 2012). In addition to shaping basin-scale warming, the IOBM also contributes to the tropical biennial oscillation and its decadal variability (Ashok et al., 2014).

1.2.2 An inhomogeneous tropical warming

Projected trends in models and associated mechanisms

The tropical SST warming in climate model projections is spatially heterogeneous (Figs. 4a; Xie et al., 2010). Coupled climate models from the CMIP database project more warming in regions that are climatologically cooler, such as the western IO, eastern Pacific and eastern Atlantic (Fig. 1.4a). The warmer Indo-Pacific warm pool warms less than the rest of the equatorial band (Fig. 1.4a). There is also a cooling in the southern subtropics relative to the rest of the tropical band, which is most marked in the southeastern Pacific.

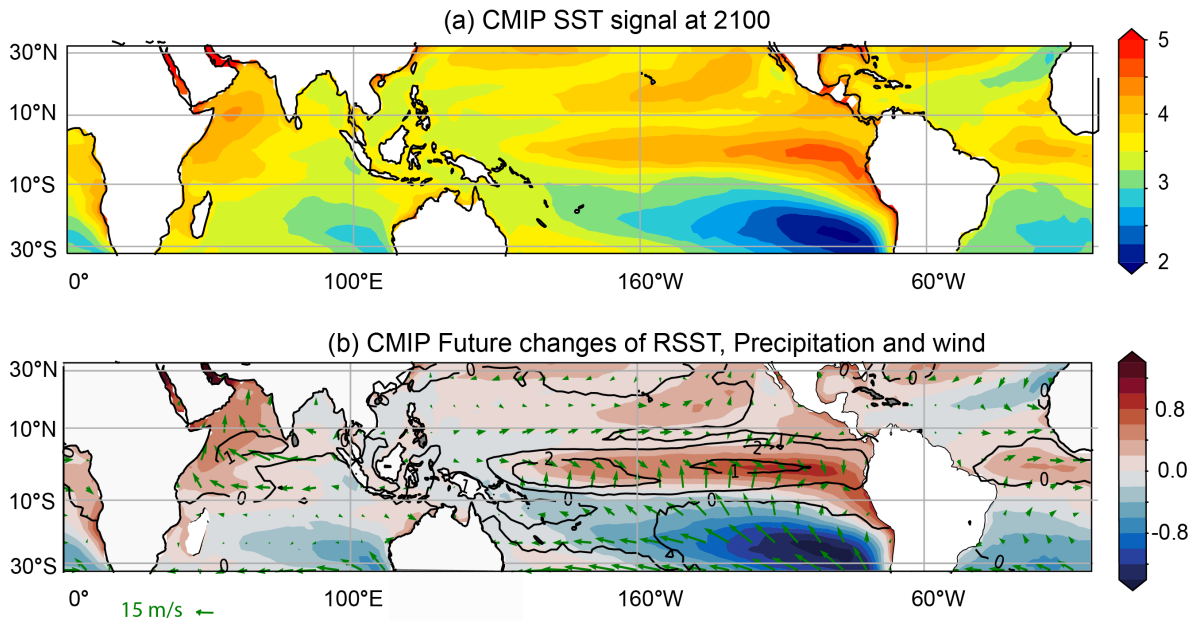


Figure 1.4: Tropical SST warming in CMIP5/6 models. (a) Map of the Projected SST warming signal from the CMIP5+6 Multi model median (MMM) in 2100. The warming signal (°C) is estimated from a regression of SST at each point to the normalised tropical average warming index of the model for the 1921-2100 period. (b) Future changes (2075:2100 - 1891-1915) of RSST (Shaded), precipitation (contour) and wind (vector) shown for the CMIP5+6 MMM. These fields represent the mean change between the two periods, not a regression-derived signal.

This tropical warming pattern has very important implications, as it influences atmospheric stability (enhanced stability in regions that cool relative to the tropical average, decreased stability in regions that warm more than the rest of the tropics, Xie et al., 2010). As a result, the warming pattern influences climatological tropical rainfall and circulation (Xie et al., 2010), cyclonic activity (Sobel et al., 2023), global teleconnection patterns, and modes of natural climate variability (Cai et al., 2013 , Cai et al., 2020). Climate sensitivity is defined as how strongly Earth's climate

responds to a doubling of GHG forcing (Langenbrunner, 2020). The tropical Pacific regional warming pattern also modulates global climate sensitivity (Andrews et al., 2015), an effect that is referred to as the ‘pattern effect’. The warming pattern indeed influences the intensity of some of the feedbacks that control Earth’s radiative response to greenhouse gases (Sherwood et al., 2020). For example, there are low clouds in the stable, subsident eastern Pacific. Enhanced warming there, destabilizes the atmosphere, thickening the atmospheric boundary layer, reducing low clouds, and therefore the planetary albedo in this region, leading to enhanced warming and increased climate sensitivity. Overall, the future surface oceanic warming pattern plays a very important role in regulating many aspects of the weather, climate and response of the climate to enhanced greenhouse gases. It is therefore necessary to project its future evolution with confidence.

A useful quantity to easily assess the warming pattern and its effect on atmospheric stability is relative SST (RSST; Fig. 1.4b; Xie et al., 2010), defined as SST minus its tropical average. By removing the tropical average SST warming, RSST first allows to better identify the more subtle regional variations in this warming, immediately identifying regions that warm more (positive RSST change) and regions that warm less (negative RSST change) than the rest of the tropics. The upper tropospheric temperature is very homogeneous in the tropics, due to its fast homogenization by equatorial wave dynamics. As a result, surface temperature changes control changes in atmospheric stability and RSST acts as a proxy for these changes in stability (e.g. Izumo et al., 2020). RSST therefore also serves as a proxy for future changes in tropical cyclones, and climatological rainfall (Xie et al., 2010). Climate models indeed project more rainfall in regions where RSST changes are positive (Fig. 1.4b): this is known as the warmer-gets-wetter mechanism.

Warming pattern: Observations vs models

The observed tropical-mean SST warming in the Multi-Observation Median (MOM), computed as the median of four observational datasets (HadISSTv1.1, ERSSTv5, Kaplan, and COBE-SST2), reaches 0.78°C in 2022 relative to the 1891–1950 climatology (Fig. 1.5a). This lies well within the 0.6–1.18°C warming range simulated

by the historical simulations from phases 5 and 6 of CMIP (CMIP5 + 6) databases (Fig. 1.5a). Future projections indicate that this warming will intensify in the coming decades, with the highest emission scenario leading to a 3⁰–5⁰C increase by the end of the twenty-first century (Fig. 1.5a).

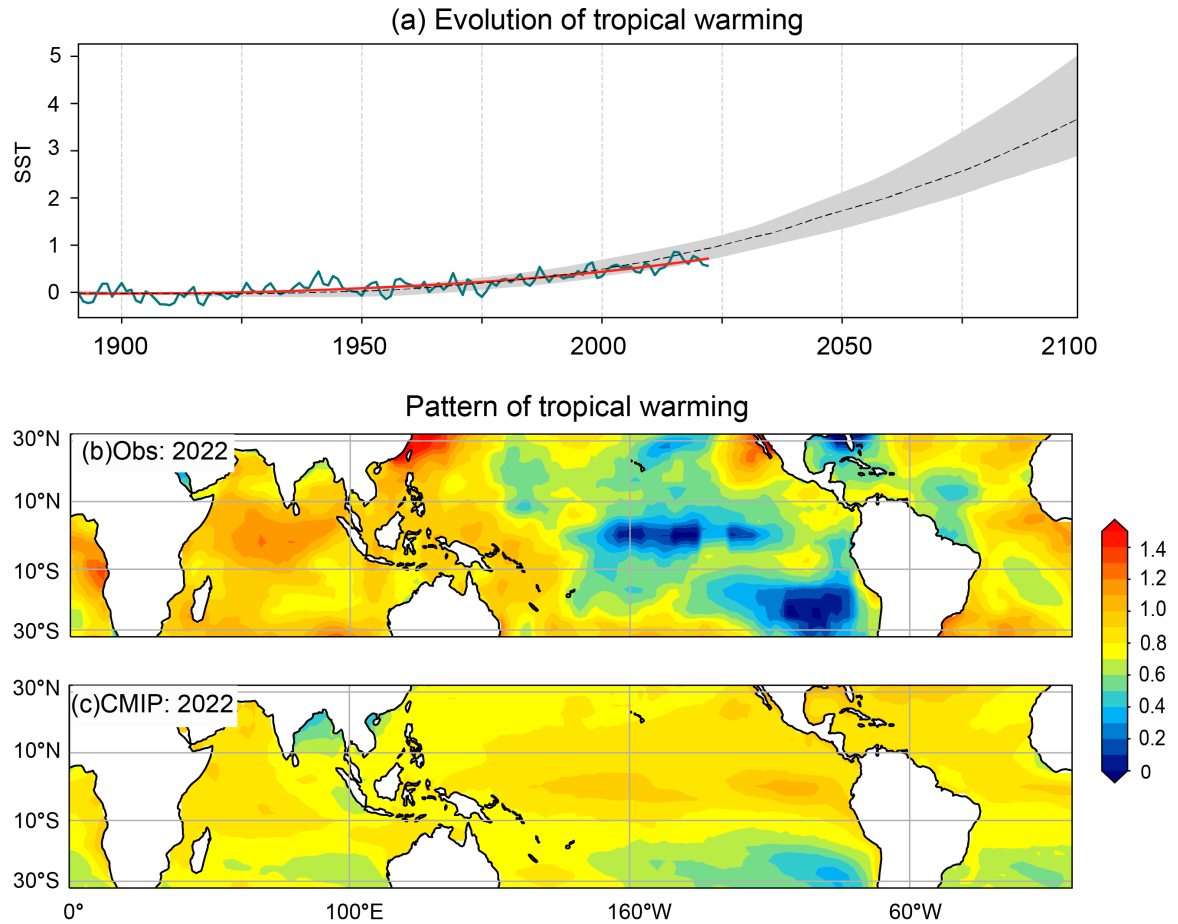


Figure 1.5: Tropical SST warming in Observations and CMIP5/6 models. (a) Time evolution of average 30°S–30°N warming (°C; relative to the 1891–1950 climatology) for the Multi-Observation Median (MOM, green line, with 4th order polynomial fit in red). This MOM is obtained as the median of four observational SST datasets: HadISSTv1.1, ERSSTv5, Kaplan, and COBE SST2. CMIP5+6 historical simulations and RCP8.5/SSP585 scenario Multi-Model Median (MMM) is the black dashed line, with a grey shading for the 10–90th percentile. Maps of the SST warming signal. (b and c) Spatial patterns of the long-term warming signal (°C) over 1921–2022 for the MOM and CMIP5+6 MMM, respectively. This long-term warming signal is estimated as in Hawkins and Sutton (2012), based on a regression of SST at each grid point to the normalised tropical-mean SST anomaly over 1921–2022. The signals are expressed as °C of warming over the entire period, relative to the 1891–1950 reference period. This method allows filtering out contributions from internal variability and obtaining an estimate of the long-term warming attributable to external forcing.

Similar to the projected future warming pattern (Fig 1.4a), the 2022 Multi-Model-Mean warming pattern is characterised by subdued warming in the southeastern tropical Pacific (Fig. 1.5c and 1.4a, Jebri et al., 2020 , Power et al., 2021),

and enhanced warming in the central and eastern equatorial Pacific. This enhanced warming in the central and eastern equatorial Pacific is often referred to as an "El-Niño like" warming pattern. The equatorial IO exhibits a pattern reminiscent of a positive IO dipole, featuring enhanced warming in the western equatorial IO and reduced warming in the east (Zheng et al., 2013; Gopika et al., 2020; Sharma et al., 2023). While model projections align with observations in terms of tropical average warming (Fig. 1.5a) and subdued SEP warming (Figs. 1.5b, c), there are significant disparities in the equatorial Pacific. Models indeed point to enhanced eastern equatorial Pacific warming and weakening trade winds (Watanabe et al., 2024), while observations indicate a muted warming or even weak cooling along stronger trade winds over recent decades. These discrepancies in eastern equatorial Pacific SST trends lead to question whether the Walker circulation has strengthened or weakened over the past century (Xie et al., 2010; Cai et al., 2013; Power et al., 2021). Similarly, in the IO, observations indicate greater warming in the central-eastern region, which differs from the "IOD-like" warming trends projected by CMIP models.

Possible reason for disagreements & mechanisms

There are several possible reasons for this disagreement between the modeled and observed warming patterns: internal variability, observational issues, or the possibility that climate model systematic biases lead to a different balance of warming pattern formation mechanisms than in observations. Each of these hypotheses is reviewed below.

Internal variability is a first possible cause of disagreement between models and observed warming pattern. The Pacific ocean indeed displays natural internal interdecadal variability (the Interdecadal Pacific Oscillation or IPO) with a spatial pattern that is similar to El-Niño Southern Oscillation (ENSO) near the equator, but with a broader meridional extension (Power et al., 2021). An IPO negative phase is associated with cooling in the eastern equatorial Pacific and enhanced trade winds. Figure 1.5c shows the multi-model mean across 69 CMIP models, which reduces the influence of internal variability modes such as the IPO (e.g. Heede and Fedorov, 2023), while the observational trend features signals associated with this internal variability.

Recent studies, however, suggest that the observed interdecadal zonal SST gradient strengthening trend in the equatorial Pacific lies outside the range of that produced by models (e.g. Wills et al., 2022). If correct, this suggests that the models do not capture the balance of mechanisms that drive the warming pattern correctly. To be able to conclude that, it is crucial to develop tools that can identify when a climate signal is detectable against the background of natural variability. Only signals that are detectable in both the models and observations can allow us to conclude if there is a disagreement between models and observations. Below, a discussion and introduction of a method for diagnosing when modelled/observed anthropogenic trends become detectable against the background climate variability.

A second possible reason for the discrepancy between modelled and observed warming is related to observational issues (Gopika et al., 2020). More accurate, global weekly estimates of the SST are indeed only available since the beginning of the satellite remote sensing era, 1980. Before that, global SST maps relied on sparse SST measurements along ship tracks (Deser et al., 2010). In chapter 3, we will discuss the possible influence of these observational issues on disagreement between modelled and observed trends, and see that they may explain some of the disagreement between models and observations in the IO.

Another possible reason for the discrepancy between modelled and observed warming lies in the inaccurate representation of the present-day mean state. CMIP models indeed exhibit significant present-day mean-state biases (Li et al., 2016a), such as an equatorial upwelling that extends to far west along the equator, leading to underestimated rainfall in the western equatorial Pacific ("cold tongue bias", e.g., Planton et al., 2021) or the cold bias in the Arabian Sea (McKenna et al., 2024). Several studies have identified statistical relationships between those present-day biases and the projected warming pattern (e.g. Li et al., 2016a, 2016b). Li et al. (2016a), for instance, finds that models with a strong cold tongue and dry western Pacific bias tend to produce a more "La-Niña-like" warming pattern. Similarly, Li et al. (2016b) find that models which overestimate IOD variability in the current climate tend to produce a spurious, too strong "IOD-like" warming pattern. This suggests that present-day mean state biases alter the balance of processes that drive the warming pattern.

A possible reason for the disparities between observed and modelled warming patterns is therefore that climate models may not accurately reproduce the balance of mechanisms that control the warming pattern in nature. Let us briefly review below processes that can lead to an "El Niño like" warming, processes that can lead to a "La Niña like" warming, and amplifying feedbacks that can strengthen those two type of changes.

Enhanced evaporation provides a strong negative feedback to warming of the ocean surface (Xie et al., 2010). Due to Clausius-Clapeyron, one expects higher evaporative cooling as the ocean warms, therefore limiting warming. The efficiency of this negative feedback is however stronger in warm than in cold regions. Indeed, the Clausius-Clapeyron equation implies a stronger evaporative cooling increase per °C of warming over climatologically warm than over climatologically cold regions. Another mechanism that could explain the "El-Niño-like" and "IOD-like" warming pattern is associated with the slowdown of the Walker cell. The Clausius Clapeyron constraint implies a +7%/K increase in boundary layer humidity, while energetics constraints imply only a 1-2%/K increase in global rainfall: the horizontal circulation therefore needs to decrease by 5-6%/K to pick up the slack (Held and Soden, 2006, Vecchi et al., 2006). The resulting Walker circulation slowdown (westerly anomaly over the Pacific and easterly anomalies over the IO) can therefore contribute to the El-Niño-like and IOD-like warming patterns.

There are also mechanisms that are believed to favour a "La-Niña-like" warming pattern. For instance, the ocean thermostat (Clement et al., 1996) refers to the cooling effect of oceanic dynamics in upwelling regions, in which the excess surface warming associated with anthropogenic forcing is partially compensated by the diluting effect of upwelling of deep, colder water. This effect reduces warming in the eastern tropical regions, as observed, but becomes less efficient over time, as the subsurface ocean progressively warms under the effect of anthropogenic forcing (e.g., Heede et al., 2020). Some studies also suggest interactions with remote regions such as the southern Ocean (e.g. Kang et al., 2023), Atlantic (e.g. McGregor et al., 2014), and IO (e.g. Luo et al., 2012) can favour the development of a "La-Niña-like" warming pattern in the Pacific Ocean.

Finally, recent studies have highlighted that some positive feedbacks known to operate at interannual or decadal timescales may also act for climate change, and be able to amplify a pre-existing warming pattern, either "El-Niño-like" or "La-Niña-like". For instance, the Bjerknes feedback is a positive retroaction loop that allows SST anomalies to self-amplify through ocean-atmosphere dynamics, which is at play for ENSO in the tropical Pacific (Bjerknes, 1972) and for the IOD in the IO (Saji et al., 1999). The Bjerknes positive feedback appears to enhance the Niño-like response in some models (e.g. Fu and Fedorov, 2023). The Bjerknes feedback also plays a central role in the dynamics of the Indian Ocean Dipole. Numerous studies have examined the structure and strength of the IOD Bjerknes feedback (e.g., Ng et al., 2014, Kämpf, 2024, Abdullah et al., 2024, Webster et al., 1999, Saji et al., 1999, Cai et al., 2014, Feng and Meyers, 2003, Fischer et al., 2005), building on the early foundational work on thermocline-wind-SST coupling in the equatorial Indian Ocean. The positive feedback between low cloud and SST can also contribute to enhancing pre-existing anomalies in the eastern Pacific. Warm anomalies in this region indeed destabilise the boundary layer, making it thicker and reducing clouds, therefore enhancing surface warming (Ying and Huang, 2016a; Ying and Huang, 2016b) pattern. Many climate models, however, do produce convective clouds instead of stratiform clouds over the eastern Pacific, leading to a negative rather than a positive feedback.

Overall, in this section, we have seen that the warming pattern arises from a delicate balance of processes, with some favouring a La-Niña -ike warming as observed, some favouring an "El-Niño-like warming" as modelled, and some amplifying the existing pattern. The relative importance of these processes can be altered by systematic biases in climate models, potentially altering their ability to correctly project the future warming pattern. This makes the comparison of the warming pattern between models and observations important, and therefore requires tools to distinguish anthropogenic signals from background climate noise

1.3 The Indian Ocean

The tropical IO (a major part of Earth's largest warm pool) plays a critical role in regional and global climate through atmospheric teleconnections and is the endpoint of the global oceanic conveyor belt (Schott et al., 2009). The IO basin accounts for about one-quarter of the global ocean heat gain since 1990 (Beal et al., 2020), and climate model projections indicate this warming will strengthen in the coming decades. This thesis focuses on characterising the projected tropical IO warming and its spatial pattern in climate models and identifying the associated mechanisms.

1.3.1 Seasonal cycle

The IO differs from the two other tropical oceans due to the Asian continent to the north. This northern boundary has several implications. First, heat cannot be transported into the northern subtropics as in other tropical basins, due to the northern boundary. The Asian continent also leads to a strong seasonal cycle and a robust monsoon system, driven by the seasonal temperature contrast between land and sea (Schott and McCreary, 2001). Winds are relatively weak over the tropical IO during the pre-monsoon season (April–May), and dominated by the zonal Walker circulation (i.e. westerlies along the equator). The Indian subcontinent and Tibetan plateau solar heating during boreal summer then initiates the Southwest Monsoon (June–September), associated with southern hemisphere southeasterlies, a strong cross-equatorial flow, and northern hemisphere southwesterlies over the Arabian Sea and Bay of Bengal (Fig. 1.6a). The southwesterlies bring rainfall to the Indian subcontinent during the summer monsoon (Fig. 1.6b). The transitional inter-monsoon period (October–November) is associated with weaker winds and is dominated by the zonal Walker circulation (westerlies along the equator). The continental north hemisphere cooling during boreal winter induces a southward pressure force, leading to a complete wind reversal relative to summer north of 10°S: this is the Northeast Monsoon (December–March, Fig. 1.6c), which brings rain to southeastern India and Sri Lanka (Fig. 1.6d).

These seasonal shifts drive a complete reversal of the monsoon currents

north of 10°S in the IO, for instance, the Somali Current (Schott et al., 2009). Another noteworthy seasonal current is the Wyrtki jet, a westward equatorial current that develops during both inter-monsoon seasons (Schott et al., 2009).

Upwelling in the tropical IO is especially strong in the Arabian Sea, during summer. Southwesterlies indeed induce offshore Ekman transport in the western Arabian Sea, lowering the sea level and SST (Fig. 1.6ab). The cold, nutrient-rich waters that are brought to the surface originate from the subsurface cross-equatorial cell northward branch. Winds are also upwelling-favourable along the southwestern coast of India, although a complex combination of local and remote forcing drives the seasonal cycle there (e.g. Suresh et al., 2016). A seasonal upwelling also develops along the coast of Java in summer when easterlies favour a southward, off-shore Ekman transport (Fig. 1.6a, where the upwelling is visible as a coastal strip of low sea level).

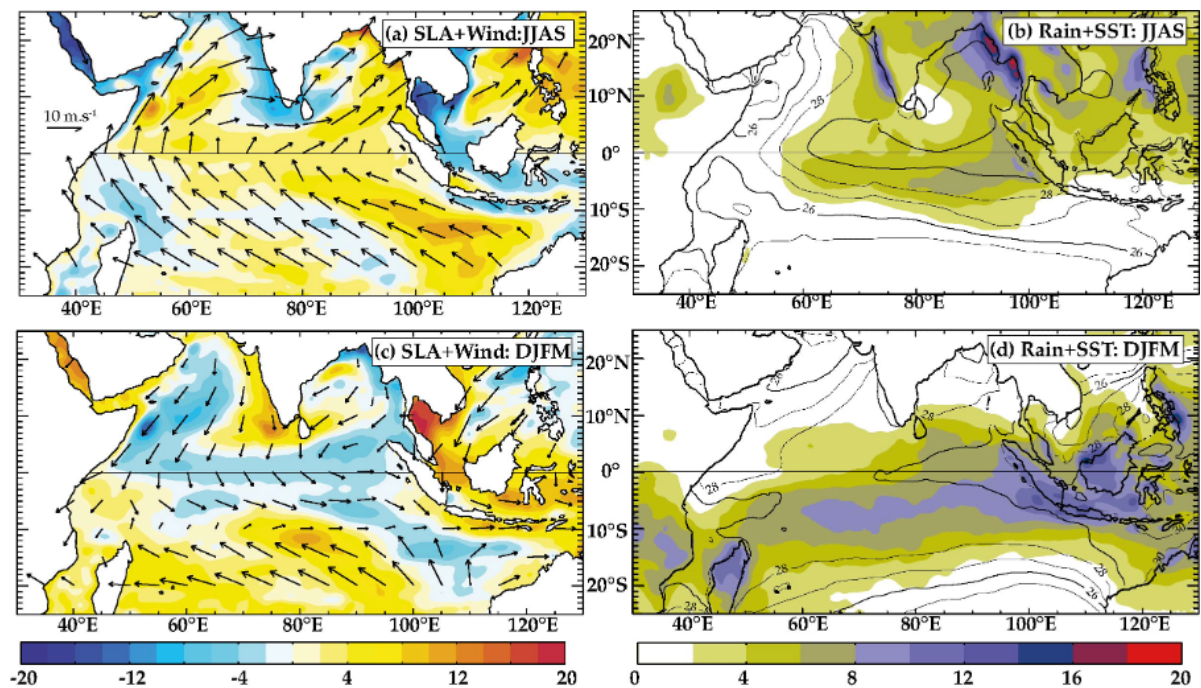


Figure 1.6: : Observed climatological pattern of boreal (left) summer (top) and winter (bottom) : climatology of (left) sea level anomalies (colour, in cm) and 10m wind (vector) and (right) rainfall (colour, in mm.d-1) and SST (contour, in $^{\circ}\text{C}$). Adapted from Samson et al., 2014.

1.3.2 Interannual variability

The first mode of interannual SST variability in the tropical IO is the IO Basin Mode (IOBM), characterised by basin-wide warming or cooling (Klein et al., 1999 ;

Yang et al., 2007). The IOBM is a remote response to the ENSO. ENSO develops due to ocean-atmosphere interactions over the tropical Pacific, but induces zonal shifts in the Walker circulation that influence the entire tropical band. El Niño (ENSO warm phase) events induce subsidence over the IO, and therefore less clouds and weaker winds, leading to a basin-wide (Yu and Rienecker, 1999 ; Klein et al., 1999). Local air-sea interactions maintain this tropical IO warming and its consequences on regional climate until after the end of the El Niño events: this effect is referred to as the IO capacitor effect (e.g Xie et al., 2009). La Niña events (ENSO cold phase) have roughly symmetric effects.

The tropical IO also displays intrinsic climate variability, primarily associated with the IO Dipole (IOD; Saji et al., 1999; Webster et al., 1999). Contrary to the IOBM, which is a remote response to ENSO, IOD events can develop independently of ENSO in the Pacific. Similar to ENSO, IOD events develop due to the Bjerknes (Bjerknes, 1972) feedback, an ocean-atmosphere retroaction loop which allows SST anomalies to self-amplify. The IOD modulates the zonal SST gradient along the equator, and is usually characterised using the Dipole Mode Index (DMI): western minus eastern equatorial IO SST anomalies (Saji et al., 1999).

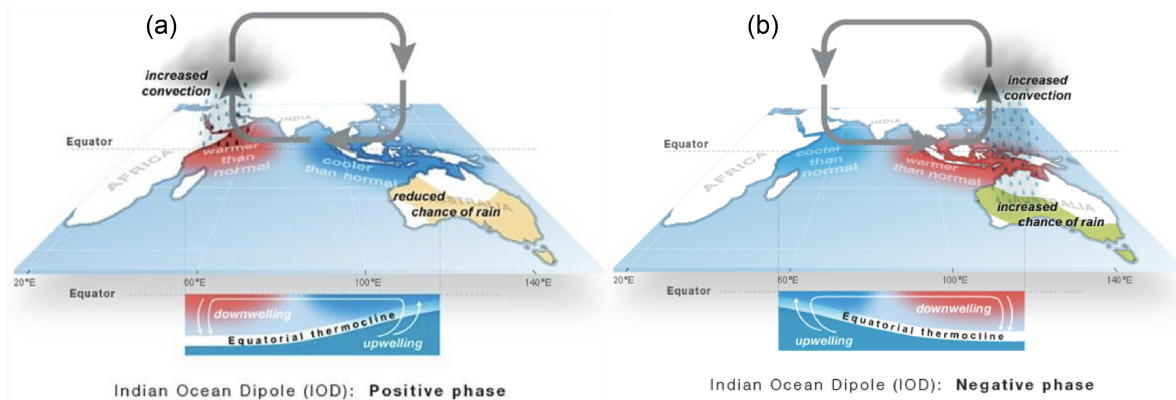


Figure 1.7: Schematic representation of the mean IO climate under (a) positive and (b) negative IOD conditions. The historical mean climate, illustrating SST patterns, surface winds, the associated Walker circulation, the mean location of convection, and the thermocline. Adapted from Abram et al., 2020.

Positive IOD phases (Fig .1.7a) are characterized by a weaker than usual SST zonal gradient, a decrease in the zonal circulation cell over the tropical IO (i.e. surface easterly wind anomalies) , wet conditions over the horn of Africa (increasing the risk of floods), droughts over Indonesia (increasing the risk of wildfires) and over

Australia. The easterly wind anomalies induce a deeper than usual thermocline in the western IO, but enhanced upwelling in the eastern equatorial IO and along the coast of Java (Fig. 1.7a). Negative IOD phases are associated with roughly symmetric climate anomalies (Figure 1.7b). There is a tendency for IOD events to co-occur with ENSO: ENSO warm phases tend to induce positive IOD events in relation with the easterly wind anomalies they induce over the tropical IO, but IOD events can also develop independently of ENSO (Schott et al., 2009).

The IOD exerts wide-ranging influences on regional and global climate (e.g., Ashok et al., 2001, Saji and Yamagata, 2003). Positive and negative IOD events modulate rainfall anomalies across East Africa, Southeast Asia, Australia and the broader Indo-Pacific through ocean–atmosphere teleconnections (e.g., Saji, 2018, Kucharski et al., 2020, Yamagata et al., 2004, Black et al., 2003, Ashok et al., 2003). The IOD further impacts tropical cyclone activity, the strength of the South Asian monsoon, and variability in the Indo-Pacific Walker circulation (e.g., Zhang and Li, 2014, Girishkumar and Ravichandran, 2012, Ashok and Saji, 2007). Beyond its interannual behaviour, the IOD also exhibits pronounced decadal variations linked to slow monsoon-ocean interactions (Ashok et al., 2004) and, more recently, to Southern Ocean processes that may enhance its decadal predictability (Feba et al., 2021). Additionally, climate model analyses show that the IOD constitutes one of the dominant statistical modes of Indian Ocean SST variability (Marathe et al., 2021), underscoring its importance in both natural variability and in the context of long-term climate change.

1.3.3 Climate Change

The tropical IO has experienced steady warming over the past century, with an accelerated rate since the 1960s (Alory et al., 2007 ; Alory and Meyers, 2009; Du and Xie, 2008; Levitus et al., 2009 ; Han et al., 2014). The IO is warming faster than other tropical ocean basins and exceeds the global average warming rate (IPCC, 2021). The tropical IO average warming amplitude over the historical period is consistent in climate models and observations (Fig. 1.8, Gopika et al., 2020). More than 90% of the IO average warming relative to the pre-industrial period is attributed to anthropogenic

forcing, with natural external forcings such as volcanic and solar variations exerting a weaker influence (Dong and Zhou, 2014a; Dong et al., 2014b). CMIP models project a continued increase in this warming trend throughout the 21st century, with 3°C warmer temperatures by the end of the 21st century under the worst-case emission scenarios (Fig. 1.9a).

Indian Ocean average SST in observation and CMIP models

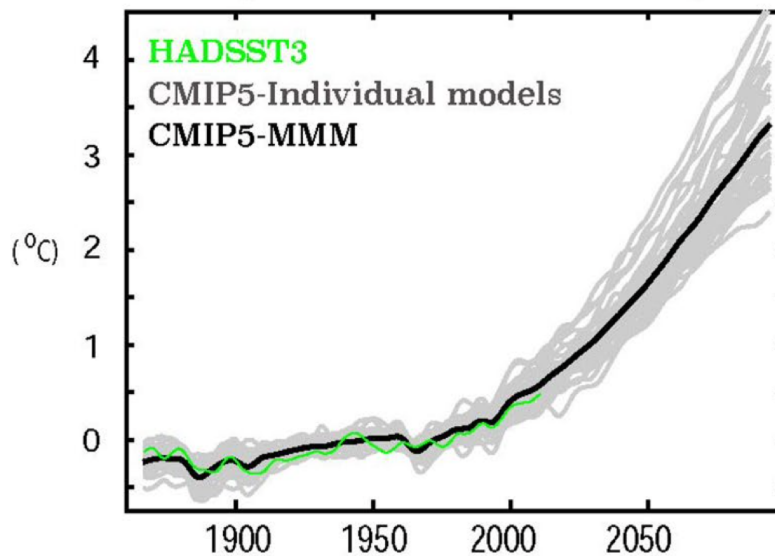


Figure 1.8: Temporal evolution of the average tropical IO SST anomalies relative to the 1860–2099 period. The green curve represents observational data from HadSST3, while the grey lines depict historical and future simulations from 36 CMIP5 models, with the ensemble mean shown as a thick black curve. Adapted from Gopika et al., 2020

The tropical IO warming has significant implication. Nearly one-third of the world’s population lives in countries along the IO rim (Beal et al., 2020). The tropical IO ocean warming is expected to reduce marine productivity due to increased stratification (Barange and Coauthors, 2014; Naqvi and Coauthors, 2009), disrupt the Indian monsoon (Sandeep and Ajayamohan, 2014 , Parvathi et al., 2017 , Swapna et al., 2014, Goswami et al., 2022, Feba et al., 2021) that sustains agriculture (Gadgil and Gadgil, 2006). The decreased availability of fish stocks and impacts on agriculture therefore threaten food security of countries around the IO (e.g. Funk et al., 2008). As in other regions of the world, warming is expected to intensify extreme weather events (Roxy et al., 2017), such as cyclones (Murakami et al., 2017), floods, droughts, and bushfires in nearby regions like Africa, Indonesia, and Australia. Furthermore, the tropical IO warming increases the frequency of marine heatwaves,

induces rising sea level (Unnikrishnan et al., 2015 ; Collins and Coauthors, 2019). At a more global scale, the tropical IO warming influences remote regions through atmospheric teleconnections that influence global climate patterns such as in West Sahel, the Mediterranean, and South America (Giannini et al., 2003 ; Hoerling et al., 2012). Given the profound regional implications for a densely populated region and the far-reaching consequences, a comprehensive understanding of the drivers of the mean tropical IO warming is imperative.

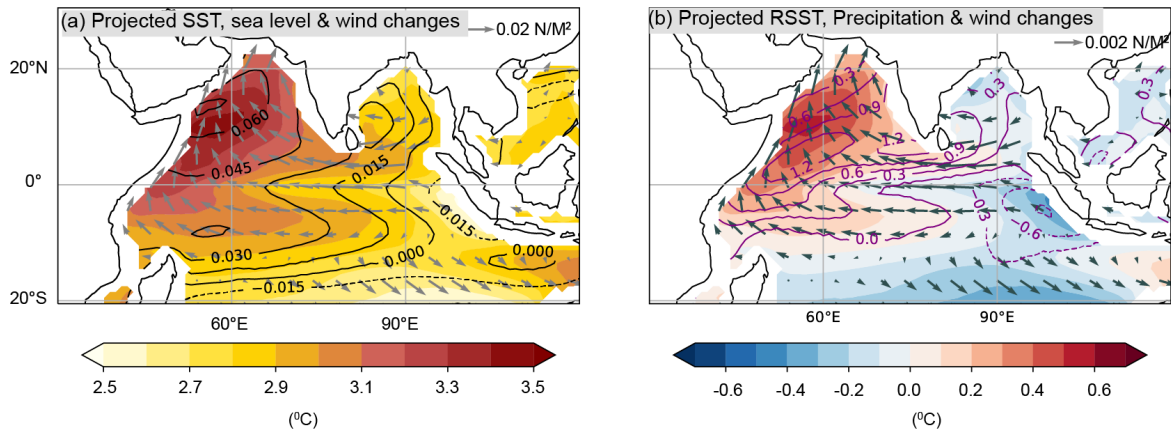


Figure 1.9: CMIP5/6 Multi-Model Mean (MMe) projected changes for (a) SST (°C, shaded), Precipitation (m, contours) and wind stress (N/m², vectors), (b) same as (a) but for RSST changes.

The tropical IO warming projected by climate models from the CMIP database is not spatially homogeneous (Fig. 1.9a), with enhanced warming in the western Equatorial IO and the Arabian Sea and reduced warming in the eastern equatorial IO (Cai et al., 2014 , Sharma et al., 2023). This pattern is similar to that observed during positive phases of the IOD (e.g. Saji et al., 1999) and is therefore often referred to as an “IOD-like” warming. This IOD-like pattern is characterized by a decrease in the equatorial zonal SST gradient (Fig. 1.9a) and a weakening of the IO branch of the tropical zonal circulation in CMIP models (e.g., Held and Soden, 2006). Alongside this zonal asymmetry, this warming is overall stronger in the northern IO (Fig. 1.9a), intensifying the interhemispheric SST gradient. This enhanced gradient shifts the Intertropical Convergence Zone northward (Byrne et al., 2018) and increases summer monsoonal rainfall (Wang et al., 2020).

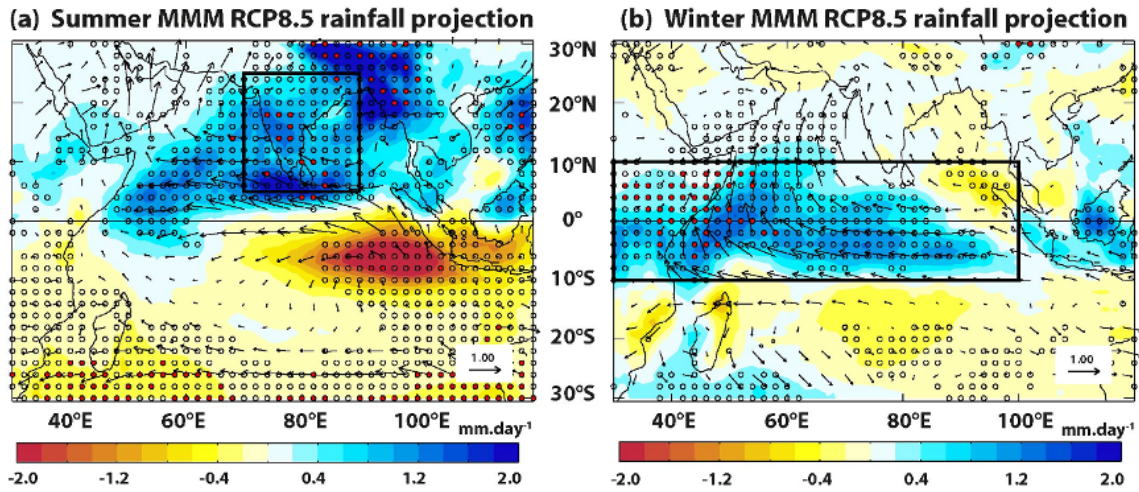


Figure 1.10: Multi-model mean projected changes in precipitation (color) and wind speed (vectors) under the CMIP RCP8.5 scenario for (a) summer (JJAS) and (b) winter (DJFM). Areas where more than 70% (90%) of models agree on the direction of wind speed change are marked with empty black (filled red) dots in panels (a) and (b). (Adapted from Parvathi et al., 2017 Supplementary Information)

As previously discussed, the SST warming pattern is important as it induces changes in atmospheric stability. RSST changes (Fig. 1.9b) are both useful to more clearly reveal changes in SST gradient, and as a proxy for changes in atmospheric stability (Fig 1.9b) e.g., Johnson and Xie, 2010 ; Izumo et al., 2020). The tropical IO experiences “warmer get wetter” changes in rainfall (Xie et al., 2010 ; Xie, 2020): there tends to be enhanced rainfall over the Northwestern IO where the ocean warms more than the tropical IO average (Fig. 1.10 and 1.9). This in turn alters atmospheric and oceanic circulation patterns and the distribution of tropical cyclones (Xie et al., 2010, Vecchi and Soden, 2007a, Murakami et al., 2017, Murakami et al., 2013). More specifically, recent studies suggest a future increase in Indian summer monsoon rainfall (Fig. 1.10a; Sooraj et al., 2015), driven by enhanced cross-equatorial flow resulting from the warming of the western IO and Arabian Sea. In contrast, winter monsoon circulation appears to be weakening (Fig. 1.10b), attributed to a reduced sea-level pressure gradient between the Arabian Peninsula and the southern IO, likely due to Arabian Peninsula warming (Parvathi et al., 2017).

IO warming mechanisms

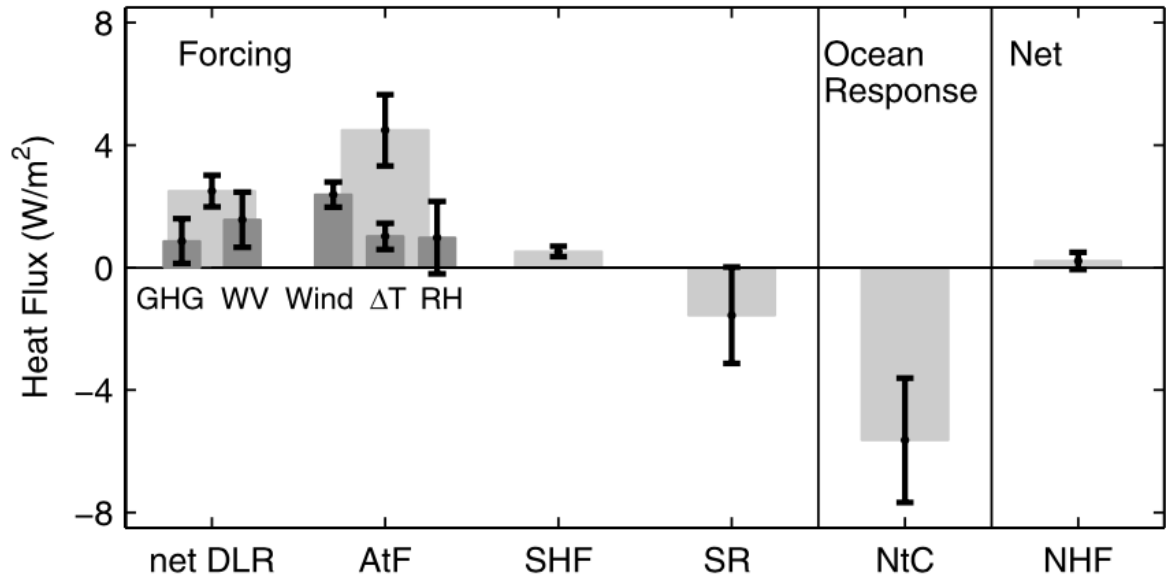


Figure 1.11: The multi-model mean linear trends in surface heat flux components show each component as a gray block representing the ensemble mean, with error bars indicating the inter-model standard deviation. Net downward longwave radiation (net DLR) includes contributions from greenhouse gas (GHG) forcing and water vapor (WV) feedback. The latent heat flux (LHF) driven by atmospheric forcing (AtF) is further broken down into contributions from changes in wind speed, air-sea temperature difference (T), and relative humidity (RH). Additionally, sensible heat flux (SHF), solar radiation (SR), and the Newtonian cooling (NtC) component of the LHF are represented, alongside the overall net surface heat flux (NHF). (Reproduced from Du and Xie, 2008)

A number of studies have sought to identify the mechanisms responsible for the mean IO warming (Fig 1.11, Du and Xie, 2008, Dong and Zhou, 2014a , Dong et al., 2014b, Zhang and Li, 2014). These studies have consistently identified two main drivers of this warming. The first contributor is increased downward longwave (Fig 1.11) radiation in response to increasing levels of anthropogenic greenhouse gases, amplified by the water vapor feedback. A warmer atmosphere indeed holds more water vapor, which is a greenhouse gas that amplifies the warming. The second is reduced evaporative cooling in response to the reduced surface winds associated with the zonal circulation slowdown. The warming resulting from these drivers is balanced by a large Newtonian cooling negative feedback associated with increased evaporation due to warmer SST. The Clausius Clapeyron relation indeed predicts a 7%/K increase in latent heat fluxes. The relative contributions of each of the above drivers varies between studies, due to differences in methodologies and datasets.

The IOD-like warming pattern in the tropical IO results from a complex interplay of heat flux adjustments and ocean dynamics (Xie et al., 2010; Liu et al., 2015).

The Bjerknes feedback seems to be a key process for amplifying the IOD-like response: coupled ocean-atmosphere dynamics result in easterly anomalies in response to an IOD-like warming, that reduce the thermocline slope, zonal SST and rainfall gradient (e.g., Zhang and Li, 2014; Liu et al., 2015). Yet, the mechanisms that initiate this pattern remain debated. One hypothesis suggests that average tropical warming weakens the Walker circulation, due to a combination of Clausius-Clapeyron and energetic constraints (Held and Soden, 2006; Ma et al., 2012), and that the resulting equatorial easterly anomalies trigger an IOD-like pattern via ocean dynamics (Sharma et al., 2023). Another hypothesis is related to the ocean dynamical thermostat mechanism (Clement et al., 1996): the cool subsurface water brought to the surface by the upwelling along Java in fall limits surface warming in the eastern equatorial IO, initiating an IOD-like pattern (Xie et al., 2010; Liu et al., 2015). The last mechanism mentioned in scientific literature is evaporative cooling (e.g., Liu et al., 2015; Zhang and Li, 2014): the climatologically warmer eastern equatorial IO induces, a stronger negative evaporative feedback compared to the cooler western IO, initiating the IOD-like pattern. Overall, consensus on the relative roles of these mechanisms remains elusive.

Even less is understood about the mechanisms driving IO inter-hemispheric SST gradient changes. Some studies attribute these changes to latent heat forcing, due to the stronger southern hemisphere winds lead to more evaporative cooling, an effect possibly reinforced by the wind-evaporation-SST feedback (Xie et al., 2010). Others highlight the role of low-cloud cover and associated shortwave radiation changes, particularly in the southern IO (Sharma et al., 2023).

1.4 Objectives of the Thesis

1. Assess the time of emergence of the spatially heterogeneous warming signals in the IO induced by the climate change with respect to that in other tropical oceans.

Is the “IOD-like” warming pattern (enhanced warming in western IO, weaker IO branch of the WC) already detectable in observations (chapter 3)?

2. Improve projections of future warming pattern in the IO.

Investigate the influence of present-day model errors on future tropical IO projections using a forced ocean modeling framework (Chapter 4,5)

3. To investigate the mechanisms of the spatially heterogeneous IO warming in response to the climate change.

Investigate the mechanisms of the spatially heterogeneous tropical IO warming in response to climate change based on the Zhang and Li (2014) (hereafter ZL14) approach, and one ocean modeling approach (chapters 4, 5)

1.5 Approach to address the thesis objectives

In this section, we discuss how chapters 3, 4 and 5 address the three aforementioned objectives of the thesis.

Observations and climate model historical simulations both indicate surface ocean warming in response to anthropogenic forcing, yet with notable differences in their spatial patterns. The following question therefore arises: do these differences arise from internal variability in the climate system, or from inabilities of coupled models to accurately reproduce the balance of processes that control the warming pattern (e.g. Watanabe et al., 2024). Chapter 3 examines this question by examining where anthropogenic signals become detectable against the background natural climate variability. Indeed, evaluating how well models capture even subtle climate change signals observed in nature is crucial for assessing their realism. The usual concept for discriminating climate change signals from background natural variability is the ToE (Hawkins and Sutton, 2012). As we will see in chapter 3, the ToE methodology is not appropriate to detect subtle climate change signals in long time series, such as those associated with RSST, which typically have a low signal to noise ratio (RSST signals being smaller than SST signals, because the large tropical average component is removed). Chapter 3, therefore, also introduces a novel method (Time of Detection (ToD)) to identify regions where climate change signals can be robustly detected in both models and observations, enabling a fair comparison. This method is applied to both SST and RSST, compared to ToE, and results for the IO are compared to those for other tropical basins.

Chapter 3 addresses the first objective of this thesis as follows. The IO averaged warming is already detectable in models and observations for several decades, and is more clearly detectable than in the tropical Pacific, where the large ENSO-related variability complicates detection. The RSST warming associated with the western pole of the "IOD-like" IO warming is detectable in both models and observations, though it may be overestimated in the latter due to observational issues in early historical records. This suggests a weakening of the IO branch of the Walker cell in both models and observations. The western IO is one of the only two regions where a regional warming signal is already detectable in both models and observations, the other one being the southeastern tropical Pacific, where a consistent negative RSST signal appears in models and observations. Chapter 3 and the associated published article (Gopika et al., 2024) , therefore, fully address the thesis's first objective.

Chapter 4 modifies the oceanic mixed-layer heat budget framework of Zhang and Li (2014) to analyze mechanisms of the warming pattern in CMIP5 and 6 models. Using a Taylor expansion, it separates surface heat flux components into SST-dependent (feedback) and independent (forcing) terms, which allows for the identification of how various mechanisms contribute to the CMIP SST changes. This chapter brings several novelties relative to the study of Zhang and Li, 2014. First, this paper focuses on the IO, discussing it in more detail than their global study. Second, chapter 4 analyses the outputs of 46 CMIP5 and 6 simulations, whereas Zhang and Li (2014) analysed 17 CMIP5 simulations, making its result more representative of the whole CMIP database. Third, Zhang and Li (2014) neglects the positive feedback from a warmer, moister atmosphere that enhances downward radiation and further warms the ocean. In contrast, this study accounts for this feedback using the analytical framework of Shakespeare and Roderick (2022). Fourth, an explicit equation for RSST changes was derived in this study, which allows to detail the mechanisms that contribute to the warming pattern more directly. Finally, Zhang and Li, 2014 only described the processes that contribute to the multi-model mean (MMM_e) warming, this study also examines the processes underlying inter-model diversity.. To the best of my knowledge, no study has explored IO warming inter-model diversity. Chapter 4 and the associated publication (Gopika et al., 2025) present several findings that

address the third objective of this thesis. First, the average tropical IO warming is dominated by a reduction of evaporative cooling related to both a reduction of surface winds and an increase in near-surface relative humidity. Second, the MMMe warming is associated with a decrease in the zonal equatorial SST gradient and an increase in the inter-hemispheric SST gradient, and the modulation of these two responses also dominates the inter-model diversity. The meridional gradient change is related to the evaporative feedback and forcing, while the Bjerknes feedback strongly modulates the zonal gradient reduction. This work enhances understanding of both the magnitude and pattern of warming, including the IOD-like warming pattern and the inter-hemispheric gradient, the latter of which has been only minimally explored in the literature.

Chapter 5 uses an ocean modelling approach, which allows for studying in more detail the oceanic response to anthropogenic climate change than the statistically based CMIP analysis developed in Chapter 4. This chapter: i) briefly introduce this approach, ii) discuss how it can be applied to mitigate the impact of coupled model systematic biases on projections (objective 2 of the thesis), and iii) discuss how its results support the warming pattern mechanisms described in chapter 4 (objective 3 of the thesis).

The ocean modeling approach used in chapter 5 (Lengaigne et al., 2024) relies on a first control simulation forced by detrended observed momentum, heat and freshwater fluxes at the air-sea interface. Which represents a reliable oceanic mean state with reduced present-day biases., The future changes in these fluxes, derived from a CMIP simulation, are then added to perform a climate change simulation, using the same decomposition of heat flux into forcing and feedback components as in chapter 4. A first interest of these simulations is to mitigate the effect of present-day biases in climate models. CMIP models exhibit significant present-day biases that may influence projected tropical IO warming pattern, such as an overly strong IOD (Li et al., 2016b; McKenna et al., 2024), cold biases in the Arabian Sea (Fathrio et al., 2017), and equatorial easterly wind biases (Long et al., 2020). Many of these CMIP5 biases persist into CMIP6 (Bhattacharya et al., 2022). Several studies have established statistical relationships between these biases and future projections, which

allow statistical corrections known as emergent constraints (Li et al., 2016a; Hoffmann et al., 2016). However, dynamic correction frameworks are considered more reliable than statistical methods (Maraun, 2016; Sanderson et al., 2021). The bias correction strategy is efficient at reducing some of the present-day biases, such as a cold bias in the Northern Arabian Sea, a strong equatorial SST gradient, etc. These analyses of Chapter 5, therefore, address the second objective of this thesis.

Finally, the forced modeling approach also enables sensitivity experiments which allow a more dynamically testing of the mechanisms highlighted in the statistical-based analysis in chapter 4. Therefore, also addressing this thesis third objective. By applying projected heat flux and wind stress changes both independently and together, it provides a comprehensive understanding of the drivers of warming. Chapter 5 shows that basin-scale warming is primarily driven by heat flux forcing, consistent with Chapter 4, which is attributed to reduced evaporation from weaker winds and higher near-surface relative humidity. It also confirms the key role of future wind changes in shaping the IOD-like pattern, with heat fluxes acting as a negative feedback, supporting Chapter 4's emphasis on the Bjerknes feedback. The future strengthening of the inter-hemispheric SST gradient is attributed to the differential evaporative feedback (stronger negative feedback in the southern hemisphere due to stronger winds), in agreement with chapter 4 and the hypothesis of Xie et al., 2010. The results further indicate that the wind and heat flux changes impact combine quite linearly and that future freshwater changes have a relatively minor effect. Overall, the modeling analyses of chapter 5 back up the interpretations from heat budgets over the entire CMIP5 and 6 database from chapter 4, therefore addressing this thesis's third objective.

Chapter 2

Data and Methods

2.1 Introduction

In this thesis, this chapter provides an overview of the observation based datasets, CMIP models, and the ocean model used. However, it does not include a description of the methodologies specific to individual chapters. Given that each chapter employs distinct methodologies, the relevant methodological details are provided within their respective chapters. This structure ensures clarity and a more effective representation of the methodologies in their specific contexts.

2.2 Observation-based datasets:

In this thesis, long-term observation-based reconstructed and reanalysis datasets are used to evaluate model simulations. Additionally, atmospheric reanalysis and climatological oceanic data from the World Ocean Atlas are employed to force and initialize the model, respectively.

2.2.1 Sea Surface Temperature Observations

Early SST observations, particularly before the 1960s, were sparse in the early record due to limited measurement capabilities. This data scarcity led to the development of observation-based reconstruction products, which use sparse historical records from various sources, such as ships, oceanographic stations, moored buoys, drifting buoys and research vessels, combined with modern assimilation and statistical techniques to create continuous gridded datasets. With the advent of satellite-based observations in 1981, these reconstructed products became significantly more reliable and accurate. For this thesis, four long-term SST reconstructed observational

products are analyzed. These datasets are detailed below:

- Hadley Centre Sea Ice and SST (HadISST v1.1; Rayner et al., 2003). HadISST uses reduced space optimal interpolation applied to SSTs from the Marine Data Bank and the International Comprehensive Ocean Atmospheric dataset (ICOADS) through 1981 and a blend of in-situ and adjusted satellite-derived SSTs for 1982 onwards. The “bucket correction” was applied to SSTs for 1871-1941. This dataset has a spatial resolution of $1^{\circ} \times 1^{\circ}$ and is available at a monthly timescale.
- Centennial In situ Observation-Based Estimates of the Variability of SST and Marine Meteorological Variables (COBE-SST2; Folland and Parker, 1995). COBE-SST2 uses a Multi Time Scale Analysis applied to SST from ICOADS. Like HadISST2, it provides a homogenised record over time to support climate studies at $1^{\circ} \times 1^{\circ}$ horizontal resolution and a monthly timescale.
- Extended Reconstructed SST v.5 (ERSSTv.5; Huang et al., 2017). ERSST dataset is derived from observations such as ICOADS and Argo floats (since 2000). Various correction methodologies implemented, different SST measurement types (ship engine room intakes, ship buckets, and buoys) are corrected using statistical methods. Before 2010, data adjustments were made by comparing uncorrected SSTs with nighttime marine air temperatures. For ship-based data collected after 2010, adjustments are based on buoy-measured SSTs. And this dataset is available for a $2^{\circ} \times 2^{\circ}$ spatial resolution and for monthly timescales.
- Kaplan extended SST (Kaplan-SST v2, Kaplan et al., 1998). KAPLANSST is produced using the MOHSST5 version of the GOSTA dataset from the U.K. Met Office as the primary SST source. Various processing steps are applied to address missing data by utilising spatial patterns from existing data along with time interpolation. It covers the period from 1856 to 2022.. This dataset is available for $5^{\circ} \times 5^{\circ}$ spatial resolution and for a monthly timescale.

2.2.2 Global Ocean Data Assimilation System (GODAS)

The Global Ocean Data Assimilation System (GODAS) is an ocean reanalysis dataset developed by the National Centers for Environmental Prediction (NCEP). It is built on the Geophysical Fluid Dynamics Laboratory's (GFDL) Modular Ocean Model version 3 (MOM.v3). GODAS is driven by momentum flux, heat flux, and freshwater flux derived from the NCEP Reanalysis 2 (R2) dataset. GODAS integrates observational data from multiple sources, including Expendable Bathythermographs (XBTs), moored buoy networks such as the Tropical Atmosphere Ocean (TAO) array, the Triangle Trans-Ocean Buoy Network (TRITON), and the Prediction and Research Moored Array in the Atlantic (PIRATA), Argo profiling floats, satellite altimetry, and other ocean observation platforms. The dataset has a temporal resolution of monthly values, covering the period from 1985 to the present. For this thesis, monthly mean sea surface height (SSH) data obtained from GODAS is used to validate the model-simulated sea surface height in Chapter 5.

2.2.3 Atmospheric Reanalysis

The analyses in chapter 5 are based on simulations with an ocean general circulation model (OGCM). Long-term atmospheric datasets are needed to force such simulations. Because observational records of surface atmospheric parameters are sparse, atmospheric reanalysis datasets that are free from spatial and temporal gaps are usually used. Reanalysis products are constructed by combining available observations with model outputs through advanced data assimilation techniques, providing a comprehensive and continuous representation of past and present climate conditions. The choice of the JRA55 dataset for forcing the OGCM simulations in chapter 5 was guided by the availability of a specific JRA55-do product, based on the Japanese global reanalysis (JRA-55) and adjusted specifically to serve as an OGCM forcing. JRA-55 is a long-term atmospheric reanalysis product covering the period from 1958 to near-present, providing four-dimensional (4D) atmospheric variables (Kobayashi et al., 2015). JRA-55-do (hereafter referred to as JRA55) refines this reanalysis dataset by incorporating satellite-based corrections, corrections from other

reanalysis products, and a more advanced data assimilation system (Tsujino et al., 2018).

2.2.4 World Ocean Atlas

The initial conditions for the OGCM simulations analysed in this study are derived from World Ocean Atlas climatology (WOA; Reagan et al., 2024). It is based on a collection of objectively analysed, quality-controlled physical (temperature, salinity) and biogeochemical (oxygen, phosphate, silicate, and nitrate) ocean properties based on profile data from the World Ocean Database (WOD).

2.3 Model simulations:

A General Circulation Model (GCM) is a numerical simulation of the Earth's surface layers, including the atmosphere, oceans, land surfaces, biosphere, and cryosphere. These mathematical models simulate the entire Earth's climate system by integrating interactions between its different components, such as the atmosphere, oceans, land surfaces, biosphere, and cryosphere.

The governing equations are simplified to allow for analytical solutions and discretised for numerical resolution. The planet is divided into a three-dimensional grid, where exchanges of energy, mass, and momentum are calculated at each grid point (NOAA-climate.gov, 2014). This method enables the representation of large-scale climate dynamics. The resolution of the model is determined by the size of the grid cells.

2.3.1 Ocean General Circulation Model (OGCM)

These dedicated OGCM experiments help correct some of the biases in CMIP simulation by using observationally-driven dataset (i.e. an atmospheric reanalysis) rather than relying on flux exchanges with an atmospheric model. In this part of my work, a single CMIP6 model, IPSL-CM6A-LR, was selected as representative of the CMIP database to correct biases and understand the processes driving the tropical IO warming. By performing sensitivity experiments with a dynamical ocean modelling

framework, this approach allows for isolating the mechanisms responsible for tropical IO warming. The following section provides a brief description of the OGCM used in this thesis.

2.3.2 Nucleus for European Modelling of the Ocean (NEMO) configuration

The Nucleus for European Modelling of the Ocean version 3.6 model (NEMO-v3.6; Madec et al., 2017) is the OGCM used in this study. It serves as the ocean model component within the selected CMIP model (IPSL-CM6-LR). The Ocean Physical component of NEMO is used. This model operates on a tripolar grid configuration with 1° horizontal resolution ($1/3^\circ$ in the equator), 75-vertical levels (thickness varies between 1 and 200m surface to deep layers) and a nonlinear evolving free surface using the variable volume formulation.

Fundamentals

The NEMO ocean model is built on fundamental physical principles and approximations that simplify ocean dynamics for numerical simulation. It relies on the assumption that Earth is an oblate spheroid, treating the ocean as a thin shell with relatively small depth compared to Earth's radius. The model also incorporates approximations such as hydrostatic balance, where vertical pressure gradients counteract buoyancy forces, and the Boussinesq approximation, which considers density variations only in relation to gravity. Additionally, turbulence effects are parameterised using large-scale approximations.

To solve ocean circulation, the model employs a widely used Arakawa 'C' grid (Fig. 2.1), where scalar variables like temperature and salinity are positioned at grid centres, while velocity components are placed at grid edges. Various parameterisation schemes are applied to represent unresolved physical processes, and external forcing fields drive the simulations. Further details on model setup, initial conditions, and experimental configurations are provided in Chapter 5 of this thesis.

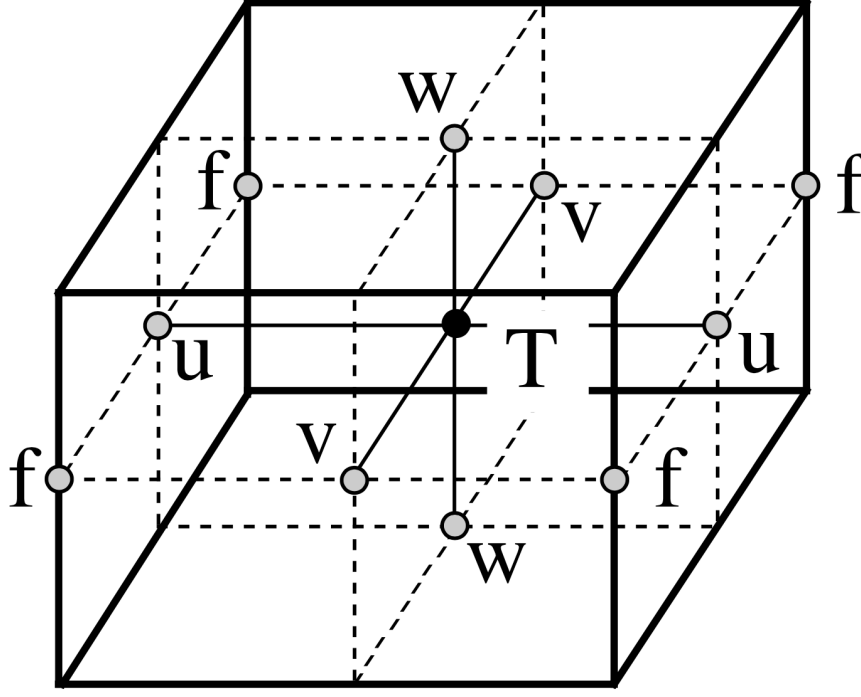


Figure 2.1: Arrangement of variables in Arakawa C - grid, T indicate scalar variables. u, v and w indicate vector velocity field, f indicate vorticity points. Madec et al., 2017

Ocean Mixed Layer Heat budget

SST is influenced by a range of physical processes occurring both at the surface and within the surface mixed layer. The mixed layer temperature heat budget reflects a balance between the different sources and sinks of heat at the mixed layer. These include net surface heat fluxes, horizontal advection, vertical mixing, and entrainment of water from below the mixed layer. The mixed layer heat budget equation provides a quantitative framework to analyse the relative contributions of these mechanisms. Several studies have presented formulations of the mixed layer heat budget with slight variations in form, but the fundamental processes involved remain consistent. A general form of the mixed layer heat budget equation (e.g., McPhaden and Hayes, 1991; Girishkumar et al., 2013) can be written as:

$$\frac{\partial T}{\partial t} = \frac{Q_{net} - Q_{pen}}{\rho C_p h} - \left(u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} \right) + W_h \frac{dh}{dt} \frac{(T - T_h)}{h} + \frac{K_z}{h} \frac{\partial T}{\partial z} + Residual \quad (2.1)$$

$\frac{\partial T}{\partial t}$ is the time rate of mixed layer temperature change (Temperature tendency). T is the average mixed layer temperature.

In this thesis, the mixed layer heat budget is examined by focusing on three dom-

inant processes:

Surface Heat Fluxes: $\frac{Q_{net}-Q_{pen}}{\rho C_p h}$ represents the net heat input at the ocean surface . Here, Q_{net} is the net surface heat flux, Q_{pen} is the penetrative solar radiation that escapes the mixed layer, ρ is density of seawater, C_p is specific heat capacity of seawater, h is mixed layer depth (MLD).

Horizontal Processes: $-\left(u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y}\right)$ is the Horizontal temperature gradient in zonal and meridional direction, respectively, which accounts for temperature changes due to horizontal movement of water. u, v are horizontal zonal and meridional velocity components.

Vertical Processes: $W_h \frac{dh}{dt} \frac{(T-T_h)}{h}$ is the Vertical Processes (sum of entrainment). W_h vertical advection below the mixed layer, T_h the temperature of water entrained into the mixed layer. $\frac{K_z}{h} \frac{\partial T}{\partial z}$ is the Vertical diffusion or vertical turbulent mixing. K_z vertical is the vertical eddy diffusivity. $\frac{\partial T}{\partial z}$ is the vertical temperature gradient just below the mixed layer.

2.3.3 Coupled Model Inter-comparison Project (CMIP)

GCMs are developed by various institutions worldwide, primarily climate research centers, universities, national meteorological agencies, and government laboratories. To coordinate the implementation of these simulations globally, the World Climate Research Programme (WCRP) launched the Coupled Model Intercomparison Project (CMIP) to harmonize climate simulations at a global scale and gather them into a single database (Meehl et al., 2007; Taylor et al., 2012, Eyring et al., 2016). CMIP was developed to facilitate comparisons between climate models and improve the estimation and understanding of differences among them. During the fifth phase of the CMIP project (CMIP5), approximately 50 models developed by 20 climate modeling centers were used. This number significantly increased in the sixth phase (CMIP6), with the participation of nearly 70 models from 33 institutions. Both CMIP5 and CMIP6 data were utilized in this thesis.

CMIP phase 5 (CMIP5) and phase 6 (CMIP6) simulations include historical simulations covering the period from 1850 to near present, using a standardized set of past reconstructed external forcing. These forcings include greenhouse gases, aerosols (including volcanic aerosols), ozone, natural solar variations, and land-use changes. By simulating past climate conditions, these historical simulations allow for an evaluation of model accuracy based on how well they reproduce observed climate trends. CMIP provides a standardized framework for assessing future climate responses under different scenario experiments. Future scenarios are based on various plausible projections of how external forcings may evolve, extending up to the year 2100. These sensitivity experiments are classified as Representative Concentration Pathways (RCPs) in CMIP5 and Shared Socioeconomic Pathways (SSPs) in CMIP6. These scenarios are designed to account for different levels of radiative forcing due to greenhouse gas emissions. While RCPs represent greenhouse gas concentration trajectories, SSPs incorporate both socioeconomic factors and emissions pathways. Among these scenarios, RCP8.5 (CMIP5) and its CMIP6 counterpart, SSP5-8.5, represent high-emission scenarios with a radiative forcing of 8.5 W/m^2 , reflecting continued fossil fuel dependence and minimal mitigation efforts. This thesis utilises the RCP8.5 and SSP5-8.5 emission scenarios. They represent high-emission pathways that assume minimal climate mitigation efforts, often referred to as "business-as-usual" scenarios (Rogelj et al., 2016; Gopika et al., 2020).

Different sets of CMIP models from phases 5 and 6 are used across various chapters of this thesis based on the availability of the variables required. For example, Chapter 3 utilised a set of 63 CMIP models as it only required the SST variable. In contrast, Chapter 4 analyses a broader range of variables, including heat flux, wind, precipitation, sea level, and SST, leading to the use of a subset of 46 available models. Chapter 5 focuses on a single CMIP model (IPSL-CM6A-LR) to implement a correction strategy on an OGCM. The choice of IPSL-CM6A-LR ensures consistency, as this CMIP model shares the same ocean model as the selected OGCM. A detailed list of the models used in each analysis is provided within the respective chapters.

While CMIP simulations are valuable tools for generating future projections and understanding the underlying mechanisms driving climate change, they exhibit per-

sistent biases in their representation of the present-day climate system. These biases stem from the complexity and coupled nature of these models, which can introduce errors in simulating key climate variables. To address this issue, this thesis employs an ocean model that is directly forced with observational data or bias-corrected simulations, reducing errors associated with coupled model biases and enhancing the reliability of the results.

2.4 Detecting tropical SST changes

Internal variability has a relatively weak influence on globally or tropically-averaged surface temperature. It, however, has a much stronger influence on regional long-term trends and strongly aliases the warming spatial pattern (Gopika et al., 2020). Identifying detectable signals from natural variability is essential to confirm climate change and understand potential discrepancies between models and observations. This helps to pinpoint regions where the climate change signal is detectable and comparable with observations. The concept of ‘Time of emergence (ToE)’ (Fig. 2.2; Hawkins and Sutton, 2012; Giorgi and Bi, 2009) is particularly useful here. ToE identify when climate change signals become distinguishable from background climate noise. This is generally done by estimating when the climate change *signal* exceeds a given fraction of the background climate variability *noise*, in other words, based on a fixed signal-to-noise ratio threshold.

While useful, for instance for impact studies, there are limitations to the ToE concept. ToE lacks a standardised threshold selection method. Variations in ToE thresholds can yield substantial differences in identified emergence times. For example, in Fig. 2.2, using threshold values of 1 and 2 (in panels a and b, respectively) results in a difference of at least 20–30 years (and the same for panels c and d). In addition, the ToE concept does not account for the fact that even a small signal can be detected when the record becomes sufficiently long. In this thesis, the Time of Detection (ToD) concept will be introduced in Chapter 3. The ToD concept is similar to the ToE, but features a proper statistical significance test of the trend instead of a given signal-to-noise ratio. This has two advantages: first, this avoids setting an

arbitrary ToE value as requested by ToE; second, this addresses the detectability of relatively small signals when the record is long enough (the observational record is already longer than a century). As will be discussed in chapter 3, ToD is not meant as a replacement for ToE. ToE is very appropriate for impact studies since it allows us to say when the climate distribution starts to shift from the present distribution. On the other hand, ToD is appropriate for comparing signals in models with those in observations.

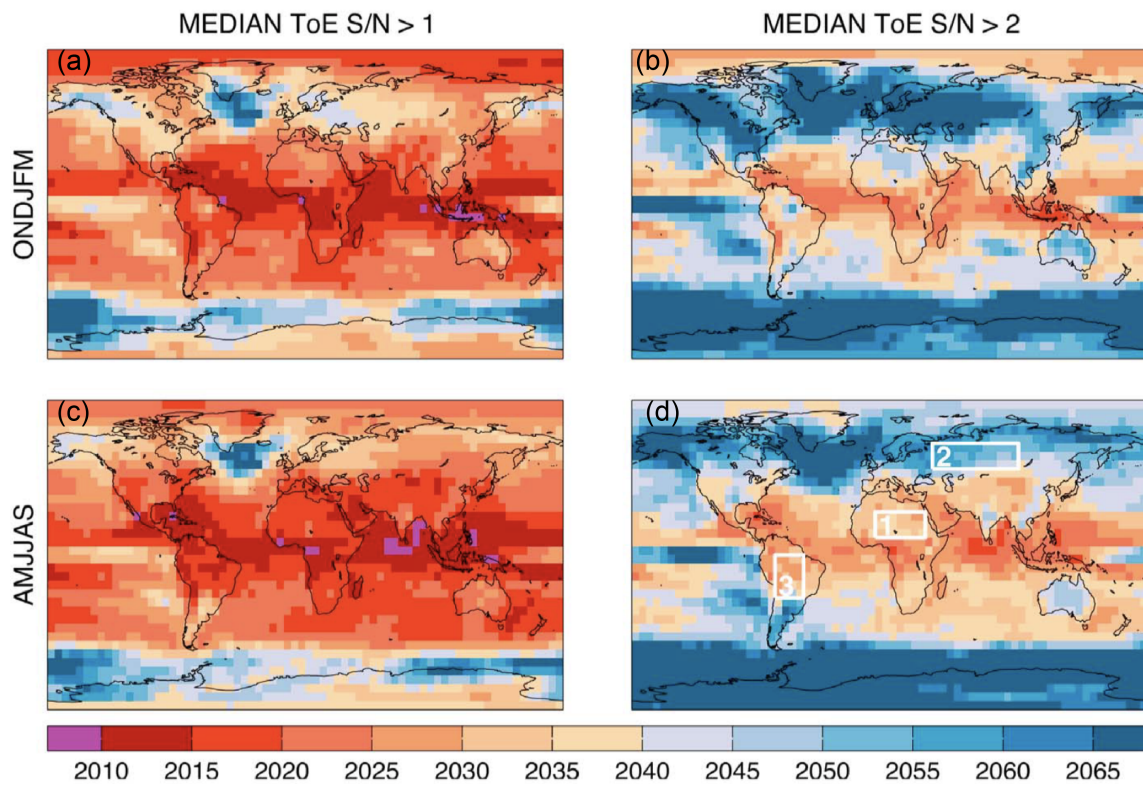


Figure 2.2: Median Time of Emergence for surface air temperature during (top) October–March and (bottom) April–September. The first year when the temperature is expected to exceed (left) $S/N > 1$ and (right) $S/N > 2$. Adapted from Hawkins and Sutton, 2012

In summary, this chapter outlined the data its sources and the general methodology used in this thesis. Methods specific to individual analyses are described in detail within the respective chapters.

Chapter 3

Time of Emergence and Detection of Climate Change Sea Surface Temperature signals

3.1 Introduction

As suggested in the introduction, while coupled models and observations generally align in terms of overall tropical-wide warming, they show notable disparities in regional warming patterns, especially in the equatorial Pacific and tropical Indian Ocean. The overall tropical warming trend can be confidently attributed to anthropogenic forcing (Bindoff et al., 2013; Fig. 1.1a). However, substantial internal climate variability also played a key role in shaping regional SST trends over the historical period (Chung et al., 2019; Gopika et al., 2020; Wu et al., 2021). For instance, the observed subdued warming in the Eastern Equatorial Pacific (EEP) may be associated with a negative phase of the IPO, which could be masking an underlying anthropogenic warming signal (e.g., Power et al., 2021). This raises a crucial question: do the inconsistent regional trends in Fig. 1.5b and c simply reflect an aliasing by the influence of internal climate variability, or do they indicate errors in tropical warming patterns in CMIP models? In essence, a meaningful comparison between models and observations is only possible in regions where long-term anthropogenic trends (hereafter referred to as the “signal”) can be clearly distinguished from the natural climate variability (hereafter referred to as the “noise”).

The Time of Emergence (ToE) estimates when climate change signals emerge from the background natural variability. ToE is usually defined as the time when the anthropogenic signal (S) to natural climate noise (N), S/N ratio permanently exceeds a given threshold (e.g., Giorgi and Bi, 2009). ToE was initially developed to estimate when local climate departs from its historical range, hence leading to impacts, espe-

cially in vulnerable ecosystems with limited adaptive capacity (Beaumont et al., 2011; Deutsch et al., 2008). ToE was first applied to terrestrial areas (Giorgi and Bi, 2009; Diffenbaugh and Scherer, 2011) and later to oceanic variables such as SST (e.g., Ying et al., 2022), sea level (e.g., Lyu et al., 2014; Walker et al., 2022) or marine ecosystem drivers (Rodgers et al., 2015; Keller et al., 2014; Schlunegger et al., 2020). For instance, Ying et al. (2022) applied ToE to tropical SST in CMIP models and observations, underlining emerging signals around 1990, except in the EEP where no discernible signal has emerged in data in half of the models and observational records. This delayed EEP ToE is related to the strong natural climate variability associated with the ENSO (Zhong et al., 2023).

Regions with detectable observed climate change signals allow assessing the realism of modelled climate change signals over the historical period. For instance, Ying et al. (2022) identified emerging EEP warming in models but not in observations, which questions the consistency of CMIP Projections and historical data in this region. The original purpose of ToE is focused on impacts rather than detection, typically using a relatively large signal-to-noise ratio (of 1 or more) to identify significant deviations from the present-day climate. However, this approach with large thresholds may miss more subtle, but yet detectable, signals. Assessing how models are able to detect even subtle climate change signals observed in nature is crucial for evaluating the realism of climate models and strengthening our confidence in their future projections. Detecting a trend amidst a noisy time series requires a statistical significance test. As detailed in section 3.3, this test involves a signal-to-noise ratio threshold, as in the ToE method. But contrary to ToE, this threshold is modulated by the length of the available time series, to account for the fact that a signal is more easily detectable with a larger sample. Here, I introduce the “Time of Detection” (ToD) methodology. Building upon the ToE principles, ToD incorporates a rigorous statistical significance test for trends. While ToE uses a fixed threshold to highlight strong changes relevant for impact studies, accounting for actual degrees of freedom makes ToD more sensitive to subtle signals, rendering it more appropriate for detection. ToD is not designed as a replacement for ToE, which remains the best tool for impact studies. Instead, ToD is designed to facilitate comparisons between climate

models and observations, particularly for detecting weak, late-emerging signals. In previous literature (e.g., Ying et al., 2022), the words ‘detection’ and ‘emergence’ were often used interchangeably to refer to ToE. In the present study, ‘detection’ will specifically refer to the date identified through the ToD methodology (i.e. a statistically significant trend), and ‘emergence’ will refer to the date identified through the ToE methodology (i.e. a signal that exceeds a given signal-to-noise ratio).

The methodology underpinning the ToD framework was originally introduced, by Gopika et al. (2020), though not explicitly labelled as ToD. Their study assessed changes in SST and RSST in the Indian Ocean. Their primary conclusion was that RSST changes become detectable much later than that of SST. This is because RSST signals are much smaller than those in SST when subtracting tropical average warming, while they both share the same “climate noise” amplitude. However, Gopika et al. (2020) did not explicitly discuss the conceptual difference between the ToD and ToE, nor compare these two metrics.

Objective of this chapter: (1) to establish a ToD precise definition, (2) to compare ToD and ToE for CMIP and observed SST, and (3) to employ ToD to identify regions where CMIP models can already be evaluated against observations.

3.2 Data and the Study region used in this chapter

The observational datasets and simulations used in this chapter are detailed in this section. Additionally, this thesis utilizes the entire tropical ocean to understand the emergence and detection, which is also described in this section.

3.2.1 Datasets and CMIP simulations used in this chapter

In this chapter, both the SST observational based products and the CMIP model simulations detailed in Chapter 2 are utilized. The SST observational based products are: COBE SST2 ; HadISST v1.1 ; ERSSTv.5 and Kaplan-SST v2. Specifically for this chapter, 34 CMIP5 models and 35 CMIP6 models were selected (listed in Table 3.1). Although the current study explicitly focus on SST, the model selection was guided by the availability of key climate variables (e.g., precipitation, wind, etc.) for

further future analysis. For models with multiple ensemble members, only the first ensemble member was used, in order to give equal weight to each model (Eg: Gopika et al., 2020). The time period considered for this chapter is 1891-2022 (Kaplan dataset available till 2022 at the time of writing) for observations and extends till 2100 for CMIP simulations. The specific time periods in the following chapters considered will depend on the objectives of the chapters.

Table 3.1: List of the 69 models (34 CMIP5 and 35 CMIP6) used in this study, with the institution name indicated first, followed by a dot and the model name. The models corresponding to the Lowest EEP Warming in Fig. 3.15 are marked with a * and those with a High EEP Warming with a @

CMIP5 Models	CMIP6 Models
BCC.bcc-csm1-1	CSIRO-ARCCSS.ACCESS-CM2
BCC.bcc-csm1-1-m@	CSIRO.ACCESS-ESM1-5
CCCma.CanESM2@	AWI.AWI-CM-1-1-MR
CMCC.CMCC-CESM	BCC.BCC-CSM2-MR
CMCC.CMCC-CMS	CAMS.CAMS-CSM1-0
CNRM-CERFACS.CNRM-CM5	NCAR.CESM2-WACCM
CSIRO-BOM.ACCESS1-3	NCAR.CESM2
CSIRO-QCCCE.CSIRO-Mk3-6-0	THU.CIESM@
FIO.FIO-ESM	CMCC.CMCC-CM2-SR5@
IPSL .IPSL-CM5A-LR	CNRM-CERFACS.CNRM-CM6-1-HR
IPSL.IPSL-CM5A-MR@	CNRM-CERFACS.CNRM-CM6-1*
IPSL.IPSL-CM5B-LR	CNRM-CERFACS.CNRM-ESM2-1*
LASG-IAP.FGOALS-s2@	EC-Earth-Consortium.EC-Earth3-Veg
MIROC.MIROC5	EC-Earth-Consortium.EC-Earth3
MIROC-ESM	CAS.FGOALS-f3-L
MIROC.MIROC-ESM-CHEM	CAS.FGOALS-g3
MOHC.HadGEM2-CC*	FIO-QLNM.FIO-ESM-2-0
MPI-M.MPI-ESM-LR@	NOAA-GFDL.GFDL-ESM4
MPI-M.MPI-ESM-MR@	MOHC.HadGEM3-GC31-LL

MRI.MRI-CGCM3	MOHC.HadGEM3-GC31-MM*
MRI.MRI-ESM1	CCCR-IITM.IITM-ESM
NASA-GISS.GISS-E2-H	INM.INM-CM4-8*
NASA-GISS.GISS-E2-H-CC	INM.INM-CM5-0*
NASA-GISS.GISS-E2-R	IPSL.IPSL-CM6A-LR
NASA-GISS.GISS-E2-R-CC	NIMS-KMA.KACE-1-0-G
NCAR.CCSM4	UA.MCM-UA-1-0@
NCC.NorESM1-M*	MIROC.MIROC-ES2L
NCC.NorESM1-ME	MIROC.MIROC6*
NIMR-KMA.HadGEM2-AO	MPI-M.MPI-ESM1-2-HR
NOAA-GFDL.GFDL-CM3	MPI-M.MPI-ESM1-2-LR
NOAA-GFDL.GFDL-ESM2G	MRI.MRI-ESM2-0
NOAA-GFDL.GFDL-ESM2M	NUIST.NESM3
NSF-DOE-NCARCESM1-BGC@	NCC.NorESM2-LM*
NSF-DOE-NCAR.CESM1-CAM5	AS-RCEC.TaiESM1*
	MOHC.UKESM1-0-LL

3.2.2 Data processing for this chapter

All the analyses in this chapter are based on annual-mean SST anomalies, computed relative to the 1891-1950; a 60-year reference period, selected because it precedes the post-1950 accelerated warming (Fig. 1.5a). To emphasize changes in the SST pattern, which influences atmospheric stability (Xie et al., 2010, Izumo et al., 2020), we employ RSST, defined by subtracting the 30°S-30°N average SST for each year, and at grid point.

The results of CMIP5 and CMIP6 are similar (Justified later in this chapter): we combined the 34 CMIP5 and 35 CMIP6 models into a single dataset, referred to as CMIP5+6. We use the Multi-Model Median (MMM) value to summarize results from this CMIP5+6 dataset (Table 3.1). We used the median, which is less sensitive to outliers than the mean. Although the mean, which is more sensitive towards the outliers, it yields similar results (not shown). Similarly, we present the Multi

Observational Median (MOM) derived from the 4 observational datasets (an extended version of the median, defined as the average of the 2nd and 3rd highest values).

3.2.3 Study region used in this chapter

As described in the introduction, understanding tropical climate change is crucial. The new time of detection methodology, along with the existing emergence time approach, is applied to the entire tropical band from 30°S to 30°N for our study (see Fig. 3.1). All datasets are interpolated onto a $2^\circ \times 2^\circ$ standardized grid. We keep a $2^\circ \times 2^\circ$ standardized grid to account for the large tropical area. However, towards the end of this chapter and in subsequent chapters, we narrow our focus to the Indian Ocean region.

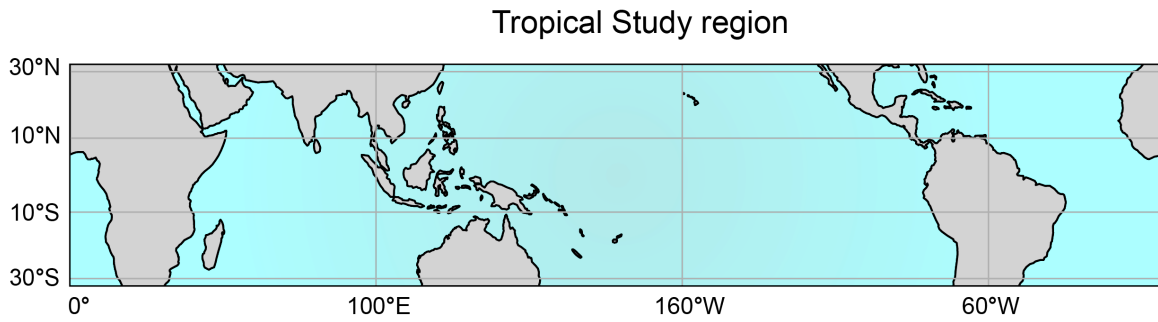


Figure 3.1: Tropical Ocean study region used in chapter 3

3.3 Methodology for estimating ToE and ToD

In this section, the methods for estimating ToE and ToD is detailed. We used the ToE estimation methodology from Hawkins and Sutton (2012) with slight modifications. The ToD methodology below is refined from that of Gopika et al. (2020). We aim for our method to be applicable to both observations and models, hence we do not compute the climate signal based on a scenario minus a pre-industrial control simulation (or their ensemble average), as some studies have done. Along the lines in Hawkins and Sutton (2012), we define a tropical warming index, which allows us to estimate that signal.

3.3.1 Tropical warming index

Linear fits are inadequate to estimate anthropogenic trends that are non-linear (curved shape of the curves on Fig. 1.5a). Hawkins and Sutton (2012) thus introduced a non-linear ‘index of global warming’. In our study, we adopt a similar approach with slight modifications. Instead of a global warming index, we create a ‘tropical SST warming index’ for each model, by averaging the SST data over tropical oceans (30°S-30°N). We then apply a 4th order polynomial fit to smooth this index over the period from 1921 to 2100 (1921-2022 for observations). The results are robust when employing a global warming index. (not shown). We denote this tropical warming index as $W(t)$. It is noteworthy that while a 3rd order polynomial fit is also effective, choosing the 4th order fit allows a fair comparison of our results with the ToE estimated using Hawkins and Sutton (2012)’s method.

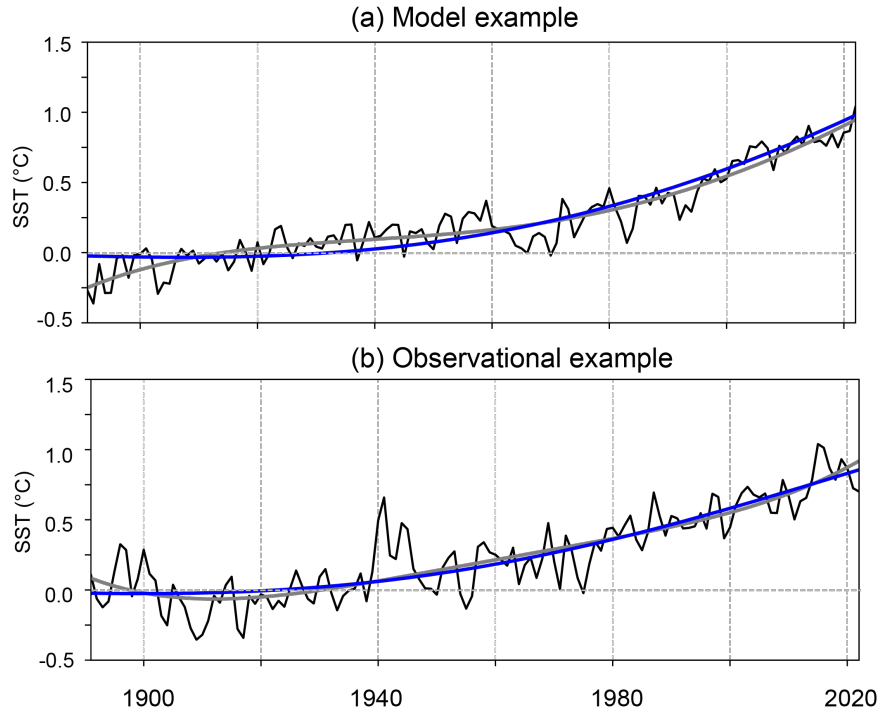


Figure 3.2: Addressing early drift / spurious signals in some datasets. The Black line indicates the 30°N-30°S average SST, the grey line is its 4th-order polynomial fit without a zero padding and the blue line is its 4th-order polynomial fit with a zero padding. This is shown for (a) a CMIP model example with an early drift; and (b) an observational dataset example with a suspicious trend at the beginning.

In some CMIP models, even after the removal of reference period, early decades of the tropical-averaged SST time series may exhibit pronounced low-frequency drifts (Fig. 3.2a), which are absent in observations (Fig. 3.2b). The presence

of these drifts can complicate the accurate estimation of trends in the early decades of the tropical SST time series. To address this issue, we added a sequence of zeros to the beginning of the tropical average SST time series, effectively padding it with zeros for 60 years (i.e., spanning the period of 1861-1920). Subsequently, we applied a 4th order polynomial fit to the data. This process helps ensure that there is a near-zero trend in the early decades of the time series. Following the polynomial fit, we removed the initial 60 years of the time series (which corresponds to the period of zero padding) and considered the resultant time series, starting from 1921, as the tropical warming index. We apply this approach to both observations and model data to facilitate more accurate trend estimation in the presence of low-frequency variations.

3.3.2 ToE estimation methodology

Our method for calculating ToE is close to that of Hawkins and Sutton (2012). At each grid point, we estimated the signal $S(t)$ by performing a regression of the local SST or RSST, denoted as $Y(t)$ (Fig. 3.3a black line for an example based on the equatorial Pacific SST in one CMIP model), onto the tropical warming index $W(t)$.

$$Y(t) = \alpha W(t) + \beta + \epsilon(t) \quad (3.1)$$

The regression described above is performed over 1921-2100 (models) or 1921-2022 (observations). We will justify estimating the climate change signal only based on post-1920 data in section 3.5.3: data coverage is questionable before the First World War (e.g., Deser et al., 2010) and leads to unstable ToD and ToE estimates. The intercept β is nearly zero because of zero-padding in early decades. $\epsilon(t)$ is the residual of the regression, representing natural climate variability.

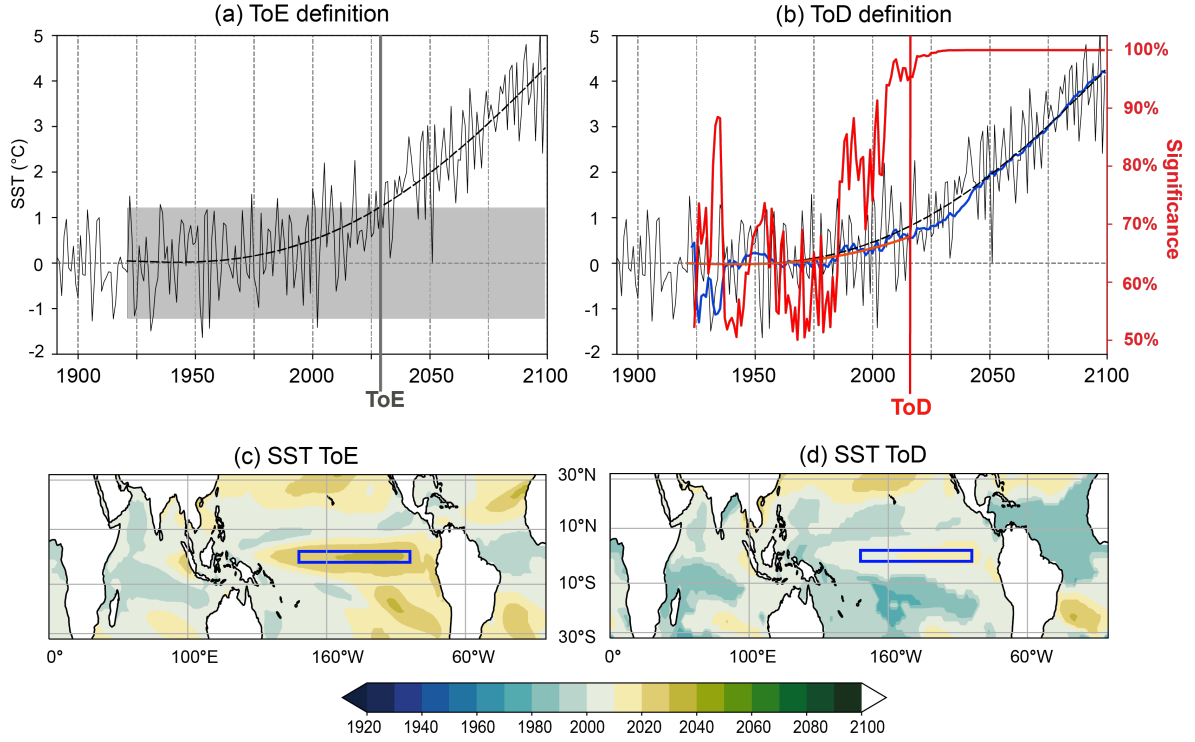


Figure 3.3: Illustration of the ToE and ToD computation methodology for SST in the MRI-ESM2-0 model. This model was chosen as an example because its ToD and ToE were close to the CMIP5+6 median values. (a) Time series of Eastern Equatorial Pacific (EEP; see box on c, d) SST relative to the 1891-1950 climatology (°C; black line) along with the anthropogenic warming signal computed following Hawkins and Sutton (2012) (dashed black line, see section 3 for details). The light grey shading indicates signals which are less than 1.6 times the noise N in absolute value. The vertical grey line marks the Time of Emergence (ToE) for an S/N threshold of 1.6 (b) Average EEP SST anomaly and estimated warming signal as in (a) as well as the signal computed over a time-varying window $[1921, T]$ (blue curve, see below and section 3c for details), and the associated statistical significance (red, see below and section 3c for details). The vertical red line indicates the Time of Detection (ToD), when statistical significance irreversibly exceeds some threshold, here set at 95%. Unlike Hawkins and Sutton (2012), where the signal is derived through a regression to the warming index over the entire period, we compute the signal at a time T through a regression over the $[1921, T]$ period (with T varied from 1922 to 2100). The red line indicates the statistical significance of the hypothesis that the regression slope is not zero. (c) ToE and (d) ToD maps for SST in this specific model.

The signal (Fig. 3.3a dashed line) is defined as:

$$S(t) = \alpha W(t) + \beta \quad (3.2)$$

The noise is defined as the standard deviation of $\epsilon(t)$. Following Hawkins and Sutton (2012), the ToE is defined as the “first” year when the signal-to-noise ratio, (dashed black line in Fig. 3.3a), crosses a specified threshold.

The ToE approach is illustrated on Figs. 3.3a and c with a threshold of 1.6 (see section 3.3.3 for a justification of this choice) for the MRI-ESM2-0 model, which exhibits ToD values (section 3.3.3) close to the CMIP5+6 median. The ToE map for

this model indicates that tropical SST warming signals have either already emerged (before 2022) or will emerge within the next decade (Fig. 3.3c).

3.3.3 ToD estimation methodology

Unlike ToE, where the regression (equation 2) is performed over the entire time series, the signal calculation for the ToD estimation is computed for a varying time window from 1921 to T . T varies from 1922 to the endpoint year T_e (2100 for models and 2022 for observations). Specifically, we perform the regression for each time interval $[1921, T]$, with T varying from 1922 to T_e :

$$Y(t) = \alpha_T W_T(t) + \beta_T + \epsilon_T(t) \quad (3.3)$$

Signals at time T are defined as:

$$Y(t) = \alpha_T W_T(t) + \beta_T \quad (3.4)$$

ToD is defined as the “last” year when the regression coefficient becomes statistically significant at a chosen significance level threshold (e.g., 95%) and remains significant until the endpoint year T_e . I.e., we define a detectable signal at date T when the time series has a regression coefficient to the tropical warming index that is statistically significant over the $[1921, T]$ period, and remains significant for later endpoints.

To test the significance of the regression coefficient, we employ a one-tailed t-test. Computing the statistical significance requires estimating the number of degrees of freedom of the time series. This is usually done by assuming that values of the time series are independent of each other, and using $n-2$ degrees of freedom, where n is the length of the time series. Bayley and Hammersley (1946) proposed a method which takes into account the potential lagged autocorrelation of the time series and estimates the effective number of degrees of freedom as $\frac{n}{\sum_{j=1}^{n/2} \rho^2(j\tau)}$, where $\rho(j\tau)$ is the lagged autocorrelation at lag j . This autocorrelation is estimated at every point in space, giving a different number of degrees of freedom for different points

in space. We use this more accurate method, although it yields similar results to the simpler method that simply uses $n-2$ degrees of freedom everywhere (not shown). The two methods give similar results because lagged autocorrelation for SST anomalies is usually weak for lags longer than one year (e.g. Deser et al., 2003), especially in tropical regions.

Note that we compared our signal estimation method with the Theil-Sen robust estimator and our significance computation with a bootstrap method that does not require Gaussian input data (Yue and Pilon, 2004, Gopika et al. (2020)). Both comparisons yielded very similar results to our approach (Fig. 3.4 and Gopika et al. (2020)), underlining the robustness of our methodology. Figure 3.4 is included only to illustrate that the ToD is robust to the choice of signal estimation method. The Theil-Sen non-parametric trend estimate and the regression yield almost identical warming signals. Because both approaches give consistent ToD estimates, we will use the less computationally intensive regression-based signal estimation.

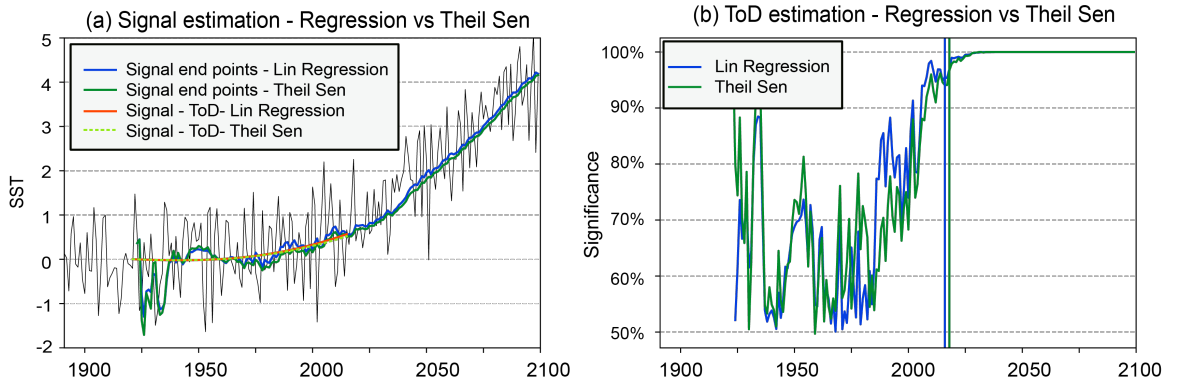


Figure 3.4: Robustness Check of ToD Calculation Methodology for SST in the MRI-ESM2-0 Model (Same as Fig 3.3b). (a) The signal computed over a time-varying window [1921, T] using our signal estimation methodology (blue curve) and the Theil-Sen bootstrapping method (green curve). The orange line (dashed light green line) indicates the signal at the time of Detection (ToD) as shown in Fig 3.3, using our method (Theil-Sen method). (b) The blue line (green line) indicates the 95% statistical significance of the hypothesis that the regression slope is not zero using our method (Theil-Sen method). The ToD is indicated by vertical lines for both methods.

Fig. 3.3b and d illustrate the ToD methodology using the same model as in Fig. 3.3a. Here, the significance of the regression coefficient α_T (red curve) crosses the 95% significance level shortly before 2020 for the eastern Pacific. The ToD indicates detectable tropical SST warming everywhere in the tropics (Fig. 3.3d). The

anthropogenic warming signals estimated using the full-period regression method of Hawkins & Sutton (2012) and our finite-window regression $[1921, T]$ are nearly identical (blue and dashed black curves in 3.3b). Figure 3.3, on the other hand, illustrates that using different thresholds (signal to noise for ToE and significance for ToD) yields different ToD and ToE estimates.

There are a few differences between the ToD computation here and in Gopika et al. (2020): Gopika et al. (2020) used a linear trend instead of the nonlinear tropical warming index, the 1891-2020 instead of the 1921-2022 period (This will be demonstrated in Section 3.5.3 that ToD and signal estimates are more robust over that data-richer period in observations), and they did not use the effective number of degrees of freedom above. We will discuss the differences between Gopika et al. (2020) and our results in the discussion.

For a normal distribution, statistical significance levels of 99%, 95%, 90% and 85% respectively correspond to signal-to-noise ratios of 2.4, 1.6, 1.3 and 1 (based on the t-distribution). The Fig. 3.3 example was provided for the comparable 1.6 S/N for ToE and 95% significance thresholds for ToD, indicating that ToD occurs earlier than ToE for comparable threshold values. This ToD/ToE comparison will be done more systematically in the following section.

3.4 Time of Detection and Emergence of Tropical SST

In this section, we compute the tropical SST ToD and ToE for CMIP5+6 models and 4 observational products. Our objectives include comparing ToD and ToE, examining their sensitivity to the chosen threshold, and comparing CMIP to observations. We will also investigate whether the inconsistent Eastern Equatorial Pacific trend and consistent Indian Ocean Basin-wide warming trend in models and observations are detectable. It is important to note that the comparisons made in this chapter do not imply that models are treated as the benchmark. Rather, they are intended to highlight the consistency and discrepancies between model-simulated and observed patterns of SST changes, particularly where CMIP models are known to overestimate or misrepresent regional warming signals (e.g., Xie et al., 2010; Power

et al., 2021).

3.4.1 ToD and ToE of Tropical SST : CMIP vs observations

We computed the emergence and detection time of CMIP models and observations. Fig. 3.5 a, b displays scatter plots of ToD versus ToE for CMIP and observed SST (across all models/datasets tropical grid points). ToD and ToE are respectively

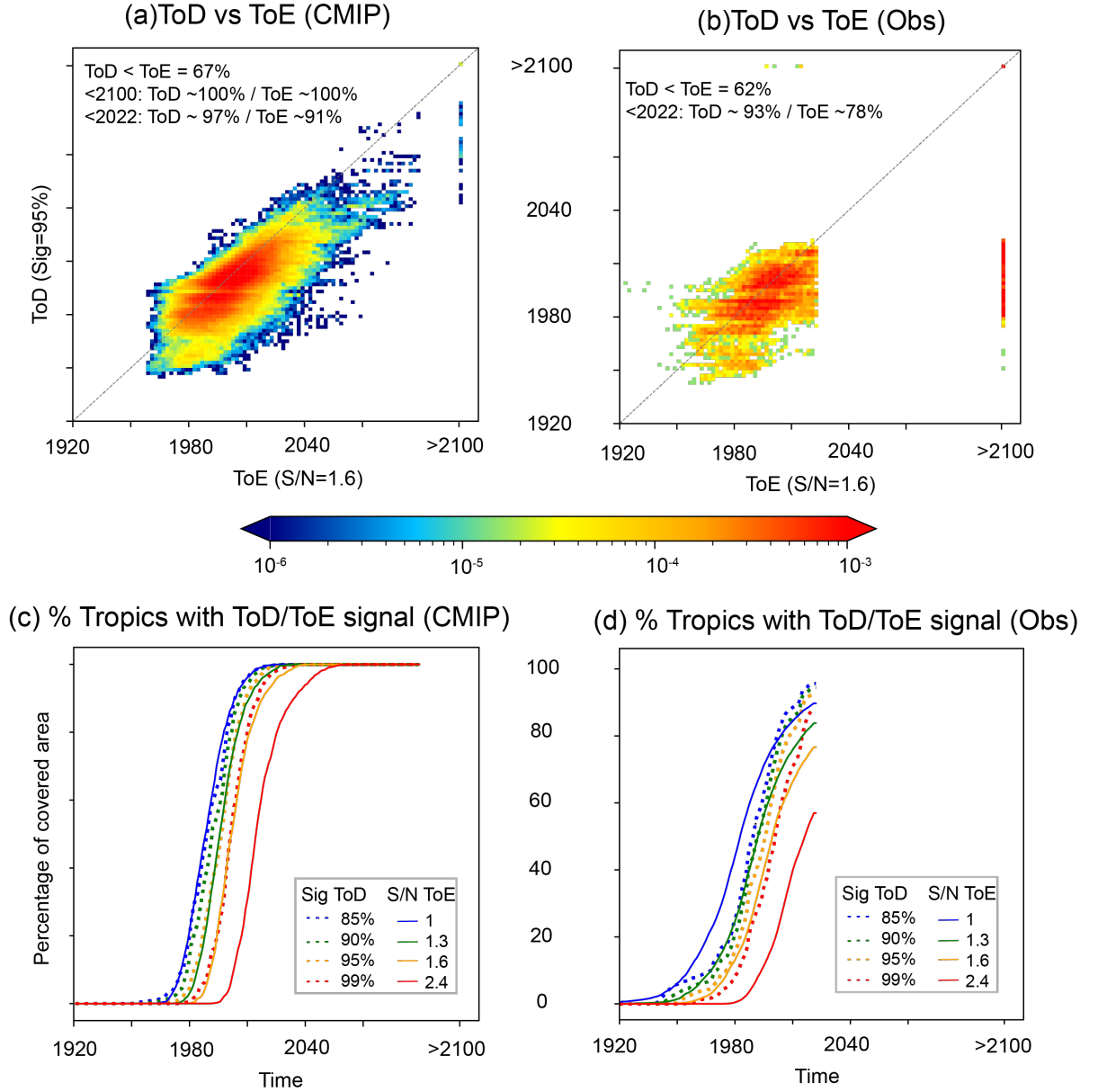


Figure 3.5: SST ToD vs. ToE in CMIP5+6 and observations. SST ToD (95% threshold) vs. ToE (1.6 S/N threshold) scatter plot (plotted as a density distribution for all grid points and datasets) for (a) CMIP5+6 models and (b) the 4 observational SST datasets. The 95% and 1.6 thresholds are comparable (see the end of section 3c for details). Percentage of the tropical ocean surface (for all grid points and datasets) where a signal is detectable (dashed lines, red for 99%, orange for 95%, green for 90% and blue for 85% significance thresholds) or has emerged (solid lines, red for 2.4, orange for 1.6, green for 1.3 and blue for 1 S/N thresholds) in (c) CMIP5+6 models and (d) the 4 observational SST datasets.

computed using comparable thresholds of 95% significance and 1.6 S/N ratio (explained in previous section). The ToD and ToE are correlated ($r=0.73$ and 0.58 in CMIP and observations, respectively), indicating that regions where a signal is detected early also tend to emerge from the background natural variability early. SST signals are generally detectable before they emerge from the background noise in both CMIP (67% of grid points across models) and observations (62%). The peak density concentration occurs primarily from 1960 to 2010 for ToD and 1970 to 2022 for ToE. ToD is thus detected earlier than ToE at equivalent thresholds, with a median ToE minus ToD of 5 (6) years in models (observations). Consequently, the SST signal is already detectable ($\text{ToD} \leq 2022$) almost everywhere in the tropics (97% of models and 93% of observational datasets grid points), while there are still regions where the SST signal has not emerged (9% in models, 22% in observations).

Accurately estimating the emergence or detection of climate change signals from internal variability requires selecting an optimal threshold value. While there is no universally fixed threshold for ToE/ToD, the choice is typically made within statistically justified ranges (e.g., Hawkins and Sutton, 2012, Turk et al., 2019), and may vary depending on the variable analysed, the available data length, and the specific research objective. The ToE thresholds used in the literature range from 1 to 3 (e.g., Turk et al., 2019). This variation in threshold values can significantly affect the results of emergence time calculations. For instance, a recent study by Geng et al. (2022), which used a threshold of 2, estimated the ToE for the eastern Pacific SST signal and found that fewer than 25% of the models showed emergence by 2020. This contrasts sharply with findings from Ying et al. (2022), who reported that over 50% of the models emerged by 2020 using a threshold of 1, as discussed earlier.

ToE is highly sensitive to the selected S/N threshold, as already shown in the literature (Eg.: Lyu et al., 2014). Here, along with re-evaluating this sensitivity of ToE, we also investigate the sensitivity of ToD to the significance threshold. Fig. 3.5 c and d provides a comparison of the percentage of tropical areas with detectable / emerging signals using the comparable thresholds discussed at the end of the previous section: 1 and 85%, 1.3 and 90%, 1.6 and 95%, 2.4 and 99%. This analysis clearly shows that ToE is more sensitive to the threshold choice than ToD for both models

(Fig. 3.5 c) and observations (Fig. 3.5 d).

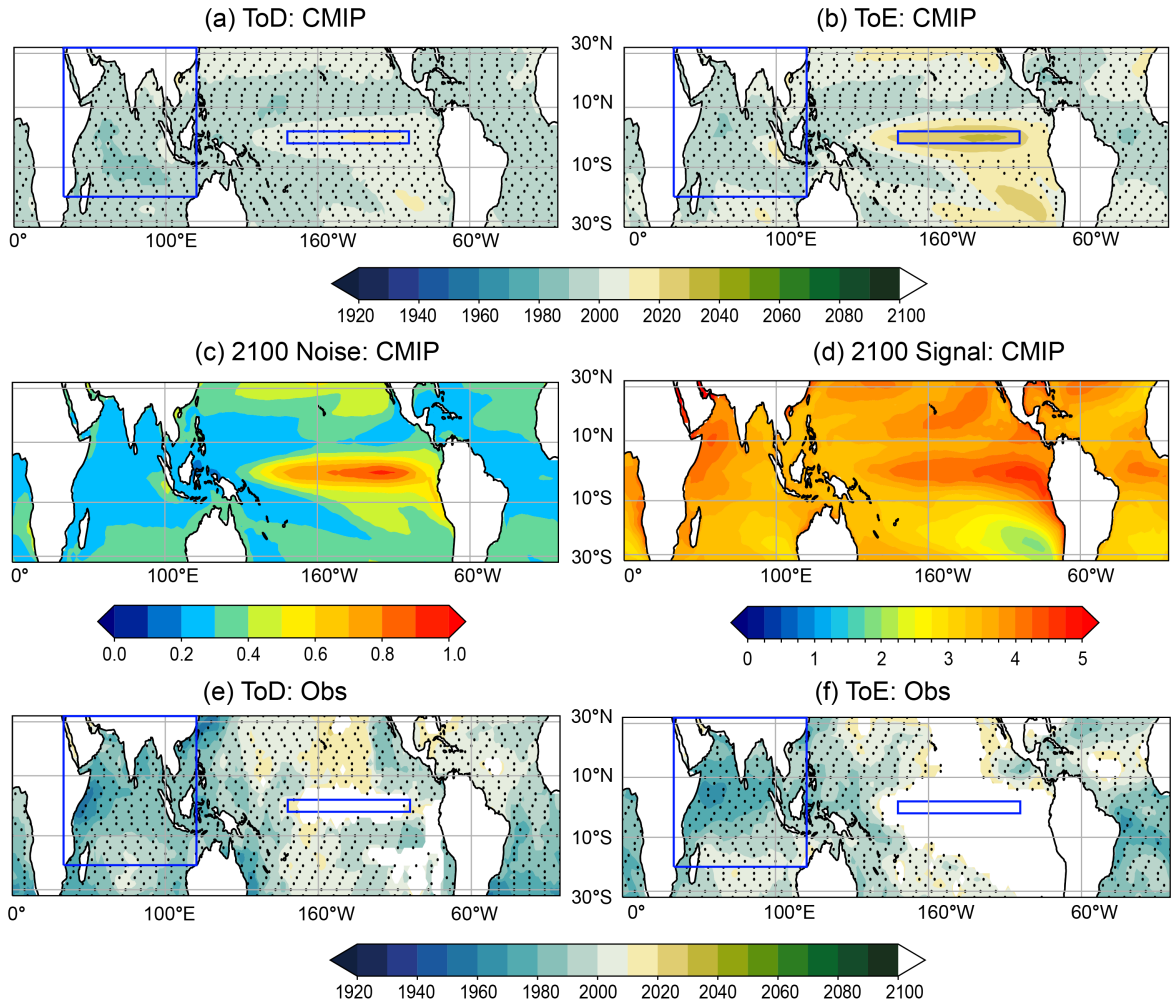


Figure 3.6: Maps of SST ToD and ToE, and their controls CMIP5+6 median SST (a) ToD (95% significance threshold); (b) ToE (1.6 S/N threshold), (c) 2100 noise, defined as the standard deviation of the regression residuals $\epsilon_T(t)$ (equation 3.3) over the full model period (1921–2100); and (d) 2100 signal obtained for the full 1921–2100 period. 4 observational datasets (HadiSSTv1.1, ERSSTv3, KAPLAN, COBESST2) median (e) ToD (95% significance threshold); (f) ToE (1.6 S/N threshold). The Eastern Equatorial Pacific (EEP) box, as defined in Ying et al. (2022), is outlined by blue frames in panels a, b, d, and e. Black dots indicate regions where 75% or more models/observations are already detectable or have emerged (i.e., ToD/ToE before 2022).

For ToE, there is indeed a range of ~ 30 years for the two extreme signal-to-noise ratio thresholds, while ToD varies by only ~ 15 years. The tropical area where a signal is detected is systematically larger than that where it has emerged for comparable thresholds. Even the most stringent detection threshold (99%) results in an earlier detection than the 1.6 S/N threshold.

Fig. 3.6 a and b respectively display the median ToD and ToE maps for CMIP5+6 models, with black dots indicating regions where more than 75% of models have a ToD/ToE before 2022. The ToD and ToE spatial patterns are quite similar.

Warming is detected (by 2022) almost everywhere, except in the equatorial and south-east Pacific. It has emerged from the background climate variability in most regions, except in the Equatorial and southeastern tropical Pacific. Comparably early detection/emergence in the Indian Ocean, central Atlantic regions, etc.

Fig. 3.6 c and d respectively display the median noise and 2100 signal for CMIP models. The ToD and ToE patterns are very similar to that of the noise, with centred pattern correlations (i.e., mean removed) of 0.77 for ToD and 0.87 for ToE. In contrast, the pattern correlation with the signal is generally weak, with values of 0.03 for ToD and -0.11 for ToE.

This indicates that the background climate variability has a more significant influence in shaping the SST ToD and ToE patterns than the amplitude of the signal. For instance, the large climate noise associated with ENSO in the eastern Pacific results in late ToE and ToD. The later ToD and ToE poleward of 20°N latitude are also associated with increased noise, attributable to factors like oceanic eddies, mid-latitude stochastic atmospheric forcing and ENSO tele-connections (e.g., Alexander et al., 2002). The Equatorial Indian Ocean tends to exhibit earlier detection and emergence due to its lower noise levels (e.g., Guemas et al., 2013).

Fig. 3.6e and 3.6f respectively provide the median ToD and ToE patterns for observations. The observed pattern resembles the one from CMIP although with approximately one to two decades earlier detection/emergence in regions such as the Equatorial Indian Ocean, Equatorial and South Atlantic and West Pacific. In contrast, the equatorial Pacific warming is not detectable in the MOM (Fig. 3.6 e), unlike in most CMIP models (Fig. 3.6 a). The detection of an equatorial Pacific warming signal in models but not in observations has recently attracted a lot of attention and could either be due to models missing a forced equatorial cooling signal in recent decades, or underestimating internal variability (reviews by Lee et al., 2022, Watanabe et al., 2024).

Also, the above results for CMIP5+6 are robust when analysing CMIP5 and CMIP6 data separately (Fig. 3.7 a, b, c and d). The emergence and detection patterns in CMIP5 and CMIP6 are similar, with late emergence/detection in the EEP and southeastern Pacific, while emergence/detection occurs earlier in the tropical IO.

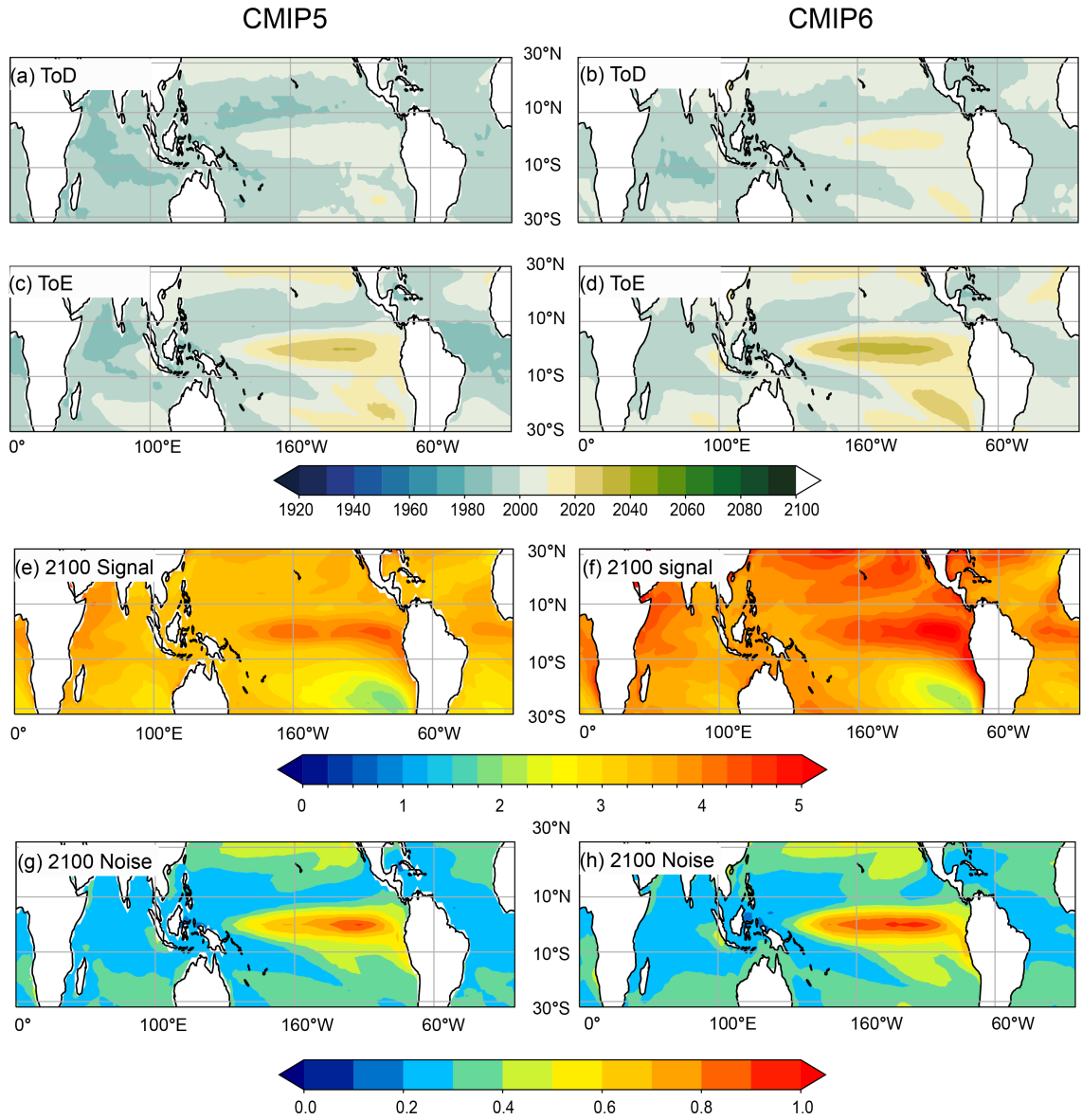


Figure 3.7: Maps of SST ToD and ToE, and their controls in CMIP5 and 6 SST (a) CMIP5 ToD (95% significance threshold); (b) CMIP6 ToD (95% significance threshold) ; (c) CMIP5 ToE (1.6 S/N threshold); (d) CMIP6 ToE (1.6 S/N threshold) (e) CMIP5 2100 signal (f) CMIP6 2100 signal (g) CMIP5 2100 noise and (h) CMIP6 2100 noise.

The CMIP6 warming signal is larger than that of CMIP5 due to the higher climate sensitivity in CMIP6 (Fig. 3.7 e and 3.7 f; Fredriksen et al., 2023). However, the internal climate variability “noise” also tends to be slightly larger in CMIP6 compared to CMIP5 (Fig. 3.7 g and 3.7 h). These differences tend to compensate for each other, resulting in similar ToD and ToE in CMIP5 and 6, although with slightly later emergence and detection times in CMIP6 (Fig. 3.7 b and d). The consistency of results across CMIP5 and CMIP6 justifies our approach of combining findings from both these very recent phases of CMIP.

Given the significance of the disagreement between models and observations highlighted in the literature and discussed above, we will explore the EEP in more detail. Similarly, the tropical Indian Ocean (IO), North of 20°S, where emergence and detection occur very early in both observations and models, will also be a focus later in this section.

3.4.2 The focus on the Eastern Equatorial Pacific

Numerous studies have underlined the EEP warming trend and the slowing down of trade winds in climate models (e.g., Xie et al., 2010; Power et al., 2021). Observations, on the other hand, point to a weak EEP warming trend or even a cooling, in response to increased trade winds. This discrepancy motivated Ying et al. (2022) to compute the EEP SST ToE. Above, we consider the same box as Ying et al. (2022): averaging SST within this box smooths small-scale noise and may result in an earlier detection/emergence than the Fig. 3.6 maps, based on point-wise data.

Fig. 3.8a presents the median EEP warming signal in CMIP5+6 models, along with its 10-90th percentile range. The median filters internal climate variability out, emphasizing the EEP warming signal, slightly above 1 °C over the past century (Fig. 3.8a). Internal variability is very consistent across the four observational datasets. Fig. 3.8b provides histograms of the 2022 EEP warming signal (continuous) and noise (dashed) for CMIP5+6 models. Vertical lines indicate the corresponding signal (continuous) and noise (dashed) for the four observational datasets. The level of observed ENSO climate “noise” is within the CMIP distribution. Three out of four observational datasets (KAPLAN, HadISST and COBE2) indicate modest warming of less than 0.5 °C, which lies outside the simulated range (0.5 to 1.7 °C). ERSST displays a larger 0.75 °C warming signal, that is more consistent with the modelled range.

The study of Ying et al. (2022) employed a smaller set of 23 models (69 here) and a less stringent S/N ToE threshold of 1 (1.6 here). Despite these differences, our results are consistent with Ying et al. (2022): approximately half of the models, but no observational dataset, indicate an emergent EEP warming (Fig. 3.8d). This led Ying et al. (2022) to argue for a model-observations discrepancy.

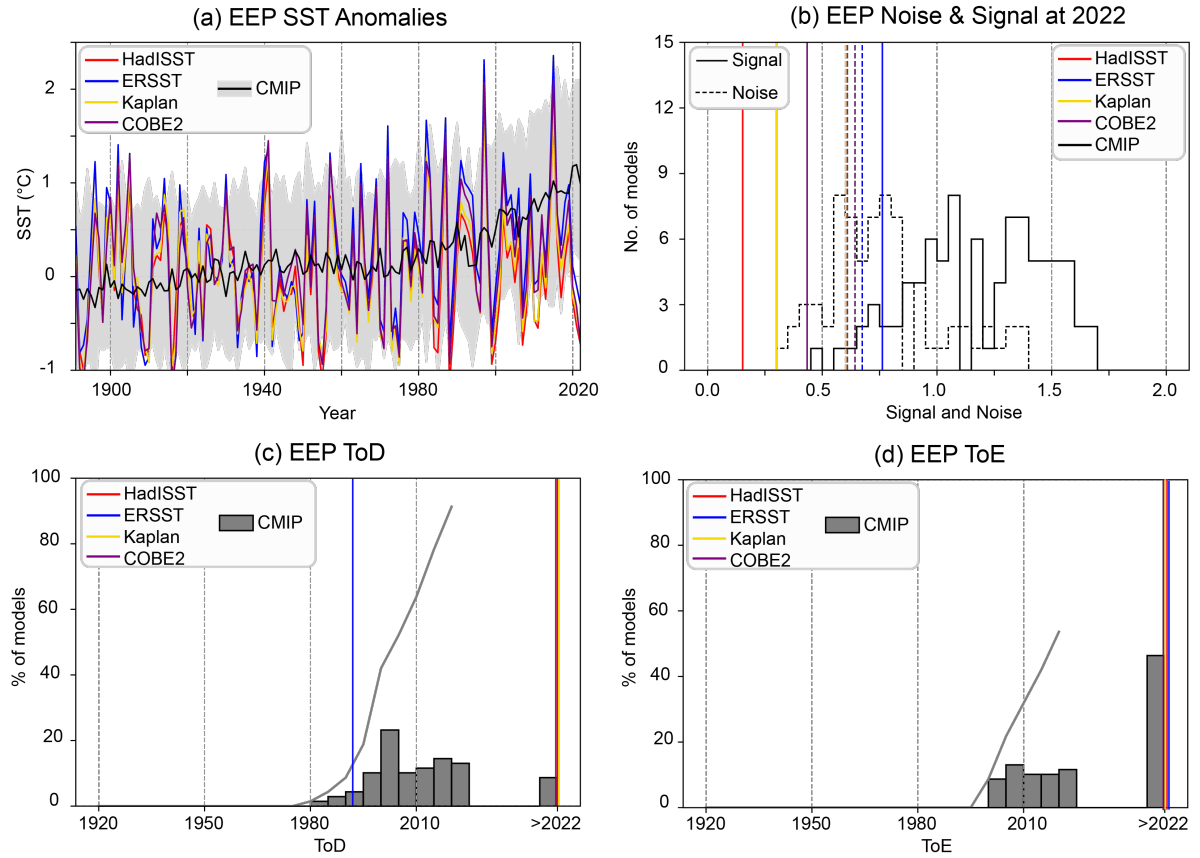


Figure 3.8: Eastern Pacific SST warming. (a) Time series of average EEP (box on Fig. 4) yearly SST anomalies (°C; relative to the 1891-1950 climatology). Colored lines show four observational products (red for HadISST, blue for ERSST, yellow for Kaplan and purple for COBE). The black line is the CMIP5+6 ensemble median of model SST anomalies, and the grey shading shows the inter-model 10-90th percentile range. Anomalies are computed relative to each model's own 1891–1950 climatology. The smoother appearance of the black curve reflects the reduction of internal variability by taking the median value. (b) Histogram of CMIP5+6 average EEP SST noise (dashed black) and signal (black) at 2022. Vertical lines mark the corresponding values for observational products (continuous for signal and dashed for noise). (c) Histogram of CMIP5+6 average EEP SST ToD (95% threshold) in 5-year bins, with the solid grey line indicating the % of models for which the EEP warming is already detectable. Vertical lines indicate ToD for the 4 observational products. (d) Same as (c) but for ToE (1.6 S/N threshold).

Let us now discuss whether using ToD instead of ToE leads to a different interpretation. EEP warming signals are already detectable (Fig. 3.8c) in 91% of the models (between 1980 and 2022), whereas only one out of four observational products detects the signal. The notable ERSST warming signal results in an early detection around 1992, at the early end of the modelled range. This detection in ERSST is robust with a stricter 99% significance threshold (not shown). But overall, using ToD does not change the conclusions of Ying et al. (2022), and still points to overestimated warming signals in models, leading to more detection (or emergence) by 2022 than in observations. This reflects the difference between the definitions of ToD and ToE. The ToE definition is

based on an S/N threshold, which does not take the number of degrees of freedom into account, whereas ToD relies on a regression-based significance test, with a higher statistical significance for longer time series (i.e. more degrees of freedom).

3.4.3 The focus on the Tropical Indian Ocean

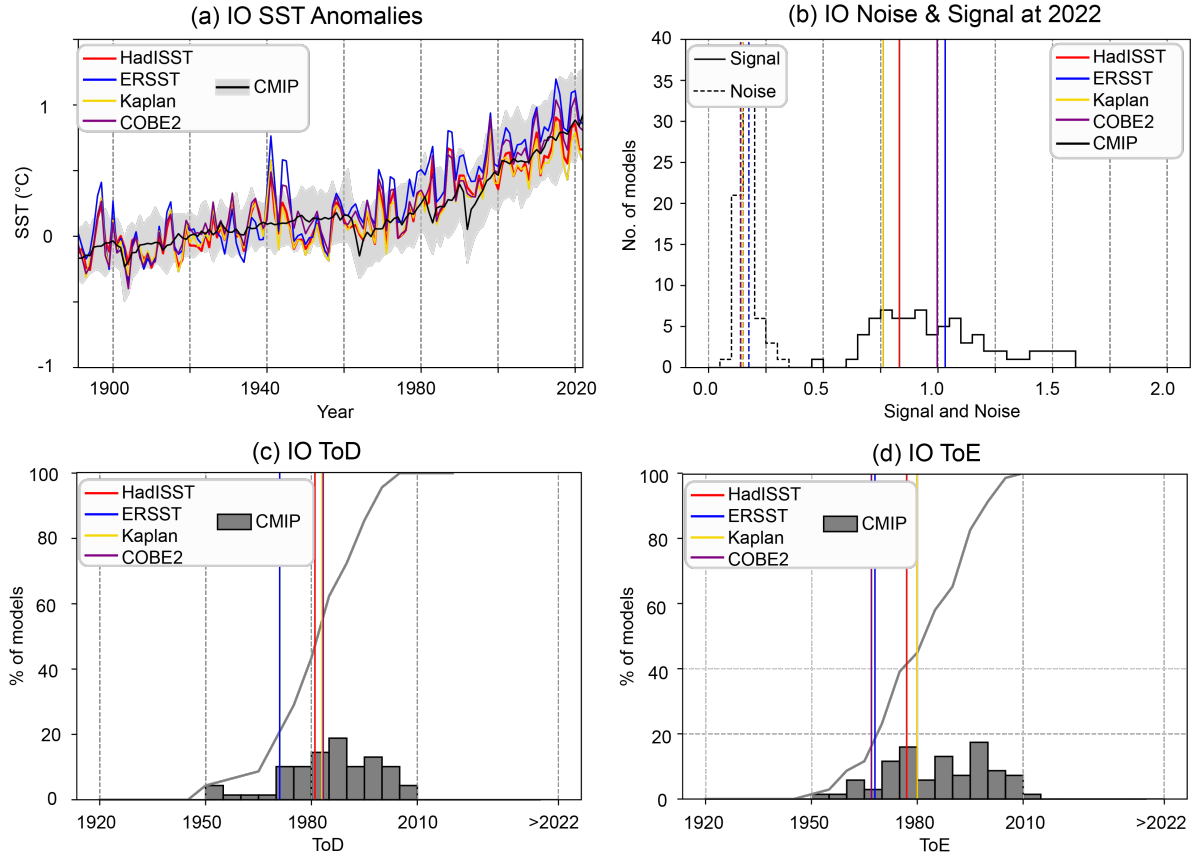


Figure 3.9: Indian Ocean SST warming. (a) Time series of average tropical IO (box on Fig. 4) yearly SST anomalies (°C; relative to the 1891-1950 climatology) for the four observational datasets (red for HadISST, blue for ERSST, yellow for Kaplan and purple for COBE), along with average tropical IO CMIP5+6 median SST signal (black) and 10-90th percentile (light grey shading). (b) Histogram of CMIP5+6 average tropical IO SST noise (dashed black) and signal (black) at 2022. Vertical lines mark the corresponding values for observational products (continuous for signal and dashed for noise). (c) Histogram of CMIP5+6 average tropical IO SST ToD (95% threshold) in 5-year bins, with the solid grey line indicating the % of models for which the tropical IO warming is already detectable. Vertical lines indicate ToD for the 4 observational products. (d) Same as (c) but for ToE (1.6 S/N threshold).

This thesis primarily focuses on the tropical IO, a region where emergence and detection occur very early in both observations and models, specifically north of 20°S. Accordingly, we also consider specific analysis on the basin-averaged tropical IO (specific IO region indicated by the box in Fig.3.6).

Fig. 3.9a shows the median IO warming signal in CMIP5+6 models, along

with its 10th-90th percentile range, similar to Fig. 3.8a. The median filters out internal climate variability, highlighting the tropical IO warming signal, which is slightly above 1 °C over the past century (Fig. 3.9a). All observational datasets fall within the modelled range. Fig. 3.9b presents the signal and noise data. Both the modelled and observed signals fall within the same range, from 0.75 to 1.6 °C. In both cases, the signal is significantly higher than the noise (in both models and observations), which remains between 0 and 0.25 °C.

This large signal-to-noise ratio contributes to early emergence and detection in both models and observations. All observational datasets show emergence and detection before 1980. Due to the significant difference between signal and noise, the range of Time of Emergence (ToE) depicted in Fig. 3.9d closely aligns with the Time of Detection (ToD) range depicted in Fig. 3.9c.

All CMIP models show emergence and detection before 2015, underscoring the urgent need to address Indian Ocean warming and understand its basin scale changes. The following chapters of this thesis will closely examine both the basin-averaged and regional warming signals of the Indian Ocean, along with the underlying mechanisms driving these changes.

3.5 Time of detection of relative SST signals

RSST highlights the SST pattern and is a proxy for atmospheric stability (Xie et al., 2010). In this section, we compute the RSST ToD for CMIP5+6 and observations. We first compare ToD and ToE in CMIP models and observations. While ToE does not allow to pick any emerging RSST signal in observations, ToD points to a detectable RSST warming in the Western Indian Ocean and cooling in the Southeastern Pacific. We therefore compare model and observed signals in those two regions in more detail. We end by discussing observational uncertainties, related to the limited pre-1920 coverage.

3.5.1 RSST ToD and ToE in CMIP5+6 and Observations

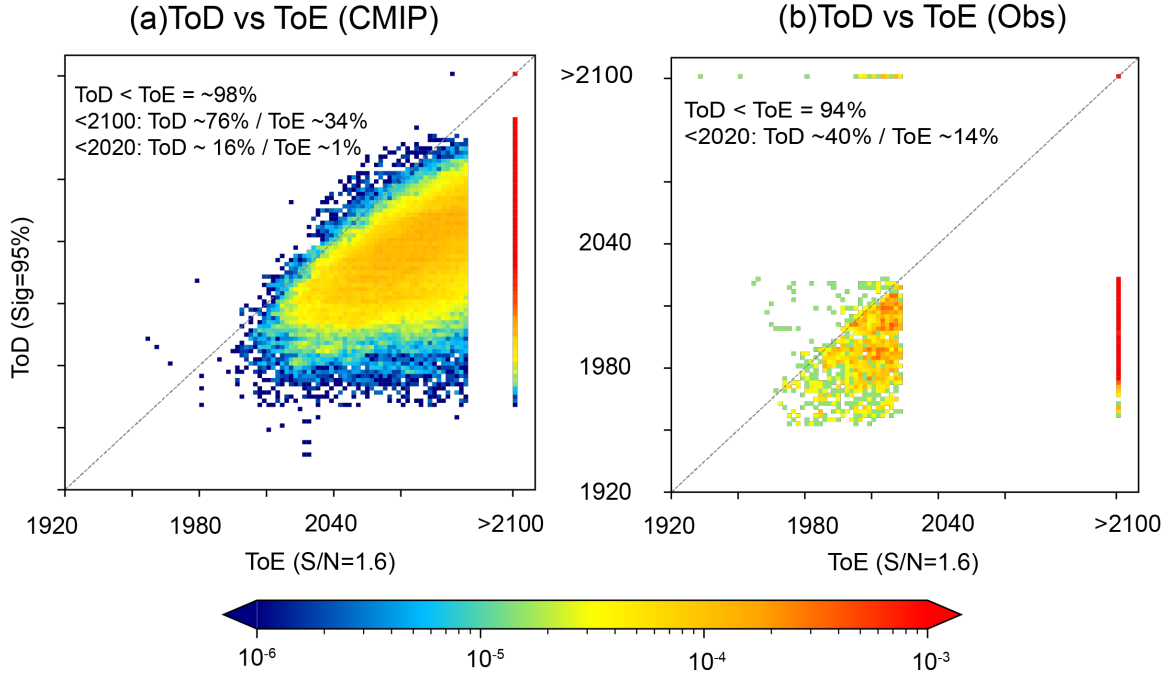


Figure 3.10: RSST ToD vs. ToE in CMIP5+6 and observations. RSST ToD (95% threshold) vs. ToE (1.6 S/N threshold) scatter plot (plotted as a density distribution for all grid points and datasets) for (a) CMIP5+6 models and (b) the 4 observational SST datasets. The 96% and 1.6 thresholds are comparable (see the end of section 3c for details).

Fig. 3.10 is similar to Fig. 3.5a and 3.5b, but for RSST. The relationship between RSST ToD and ToE (Fig. 3.10a) is weaker than that of SST (Fig. 3.5a) ($r=0.5$ against 0.73 in CMIP; $r=0.4$ against 0.58 in observations). These insignificant correlations indicate that the early detection of an RSST signal does not consistently correspond to an early emergence, unlike was the case for SST. The temporal lag between ToE and ToD is also considerably larger for RSST (~ 35 years) than for SST (~ 5 years). RSST signals are almost always detectable before they emerge from the background noise in both CMIP (98%) and observations (93%). Consequently, the modelled (observed) RSST signal is already detectable on 16% (40%) of tropical oceans but has only emerged over 1% (14%). RSST becomes detectable in over 76% of the tropical oceans by the end of the 21st century in models, against 34% for ToE. These large differences between ToE and ToD arise from accounting for the number of degrees of freedom in the ToD computation. This makes the detection of signals more sensitive as the length of the time series and therefore the number of degrees of freedom ‘ n ’ increases,

effectively reducing the noise level by a factor of $\frac{1}{\sqrt{n}}$. This reflects the difference between the definitions of ToD and ToE. The ToE definition is based on a S/N threshold which does not take the number of degrees of freedom into account, whereas ToD relies on a regression-based significance test, with a higher statistical significance for longer time series (i.e. more degrees of freedom) ToD will thus indicate a much earlier date than ToE for signals which tend to emerge late, such as RSST (Gopika et al., 2020).

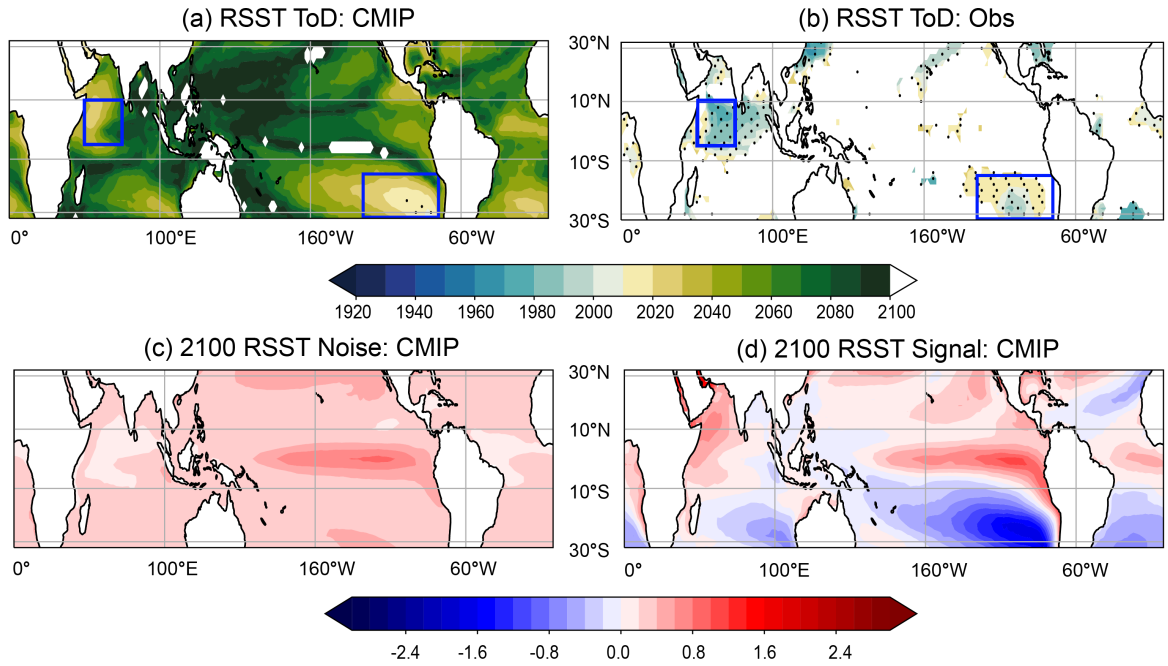


Figure 3.11: Maps of RSST ToD and their controls. Median RSST ToD (95% threshold) for (a) CMIP5+6 and (b) the four observational datasets. Black dots indicate regions where 75% or more models/observations are already detectable or have emerged by 2022. The blue frames in panels a, b indicate the WIO and SEP boxes for Observed and CMIP RSST ToD. CMIP5+6 median RSST (c) noise and (d) 2100 signal.

Fig. 3.11a displays the median map of the CMIP5+6 ToD, with black dots indicating grid points where more than 75% of models have ToD/ToE before 2022. While SST signals are already detectable in nearly all tropical areas (97%), RSST signals are only currently detectable in a few regions (16%), specifically the southeastern Pacific and western Indian Ocean. On average, RSST signals become detectable 60–70 years later than SST signals (also a result of Gopika et al., 2020). As detailed in Gopika et al. (2020), this is because RSST signals are considerably weaker (Fig. 3.11d) than SST signals (Fig. 3.6d), as the mean tropical warming signal is removed when calculating RSST, but the noise (inter-annual SST variability) is the

same for SST and RSST. This smaller signal but similar noise for RSST leads to a later detection (and emergence) than for SST. The late RSST emergence and detection implies a longer time series, more degrees of freedom, and therefore a larger difference between ToD and ToE for RSST. By the end of the 21st century, RSST signals become detectable in most regions (76%) (Fig. 3.11a).

The RSST ToD spatial pattern is very different from that of SST, with a pattern correlation of -0.09 between Fig. 3.11a (RSST ToD) and Fig. 3.6a (SST ToD). Unlike SST, the RSST ToD pattern is primarily controlled by the spatial structure of the RSST signal amplitude (pattern correlation of -0.73 between Fig. 3.11a and Fig. 3.11d), rather than by the RSST noise (pattern correlation of 0.05 between Fig. 3.11a and Fig. 3.11c). This leads to earlier detection in regions of large RSST signals such as the southeastern Pacific, western Indian Ocean, and equatorial Atlantic. The central equatorial Pacific is an exception: the signal is large, but the ENSO-related noise delays detection.

Fig. 3.11b displays the median ToD map based on observations. Consistent with CMIP results (Fig. 3.11a), observed signals are detected in two main regions: the southeastern Pacific and the equatorial Indian Ocean (but shifted east relative to CMIP). We investigate these two regions in the following subsection.

3.5.2 The southeastern Pacific (SEP) and western Indian Ocean (WIO) focus

Fig. 3.12 presents a regional analysis of RSST ToD from CMIP5+6 models and observations, focusing on the southeastern Pacific and western Indian Ocean. Here, we specifically examine the influence of signal and noise on the RSST ToD.

Fig. 3.12a presents the CMIP5+6 median southeastern Pacific RSST evolution and its 10–90th percentiles. The CMIP RSST signal started decreasing after 1980, reaching -0.2 °C in 2022. All observational datasets align with the timing and amplitude of this CMIP relative cooling. Fig. 3.12b provides an RSST ToD histogram for this region. The SEP relative cooling is detected before 2022 in ~80% of the models, with ToD ranging from 1970 to 2022. Observed ToD values (ranging from 1990 to 2015) fall within the CMIP distribution. This agreement can be attributed to the consistent

signal and noise levels in models and observations (Fig. 3.12c).

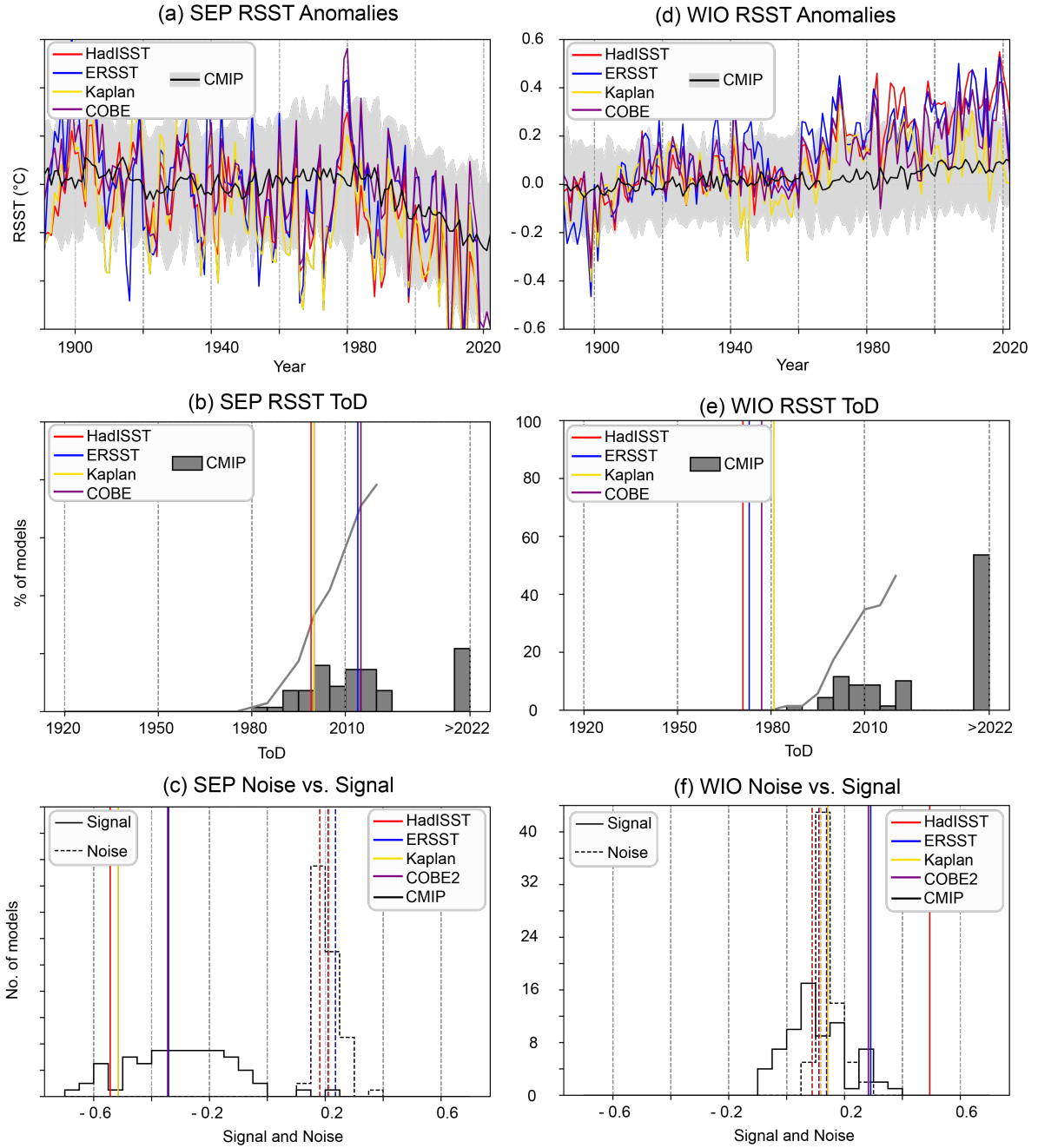


Figure 3.12: South-Eastern tropical Pacific (SEP) and Western Indian Ocean (WIO) average RSST ToD. (a) Time series of annual mean average SEP (see Fig. 7) RSST anomalies ($^{\circ}\text{C}$; relative to the 1891-1950 climatology) for the four observational products (red for HadISST, blue for ERSST, yellow for Kaplan and purple for COBE), along with average SEP CMIP5+6 median RSST signal (black) and 10-90th percentile (light grey shading). (b) Histogram of CMIP5+6 average SEP RSST ToD (95% threshold) in 5-year bins, with the solid grey line indicating the percentage of models for which the SEP relative warming is detectable. Vertical lines indicate ToD for the 4 observational products. (c) Histogram of the CMIP5+6 average SEP RSST noise (dashed black) and 2022 signal (continuous black). The corresponding observational product values are marked by vertical lines (continuous for signal and dashed for noise). (d,e,f) same as (a,b,c) for WIO RSST.

Fig. 3.12d displays the model and observed WIO RSST evolution. The

observed relative warming is about 4 times larger than that of the CMIP MMM (Fig. 3.12d) and above the modelled range (Fig. 3.12f). This leads to a consistently earlier ToD in observations (in the 70s) than in models (mostly after the 90s, with only 45% of detectable signals today; Fig. 3.12e).

Overall, this subsection points to detectable warming pattern signals that are consistent in observations and models in the southeastern tropical Pacific (relative cooling) and in the western Indian Ocean (relative warming).

3.5.3 The Observational Uncertainties

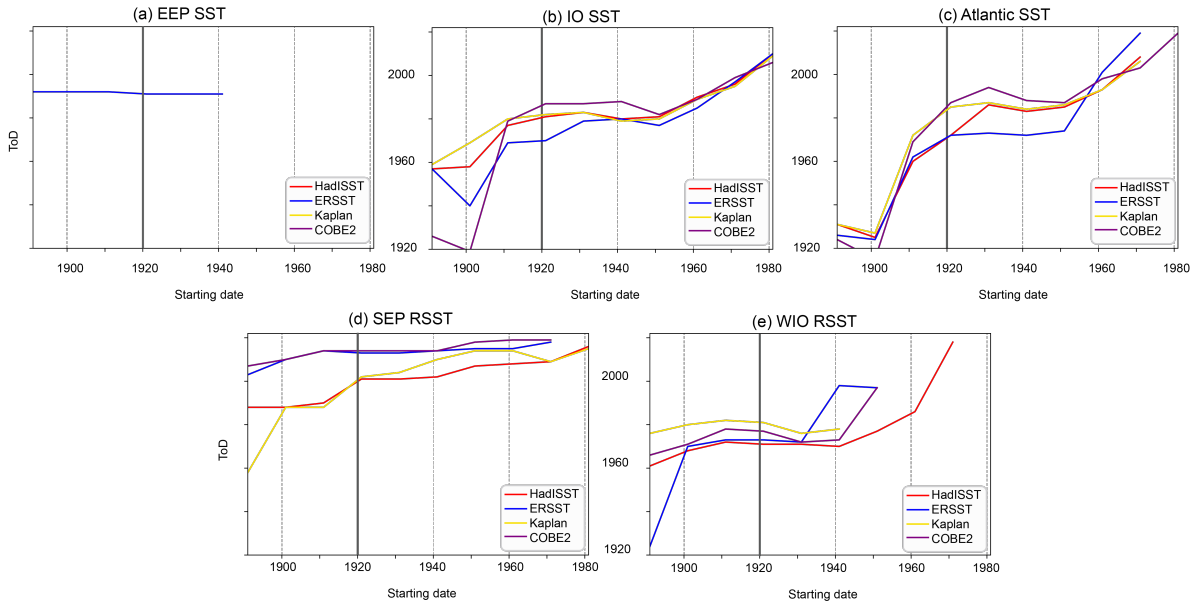


Figure 3.13: Observational ToD uncertainties: ToD (95 % significance) sensitivity to the starting date of the estimation period (varied from 1890 to 1980, with the end of the period set to 2022) for four observational products (red for HadISST, blue for ERSST, yellow for KAPLAN and purple for COBE) for (a) EEP SST, (b) IO SST (c) Atlantic (320°E:357°E and 30°S:5°N) SST (d) SEP RSST and (e) WIO RSST. The vertical gray line indicates 1920, the starting date that is considered for estimating ToD and ToE throughout the paper

The observed ToD is highly sensitive to the observational dataset: the equatorial Pacific SST ToD, for instance, varies between 1992 and no detection (subsection 3.4.2). This uncertainty likely stems from the limited observational coverage before the satellite era, which started in 1979. Fig. 3.13 illustrates the observed ToD sensitivity to the trend estimation starting date, varied from 1890 to 1980, for the EEP SST (Fig. 3.13a); IO SST (Fig. 3.13b); Atlantic SST (Fig 3.13c), SEP (Fig. 3.13d) and WIO (Fig. 3.13e) RSST.

Throughout the paper, we have estimated ToD (and ToE) for post-1921 (vertical line in Fig. 3.13) data. This choice is partly guided by the data gaps during the First World War period (e.g., Gopika et al., 2020; Deser et al., 2010; Izumo et al., 2013). Fig. 3.13 confirms a substantial ToD sensitivity to starting dates before 1921 in the SEP for Kaplan (Fig. 3.13d) and in the WIO for Kaplan and COBE2 (Fig. 3.13e) with ERSST before the 1930's. Considering data prior to 1921 also leads to a dubious pre-1940 warming detection in the tropical IO and South tropical Atlantic in all observational products (Fig. 3.13 b and c). This justifies our consistent use of the 1921 start date throughout the paper.

The EEP SST warming ToD for the ERSST dataset (only dataset for which a warming is detected) is robust (i.e., insensitive to choosing any starting date). The SEP relative cooling ToD is robust for post-1920 starting dates, with clear detection in the four products for start dates until 1970 (Fig. 3.13d). In contrast, the ToD for the WIO relative warming is very sensitive to the starting date (Fig. 3.13e). This sensitivity is related to two periods of fast warming in the WIO during 1900-1920 and shortly after 1960 (Fig. 3.12d). Those fast and early signals are very unlikely attributable to anthropogenic forcing (they occur before the strong anthropogenic forcing period), and are probably rather attributable to large data gaps in the Indian Ocean during both World Wars (Deser et al., 2010; Gopika et al., 2020), which may be responsible for those “jumps” in all observational time series (Fig. 3.12d). Restricting the period to post-1960 higher quality data only yields detection in a single observational dataset (Fig. 3.13 c), and weaker signals that are more consistent with those in models (not shown). The observed WIO relative warming detection is therefore questionable (e.g., Gopika et al., 2020). Similarly, the IO SST and Atlantic SST also exhibit high sensitivity to the starting period (Fig. 3.13b and c). However, for the tropical IO basin-averaged SST, observational datasets are mostly consistent (Fig. 3.9a), which contributes to the consistency in detection after 1920.

3.6 Summary and discussion

3.6.1 Summary

Evaluating the ability of models to detect even subtle climate change signals observed in nature is essential for assessing their realism and increasing our confidence in their future projections. This goal is contingent upon determining if these signals can be distinguished from the background natural variability. To that end, we introduce the ToD, measuring when the fit of a local time series to a nonlinear tropical-average warming index becomes and stays statistically significant. Unlike ToE which relies on a signal-to-noise ratio, ToD adjusts this ratio based on the effective number of degrees of freedom in the time series, enabling the detection of subtle signals in long time series. ToD is meant to detect subtle signals that do not emerge using the standard ToE definition.

We have computed ToD and ToE for SST and RSST (a proxy for the warming pattern, and for changes in atmospheric stability and circulation) in four observational datasets and 69 CMIP5/6 historical and future simulations under the RCP85/SSP585 scenarios. Our analysis excludes pre-1921 data, due to the scarcity of observations during this period. ToD is less sensitive to the chosen significance level than ToE is to the selected signal-to-noise threshold. ToD and ToE patterns are relatively similar and determined by the noise level for SST and by the signal amplitude for RSST. However, for comparable thresholds, detection precedes emergence, with a lead of ~ 5 years for SST and ~ 35 years for RSST.

The tropical SST warming signal is detectable everywhere before 2022 in models and observations, except in the equatorial Pacific. In EEP, warming is detectable in 91% of models, but only in 1 (ERSST) of the 4 observed datasets due to weaker observed warming signals than in models (Fig. 3.14 a). This detection of an EEP warming in ERSST is robust to the trend estimation period. Tropical IO is one region that shows very early detection and emergence in both observations and models. And this detection is sensitive to the trend estimation period (fig 3.14 b)

Summary of Regional signals detection in observation and models

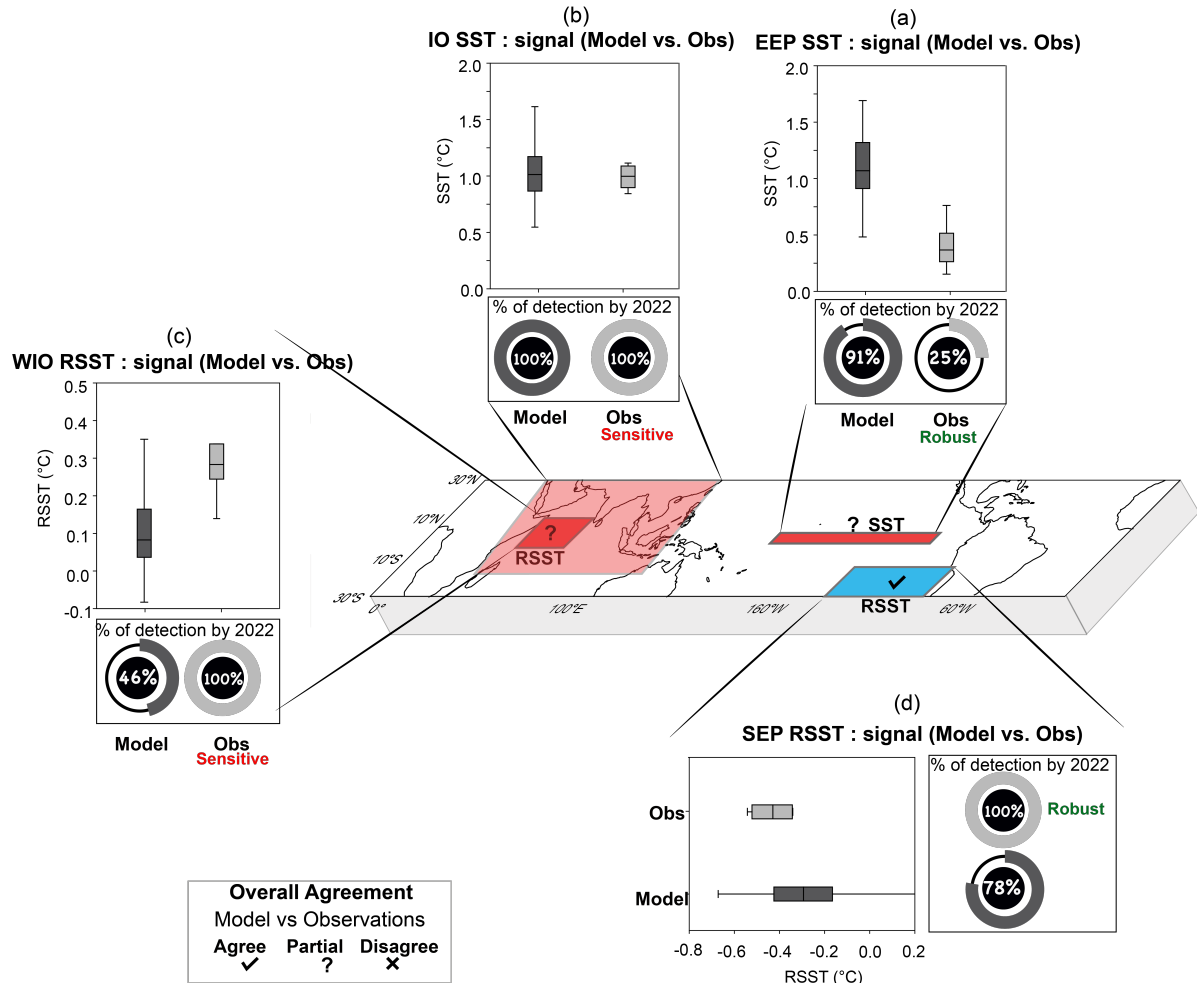


Figure 3.14: Summary of regional SST and RSST signals detection in models and observations for selected boxes. Average 2022 SST signal (Whiskers, °C, relative to 1891–1950) and percentage of detection before 2022 (pie charts, % based 95% threshold ToD) for (a) EEP SST, (b) WIO RSST and (c) SEP RSST. The sign of the SST / RSST signal is indicated by shading (Red for warming and blue for cooling), and the overall agreement between model and observation by a tick mark (agree) or question mark (partial agreement).

RSST signals are considerably smaller than SST signals (due to the tropical-average warming signal subtraction), but with the same noise level (associated with SST internal variability). Consequently, RSST detection lags that of SST by ~60–70 years. And while SST signals have not emerged, two regions exhibit detectable RSST signals in observations and models. An RSST cooling is already detectable in the SEP in all observational datasets and ~80% of the CMIP5+6 models. This observed detection is robust, with consistent signal amplitudes with models (Fig. 3.14d). An RSST warming trend is detectable in the WIO since the second half of the 20th century in observations, but only after the eighties in ~45% of the models. This observed RSST warming detection is sensitive to the trend estimation period, with detection in one

dataset only when excluding dubious pre-1960 data (Fig. 3.14 c).

Overall, the EEP SST and WIO RSST signals are only detectable in one out of four observational datasets. In contrast, the SEP relative cooling detection is robust in observations, and the observed signals amplitude agree with the modelled ones (Fig 3.14 d). The SEP is therefore an appropriate region to serve as a test bed to evaluate the ability of climate models to replicate regional warming trends. In the next subsection, we discuss the implications of these results for the realism of circulation changes projected by CMIP models.

By applying a rigorous statistical significance test, which reduces the critical signal-to-noise ratio as the length of the considered time series increases, the ToD framework allows the detection of subtle signals that have not yet emerged. This is for instance the case for the observed SEP relative cooling, allowing it to confirm consistent signals in models in this region. ToD is therefore more appropriate than ToE for comparing model with observations, while ToE (which focuses on larger signals) is more adapted for impact studies.

3.6.2 Discussion

The ToD methodology was originally applied to the Indian Ocean warming by Gopika et al. (2020). The present study refines the ToD methodology in (i) adopting a nonlinear instead of a linear trend estimate, (ii) estimating trends since 1921 rather than since 1891, and (iii) incorporating an improved estimate of the effective number of degrees of freedom (Bayley and Hammersley, 1946). The use of a linear trend tends to under-estimate signal and overestimate noise, delaying detection. Section 3.5.3 also demonstrates that excluding the data-poor 1891–1920 period makes the ToD estimates more robust. We thus estimate that our refined method is more robust than that in Gopika et al. (2020). Moreover, Gopika et al. (2020) used a different significance threshold (90% instead of 95%), focused on regional warming differences (Arabian Sea minus the Bay of Bengal, or western minus eastern IO) instead of RSST, and different averaging boxes. It is thus difficult to compare the results between the two studies. Both studies, however, point to a broad observed relative warming in the western IO,

which is sensitive to the trend estimation period (Fig. 3.14c).

We find a robust SEP relative cooling in observations and models since the eighties (Fig. 3.14 d). This early detection matches the early emergence of decreasing sea level signals in the south tropical Pacific (Lyu et al., 2014). The SEP relative cooling is attributed to the poleward expansion of the Southern Hemisphere Hadley cell since 1979 (Belmadani et al., 2014 ; **jebri2022**), a response attributed to ozone depletion and rising concentration of greenhouse gases (e.g., Grise and Davis, 2019). This expansion intensifies the southeastern Pacific trade winds, coastal upwelling, and evaporative cooling, thereby tempering the warming trend in this area (Power et al., 2021). Our results furthermore indicate a similar timing between this cooling trend and the reported Hadley Cell shift. Overall, these results provide strong evidence for a detectable poleward expansion of the Hadley cell in response to anthropogenic forcing.

We identified a WIO relative warming in all observational datasets, but its detection is sensitive to the trend estimation period, with weaker signals and detection in only one out of four datasets when excluding pre-1960 dubious data. This may explain the mismatch with the weaker relative warming that is only detectable in 45% of models (Fig. 3.14 c). This enhanced warming is potentially important, as it has been linked to the Indian monsoon rainfall observed decreasing trend (Roxy et al., 2015). This relative warming has either been linked to the WIO thermocline deepening in response to a slowdown of the IO branch of the Walker cell (Dong et al., 2014b, Vecchi and Soden, 2007b), enhanced downwelling long wave radiation (Xie et al., 2010, Zhang and Li, 2014) or an increase in the frequency of positive IOD (Rao et al., 2011) or El Niño events (Roxy et al., 2014). Li et al., 2016a have questioned the realism of this modelled WIO relative warming, connecting it to present-day biases within CMIP models. The limited detection in models, the sensitivity of the observational results and the potential impacts of model biases all question the reality of this relative WIO warming. While plausible, more research is required to confirm its reality.

Recent studies have underlined the inconsistency between the EEP observed cooling and CMIP warming trends over recent decades. While some interpret the

observed cooling trend as internal variability associated with the IPO (Chung et al., 2019 ; Watanabe et al., 2020), others question the accuracy of CMIP projections (Kociuba and Power, 2015; Seager et al., 2022). This mismatch might stem from the model underestimating processes that impede EEP warming. An example is the ocean thermostat (Clement et al., 1996), by which upwelling of cold deep water counters surface anthropogenic warming. Alternatively, this discrepancy could result from an overestimation of processes that amplify the warming, such as the evaporative damping reduction over the cold EEP or cloud feedback (Power et al., 2021). Differing from most previous studies that focused on recent decades, our analysis spans the entire 1921-2022 period. We identified a weaker EEP warming trend in the 4 observational products than in models, detectable in only one of them for which the warming lies in the lower range of CMIP models (Fig. 3.8 b). This aligns with previous studies pointing to an overestimated EEP warming in models.

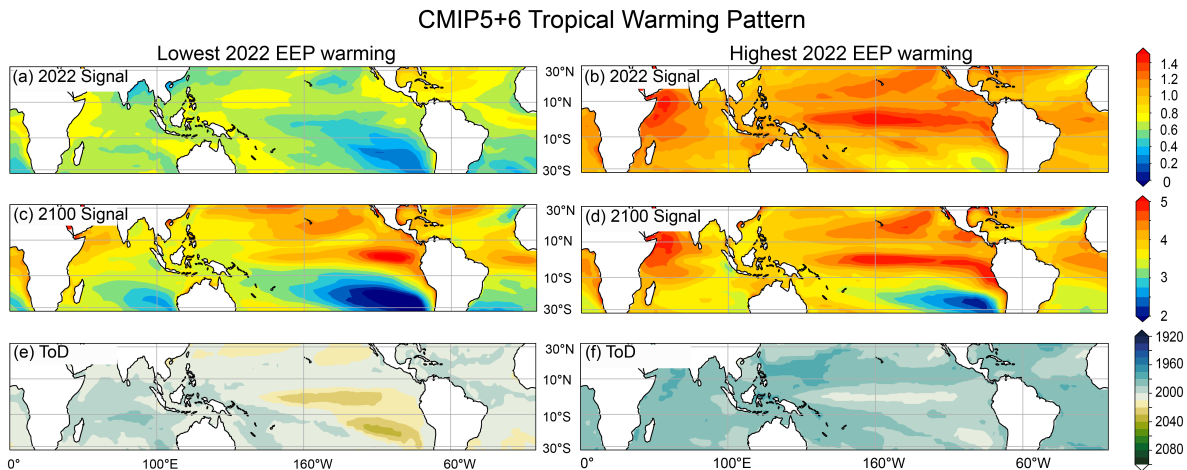


Figure 3.15: Tropical SST warming pattern diversity in CMIP5/6. Average SST warming pattern in (a) 2022, (c) 2100 and (e) corresponding ToD for the 10 models with the weakest 2022 EEP warming. (b,d,f) As (a,c,e) but for the 10 models with the largest 2022 EEP warming. The 10 models with the strongest and weakest 2022 EEP warming are listed in Table 3.1.

To develop this point, Fig. 3.15 displays the average 2022 and 2100 warming and ToD maps for the 10 models with, respectively, the weakest and strongest 2022 EEP warming. In the “Weakest” group, the tropical Pacific warming pattern displays weaker warming in the EEP region, resembling observations (Fig. 1.5b). Conversely, models in the “Strongest” group (Fig. 3.15 b) display an enhanced EEP warming. Both groups converge toward an enhanced EEP warming (relative warming) by the end of

the 21st century, albeit with a larger amplitude in the “Strongest” group. This result can be interpreted as an initially stronger oceanic thermostat in the “Weakest” group, that later becomes less efficient as the warming signal makes its way to the equatorial thermocline (Heede and Fedorov, 2021, Heede and Fedorov, 2023), so that all models simulate enhanced equatorial warming by the end of the 21st century. Additionally, models in the “Weakest” group show a ToD near 2020 in the EEP region (2021 median, versus 2000 for the “Strongest” group), aligning with an observed warming trend on the brink of detection.

A CMIP5+6 subset is thus quite consistent with observed SST trends, with subdued EEP warming, potentially linked to the ocean thermostat mechanism (Heede and Fedorov, 2021, Heede and Fedorov, 2023). But what about the longer-term Walker cell weakening and “El Niño like” warming pattern common to most CMIP models? Our results indicate that the EEP relative SST warming will not be detectable before several decades, due to the strong ENSO “climate noise”.

Turning our attention to the IO branch of the Walker cell might offer insights. The borderline detection of a WIO warming in our results may point to an already weakened zonal circulation in that basin. As changes in the Walker Cell exert significant impacts on the global climate, further research is needed to unravel their mechanisms in models and observations.

Beyond the broader tropical considerations, the tropical IO stands out as a region of particular interest. The early detection and emergence of basin-averaged warming in the tropical IO is consistently robust across datasets and model simulations. The latest IPCC report highlights that the IO is the fastest-warming ocean basin in the world (IPCC, 2021). Even though models and observation agree on the amplitude of basin average warming, the spatial pattern of this warming differs significantly between them, which is reflected in discrepancies in the detection time of RSST changes. This raises the need for a deeper understanding of the underlying processes driving tropical IO warming in climate model projections. Addressing these gaps is crucial for improving future model performance and capturing key climate processes more accurately. The following chapters, therefore, focus on the mechanism driving amplitude and pattern of tropical IO warming in climate models in more detail.

Chapter 4

Drivers of the Indian Ocean Warming – A statistical Approach applied to CMIP models

4.1 Introduction

As discussed in Chapter 3, the tropical IO has undergone rapid warming, with clear climate change-related SST signals detected prior 2022. By narrowing the focus to this region, the rest of this thesis seeks to identify the key processes driving its warming patterns in CMIP models. Gaining a deeper understanding of these processes is essential for refining future coupled climate model regional projections. Furthermore, the analytical framework developed in this chapter will inform the dynamical bias correction methodology introduced in Chapter 5, thereby contributing to the second objective of this thesis. Additionally, this chapter partially addresses the final objective of this thesis by exploring the mechanisms behind the tropical IO warming, which will be later reassessed in Chapter 5 through bias-corrected oceanic simulations.

4.1.1 Connection in the literature and objective of this chapter:

As stated in the introduction, the tropical IO has been warming steadily since the 1950s (IPCC, 2021), primarily driven by anthropogenic forcing . The mechanisms behind this heightened future warming (Du and Xie, 2008, Dong et al., 2014b, Dong and Zhou, 2014a, Zhang and Li, 2014) and the spatially heterogeneous 'IOD-like' warming pattern (Xie et al., 2010, Liu et al., 2015, Ma et al., 2012, Sharma et al., 2023) have been investigated in the literature. However, a lack of consensus among previous findings highlights the need for a more reliable approach. Also, previous investigations of the IO warming mechanisms have either relied on a single model

(e.g., Dong et al., 2014b, Liu et al., 2015, Sharma et al., 2023) or focused on explaining the CMIP Multi-Model Mean (MMM) response (e.g., Du and Xie, 2008, Zhang and Li, 2014). Although our focus is on the forced IOD-like warming pattern, there are multiple studies examining the multiscale variability of the IOD and the underlying ocean-atmosphere interactions (Ashok et al., 2004, Feba et al., 2021, Marathe et al., 2021), which provide useful context for understanding the forced IOD-like warming pattern discussed here.

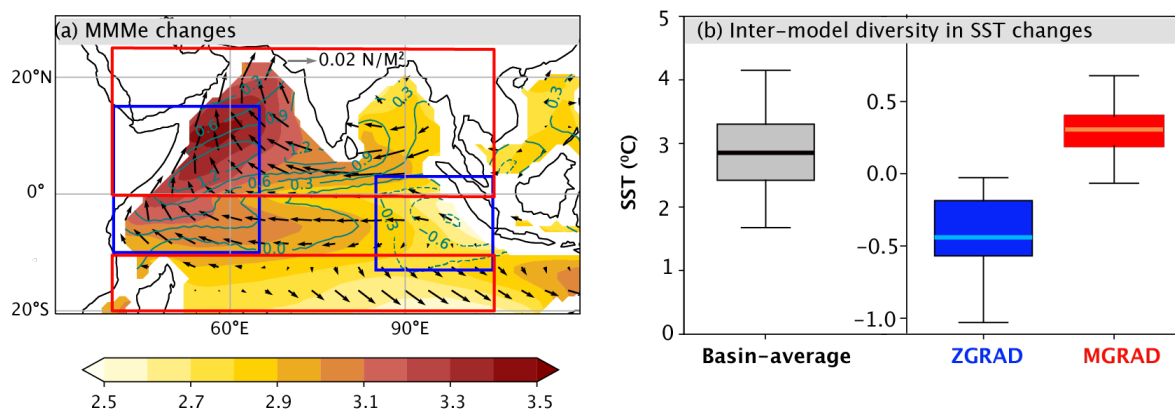


Figure 4.1: CMIP5/6 projected changes in the Indian Ocean (IO). (a) Multi-Model Mean (MMM) projected changes for Sea Surface Temperature (SST, °C, shaded), precipitation (mm.day^{-1} , contours) and wind stress (N.m^{-2} , vectors). (b) Distribution of the projected changes in basin-averaged SST, zonal equatorial SST gradient (ZGRAD) and meridional inter-hemispheric SST gradient (MGRAD) across models. Horizontal lines indicate the MMM, the box edges indicate the lower and upper quartiles, and whiskers the 10th and 90th percentiles. ZGRAD is calculated as SST changes averaged over the eastern Equatorial IO (EEIO; 85°E–105°E; 13°S–3°N) minus those over the western Equatorial IO (WEIO; 40°E–65°E, -10°S–15°N), displayed as blue boxes on panel (a). MGRAD is calculated as SST anomalies averaged over the Northern tropical IO (NIO, 30°E–120°E; 0°–25°N) minus those averaged over the southern tropical IO (SIO; 30°E–120°E; 20°S–10°S), displayed as red boxes on panel (a).

However, there is substantial inter-model diversity in CMIP projections. Under high-emission scenarios, 2100 basin-averaged warming ranges from +1.7 °C to +4.2 °C (Fig. 4.1b). Projections for changes in the equatorial zonal SST gradient (ZGRAD), defined as the difference between SST changes in the Eastern Equatorial Indian Ocean (EEIO) and the Western Equatorial Indian Ocean (WEIO) (represented by blue boxes in Figure 4.1a), range from 0 °C to -1 °C. Note that the ZGRAD box was specifically designed to capture the long term RSST pattern in CMIP models: it is similar (40°–65°E, 10°S–15°N for the west; 85°–105°E, 13°S–3°N for the east) but not identical to the Dipole Mode Index (DMI) boxes usually used to characterize the IOD

(Saji et al., 1999; 50°–70°E, 10°S–10°N and 90°–110°E, 10°S–0°). And, changes in the interhemispheric SST gradient (MGRAD), calculated as the SST difference between the Northern tropical Indian Ocean (NIO) and the Southern tropical Indian Ocean (SIO) (depicted by red boxes in Figure 4.1a), vary between 0°C and +0.5°C (Figure 4.1b). Understanding the drivers behind these SST pattern variations is crucial for narrowing uncertainties in projected rainfall (Ma and Xie, 2013, Long et al., 2016). Although studies have examined the causes of inter-model diversity in SST patterns over regions such as the tropical Pacific (Ying and Huang, 2016a, Ying and Huang, 2016b), tropical Atlantic (Long and Xie, 2015) and Arctic (Yim et al., 2017), similar analyses for the Tropical IO remain limited.

Determine the mechanisms that drive the tropical IO average warming and warming pattern in CMIP5 and 6 projections, both in terms of MME and inter-model diversity. Beyond exploring the drivers of the IOD-like warming pattern and its variability across models, we provide detailed analyses of an underexplored yet prominent Tropical IO warming pattern: the strengthening of the interhemispheric SST gradient. To that end, we use a simplified upper ocean heat budget method similar to that of Zhang and Li (2014) (hereafter; ZL14). The method, detailed in section 4.2, involves splitting surface net air-sea flux changes into two parts. Throughout the thesis, we define *feedback* as the part of the flux changes that depends locally on SST (e.g. latent heat flux increase at high SST due to Clausius Clapeyron). And *forcing* as the SST-independent part (e.g. wind-driven latent heat flux changes and greenhouse gases radiative forcing). ZL14 regarded downward long-wave changes as a forcing. Recent research (Pendergrass et al., 2018 ; Vargas Zeppetello et al., 2019 ; Shakespeare and Roderick, 2022) demonstrated that most of the downward long-wave heat flux warming arises from feedback processes. The warmer surface ocean indeed warms the lower-heat capacity atmosphere, leading to increased downward long-wave radiation due to changes in atmospheric temperature, humidity, and vertical structure. Additionally, this work extends the ZL14 methodology by deriving equations for both SST changes and RSST changes, enabling a detailed analysis of spatial variations in Tropical IO warming. These methodological advancements collectively provide novel insights into the magnitude and spatial structure of Tropical IO warming and

its inter-model diversity.

4.2 Data

This section provides details of the CMIP models used in this chapter. Additionally, from this chapter onwards, the focus narrows to the Indian Ocean region to better understand the underlying mechanisms.

4.2.1 CMIP simulations

Specifically for this chapter, we use the outputs from 46 CMIP simulations (Table 4.1), specifically 18 models from CMIP5 (Taylor et al., 2012) and 28 models from CMIP6 (Eyring et al., 2016). Fewer models are used in this chapter compared to the previous one, as the selection is based on the availability of key variables at the monthly frequency, including SST, surface heat flux components, near-surface wind speed, surface air temperature and humidity, cloud fraction, wind stress, precipitation, and sea surface height. For models with multiple ensemble members, only the first ensemble member was used, in order to give equal weight to each model (Eg: Gopika et al., 2020).

Table 4.1: List of the 46 models (18 CMIP5 and 28 CMIP6) used in this study, with the institution name indicated first, followed by a dot and the model name. .

CMIP5 Models	CMIP6 Models
CSIRO-BOM.ACCESS1-0	CSIRO-ARCCSS.ACCESS-CM2
CSIRO-BOM.ACCESS1-3	CSIRO.ACCESS-ESM1-5
BCC.bcc-csm1-1	CCCma.CanESM5
BCC.bcc-csm1-1-m	CAS.CAS-ESM2-0
CCCma.CanESM2	NCAR.CESM2-WACCM
CNRM-CERFACS.CNRM-CM5	NCAR.CESM2
CSIRO-QCCCE.CSIRO-Mk3-6-0	CMCC.CMCC-CM2-SR5
NOAA-GFDL.GFDL-CM3	CMCC.CMCC-ESM2
NOAA-GFDL.GFDL-ESM2G	CNRM-CERFACS.CNRM-CM6-1
NOAA-GFDL.GFDL-ESM2M	CNRM-CERFACS.CNRM-ESM2-1

INM.inm-cm4	EC-Earth-Consortium.E3SM.E3SM1-1
IPSL.IPSL-CM5A-LR	EC-Earth-Consortium.EC-Earth3
IPSL.IPSL-CM5A-MR	EC-Earth-Consortium.EC-Earth3-CC
IPSL.IPSL-CM5B-LR	EC-Earth-Consortium.EC-Earth3-Veg
MIROC.MIROC-ESM	EC-Earth-Consortium.EC-Earth3-Veg-LR
MIROC.MIROC-ESM-CHEM	CAS.FGOALS-g3
MIROC.MIROC5	NOAA-GFDL.GFDL-CM4
MRI.MRI-CGCM3	NOAA-GFDL.GFDL-ESM4
	IPSL.IPSL-CM6A-LR
	MIROC.MIROC-ES2L
	MIROC.MIROC6
	MPI-M.MPI-ESM1-2-HR
	MPI-M.MPI-ESM1-2-LR
	MRI.MRI-ESM2-0
	NCC.NorESM2-LM
	NCC.NorESM2-MM
	AS-RCEC.TaiESM1
	MOHC.UKESM1-0-LL

All simulations were linearly interpolated to a $1^\circ \times 1^\circ$ grid over 30°E - 120°E , 20°S - 30°N (fig. 4.1a). Some models had already undergone interpolation to a standardised grid but exhibited significant discontinuities in latent and sensible heat fluxes near coasts. An ad-hoc mask was therefore applied to all variables and models, resulting in the loss of some data points close to coasts. The “present-day” period is defined as the 1958-1977 average. The “future” period is defined as the 2068-2087 average. Future changes are denoted as Δ , representing the difference between the future and present-day averages. These periods were selected to maintain consistency with Chapter 5, which is constrained by the availability of reanalysis data. Nevertheless, our findings remain robust when considering more commonly used period definitions (e.g., 1900-1920 and 2080-2099). The MMe is the average across the 46 available CMIP5 and CMIP6 simulations.

Surface fluxes are considered positive when downward (i.e., when they warm the ocean). Quantities averaged over the Tropical IO (oceanic regions between 30°E and 120°E, 20°S to the northern boundary) are denoted with an overbar, while deviations from these average Tropical IO quantities are noted with a prime and referred to as “relative. RSST is a proxy for atmospheric vertical stability, which highlights the spatial pattern of the SST change (e.g. Xie et al., 2010). The conventional RSST definition involves subtracting the tropical (20°N-20°S) mean SST rather than the tropical IO mean. However, subtracting the Tropical IO (30°E-120°E, 20°S-30°N) mean yields nearly identical results (with a correlation of 1). Four seasons were defined, corresponding to the Southwest (JJAS; June-September) and Northeast (DJFM; December-March) monsoons and the Spring (AM; April-May) and Fall (ON; October-November) inter-monsoons. Analyses that are not explicitly referred to as seasonal were conducted on annual averages.

4.3 Simple equation for the SST change

This section presents a simple heat budget for diagnosing mechanisms that drive future SST and RSST changes. Section 4.3.1 explains how this budget was implemented in ZL14. Section 4.3.2 details our refinements, mainly incorporating a downward long-wave flux feedback. Section 4.3.3 derives equations for basin-averaged SST ($\overline{\Delta T}$) and RSST ($\Delta T'$) changes and explains our decomposition of the inter-model variances in these two quantities.

Table 4.2: List of notations and acronyms used in Chapter 4 to explain the simple heat budget framework by ZL14 and its modifications.

Notation and Acronyms	Definition
Δ	Future changes
$\langle \rangle$	MMMe
Overbar $\overline{}$	Quantities averaged over the Tropical IO
Prime symbol $'$	Perturbations from mean
T	SST

Q	Net surface heat flux
O	Oceanic processes (advection, mixing, entrainment)
SW	Net shortwave radiation
LWU	Upward longwave radiation
LWD	Downward longwave radiation
LH	Latent heat flux
SH	Sensible heat flux
σ	Stefan-Boltzmann constant ($5.6 \times 10^{-8} \text{ W}\cdot\text{m}^{-2}\cdot\text{K}^{-4}$)
ρ	Surface air density
L	Latent heat of evaporation
C_E, C_H	Transfer coefficients for latent and sensible heat fluxes
C_P	Specific heat capacity at constant pressure
V	Wind speed
T_s, T_a	SST and Air Temperature
q_s, q_a	Specific humidity at the sea surface and 10m above surface air
$\Delta LH_{\text{For}}, \Delta LH_{\text{Feed}}$	Forcing and feedback components of LH
$\Delta LWU_{\text{For}}, \Delta LWU_{\text{Feed}}$	Forcing and feedback components of LWU
$\Delta LWD_{\text{For}}, \Delta LWD_{\text{Feed}}$	Forcing and feedback components of LWD
$\Delta LW_{\text{For}}, \Delta LW_{\text{Feed}}$	Forcing and feedback components of LW
γ_1, γ_2	Coefficients relating latent and sensible heat feedback to SST
α	Total feedback coefficient (this study)
α_{ZL14}	Feedback coefficient from ZL14

$\alpha_{LH}, \alpha_{LWU}, \alpha_{LWD}$	Feedback coefficients of LH, LWU, and LWD
τ	Effective optical depth
q_c	CO ₂ concentration
$\mathcal{H}$	E-folding height of water vapor
R, R_{cs}	Radiative forcing components
c	Cloud cover
$\alpha_{LWD_{T_a}}, \alpha_{LWD_{q_c}}, \alpha_{LWD_{\mathcal{H}}}, \alpha_{LWD_c}$	Feedback coefficient contributions from changes in T_a , q_s , $\mathcal{H}$, and C

4.3.1 Zhang and Li (2014) original equation

The study ZL14 adopted the simple surface budget approach proposed by Xie et al. (2010) to derive their diagnostic equation for projected SST changes ΔT (equation 8 in their article). This approach allows for identifying processes that control the SST changes, by assuming a balance between the net surface heat flux changes (ΔQ) and changes in the oceanic fluxes into the mixed layer (hereafter referred to as ocean processes, ΔO , which includes lateral and vertical advection, lateral and vertical mixing, and entrainment), I.e., $\Delta O = -\Delta Q$, both expressed in $W.m^{-2}$. This balance holds under the assumption that, the mixed layer is in quasi-equilibrium with external forcing, and mixed layer heat content change are small and one magnitude lower compared to spatial variations in surface fluxes (Eg. Xie et al., 2010). I.e.,

$$\Delta Q + \Delta O = 0 \quad (4.1)$$

ΔQ is broken into its changes in net shortwave (SW), upward and downward longwave (LWU and LWD), latent (LH) and sensible (SH) heat fluxes:

$$\Delta Q = \Delta SW + \Delta LWD + \Delta LWU + \Delta LH + \Delta SH \quad (4.2)$$

Where, as stated earlier, the convention is already accounted, radiation incoming to the ocean (SW and LWD) is considered positive, while radiation lost from the ocean

(LWU, LH and SH) is considered negative

The next step is to decompose the heat fluxes. Here, the ΔQ is further decomposed into two components: $\Delta Q_{For} - \alpha \Delta T$, where $-\alpha \Delta T$ represents the *feedback* component, which explicitly depends on local SST changes, and ΔQ_{For} the *forced* component, which is not explicitly dependent on local SST changes (the part that does not explicitly depend locally on SST, e.g. wind-driven latent heat flux change). This decomposition for different flux components is given below:

Decomposition of flux components into *feedback*:

LWU: The change in LWU at the ocean surface depends entirely on SST, following Stefan-Boltzmann's law. Therefore, it is considered completely a *feedback* part (denote subscript *Feed*), which can be expressed as,

$$\Delta LWU_{Feed} = 4\sigma[T]^3 \Delta T \quad (4.3)$$

Where T denote SST and brackets $[]$ indicate present-day mean state, Δ denotes future changes and the Stefan-Boltzmann constant $5.6 \times 10^{-8} \text{ kg s}^{-3} \text{ K}^{-4}$. Then the ΔLWU feedback coefficient is $\alpha_{LWU} = 4\sigma[T]^3$. Equation (4.3) is obtained by applying a first-order Taylor expansion to the Stefan-Boltzmann equation $\sigma(T + \Delta T)^4 = \sigma T^4 + \frac{d}{dT}(\sigma T^4) \Delta T = \sigma T^4 + 4\sigma T^3 \Delta T$, as in (e.g., Xie et al., 2010; ZL14). The same first-order Taylor expansion is also applied later in this chapter to obtain Eqs. 4.6 and 4.7.

LH and SH: The bulk aerodynamic formula for LH and SH are,

$$LH = \rho L C_E V (q_s - q_a) \quad (4.4)$$

$$SH = \rho C_H C_P V (T_s - T_a) \quad (4.5)$$

Here, ρ represents the surface air density. L is the latent heat of evaporation, a measure of the energy required for water to change from liquid to vapour. C_E and C_H are the transfer coefficients for LH and SH. C_P is the specific heat capacity at constant pressure. V is the wind speed. T_s and q_s are SST and specific humidity at

the sea surface, which depend on SST. While T_a and q_a denote the air temperature and specific humidity of the air at 10 meters above the sea surface. Both LH and SH vary in response to oceanic (SST changes) and atmospheric factors (E.g. wind speed, humidity). So, previous studies decomposed the *feedback* and *forcing* parts:

The surface LH (Equation 4.4) *feedback* is Newtonian cooling, and following the formulations of ZL14 (Equation 3 and 5) and Xie et al. (2010) (Equations 3 and 4), can be expressed as,

$$\Delta LH_{feed} = \gamma_1 [LH] \Delta T \quad (4.6)$$

Similarly, following ZL14 (Equation 6), the change in SH with respect to change in SST (Equation 4.5) can be expressed as,

$$\Delta SH_{Feed} = \gamma_2 [V] \Delta T \quad (4.7)$$

Where, $\gamma_1 = 0.06 \text{ K}^{-1}$ for tropics, is obtained from the Clausius Clapeyron relation and the γ_2 is $\rho C_H C_P (\partial \Delta T / \partial T_s)$ and V is wind speed. So the Feedback coefficient of ΔLH is $\alpha_{LH} = \gamma_1 [LH]$ and of ΔSH is $\alpha_{SH} = \gamma_2 [V]$. Equations 4.6 and 4.7 follow directly from the linearised bulk formulations used in Xie et al. (2010)(their Eqs. 3–4) and Zhang and Li (2014) (their Eqs. 3, 5, and 6).

Decomposition of flux components in to *forcing*:

In the above equations 4.6 and 4.7, both ΔLH and ΔSH are expressed in terms of *feedback*, then the *forcing* (denoted by subscript For) part can be written as,

$$\Delta LH_{For} = \Delta LH - \Delta LH_{Feed} \quad (4.8)$$

$$\Delta SH_{For} = \Delta SH - \Delta SH_{Feed} \quad (4.9)$$

In case of LWU, which is completely dependent on SST (Equation 4.3), there is no forcing part,

$$\Delta LWU_{For} = 0 \quad (4.10)$$

SST Reconstruction equation (ZL14):

Here $\alpha\Delta T$ of ZL14 from the above equations 4.3, 4.6, and 4.7 can be expressed as,

$$\alpha_{ZL14}\Delta T = (4\sigma[T]^3 + \gamma_1[LH] + \gamma_2[V])\Delta T \quad (4.11)$$

Equation 4.1 can be written as:

$$\Delta SW + \Delta LWD + 4\sigma[T]^3\Delta T + \Delta LH_{For} + \gamma_1[LH]\Delta T + \Delta SH_{For} + \gamma_2[V]\Delta T + \Delta O = 0 \quad (4.12)$$

And can be rearranged to ZL14 SST change equation:

$$\Delta T = \frac{\Delta SW + \Delta LWD + \Delta LH_{For} + \Delta SH_{For} + \Delta O}{4\sigma[T]^3 + \gamma_1[LH] + \gamma_2[V]} \quad (4.13)$$

The ZL14 treated the SW and LWD entirely as a forcing (no feedback term). The total feedback coefficient in ZL14 (α_{ZL14}) consists of α_{LWU} , α_{LH} , and α_{SH} , therefore, from equation 4.11,

$$\alpha_{ZL14} = 4\sigma[T]^3 + \gamma_1[LH] + \gamma_2[V] \quad (4.14)$$

This framework allowed ZL14 to diagnose SST changes based on a balance between surface heat flux forcing, feedback processes, and oceanic heat adjustments.

Note that we defined the total feedback coefficient α as $\Delta Q = \Delta Q_{For} - \alpha\Delta T$. The minus sign in front of α therefore implies that stabilising (negative) feedbacks correspond to positive values of α and its constituents. The IO average value of the total feedback is $15.1 \text{ W.m}^{-2}\text{.}^\circ\text{C}^{-1}$. α_{SH} is negligible (not shown, ZL14). α_{LH} is the largest contributor, with an IO-averaged value of $8.9 \text{ W.m}^{-2}\text{.}^\circ\text{C}^{-1}$ (Fig. 4.2c). α_{LWU} (Fig. 4.2b) has a Tropical IO-averaged value of $6.2 \text{ W.m}^{-2}\text{.}^\circ\text{C}^{-1}$ and is relatively spatially uniform across the region (Fig. 4.2b). The spatial structure of α_{ZL14} is primarily shaped by the distribution of α_{LH} (Fig. 4.2a,c). α_{LH} reflects the effects of the Clausius-Clapeyron relation, which drives evaporative cooling in response to warming. Its spatial distribution is influenced by present-day SST and wind patterns, with the strongest feedback values occurring in regions of high SST and/or strong winds (not

shown).

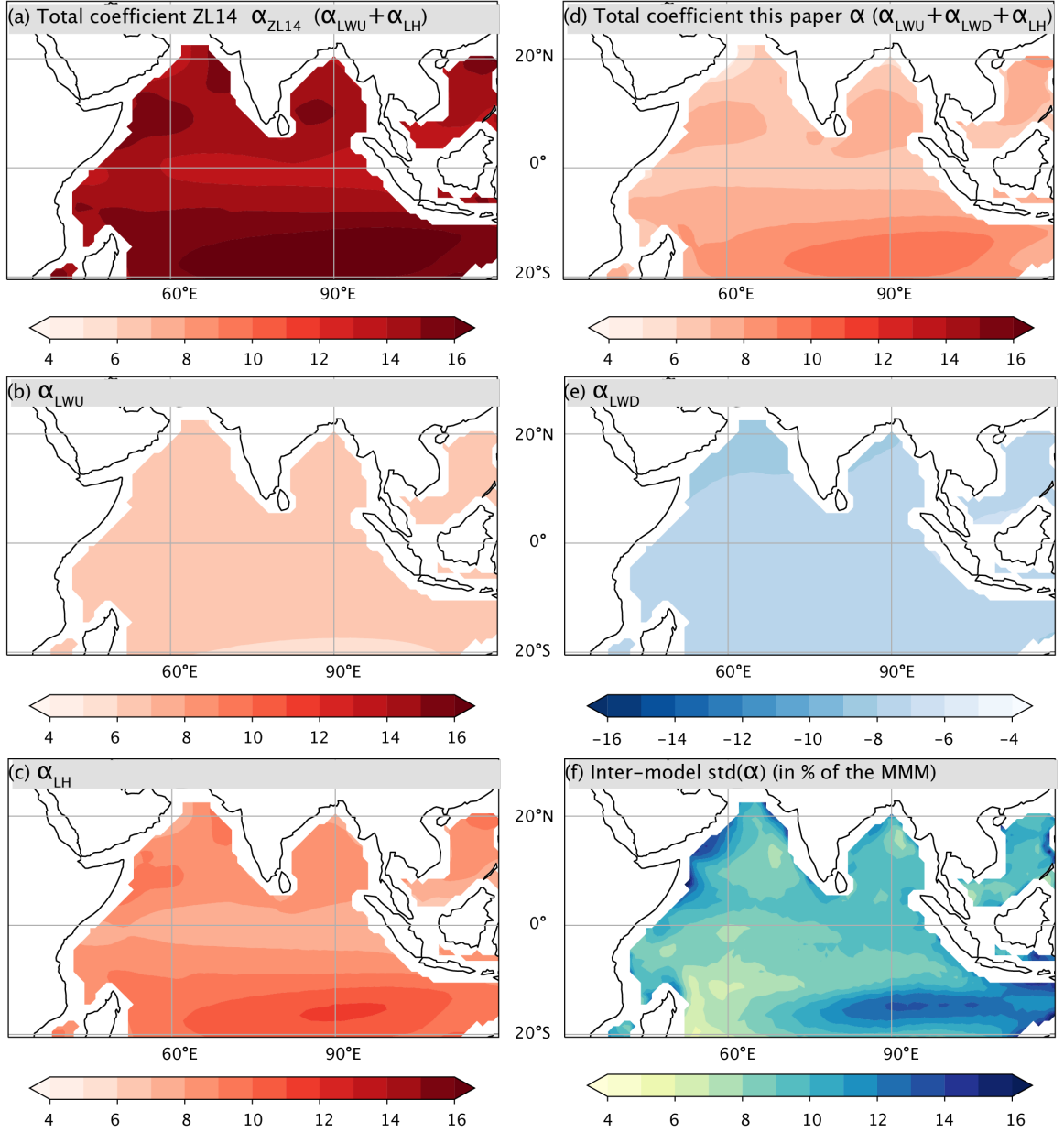


Figure 4.2: Air-sea heat flux feedback coefficients in CMIP5/6 model. MME feedback coefficients ($\text{W.m}^{-2}.\text{°C}^{-1}$): (a) Total coefficient (α_{ZL14}) from Zhang and Li (2014) (ZL14), which includes contribution from (b) latent heat flux (α_{LH}) and (c) upward longwave radiations (α_{LWU}). (d) Total coefficient (α) used in the present paper, incorporating α_{LH} , α_{LWU} and (e) downward longwave (α_{LWD}) coefficients. (f) Inter-model standard deviation of α expressed as a percentage of the MME. Due to the sign convention, feedback coefficients have opposite signs to the corresponding feedback (e.g., negative α_{LH} , α_{LWU} indicating positive feedback, while positive α_{LWD} indicates negative feedback, see Equation 4.13 or ZL14).

4.3.2 Our refinement to the ZL14 equation

In this subsection, we present our refinements to the ZL14 framework. First, we excluded the SH feedback term for two reasons: (i) the SH feedback as computed

by ZL14 is negligible with respect to other feedback terms (e.g. figure 3d in ZL14), and its omission has negligible influence on the results (not shown), and (ii) the linearization of the LH flux assumes that the air-sea temperature difference remains unchanged in a future climate, implying no SST-driven change in SH fluxes.

The main refinement to ZL14 is the inclusion of the downward longwave radiation feedback. following the analytical approach of Shakespeare and Roderick (2022), hereafter, SR22. The analytical expression of its coefficient α_{LWD} is derived using equation 16 in Shakespeare and Roderick (2022) (hereafter SR22; SR22 for details). The SR22 approach assumes that the atmosphere remains in quasi-equilibrium with the slowly warming ocean. As the high heat-capacity ocean warms, the overlying atmosphere adjusts by becoming warmer and moister, modifying its vertical temperature and humidity structure, and consequently emitting more downward infrared radiation toward the surface (e.g., Held and Soden, 2006, Shakespeare and Roderick, 2022). SR22 define clear-sky (in this thesis, clear-sky is indicated by a subscript cs) LWD (LWD_{cs}) at the surface as a function of near-surface air temperature (T_a) and effective optical depth (τ) as follows:

$$LWD_{cs} = \sigma T_a^4 (1 - e^{-\tau}) \quad (4.15)$$

τ , the effective optical depth, represents the extent to which radiation is absorbed or scattered by the near-surface atmosphere. And it is calculated for an idealised slab atmosphere at the surface, with corresponding values provided in SR22. The τ depends on factors such as: Near-surface specific humidity (q_s), CO2 concentration (q_c) and the e-folding height of water-vapour ($\mathcal{H}$). By considering these factors collectively, at the ocean surface, the concentration of LWD_{cs} primarily depends on T_a , q , q_c , and $\mathcal{H}$ (Equation 1-8 of SR22). Among these, only q_c is due to external forcing, while variations in the other factors are feedback to this forcing. SR22 expresses the total change in ΔLWD_{cs} as the sum of contributions from each variable. It distinguishes between clear-sky radiative forcing (R_{cs} ; due to changes in clear-sky q_c forcing) and the feedback resulting from subsequent changes in other properties (Equations 4-6 in SR22). SR22 separates the forced changes and their feedback from

the LWD_{cs} component as:

$$\Delta LWD_{cs} = R_{cs} + \alpha_{LWD_{cs}} \Delta T_a \quad (4.16)$$

where,

$$\alpha_{LWD_{cs}} = \alpha_{LWD_{T_a cs}} + \alpha_{LWD_{q_{scs}}} + \alpha_{LWD_{\mathcal{H}_{cs}}} \quad (4.17)$$

$\alpha_{LWD_{cs}}$ feedback consists of feedback coefficients of T_a ($\alpha_{LWD_{T_a cs}}$), q ($\alpha_{LWD_{q_{scs}}}$), and $\mathcal{H}$ ($\alpha_{LWD_{\mathcal{H}_{cs}}}$). SR22 for further reading.

In the clear sky LWD formulation, the effects of clouds are omitted. However, clouds have a two-fold impact on LWD: they influence the Stefan-Boltzmann law and mask the LWD escaping to the atmosphere. To address this, SR22 later included the effect of clouds by considering a reasonable low cloud approximation, modelled as a single layer of cloud under a slab atmosphere with a temperature equal to T_a . Thus, the cloud contribution to LWD can be expressed as,

$$\Delta LWD_{cloud} = C(\sigma T_a^4 - LWD_{cs}) \quad (4.18)$$

so the, all-sky (clear sky + cloud contribution) LWD can expressed as,

$$LWD = LWD_{cloud} + LWD_{cs} \quad (4.19)$$

The changes in this contribution in equation 4.18, after applying first-order differentiation using the product rule, can be expressed as follows:

$$\Delta LWD = R + \alpha_{LWD} \Delta T_a \quad (4.20)$$

where the all-sky feedback α_{LWD} can be written as,

$$\alpha_{LWD} = \alpha_{LWD_{T_a}} + \alpha_{LWD_{q_s}} + \alpha_{LWD_{\mathcal{H}}} + \alpha_{LWD_C} \quad (4.21)$$

In this thesis, our calculations account for the feedback contributions from changes in T_a , q and $\mathcal{H}$ of SR22 ($\alpha_{LWD_{T_a}}$, $\alpha_{LWD_{q_s}}$, $\alpha_{LWD_{\mathcal{H}}}$), because these changes are

strongly related to those in SST. We do not, however, include the effects of cloud feedback, because changes in cloud cover are poorly related to those in SST changes across CMIP (see Fig. 3 of SR22 for details):

$$\alpha_{LWD} = \alpha_{LWD_{T_a}} + \alpha_{LWD_{q_s}} + \alpha_{LWD_{\mathcal{H}}} \quad (4.22)$$

Thus, the change in LWD feedback and forcing components are as follows:

$$\Delta LWD_{feed} = \alpha_{LWD} \Delta T_a \quad (4.23)$$

$$\Delta LWD_{for} = \Delta LWD - \Delta LWD_{fbk} \quad (4.24)$$

We represent the combined longwave flux change as $\Delta LW = \Delta LW_u + \Delta LWD$ and the combined feedback (Equation 4.3 and 4.23) and forcing (Equation 4.11 and 4.24) terms are,

$$\Delta LW_{feed} = \Delta LWU_{feed} + \Delta LWD_{feed} \quad (4.25)$$

$$\Delta LW_{for} = \Delta LWU_{for} + \Delta LWD_{for} \quad (4.26)$$

By incorporating the new changes, the revised version of the ZL14 (equation 4.13) for ΔT :

$$\Delta T = \frac{\Delta SW + \Delta LW_{For} + \Delta LH_{For} + \Delta SH_{For} + \Delta O}{\alpha} \quad (4.27)$$

The total feedback coefficient (α) is therefore :

$$\alpha = 4\sigma[T]^3 + \gamma_1[LH] + \alpha_{LWD} \quad (4.28)$$

Figure 4.2 illustrates the impact of incorporating α_{LWD} on the total feedback coefficient α . As previously noted, α_{SH} is negligible (not shown), so that $\alpha \approx \alpha_{ZL14} + \alpha_{LWD}$. The feedbacks we have discussed so far (LH, LWU) are negative feedbacks, but the LWD feedback is positive (expressed as negative α_{LWD} under our sign convention, Fig. 4.2e) with a basin average value of $-7.5 \text{ Wm}^{-2}\text{C}^{-1}$. This negative α_{LWD} largely offsets the positive α_{LWU} and reduces the basin-averaged total coefficient from 15.1

$\text{Wm}^{-2}\text{C}^{-1}$ in ZL14 to $7.6 \text{ Wm}^{-2}\text{C}^{-1}$ in our study (Fig. 4.2c,f). Similar to its upward counterpart, the LWD feedback coefficient has little spatial variation. As a result, the spatial pattern of α is primarily determined by α_{LH} , with a clear equatorial minimum (Fig. 4.2c,d). Overall, incorporating the downward longwave feedback reduces the total feedback coefficient by half relative to ZL14 and increases the relative importance of spatial variations. Figure 2f finally displays the inter-model standard deviation of α , expressed as a percentage of the MMe value. α exhibits relatively small inter-model variability, with deviations of less than 10% of the MMe value in the equatorial region and up to 15% near the western Arabian Sea coast and in the southeastern Indian Ocean near 15°S .

4.3.3 Equations for changes in basin-averaged SST and RSST

From equation (4.27), we derived equations for the IO basin averaged ΔT ($\overline{\Delta T}$), and for deviations from that basin mean change (i.e., for the RSST $\Delta T'$)

The SST change reconstruction equation (Equation 4.27), in its simplified form in terms of forcing (*for*) and ocean dynamics (*O*) can be written as:

$$\Delta T = \frac{\Delta Q_{\text{for}} + \Delta O}{\alpha} \quad (4.29)$$

To understand basin-average warming and pattern changes, further decomposed Equation 4.29 into mean and perturbation using the Reynolds decomposition formula:

$$\Delta T = \overline{\Delta T} + \Delta T' \quad (4.30)$$

In which, ΔT represents the total temperature change, an overbar ($\overline{\quad}$) and prime ($'$) denote the tropical IO basin average warming and perturbations from the mean, respectively. Likewise, the above Equation 4.29 can be written as:

$$\overline{\Delta T} + \Delta T' = \frac{\left(\overline{\Delta Q_{\text{for}}} + \Delta Q'_{\text{for}}\right) + \left(\overline{\Delta O} + \Delta O'\right)}{(\overline{\alpha} + \alpha')} \quad (4.31)$$

rearranged to:

$$\overline{\Delta T \bar{\alpha}} + \Delta T' \bar{\alpha} + \overline{\Delta T \alpha'} + \Delta T' \alpha' = \overline{\Delta Q_{\text{for}}} + \Delta Q'_{\text{for}} + \overline{\Delta O} + \Delta O' \quad (4.32)$$

For the basin average warming, we averaged Equation 4.32, considering the mean of the mean is mean, and the mean of perturbations is zero. Upon calculation, we find the term $\overline{\Delta T' \alpha'}$ is negligible, and the final equation for basin average warming is:

$$(\overline{\Delta T})' = \frac{\overline{\Delta Q_{\text{for}}} + \overline{\Delta O}}{\bar{\alpha}} \quad (4.33)$$

By subtracting the equation 4.33 from the equation 4.29, we get the equation for the perturbations (ie for RSST):

$$\Delta T' = \frac{\overline{\Delta Q_{\text{for}}} + \overline{\Delta O} - \alpha' \overline{\Delta T}}{\alpha} \quad (4.34)$$

Where, $\alpha' \overline{\Delta T}$ represents the contribution of the spatial inhomogeneity of the total feedback coefficient to $\Delta T'$ (e.g. the fact that reduced negative feedback from evaporative cooling in climatologically colder regions results in less warming, as discussed in e.g. Xie et al. 2010).

To simplify the formulation, and to ensure uniformity in assessing component contributions across models and regions, we approximate the feedback coefficient α by its MMM value, $\langle \alpha \rangle$ in equations 4.33 and 4.34, justified by the relatively small inter-model coefficient diversity of α (less than 15%; Fig 4.2f). We verified that this approximation yields comparable results to exact computations. In these equations, the angle brackets ($\langle \rangle$) indicate the MMMe value. The equation for $\overline{\Delta T}$ is:

$$\overline{\Delta T} = \frac{\overline{\Delta \text{For}} + \overline{\Delta O}}{\langle \alpha \rangle} \quad (4.35)$$

and for $\Delta T'$ is:

$$\Delta T' = \frac{\Delta \text{For}' + \Delta O' - \alpha' (\overline{\Delta T})}{\langle \alpha \rangle} \quad (4.36)$$

To quantify the contribution of each process to the inter-model diversity of $\overline{\Delta T}$ or $\Delta T'$, we express the variance of these quantities as the sum of the covariances

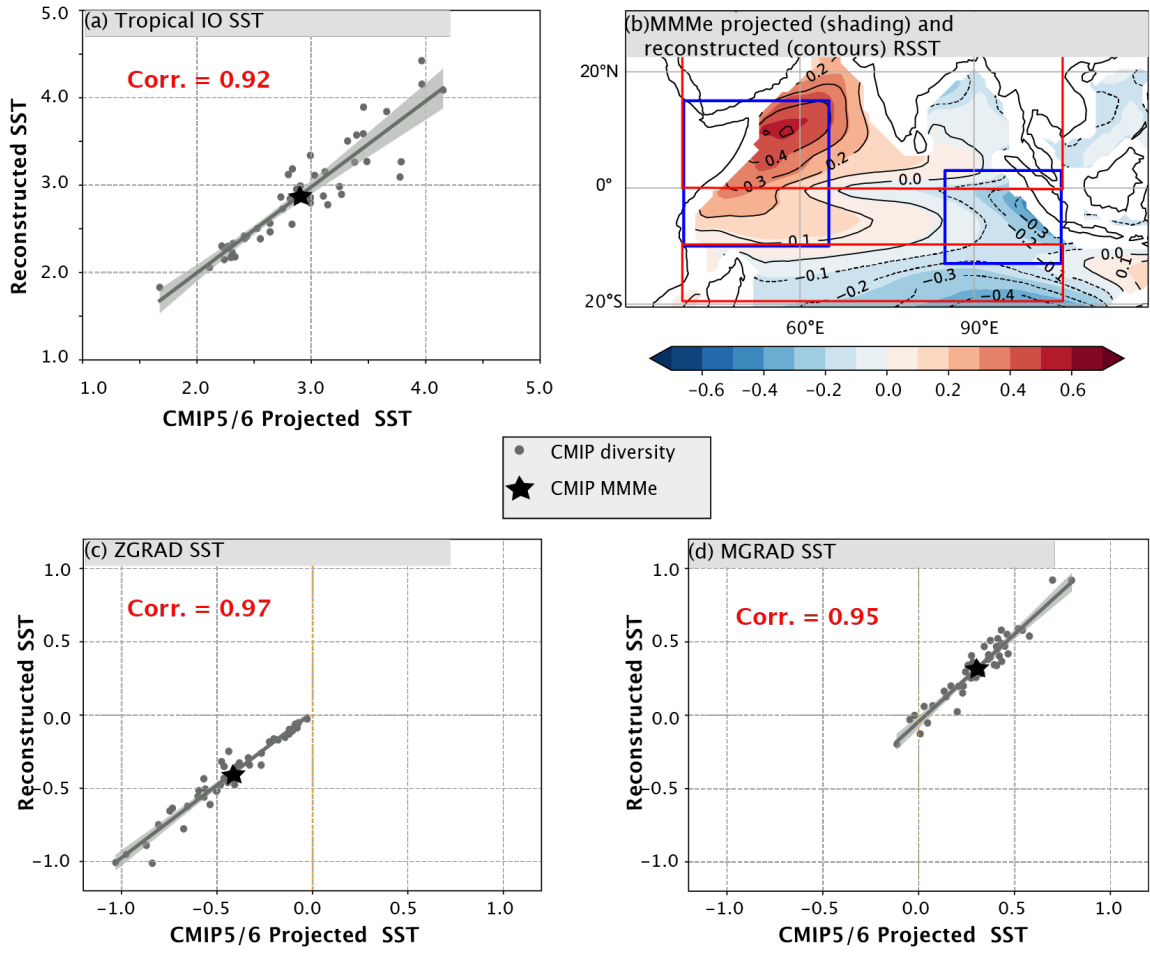


Figure 4.3: Comparison between reconstructed vs. CMIP5/6 projected basin-averaged warming ($\overline{\Delta T}$) and Relative SST (RSST, $\Delta T'$) patterns. (a) Scatterplot of $\overline{\Delta T}$ reconstructed using equation (4) versus CMIP projected values. (b) $\langle \Delta T' \rangle$ from CMIP dataset (shading) and reconstructed values using equation (5) (contours). Scatterplots of the reconstructed versus CMIP $\Delta T'$ for the (c) zonal SST gradient (ZGRAD) and (d) meridional SST gradient (MGRAD). Blue boxes on panel (b) indicate the WEIO and EEIO regions used to compute ZGRAD, while red boxes on panel (b) indicate the NIO and SIO regions used to compute MGRAD. Each grey dot on panels (a), (c) and (d) represents an individual model, with the black star indicating the MME. The grey line represents the least-square regression slope, with the 95% confidence interval shown as a light gray shading. Correlation values are displayed in red.

between each term on the right-hand side of equations 4.35 and 4.36 with $\overline{\Delta T}$ or $\Delta T'$, respectively. For example, the variance of the total temperature change ΔT can be expressed as the sum of the covariances of each contributing term in Equation (4.29):

$$\Delta T = \frac{\Delta Q_{\text{for}}}{\alpha} + \frac{\Delta O}{\alpha} \quad (4.37)$$

The corresponding variance is given by:

$$\text{Var}(\Delta T) = \text{Cov} \left(\frac{\Delta Q_{\text{for}}}{\alpha}, \Delta T \right) + \text{Cov} \left(\frac{\Delta O}{\alpha}, \Delta T \right) \quad (4.38)$$

Similar calculations are applied for the basin-mean (Equation 4.35) and RSST (Equation 4.36) equations.

As for the original ZL14 equation (not shown), equation (4.35) successfully reproduces the ΔT in CMIP5/6 (with the reconstructed MMMe differing by less than 1% from the actual CMIP5/6 value and an inter-model correlation of 0.92; Fig 4.3a). Similarly, the reconstructed MMMe $\langle \Delta T' \rangle$ pattern reconstructed from equation (5) closely resembles that of CMIP5/6 MMMe (compare the contours and shading on Fig 4.3b, pattern correlation of 0.99). Figure 4.3 c and d further indicate that equation (5) accurately captures the inter-model diversity in $\Delta T'$, with correlations of 0.97 and 0.95 for the zonal (ZGRAD) and meridional (MGRAD) SST gradients, respectively.

4.4 Basin-average warming

In this section, I will use equation (4.35) to explore the drivers of the CMIP5/6 IO-average warming $\overline{\Delta T}$. First discuss the MMMe (Section 4.4.1) and then investigate the inter-model spread (Section 4.4.2).

4.4.1 Drivers of the MMMe basin-average warming

The MMMe IO-average warming $\langle \overline{\Delta T} \rangle$ is slightly below 3°C and primarily driven by the MMMe IO-averaged SST-independent part of the surface net heat flux change $\langle \overline{For} \rangle$. The ocean dynamics $\langle \overline{\Delta O} \rangle$ contributes negligibly (Fig 4.4a). The net surface flux forcing is further decomposed into its four components. ZL14 identified downwelling longwave radiation forcing $\langle \overline{\Delta LWD_{For}} \rangle$, as the dominant contributor to the IO-averaged warming. In ZL14, the entire TIO-average MMMe LWD change (28.5 Wm⁻²) was treated as a forcing term.

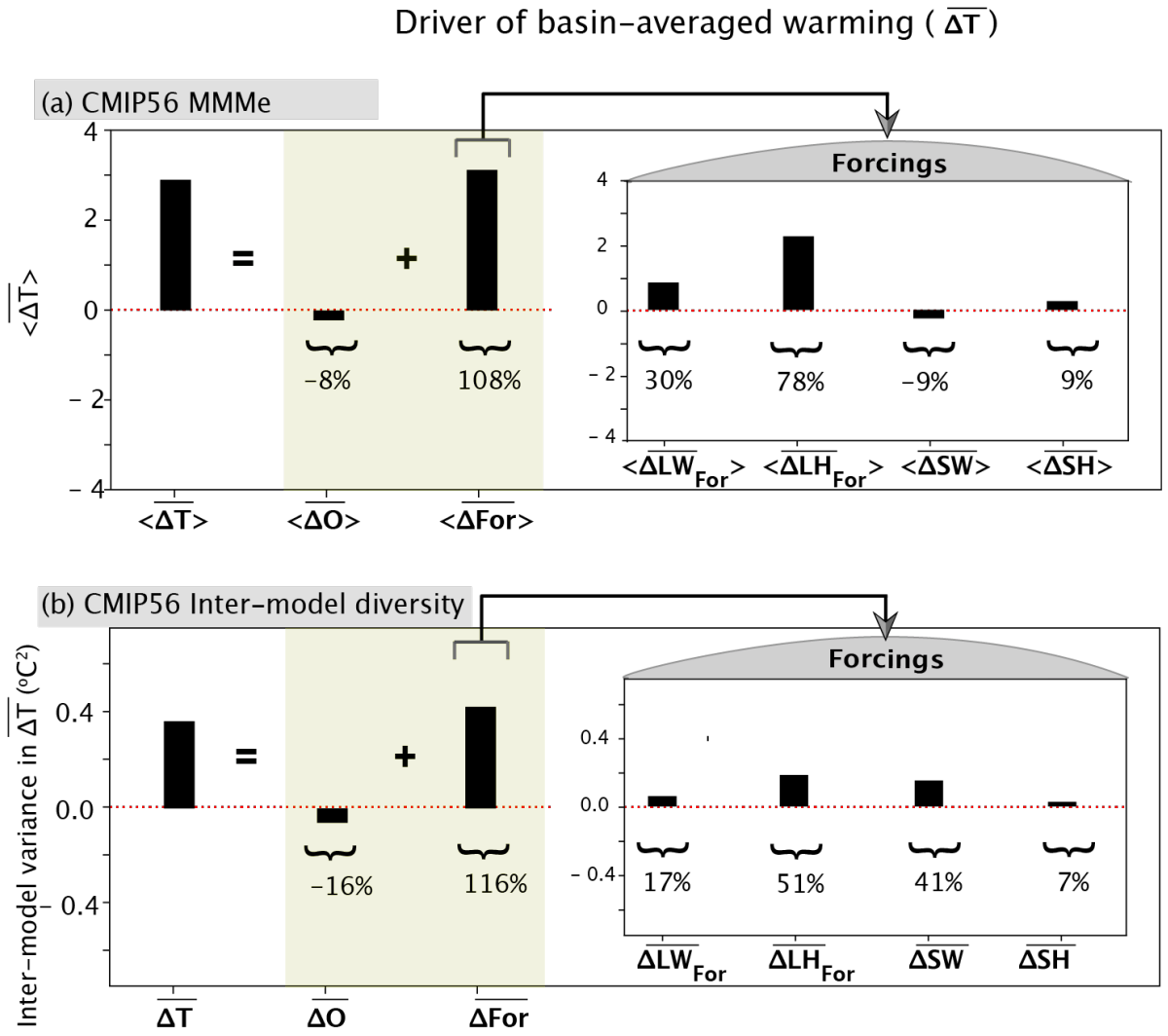


Figure 4.4: Drivers of the basin-averaged warming MME ($\overline{\Delta T}$) and of its inter-model diversity ($\overline{\Delta T}$). (a) MME basin-averaged warming $\overline{\Delta T}$ from equation (4.35), and contributions from changes in ocean dynamics ($\overline{\Delta O}$) and changes atmospheric forcing ($\overline{\Delta For}$). $\overline{\Delta For}$ is further decomposed in forcing contributions from longwave radiation ($\overline{\Delta LW}_{For}$), latent heat flux ($\overline{\Delta LH}_{For}$), shortwave radiation ($\overline{\Delta SW}$) and sensible heat flux ($\overline{\Delta SH}$). (b) Decomposition of the inter-model variance of basin average warming ($\overline{\Delta T}$, $^{\circ}C^2$) into the contributions from ($\overline{\Delta O}$), ($\overline{\Delta For}$) and its four components. The percentages below each bar represent the contribution of individual contributions to the total basin average warming MME (a) or inter-model variance (b).

In our study, however, a large fraction of this change (21.7 Wm^{-2}) is accounted for by the downwelling longwave radiative feedback term $-\alpha_{LWD} \overline{\Delta T}$ accounts for a large fraction of this change (21.7 Wm^{-2}), reducing the downwelling longwave radiation forcing by 76%

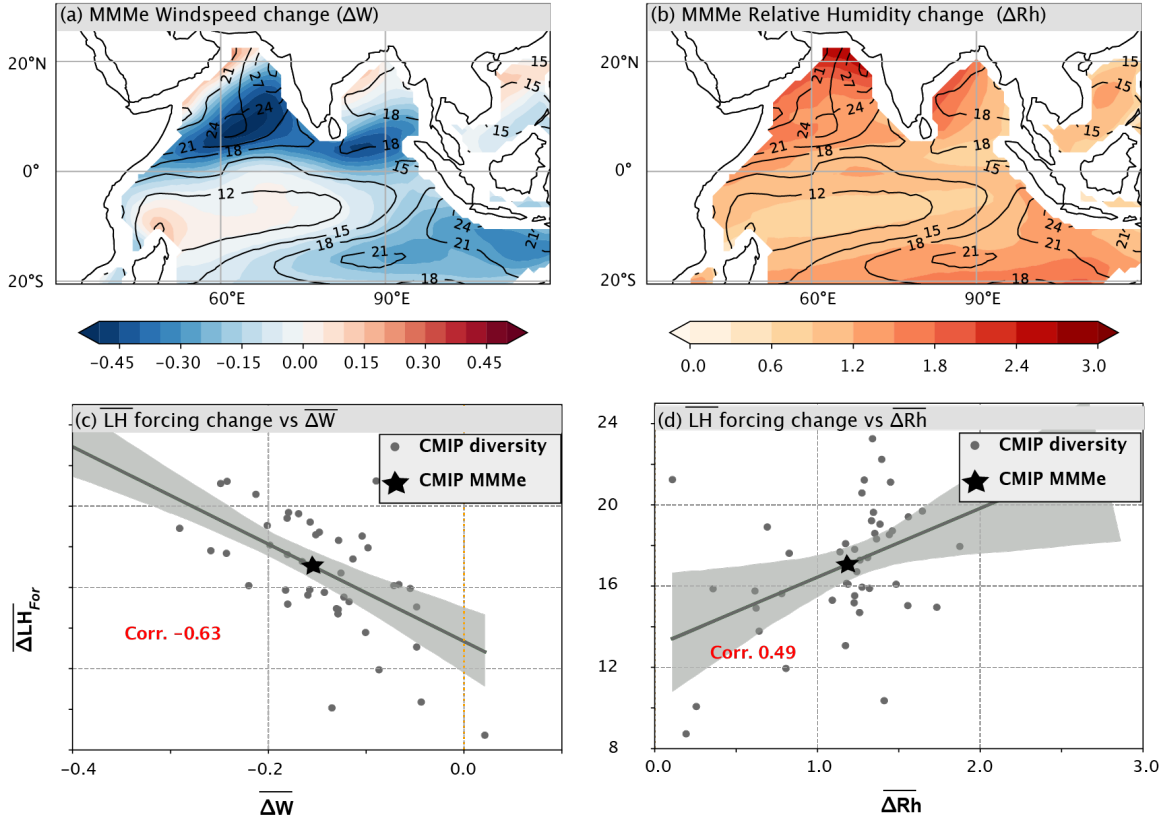


Figure 4.5: Factors controlling Tropical IO latent heat flux forcing. (a) MME wind speed (ΔW) and (b) relative humidity (Rh) changes (shading), with latent heat flux forcing changes overlaid as contours. (c) Relationship between basin-averaged latent heat flux forcing and wind speed changes (ΔW) ($m.s^{-1}$) across CMIP models. (d) Relationship between basin-averaged latent heat flux forcing and relative humidity (ΔRh) (%). Each dot represents an individual model, and stars indicate the MME. The grey line represents the least-square regression slope, with the 95% confidence interval shown as a light gray shading. Correlation values are displayed in red.

compared to ZL14 . As a result, the contribution of downward longwave forcing to the MME TIO-averaged SST change is much smaller in our study than in ZL14 (Fig. 4a). The dominant contributor to $\langle \overline{\Delta T} \rangle$ is the basin-averaged surface net heat flux forcing change, $\langle \overline{\Delta LH_{For}} \rangle$, accounting for $\sim 78\%$ of the total warming, with the remainder attributed to $\langle \overline{\Delta LW_{For}} \rangle$ (30 %), $\langle \overline{\Delta SH} \rangle$ (9 %) and $\langle \overline{\Delta SW} \rangle$ (-9 %). The Tropical IO average warming and its contributors do not vary across seasons (not shown).

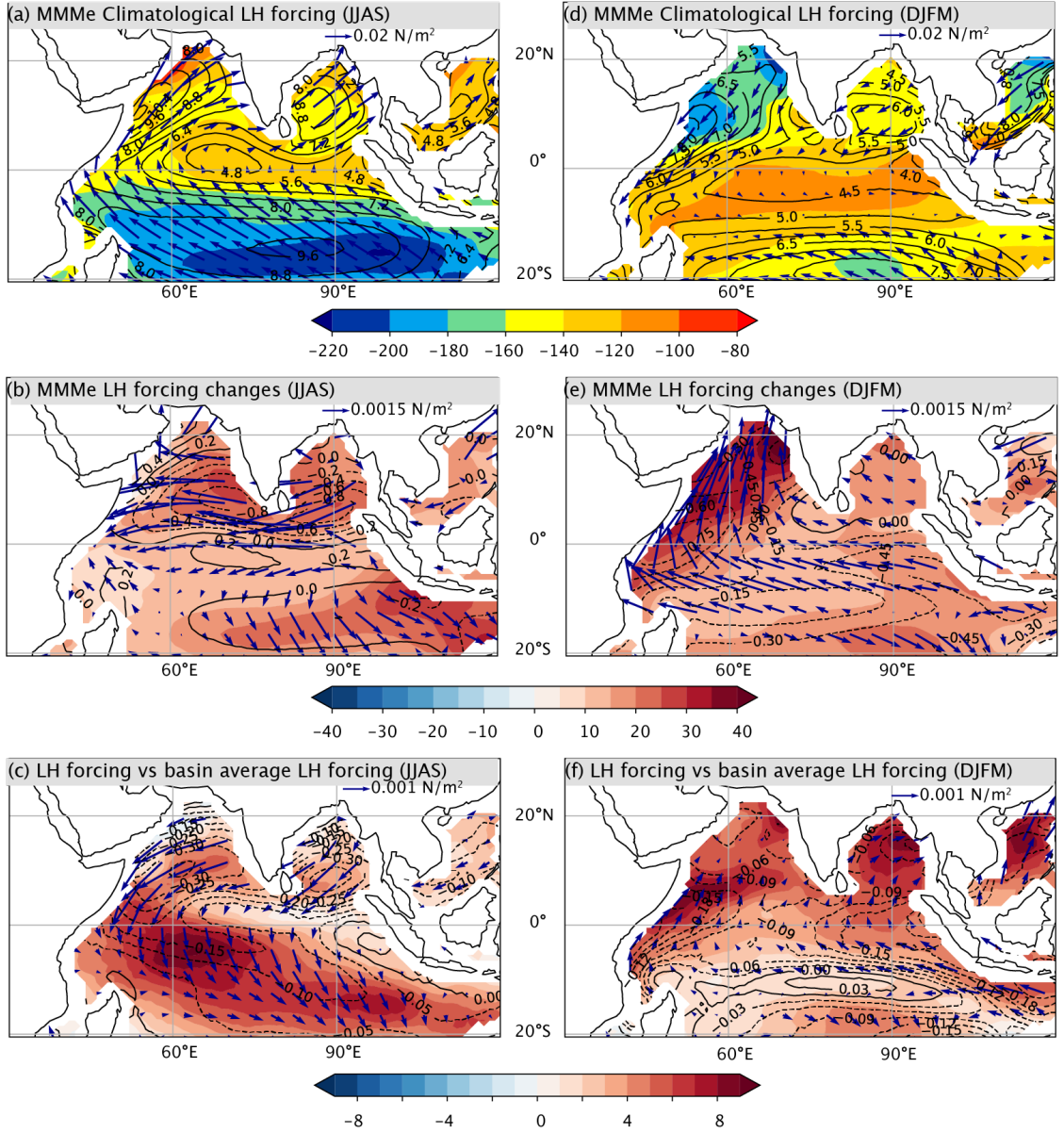


Figure 4.6: Annual circulation slowdown related to seasonal monsoonal circulation reduction. MME latent heat forcing (shading), windspeed (contours) and windstress (arrows). (a,b) climatology and (c,d) changes in summer (JJAS) and winter (DJFM), respectively. (e,f) Linear regression of latent heat flux forcing (shading), windspeed (contours) and wind stress (arrows) changes onto basin-averaged latent heat flux forcing across CMIP models for summer and winter, respectively.

Linearizing the bulk formula indicates that LH forcing depends on wind speed and near-surface relative humidity changes (e.g. ZL14). Fig. 4.5ab displays surface wind speed (fig 4.5a) and relative humidity (fig 4.5b) changes, with the $\langle \Delta LH_{For} \rangle$ overlaid as contours. There is a -.69 pattern correlation of $\langle \Delta LH_{For} \rangle$ with the wind change, and .70 with the relative humidity change, suggesting similar contributions of wind and relative humidity changes to $\langle \Delta LH_{For} \rangle$. Relative humidity increases in CMIP projections (Fig. 4.5b), leads to more saturated near-

surface air, which suppresses surface evaporation, and also contributes to the positive $\langle \Delta LH_{For} \rangle$. The basin-wide windspeed reduction leads to reduced evaporative cooling, with the largest decrease occurring over the Arabian Sea, the southern Bay of Bengal and the southeastern IO. As illustrated in Figure 4.6, the MMMe wind reduction reflects a weakening of both the summer and winter monsoonal circulations, with wind changes (Fig. 4.6 b,e) generally opposing their present-day climatology (Fig. 4.6a,d). Inter-model regressions to the basin-average latent heat forcing $\langle \Delta LH_{For} \rangle$ (Fig. 4.6c,f) indicate that the southern hemisphere wind reduction dominates in summer, while the northern hemisphere contributes most in winter.

4.4.2 Drivers of basin-average warming diversity

Fig. 4.4b illustrates the decomposition of the inter-model variance in $\overline{\Delta T}$ into contributions from the terms in equation (4.35). As for the MMMe, the inter-model diversity in $\overline{\Delta T}$ is driven by $\overline{\Delta For}$, with a weak opposing contribution from oceanic processes. The atmospheric forcing contribution can further be decomposed, with the strongest contribution from $\overline{\Delta LH_{For}}$ (51 %), followed by $\overline{\Delta SW}$ (41 %), with weaker contributions from $\overline{\Delta LW_{For}}$ (17%) and $\overline{\Delta SH}$ (7%). As for the MMMe pattern, the level of warming induced by $\overline{\Delta LH_{For}}$ is predominantly controlled by the magnitude of the wind speed reduction across models (-0.63 correlation, Fig. 4.5c). The amplitude of this wind reduction reflects the impact of the summer monsoon winds on evaporation in the southern hemisphere, and that of the winter monsoon in the northern hemisphere (Fig. 6ef). In other words, the summer and winter monsoon weakening intensities both contribute to the inter-model diversity in IO-average warming. Relative humidity also contributes to $\overline{\Delta LH_{For}}$ but to a lesser extent (correlation of 0.49, Fig. 5d). These two factors, windspeed reduction and relative humidity increase, are largely independent (correlation of -0.11), and their combined effect in a bi-linear regression model raises the correlation to 0.76. In addition, shortwave radiation changes can be related to cloud cover changes, with a correlation of -0.64 (not shown). As for the MMMe, diversity in the warming magnitude and their related drivers remains consistent across seasons (not shown).

The process contributions discussed in this section refer specifically to the decomposition of the inter-model diversity (Fig. 4.4b). Note that the inter-model spread in average tropical IO warming is relatively small (a MMe warming of about 4°C , while its std is about $(0.4)^{1/2} = 0.6^{\circ}\text{C}$; left bars in Figs. 4.4ab). In summary, there are three key drivers of the inter-model diversity in the basin-averaged Tropical IO warming. The slowdown of the summer and winter monsoonal circulations and increase in near-surface relative humidity operate through their influence on evaporative cooling, and cloud cover changes through their impact on shortwave heat fluxes. In contrast, the direct effect of the greenhouse gases on the net surface longwave flux changes plays a much smaller role, underlining the importance of latent heat forcing in determining the basin-averaged warming amplitude.

4.5 Warming patterns

This section examines the mechanisms driving the tropical IO warming pattern in CMIP models. Section 4.5.1 identifies two key features of the projected pattern: changes in the zonal equatorial SST gradient (IOD-like warming) and the interhemispheric gradient, both of which contribute to inter-model diversity. Section 4.5.2 analyses the drivers of these patterns using equation (4.36), considering both the MMe response and inter-model diversity.

4.5.1 Main features of inter-model diversity

The largest $\Delta T'$ inter-model variations occur in the western tropical IO, particularly off the coasts of Somalia and Oman, and in the equatorial eastern Indian Ocean and southern Indian Ocean, near Java and Sumatra (Fig. 4.7a). In these regions, the standard deviation represents a substantial fraction of the MMe change. To identify dominant modes of inter-model diversity in $\Delta T'$ patterns, we perform an Empirical Orthogonal Function (EOF) analysis across CMIP models. The first EOF,

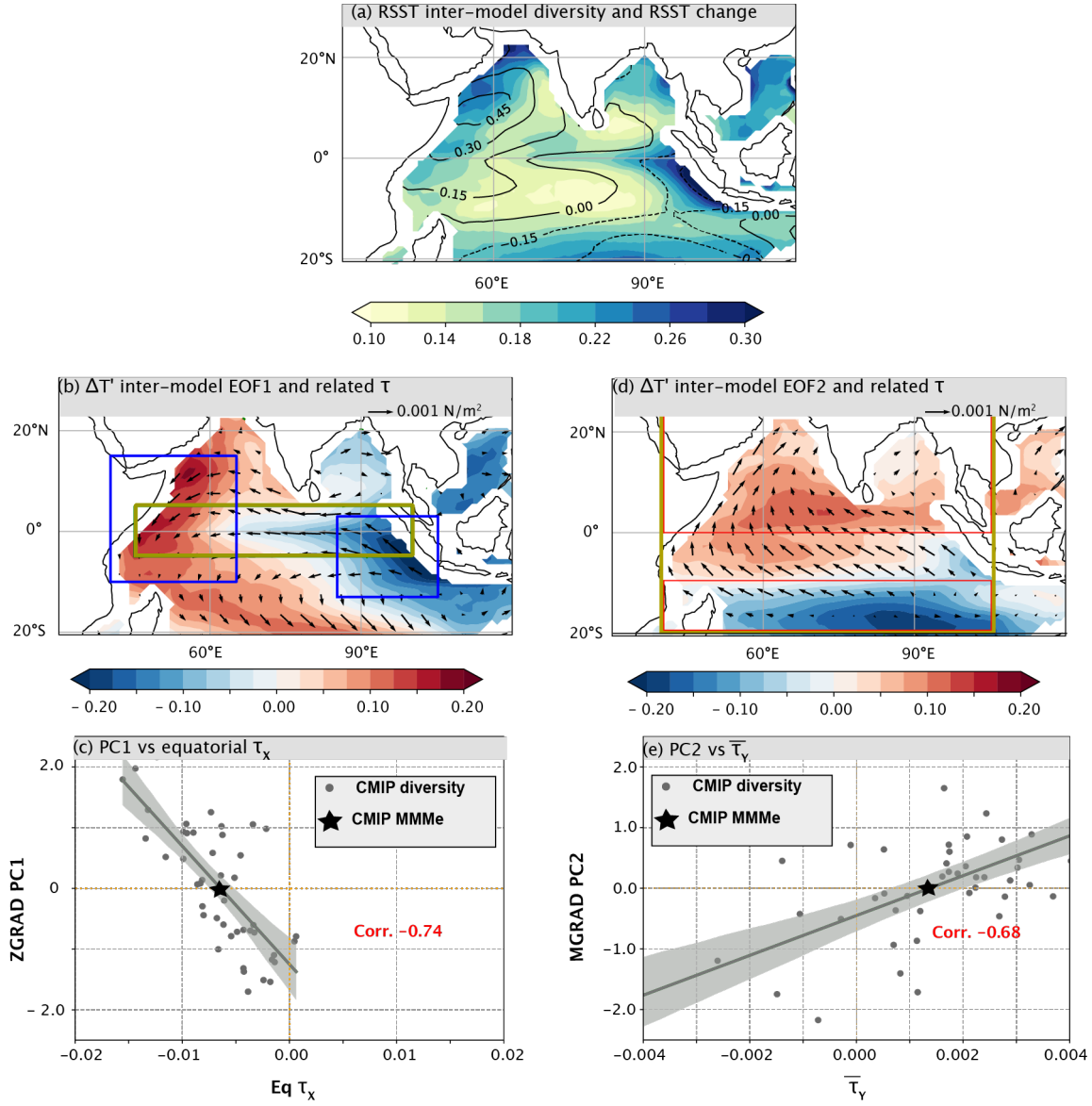


Figure 4.7: Warming pattern inter-model diversity and its drivers. (a) $\Delta T'$ standard deviation (shading) across CMIP models and MMe $\Delta T'$ (contour). (b) First and (d) second EOF modes of $\Delta T'$ (computed across the model space, shading) and associated wind stress signals (vectors) obtained through linear regression to the associated normalised principal component PC1 and PC2, respectively. (c) Scatterplot of the normalised PC1 vs the average zonal wind stress change in the Equatorial box (45°E:100°E and 5°S:5°N) displayed as a green frame on panel (b). (e) Scatterplot of the normalised PC2 vs the average meridional wind stress change over the entire tropical IO domain (30°E-100°E; 20°S-30°N) displayed as a green frame on panel (d). The grey line represents the least-squares regression slope, with the 95% confidence interval shown as a light grey shading. Correlation values are displayed in red.

accounting for 29% of the total variance, reveals a distinct zonal between the EEIO and WEIO (Fig. 4.7b). The associated inter-model diversity in wind stress changes, obtained by regressing wind stress anomalies on the normalised principal component, shows equatorial easterly wind anomalies, flowing from negative to positive $\Delta T'$ regions (Fig. 7b). This pattern closely resembles the MMe wind changes and IOD-like

warming pattern (Fig. 4.1a). The -0.74 correlation with the first principal component indicates a robust link between the IOD-like warming amplitude and equatorial easterly wind stress changes (Fig. 4.7c). The second EOF mode explains 22% of the variance and displays a north-south dipole (Fig. 4.7d). The associated inter-model diversity in wind stress changes features southerly wind anomalies, flowing from negative to positive $\Delta T'$ regions (Fig. 4.7d). The -0.70 correlation with the second principal component indicates a close relationship between the interhemispheric $\Delta T'$ gradient strengthening and the cross-equatorial change (Fig. 7e). The two leading modes (51% of variance) of inter-model diversity can be described as amplitude modulations of the (1) MMMe IOD-like warming and associated zonal circulation slowdown and (2) interhemispheric temperature gradient and associated cross-equatorial circulation changes.

4.5.2 Drivers of the Tropical IO warming pattern

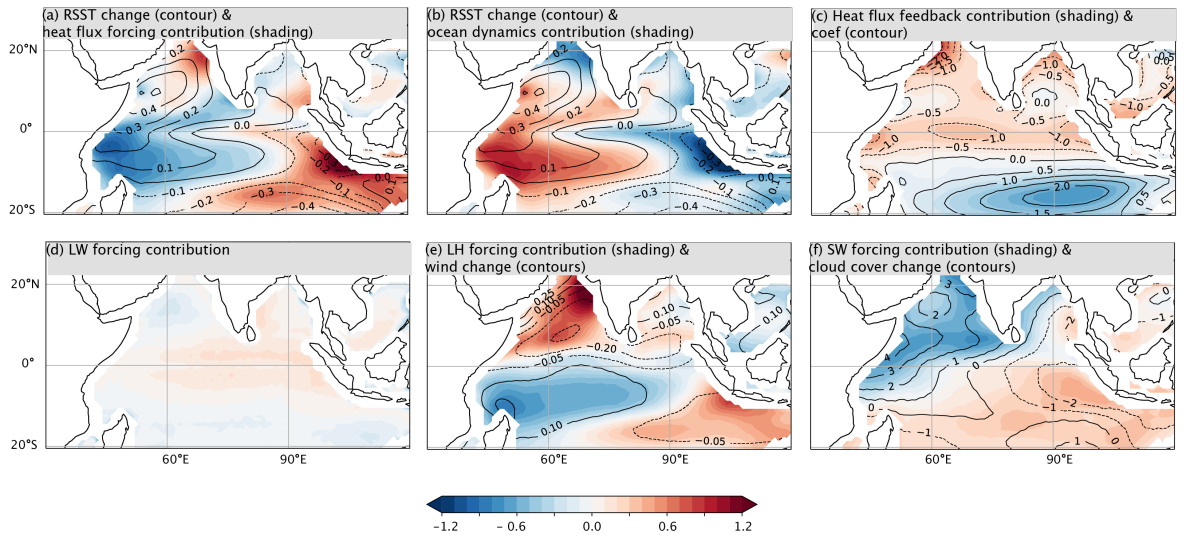


Figure 4.8: Drivers of MMMe IO warming pattern. Contributions $\langle \Delta T' \rangle$ from (a) surface heat flux forcing ($\langle \Delta For' \rangle$), (b) oceanic processes ($\langle \Delta O' \rangle$) and (c) heat flux feedback coefficient ($\alpha' \overline{\Delta T}$). Contours represent $\langle \Delta T' \rangle$ (°C) in panels (a) and (b) and $'$ ($W.m^{-2}.K^{-1}$) in panel (c). The surface heat flux forcing in panel (a) is further decomposed into contributions from (d) net longwave radiation ($\langle \Delta LW \rangle$), (e) latent heat flux ($\langle \Delta LH'_{For} \rangle$, shading), with MMMe windspeed change ($m.s^{-1}$) overlaid as contours, and (f) shortwave radiation ($\langle \Delta SW' \rangle$, shading), with MMMe cloud cover (%) overlaid as contours.

Figure 4.8 displays the contributions of individual processes to the MMMe change $\langle \Delta T' \rangle$, as derived from equation (5). $\langle \Delta O' \rangle$ exhibits an east-west equa-

torial dipole that matches the projected $\langle \Delta T' \rangle$ pattern (Fig. 4.8b). In contrast, $\langle \Delta For' \rangle$ (Fig. 4.7a), primarily driven by $\langle \Delta LH'_{For} \rangle$ and $\langle \Delta SW' \rangle$ (Fig. 8e,f), largely mirrors $\langle \Delta O' \rangle$ but with the opposite sign. The inhomogeneity of the feedback coefficient, $\langle \alpha' \overline{\Delta T} \rangle$, warms the northern hemisphere and cools the southern hemisphere (Fig. 4.8c).

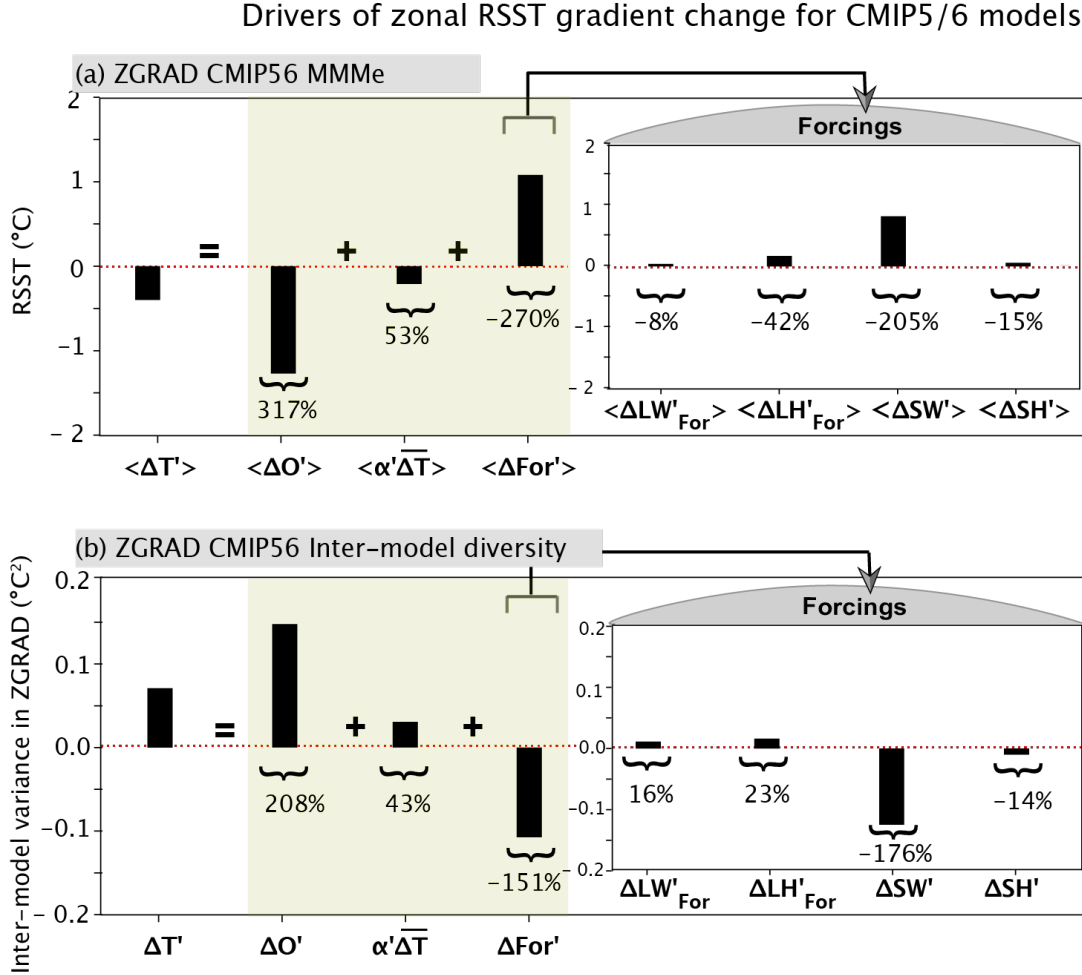


Figure 4.9: Drivers of the projected zonal equatorial $\Delta T'$ gradient change (ZGRAD) MME and of its inter-model diversity. (a) MME ZGRAD, defined as the difference between $\Delta T'$ changes in the EEIO and WEIO (see regions in Fig. 6a), and contributions from changes in ocean dynamics ($\langle \Delta O' \rangle$), feedback coefficient inhomogeneity ($\langle \alpha' \overline{\Delta T} \rangle$) and atmospheric forcing ($\langle \Delta For' \rangle$). $\langle \Delta For' \rangle$ is further decomposed into forcing contributions from longwave radiation ($\langle \Delta LW'_{For} \rangle$), latent heat flux ($\langle \Delta LH'_{For} \rangle$), shortwave radiation ($\langle \Delta SW' \rangle$) and sensible heat flux ($\langle \Delta SH' \rangle$), shown in a separate box. (b) Decomposition of the inter-model variance in ZGRAD into contributions from $\Delta O'$, $\alpha' \overline{\Delta T}$, $\Delta For'$, along with its four components. The percentages below each bar represent the relative contribution of each term to the inter-model variance of ZGRAD ($^{\circ}\text{C}^2$). The percentages below each bar represent the contribution of individual contributions to the ZGRAD MME (a) or inter-model variance (b).

This hemispheric asymmetry is linked to a stronger latent feedback coefficient, leading to less warming in the southern hemisphere (Fig. 2c,d). Overall, this analysis

indicates that oceanic processes drive the MMMe IOD-like warming pattern, while atmospheric forcing opposes this change. Meanwhile, interhemispheric asymmetries in the feedback coefficient drive the MMMe interhemispheric SST gradient strengthening.

4.5.3 Drivers of the zonal equatorial SST gradient change (IOD-like warming pattern)

Given the equatorial zonal SST gradient (ZGRAD) influence on the Walker Cell, we first focus on processes governing its change (blue frames on Fig. 4.7b). We do not detail changes in the EEIO and WEIO boxes, as they largely mirror each other (not shown). Consistent with Figure 4.8, the ZGRAD reduction is predominantly

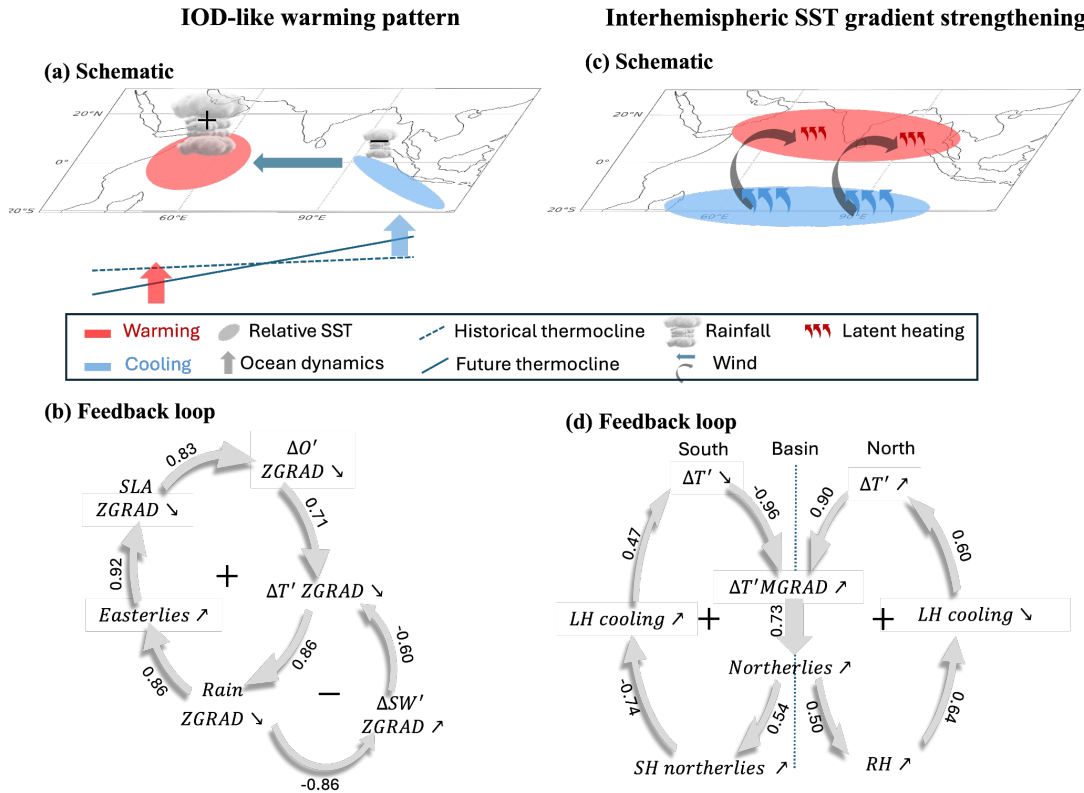


Figure 4.10: Mechanisms driving the two dominant warming patterns in the Tropical IO. (a) Schematics representation of the processes driving the IOD-like warming pattern and (b) the associated feedback loop. Correlations along the feedback loop indicate inter-model relationships between variables. The sign of the feedback is indicated in the center of the loop. (c, d) Similar schematic and feedback loop for the strengthening of the interhemispheric SST gradient.

attributable to $\langle \Delta O' \rangle$, while $\langle \Delta For' \rangle$ opposes this change (Fig. 4.9a). This opposing contribution is mainly driven by $\langle \Delta SW' \rangle$ and to a lesser extent $\langle \Delta LH'_{For} \rangle$.

The heterogeneity of the feedback coefficient, specifically the weaker negative evaporative feedback in the climatologically colder western Indian Ocean, also modestly contributes to $\langle \Delta T' \rangle$.

Figure 4.9b shows the decomposition of the ZGRAD inter-model variance into contributions from the different terms in equation (4.34). Similar to the MME results, ZGRAD inter-model diversity is driven by differences in $\Delta O'$, with the spatial heterogeneity of the feedback coefficient playing a secondary role. $\Delta For'$ generally opposes the gradient change. The ZGRAD inter-model spread is substantial: its MME is about -0.5°C (left bar on 4.9a) for a standard deviation of $(0.75)^{1/2} \approx 0.9^\circ\text{C}$. In other words, some models project a positive ZGRAD change while others project a negative one. This highlights the importance of understanding the processes that contribute to this strong spread (Fig. 4.4b).

Figure 4.10a,b highlights the mechanisms determining the amplitude of the IOD-like warming across CMIP models. Following the “warmer-get-wetter” paradigm, a negative ZGRAD ($\Delta T'$ warming in the WEIO and cooling in the EEIO) intensifies convection in the WEIO and suppresses it in the EEIO (Fig. 4.10a), with an inter-model correlation of 0.86 (Fig. 4.10b). The Gill response to this east-west convective dipole consists in equatorial easterly changes (0.86 correlation). The equatorial Sverdrup balance implies a thermocline deepening in the western Equatorial IO (WEIO) and shoaling in the EEIO, in response to these equatorial easterly changes (correlation of 0.92). The thermocline feedback implies enhanced cooling through oceanic processes in the EEIO, and reduced cooling in the WEIO (inter-model correlation of 0.83). The 0.71 correlation between changes in the $\Delta O'$ zonal gradient $\Delta T'$ closes the feedback loop. This positive feedback loop on the zonal SST gradient is characteristic of the Bjerknes feedback.

There is also a stabilising negative feedback from shortwave fluxes. A stronger IOD-like pattern yields an increased rainfall and cloudiness dipole, strengthening the shortwave flux dipole (-0.86 correlation) and ZGRAD damping (-0.60 correlation). The strong correlations at each step of these feedback loops illustrate the Bjerknes feedback pivotal role in setting the IOD-like warming amplitude, with shortwave fluxes acting as a damping process. While these feedback mechanisms can

adjust the level of ZGRAD changes, they do not explain the initial trigger which starts

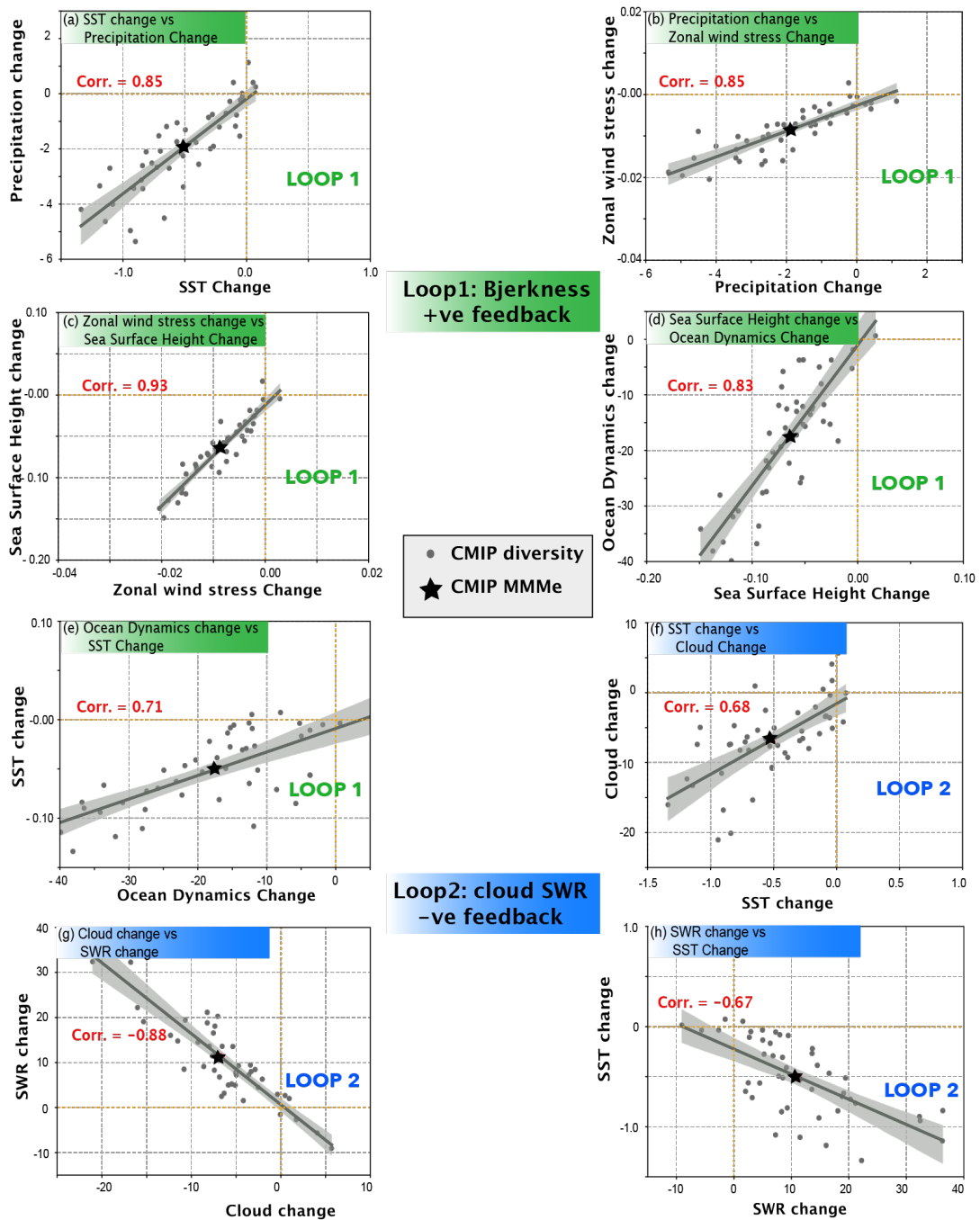


Figure 4.11: Bjerknes feedback for the boreal summer and fall zonal circulation changes. Scatterplots of changes in boreal summer and fall (June to November average) (a) zonal rainfall gradient (mm.day^{-1}) vs. zonal SST gradient (K); (b) Equatorial zonal wind stress (Nm^{-2}) vs. Zonal rainfall gradient (mm.day^{-1}); (c) zonal sea surface height gradient (m) vs. Equatorial zonal wind stress (Nm^{-2}); (d) Zonal gradient of changes in oceanic dynamics ($\Delta O'$) vs zonal sea surface height gradient (e) Zonal SST gradient (K) vs Zonal gradient of changes in oceanic dynamics ($\Delta O'$) (f) Cloud fraction gradient (%) vs Zonal SST gradient (K) (g) Zonal SWR gradient (W/m^2) vs zonal Cloud fraction gradient (%) (h) zonal SST gradient vs. zonal SWR gradient (W/m^2). The loop1 (indicated in green colour in each plot) represents the Bjerknes positive feedback loop and the Loop2 (blue colour) indicate the Cloud SWR negative feedback loop. Each grey dot represents a CMIP56 model, and the black star the MME. The black line is the slope, with the 95% confidence interval in light grey shading (correlation values in red). The gradients are estimated from average values in the EEIO minus those in the WEIO.

weakening ZGRAD. We will discuss potential trigger mechanisms in Section 6.

Unlike the basin-wide warming, ZGRAD changes display a seasonal modulation (Fig. 4.11), with the strongest MME IOD-like warming and inter-model diversity in summer and fall. During these seasons, the thermocline is climatologically shallower in the EEIO, amplifying the efficiency of the Bjerknes feedback loop (Fig. 4.11).

4.5.4 Drivers of the inter-hemispheric SST gradient change

We then turn our focus on the meridional SST gradient (MGRAD; red frames on Fig. 4.7d) changes, given its importance in shaping the Hadley Cell, Intertropical Convergence Zone, monsoonal circulation and rainfall. Consistent with Figure 4.8, the MME MGRAD strengthening is predominantly driven by the inhomogeneity of the feedback coefficient (Fig. 4.12a), $\langle \alpha' \overline{\Delta T} \rangle$ due to a stronger negative evaporative feedback in the SIO, where winds are climatologically stronger (Fig. 4.2).

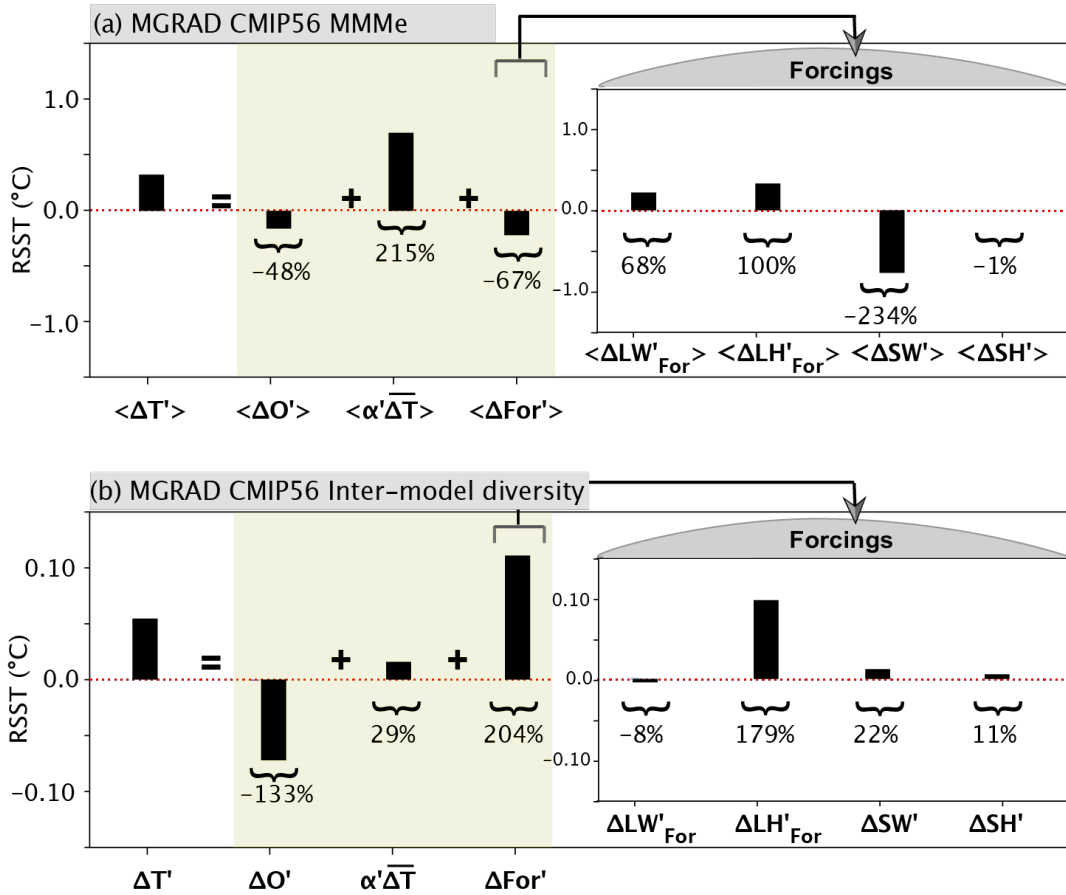


Figure 4.12: Drivers of the projected meridional interhemispheric $\Delta T'$ gradient change (MGRAD) MME and of its inter-model diversity. Same as Figure 4.9, but for MGRAD instead of ZGRAD.

$< \Delta For' >$ generally opposes this change (Fig. 4.12a), mainly through shortwave radiation changes, because cloudiness increases in the northwestern Indian Ocean due to the warmer gets wetter mechanism.

Figure 4.12b shows the decomposition of the MGRAD inter-model variance into contributions from the different terms in equation (4.34). In contrast to the MMMe results, MGRAD inter-model diversity is mainly attributable to the differences in $\Delta For'$, with the diversity in $\alpha' \overline{\Delta T}$ playing a much weaker role, and $\Delta O'$ resisting the change. $\Delta LH'_{For}$ is the largest contributor to the diversity in $\Delta For'$. MGRAD has a weaker seasonal modulation than ZGRAD (not shown).

Figure 4.10c,d illustrates the mechanisms driving the strengthening of MGRAD in CMIP models. On average, this gradient is set up by a differential interhemispheric evaporative feedback, linked to stronger climatological winds in the SIO compared to the NIO. This feedback results in $\Delta T'$ cooling in the SIO and warming in the NIO, which induces southerly cross-equatorial wind anomalies of varying magnitude across CMIP models (0.73 correlation). Stronger cross-equatorial wind anomalies amplify wind speeds in the SIO (0.54 correlation), increasing latent heat cooling (-0.74), which cools the southern hemisphere (0.47) and strengthens the MGRAD (-0.96). Simultaneously, stronger southerly winds decrease the southward transport of dry continental air by the winter monsoon, increasing NIO relative humidity (0.50). This higher relative humidity reduces latent heat cooling (0.64), enhancing the northern hemisphere warming (0.60), and strengthening MGRAD (0.90). The lowest correlation above (0.47) is significant at the 99.9% level, indicating a robust feedback loop, although less robust than for ZGRAD.

These results indicate that the trigger of the MMMe interhemispheric temperature gradient strengthening is the stronger southern hemisphere evaporative cooling, in relation to stronger winds. A feedback loop between the interhemispheric gradient change, winds and evaporation further controls the MGRAD inter-model diversity. This feedback loop involves wind changes in both hemispheres, a modulation of latent heat flux forcing by windspeed in the south and relative humidity variations in the north.

4.6 Summary and Discussion

The level of tropical IO warming is critical for its impacts on regional land and ocean climates, while the specific pattern of this warming influences atmospheric stability and circulation. This study examines the mechanisms behind the average tropical IO warming using projections from 46 CMIP5/6 historical simulations and unmitigated projections, applying an upper ocean heat budget framework adapted from ZL14. By assessing contributions from oceanic processes, SST-independent heat flux forcing, and SST-dependent heat flux feedback, we refine the understanding of Tropical IO warming drivers. Beyond the basin-wide warming, our analysis highlights two distinct warming patterns that together explain half of the total inter-model RSST variance: the zonal equatorial "IOD-like" warming pattern (Cai et al., 2014) and a less-documented modulation of the interhemispheric SST gradient.

ZL14 primarily attributed warming to downward longwave, treating it entirely as a forcing. In contrast, we apply recent analytical advances, which attribute most of the downward longwave change to a positive feedback linked to SST-driven atmospheric warming and moistening SR22. Consequently, we find a smaller role for downward longwave radiation than ZL14. Instead, our results rather indicate that latent heat flux forcing dominates the MME basin-averaged warming and its inter-model diversity, aligning with previous studies (Du and Xie, 2008; Dong and Zhou, 2014a). This reduced evaporative cooling results from a combination of weaker surface winds and higher near-surface relative humidity (Lainé et al., 2014). The wind reduction is tied to weakened monsoonal circulation during both summer and winter (Sooraj et al., 2015; Parvathi et al., 2017), while the mechanisms driving the relative humidity increase remain poorly understood (Shakespeare and Roderick, 2024). We also find that cloud cover variations also contribute to inter-model diversity through their effect on shortwave radiation, consistent with studies linking global warming uncertainty to cloud feedbacks (e.g., Zelinka and coauthors, 2020). However, our analysis treats shortwave radiation purely as a forcing due to the difficulty of establishing an explicit relationship between cloud cover and SST changes, underscoring the need to better account for cloud feedback effects. These findings highlight that

reducing uncertainties in monsoonal wind changes and cloud feedback processes is critical for improving Tropical IO warming projections in CMIP models.

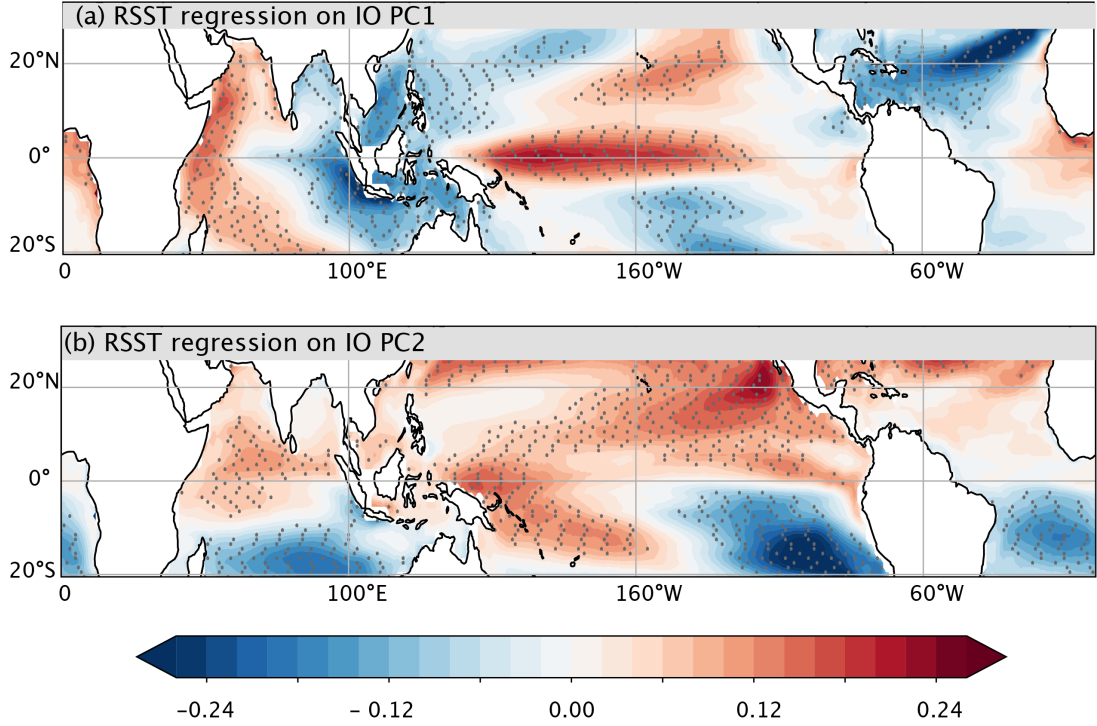


Figure 4.13: Teleconnections of the two Tropical IO warming patterns with other tropical basins. Map of inter-model regressions $\Delta T'$ over the entire tropical band to the normalised (a) PC1 and (b) PC2. Stippled regions indicate areas where regression values are significantly different from zero at over the 95% confidence level.

One of the two major tropical IO warming patterns highlighted in this study is the well-documented IOD-like warming (e.g. Zheng et al., 2013). We find that the Bjerknes feedback loop largely determines both its MME amplitude and inter-model variability, as indicated by the dominant contribution of oceanic processes. While this positive feedback amplifies zonal SST gradient changes, it does not fully explain the initial trigger of its weakening. A stronger negative evaporative feedback over the warmer EEIO compared to the cooler WEIO contributes to both the MME zonal gradient weakening and its inter-model diversity (Fig. 4.9), suggesting it may help initiate this pattern, consistent with previous studies (e.g., Liu et al., 2015; ZL14). Additionally, some studies reveal a weakening of the Walker circulation in response to spatially homogeneous warming (Ma et al., 2012; Zhang and Li, 2017; Sharma et al., 2023S), which could initiate the zonal SST gradient weakening by altering the equatorial thermocline slope. Others point to the ocean thermostat mechanism (Liu et al.,

2015), where seasonal upwelling in the EEIO Ocean during boreal summer and fall moderates warming by bringing up deeper cooler water, consistent with our analyses indicating a reduced warming through oceanic processes in the EEIO (Fig. 4.8b).

We explore another potential trigger for the weakening of the Tropical IO zonal equatorial SST gradient: interactions with other tropical basins (Cai et al., 2019). Figure 12a highlights that models projecting the strongest IOD-like warming pattern also display an enhanced warming in the western and central Pacific. This Pacific warming may initiate the IOD-like warming pattern by inducing easterly anomalies over the equatorial Indian Ocean, similar to how El Niño events promote positive IOD events at interannual timescales (Cai et al., 2013).

However, this Indo-Pacific connection may be exaggerated in models due to a cold and dry western Pacific bias (Li et al., 2016b), which shifts the atmospheric response westward and may artificially amplify the IOD-like pattern. Additionally, biases specific to the TIO, such as overestimated IOD amplitude (Li et al., 2016a) and an unrealistically shallow thermocline in the EEIO (Wang et al., 2021), further challenge the robustness of this projected pattern. These biases have opposing effects: an overestimated IOD amplitude enhances future IOD-like warming (Li et al., 2016a)], while an underestimated thermocline slope weakens it (Wang et al., 2021). These findings underscore the urgent need to reduce the impact of present-day model biases on Tropical IO warming projections (Lengaigne et al., 2024).

Our results reveal another prominent but less studied warming pattern: the strengthening of the interhemispheric SST gradient. This MMMe gradient increase is primarily driven by differential evaporative feedback, where stronger climatological winds in the SIO reduce negative latent feedback in that region. Inter-model variability in this pattern is largely linked to differences in cross-equatorial winds changes, which modulate interhemispheric contrasts in latent heat flux forcing. Specifically, stronger SIO winds increase latent heat cooling in the southern hemisphere during boreal summer, while weakened winter monsoon northerlies enhance near-surface humidity in the NIO, reducing evaporative cooling.

To date, Sharma et al. (2023) is the only study to specifically investigate the mechanisms behind the interhemispheric SST gradient strengthening, focusing on a

single CMIP model (Large ensemble simulations of CESM2) projects a reduced inter-hemispheric SST gradient – which is an outlier among CMIP models. Our heat budget analysis for this model (single member of CESM2; not shown) confirms Sharma et al. (2023)'s interpretation that SIO low-cloud cover and shortwave radiation changes drive this weakening. However, it also underscores the model's outlier status, not only due to its atypical interhemispheric SST gradient reduction but also because cloud changes rarely play a dominant role in the 44 other CMIP5/6 models examined. These findings emphasize the importance of broad multi-model analyses to establish robust mechanisms for regional climate change signals.

Figure 4.13b reveals that the tropical IO interhemispheric SST gradient change is part of a broader pan-tropical pattern, with similar features in the Pacific and Atlantic Oceans. Our results emphasize the role of enhanced evaporative cooling in driving the MME cooling in the SIO, whereas reduced warming in the southeastern Pacific has been attributed to future increases in wind speed (Xie et al., 2010). Beyond the interhemispheric asymmetry in land distribution (Stouffer et al., 1989), recent studies suggest that enhanced North Atlantic and Pacific warming is linked to the North Atlantic warming hole, which strengthens non-radiative fluxes in the Northern Hemisphere (Park et al., 2024). Given the climatic implications of this asymmetrical oceanic warming pattern, particularly its impact on atmospheric circulation and rainfall (Kang et al., 2008; Byrne et al., 2018; Wang et al., 2020), further research is needed to better understand the mechanisms driving interhemispheric SST changes in the tropics and beyond.

While the statistical approach in this chapter provides valuable insights, it lacks the depth of modelling studies that allow for a more detailed investigation of underlying mechanisms. Next chapter will use oceanic simulations forced with projected changes in forcing patterns to assess the impact of present-day model biases on tropical IO SST projections and to better quantify the respective contributions of heat fluxes and wind stress changes to projected SST changes.

Chapter 5

Drivers of the Indian Ocean Warming – A Modelling Approach

5.1 Introduction

The previous chapter addressed part of Objective 3 of this thesis, by investigating the mechanisms controlling the amplitude and spatial pattern of IO warming across CMIP models, using a statistical heat budget framework. While this approach yielded valuable insights, it also presents several limitations. First, it relies on underlying assumptions inherent in the heat budget framework, considering for instance that the simulations are always at equilibrium which is obviously not valid when analysing transient simulations. More importantly, the purely statistical nature of the analysis, based on correlations, regressions, and covariances, does not allow for establishing causal relationships between the identified drivers of SST changes. Furthermore, a major challenge in projecting future IO warming arises from significant present-day biases in CMIP simulations (e.g., Li et al., 2016a). These biases arise from physical approximations, parameterization schemes, and the coupled nature of the ocean-atmosphere system. The statistical approach used in the previous chapter does not allow for a direct identification of the mechanisms through which such biases affect future oceanic projections.

To overcome these limitations, this chapter adopts a dynamical approach based on the experimental framework proposed by Lengaigne et al. (2024). This methodology offers several advantages. First, the use of ocean-only simulations forced with surface fluxes allows for an explicit separation of the respective contributions of changes in heat, momentum and freshwater fluxes to projected IO warming. It also enables a direct comparison with the statistical results from the previous chapter, pro-

viding a way to assess their robustness and consistency. Second, this approach allows correcting the mean-state biases present in CMIP models. As such, it offers a valuable tool to quantify how present-day biases influence projected oceanic IO changes.

5.2 Data and Methods

This study builds on the experimental framework developed by Lengaigne et al. (2024) , which involves two steps. The first step entails performing a control simulation using surface fluxes derived from an atmospheric reanalysis product (detailed in data and method chapter 2), with long-term climate change trends removed. This simulation serves as a baseline, reflects a bias-corrected present-day ocean state unaffected by climate change signals. In the second step, a series of climate change experiments are conducted by superimposing historical and future anomalies in surface heat, freshwater, and wind stress fluxes derived from the selected climate model onto baseline reanalysis fluxes forcing. This strategy allows us to isolate the particular influence of each model’s projected climate perturbations on the future ocean state.

5.2.1 The IPSL-CM6-LR model

Although this framework can be applied to a wide range of climate models, this chapter focuses on the IPSL-CM6A-LR model due to its representativeness of tropical IO warming projections across CMIP6 models. This model indeed matches reasonably well the MMMe in terms of IO amplitude of warming, ZGRAD reduction, and MGRAD increase. Figure 5.1 illustrates these comparisons between the IPSL and MMMe, and their respective drivers, using the simplified upper ocean heat budget. The IO-averaged warming is similar although slightly larger for the IPSL model than for the MMMe, owing to a marginally stronger warming through atmospheric forcing (mainly latent forcing) and weaker damping by ocean dynamics (Fig 5.1a).

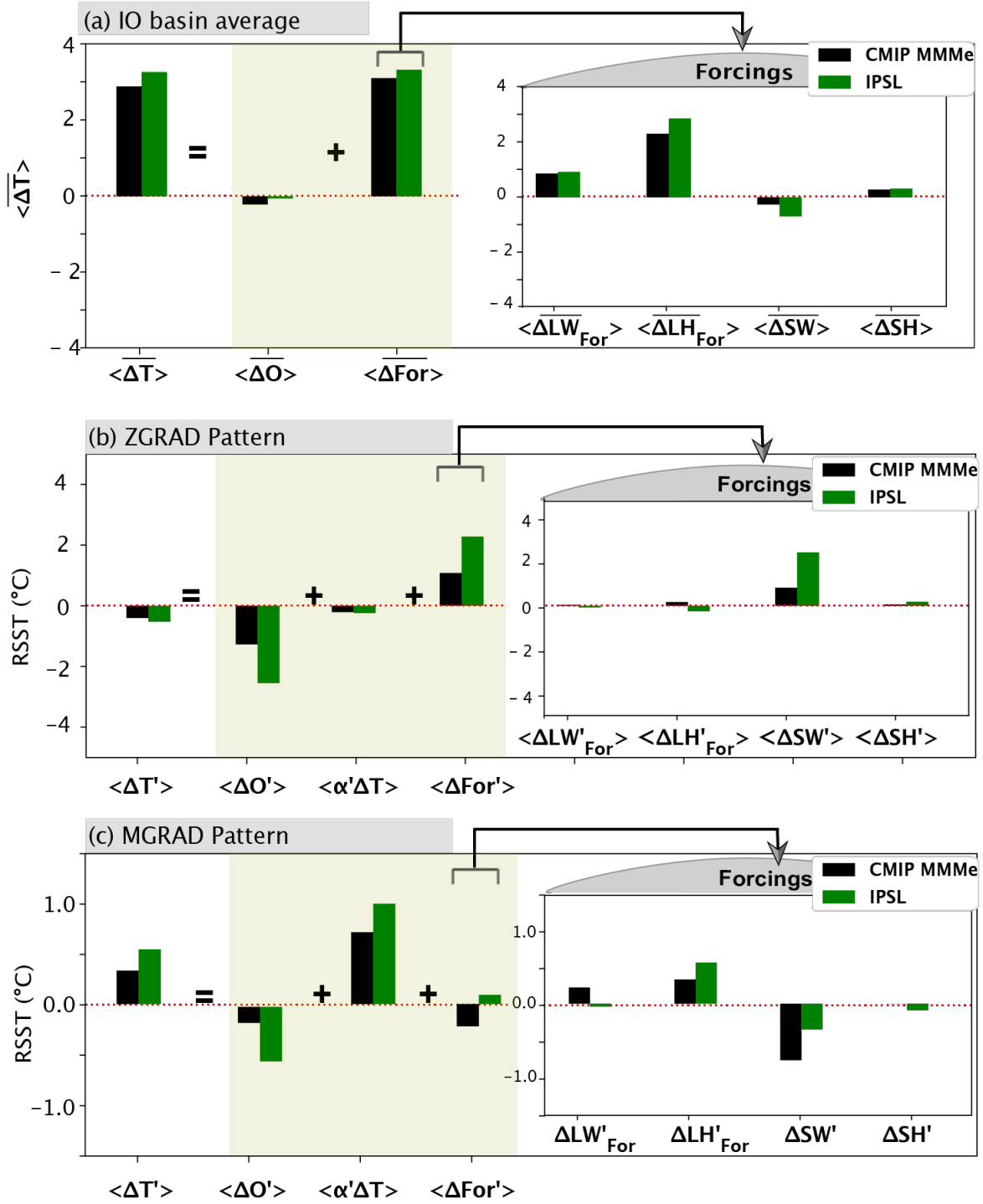


Figure 5.1: Comparison of the drivers of the basin-averaged warming in IPSL-CM6A-LR to that of MME ($\langle \Delta T \rangle$). (a) MME basin-averaged warming $\langle \Delta T \rangle$ from equation (4.35), and contributions from changes in ocean dynamics ($\langle \Delta O \rangle$) and changes atmospheric forcing ($\langle \Delta For \rangle$). $\langle \Delta For \rangle$ is further decomposed in forcing contributions from longwave radiation ($\langle \Delta LW_{For} \rangle$), latent heat flux ($\langle \Delta LH_{For} \rangle$), shortwave radiation ($\langle \Delta SW \rangle$) and sensible heat flux ($\langle \Delta SH \rangle$). (b) Decomposition of the inter-model variance in (ΔT) from equation (4.35) into the contributions from (ΔO), ($\langle \Delta For \rangle$) and its four components. The green bar represent IPSL-CM6A-LR and the black bar represent MME.

The ZGRAD reduction is also slightly larger in the IPSL than in the MME, primarily due to a stronger contribution from ocean dynamics, which is only

partially offset by enhanced atmospheric damping, mainly from shortwave radiation (Fig 5.1b). The IPSL also projects a stronger increase of the interhemispheric SST gradient than the MMMe, driven by greater contributions from differential evaporative cooling and atmospheric forcing (Fig 5.1c). Despite those minor differences, this analysis confirms that the IPSL-CM6A-LR model is qualitatively consistent with the MMMe, both in terms of warming patterns and underlying mechanisms. This broad agreement justifies the choice of this model to study its warming pattern mechanisms using the modelling framework of chapter 5.

5.2.2 The ocean model

The IPSL-CM6-LR model incorporate NEMO3.6 (Nucleus for European Modelling of the Ocean) as their ocean general circulation model Madec et al. (2017). NEMO3.6 features a nominal horizontal resolution of one degree, which increases to one-third of a degree near the equator to better capture tropical dynamics. Vertically, the model is discretized into 75 levels, with fine resolution (1 meter) near the surface, gradually increasing to 200 meters in the deep ocean. This vertical structure allows for detailed representation of the entire water column.

This model couples several oceanic components. The physical component is OPA (Océan PARallélisé), which is coupled with the LIM3 sea ice model (Louvain-la-Neuve Ice Model) developed by Rousset et al., 2015, as well as with the biogeochemical model PISCES-v2 (Pelagic Interaction Scheme for Carbon and Ecosystem Studies) Aumont et al., 2015. This configuration enables an integrated simulation of oceanic physical, cryospheric, and biogeochemical processes. While the focus of this thesis is centered on the physical processes that govern the IO warming and its pattern, the inclusion of a biogeochemical component will also allow investigating IO productivity and oxygen changes in the future.

However, in our framework, the ocean model does not include the sea ice component, because of the use of a flux-forced approach. This can produce thermal anomalies, such as locally sub-freezing ocean temperatures in polar regions. To address this issue, we follow the solution proposed by Silvy et al. (2022), where ocean

temperature is artificially capped at the freezing point in both the equation of state and the calculation of the Brunt–Väisälä frequency. This method preserves the physical consistency of the model even in the absence of explicit sea ice representation.

5.2.3 Control simulation

I first establish a control simulation that represents a stable mid-20th century ocean state, capturing realistic natural variability while excluding any anthropogenic climate change signals. To this end, a linear detrending to atmospheric input variables from the JRA-55 reanalysis dataset (Kobayashi2015) over the period 1958–2022, including 10-meter air temperature, surface specific humidity, and surface wind speed. The resulting detrended data are then used to force the ocean model NEMO-PISCES in an initial bulk simulation. This simulation employs bulk formulae (Large2004) and is initialized using the World Ocean Atlas datasets (Locarnini et al., 2018, Mishonov et al., 2024, Reagan et al., 2024).

The simulation is repeated over seven 65 years cycles (455 years in total) to ensure stabilization, particularly of deep ocean biogeochemical variables (Lengaigne2024). To derive the surface boundary conditions (in the form of fluxes) required for the climate change simulations, we extract these fluxes from the final three cycles of the bulk simulation. These fluxes are then used to force a new set of simulations beginning at the end of the fourth bulk cycle. This second phase includes a 65-year adjustment period followed by two cycles that constitute the final control simulation (CTL). The CTL simulation provides a stable reference state for assessing climate change response.

5.2.4 Climate change simulations

Once the CTL simulation is completed, climate change simulations are performed (referred to as CC-; Table 5.1). These simulations use the same surface fluxes as in CTL experiment, but with the addition of perturbations representing historical and future changes in surface fluxes (heat, freshwater, and wind stress) associated with anthropogenic forcing.

These perturbations are derived from the monthly mean surface fluxes sim-

ulated by ensemble simulations of the IPSL-CM6A-LR model covering both historical and future periods under the SSP585 scenario. Averaging multiple ensemble members from a single CMIP6 model is an effective approach to reduce internal climate variability. For the IPSL-CM6A-LR, we average all available ensemble members: 32 members for the historical period (1850–2024) and 7 members for the SSP5-8.5 scenario.

The future changes in air-sea fluxes are calculated as:

$$\Delta F(i, j, t) = F(i, j, t) - \overline{F(i, j, t)} \quad (5.1)$$

where i, j denote the model grid coordinates and t is time. The overbar represents the temporal average over the 1948–1967 period, centered on 1958, the start of the JRA-55 dataset. the term $F(i, j, t) = \langle F(i, j, t, k) \rangle_{k=1,2,\dots,n}$ corresponds to the ensemble mean flux across all available ensemble members k . A 25-year running mean is applied to further reduce internal variability.

In this setup, natural variability (e.g., ENSO, IOD) in the CTL (Table 5.1) experiment originates from the detrended and repeated JRA-55 dataset. For the climate change simulations, this internal variability is exactly the same, while only the long-term changes in surface fluxes are added. This approach isolates the externally forced response, while still accounting for potential rectification of internal variability by changes in the mean state.

As detailed in the previous chapter, surface heat flux changes can be decomposed into two components: a feedback component dependent on SST and a forcing component independent of SST. Since the feedback component is tied to SST, using it directly from coupled models would introduce inconsistencies, as it would reflect the SST mean state of the coupled simulation rather than that of our CC-ALL experiment. Therefore, it is important to explicitly separate these two contributions.

To isolate the forcing component of latent (ΔQ_{LH}^{For}) and longwave (ΔQ_{LW}^{For}) heat flux perturbations, the SST-driven feedback are subtracted for the total pertur-

bations as follows:

$$\Delta Q_{LW_{IPSL}}^{For}(i, j, t) = \Delta Q_{LW_{IPSL}}(i, j, t) - (\lambda_{LW_{IPSL}}(i, j, t_{seas}) * \Delta SST_{IPSL}(i, j, t)) \quad (5.2)$$

$$\Delta Q_{LH_{IPSL}}^{For}(i, j, t) = \Delta Q_{LH_{IPSL}}(i, j, t) - (\lambda_{LH_{IPSL}}(i, j, t_{seas}) * \Delta SST_{IPSL}(i, j, t)) \quad (5.3)$$

Here, $\Delta Q_{LW_{IPSL}}(i, j, t)$ and $\Delta Q_{LH_{IPSL}}(i, j, t)$ are the longwave and latent heat flux changes. The seasonally varying feedback coefficients $\lambda_{LW_{IPSL}}(i, j, t_{seas})$ and $\lambda_{LH_{IPSL}}(i, j, t_{seas})$ are computed from the IPSL-CM6-LR model outputs as detailed in the previous chapter. $\Delta SST_{IPSL}(i, j, t)$ represents the SST anomalies relative to the historical period, calculated similarly to $\Delta Q(i, j, t)$.

In the forced ocean simulations, the total heat flux perturbation is then:

$$\Delta Q_{tot}(i, j, t) = (\Delta Q_{SW_{IPSL}} + \Delta Q_{SH_{IPSL}} + \Delta Q_{LW_{IPSL}}^{For} + \Delta Q_{LH_{IPSL}}^{For})(i, j, t) + \Delta Q_{Feed}(i, j, t) \quad (5.4)$$

Here, $\Delta Q_{tot_{IPSL}}$ represents the total heat flux perturbation applied to the ocean model. $\Delta Q_{SW_{IPSL}}$ and $\Delta Q_{SH_{IPSL}}$ are the shortwave and sensible heat flux changes, directly derived from the IPSL outputs. $\Delta Q_{Feed}(i, j, t)$ is SST-dependent part of the surface heat flux changes, represented as a linear relaxation toward the SST from the CTL simulation in our CC-ALL experiment as:

$$\Delta Q_{Feed}(i, j, t) = \lambda_{tot_{IPSL}}(i, j, t_{seas}) * \Delta SST_{CC-ALL}(i, j, t) \quad (5.5)$$

where the total feedback coefficient is defined as $\lambda_{tot_{IPSL}} = \lambda_{LW_{IPSL}} + \lambda_{LH_{IPSL}}$, and $\Delta SST^{CC-ALL}(i, j, t)$, the SST anomaly from the climate change simulation, is:

$$\Delta SST^{CC-ALL}(i, j, t) = SST^{CC-ALL}(i, j, t) - SST^{CTL}(i, j, t) \quad (5.6)$$

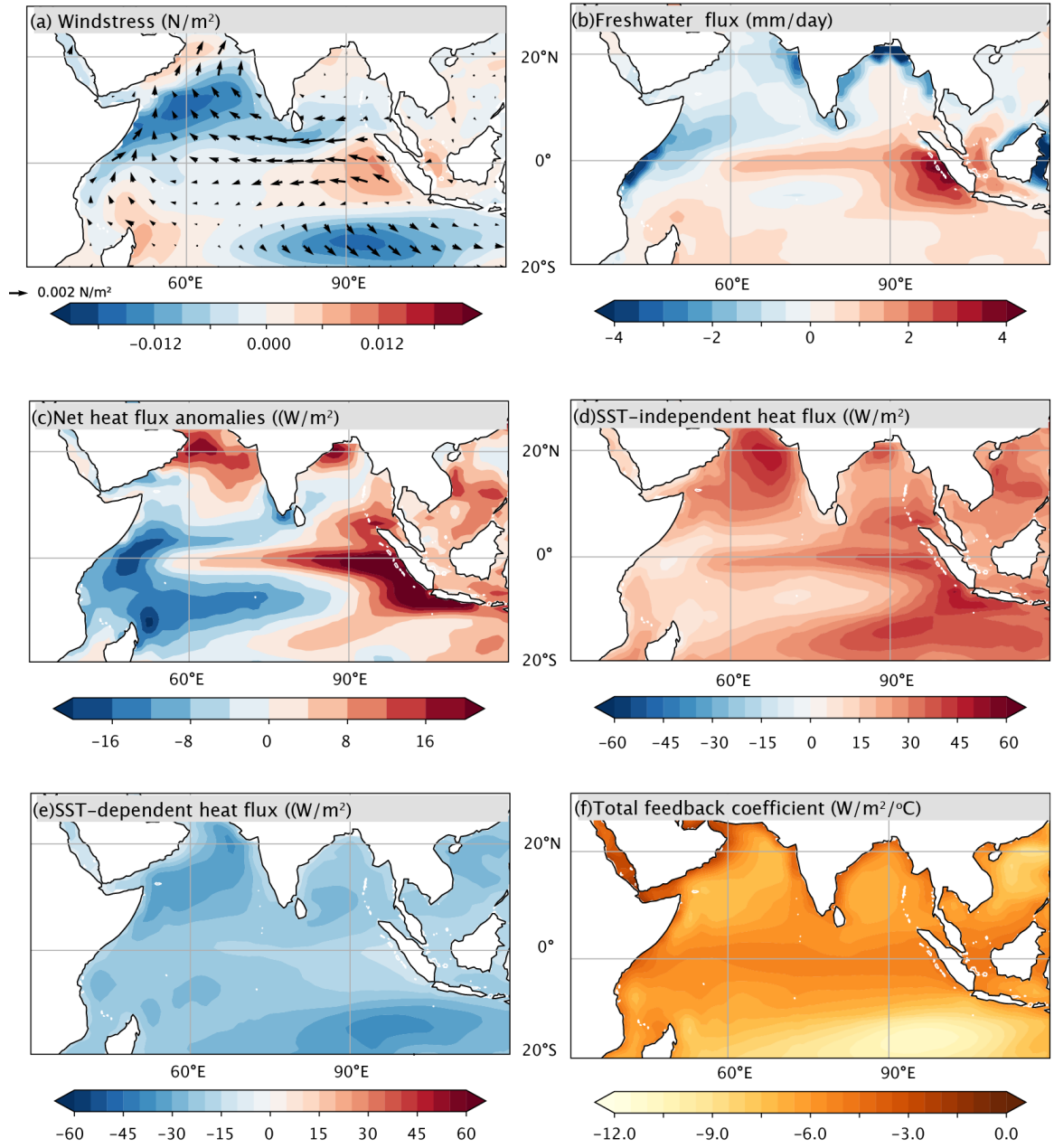


Figure 5.2: *IPSL climate change anomalous forcing. IO maps of climate change anomalous forcing over the single timestep of 2068–2087 period. The climate change flux anomalies, derived from the IPSL historical + SSP5-8.5 multi-member ensemble mean. (a) freshwater flux (mm/day), (b) surface wind stress ($\text{N}\cdot\text{m}^{-2}$), (c) net heat flux anomalies applied to the ocean (W/m^2), (d) SST-independent heat flux forcing (W/m^2), (e) negative SST-dependent heat flux feedback term (W/m^2), and (f) total feedback coefficient diagnosed from the IPSL model ($\text{W}/\text{m}^2\cdot^\circ\text{C}^{-1}$).*

This setup ensures a physically consistent feedback and forcing components of surface heat flux changes.

The flux anomalies used in CC-ALL simulation relative to control runs are illustrated in fig. 5.2 for the period 2068–2087. Figure 5.2a indicates a weakening of wind-stress over the Arabian Sea and a strengthening over the eastern Indian Ocean, along with a reversal of equatorial winds, indicative of a slowdown of the

Walker circulation (relative to control run). Freshwater flux anomalies (Fig. 5.2b), defined as evaporation minus precipitation minus runoffs, indicate enhanced rainfall in the western equatorial Indian Ocean and drying in the eastern equatorial Indian Ocean, consistent with the ‘warmer-gets-wetter’ paradigm. Net surface heat flux changes (Fig. 5.2c) are negative in the WEIO and positive in the EEIO. Decomposing this into SST-independent (Fig. 5.2d) and SST-dependent (Fig. 5.2e) components reveals that the former dominates, with strong warming over the WEIO and Arabian Sea primarily due to wind and humidity effects on latent heat flux. In contrast, the SST-dependent component exerts a cooling influence via Newtonian damping. The feedback coefficient (Fig. 5.2f), which governs this damping, is larger in the Southern Hemisphere compared to the Northern Hemisphere. This pattern is largely controlled by the structure of the latent heat feedback, as described in Chapter 4. Table 5.1 summarises all the simulation used in this study.

Table 5.1: Synthesis of the simulations used in this chapter

Category	Name	Forcing	Description
Control	CTL	Detrended JRA	Control simulation with climate change signals
Climate Change	CC-ALL	Detrended JRA + all IPSL flux anomalies	Ocean response to all fluxes changes
	CC-Q	Detrended JRA + IPSL heat flux anomalies	Ocean response to heat flux changes only
	CC- τ	Detrended JRA + IPSL momentum anomalies	Ocean response to wind stress changes only
	CC-F	Detrended JRA + IPSL freshwater anomalies	Ocean response to freshwater changes only

The NEMO climate change simulation was carried out for the period 1958–2087. One of the added values of our experimental framework lies in its ability to perform sensitivity experiments to isolate the effect of individual surface flux

components in the climate change simulations. These simulations are performed by applying separately perturbations associated with heat fluxes (CC-Q), wind stress (CC- τ), and freshwater fluxes (CC-F). Comparing these experiments with their corresponding CC-ALL simulations allows us to evaluate the relative contribution of each forcing process and to identify the dominant mechanisms influencing the IO response to anthropogenic forcing.

5.3 Results

5.3.1 Simulations evaluation

To assess the reduction of the present-day mean state biases in CC-ALL relative to the coupled IPSL-CM6-LR simulation, we compare their SST and sea-surface height (SSH) fields against observations (Fig. 5.3). CC-ALL reduces biases associated with errors in air-sea fluxes over the present period, which are usually large in coupled models, but it won't remove biases intrinsic to the ocean model used.

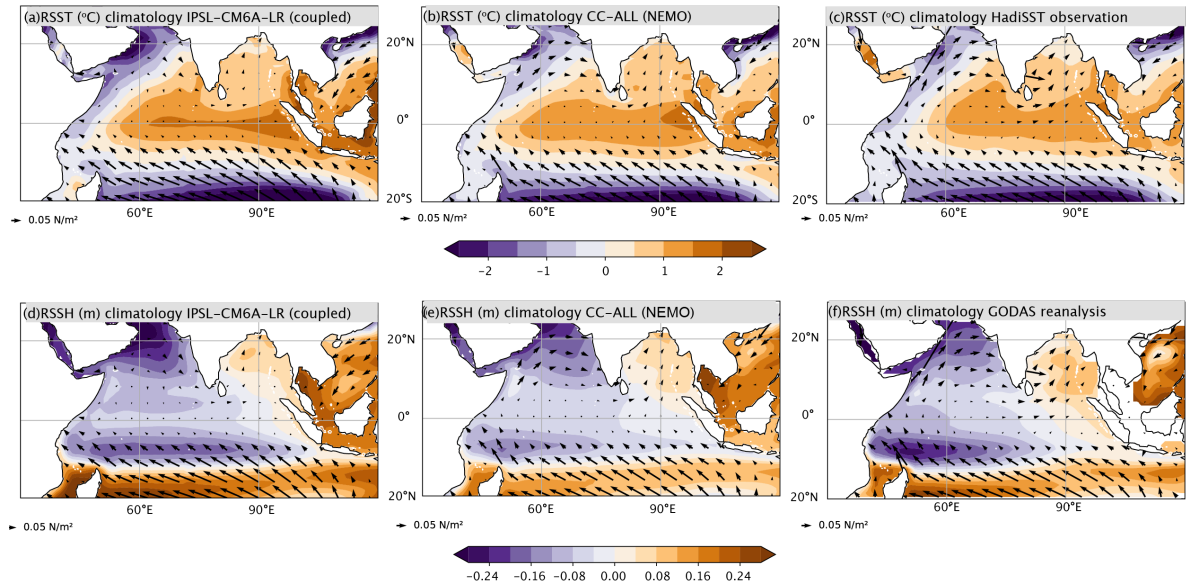


Figure 5.3: Effectiveness of present-day mean state bias correction in the IO. RSST climatology for 1981–2010 from: (a) IPSL-CM6A-LR, (b) the climate change Full simulation, and (c) HadISST observations. And the RSSH climatology for 1981–2010 from: (d) IPSL-CM6A-LR, (e) the climate change Full simulation, and (f) GODAS observation-based reanalysis product.

The IPSL SST and SSH patterns already agrees reasonably well with observations. Some of the present-day biases are however mitigated in CC-ALL simulation. For

instance, the EEIO RSST is warmer than observed by about 0.5°C (Fig. 5.5a,c) east of 60°E along the equator, while this bias is absent in CC-ALL simulation (Fig. 5.5b). Another prominent bias in the IO is the excessive cold bias in the western Arabian Sea (McKenna et al., 2024), along the Oman and Somalia upwellings. The cold bias in the upwelling regions does not only affect SST projections but also influences upwelling dynamics and biogeochemistry. In the CC-ALL simulation, this bias is considerably reduced (Fig. 5.5b). Additionally, climatological wind stress is also improves in CC-ALL simulation compared to the IPSL model, which underestimates climatological wind stress in the northern IO and overestimate in the southern IO.

SST biases reduction has direct implications for SSH (Fig 5.3 d,e and f), which serves as a proxy for thermocline depth. In the Arabian Sea, an overly shallow thermocline/ low SSH in the original IPSL simulation is effectively corrected. The southwestern IO is characterized by an offshore upwelling region near 7°S in response to the strong wind curl there. This region is often refer to as the Seychelles-Chagos Thermocline Ridge in the literature (Hermes and Reason, 2008). This upwelling is overestimated and extends too far east in the IPSL simulation. This bias is considerably reduce in CC-ALL simulation, despite an underestimation of its intensity compared to observations.

5.3.2 The basin-wide IO warming

This section revisits three key mechanisms contributing to IO warming, which were previously analyzed in Chapter 4 using statistical methods: IO basin-average warming amplitude, ZGRAD warming pattern, and interhemispheric MGRAD warming pattern. Here, we extend this analysis by using dynamical simulations to validate these mechanisms in CMIP models. Particularly through sensitivity experiments that isolate thermodynamical and dynamical components, confirming their role in IO warming. Before examining these mechanisms in detail, the alignment of the IPSL-CM6A-LR model with the MMMe is assessed using the methodology established in Chapter 4. Following this comparison, the section systematically revisits each mechanism to provide a deeper understanding.

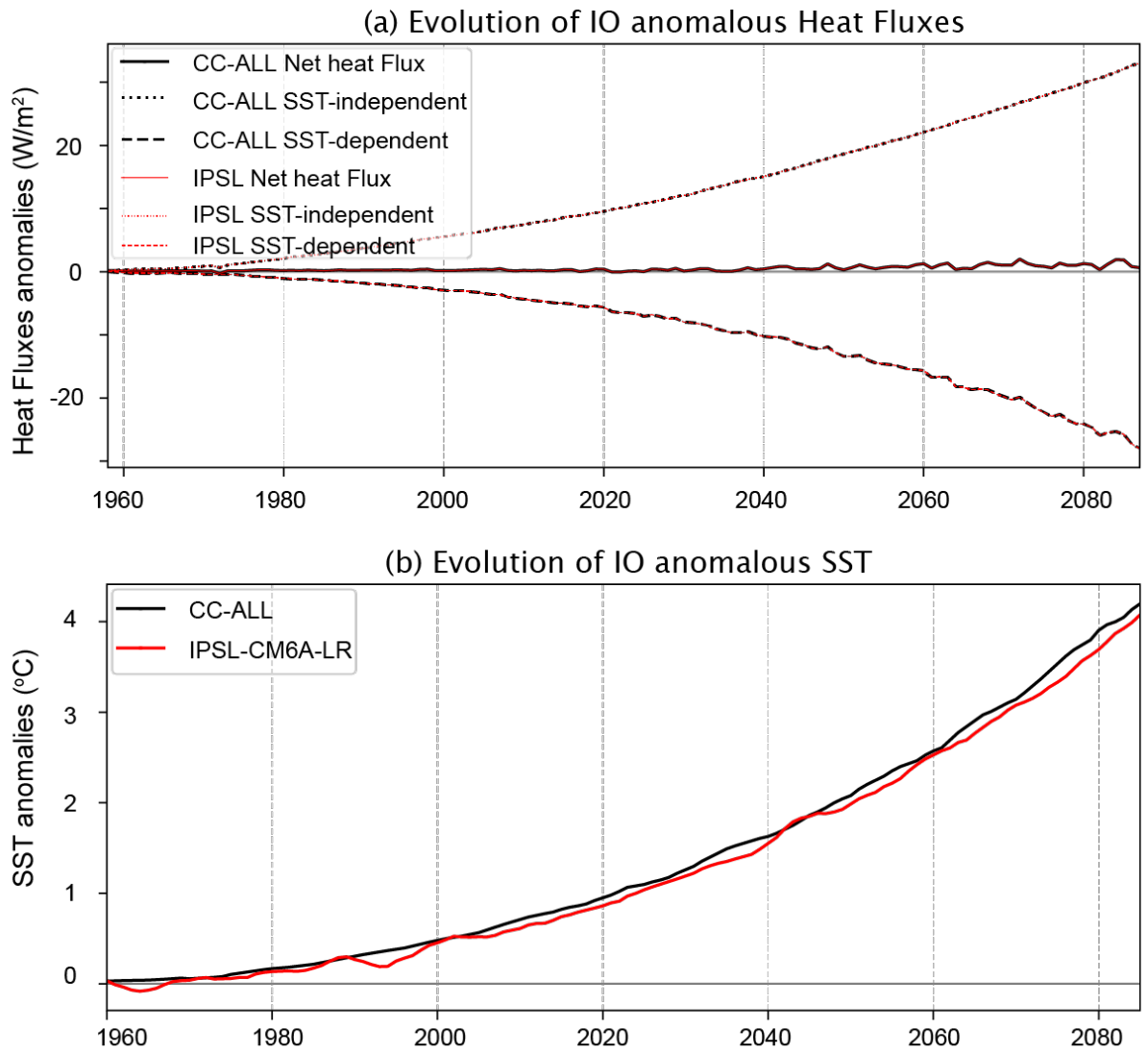


Figure 5.4: Comparison of the time evolution of anomalous heat flux and SST in the IPSL-CM6A-LR versus the climate change-Full simulation. (a) Time-series of the anomalous net heat flux (solid line), SST-dependent heat flux feedback (dashed line), and the SST-independent heat flux forcing (dotted line) (W/m²) for the climate change Full simulation (black) and IPSL-CM6A-LR (red). Panel (b) a similar comparison for anomalous SST.

The impact of the bias correction strategy on simulated IO basin-averaged warming is evaluated first. As shown in Fig. 5.4a, correcting for climatological biases does not significantly affect the IO-averaged heat flux evolution in the climate change Full simulation. The total heat flux, along with its SST-independent and SST-dependent components, closely matches those from the IPSL simulation. Consequently, correcting the IO mean state does not change the amplitude of the basin-averaged IO warming (Fig. 5.4b), reaching 4°C in both IPSL and CC-ALL simulation.

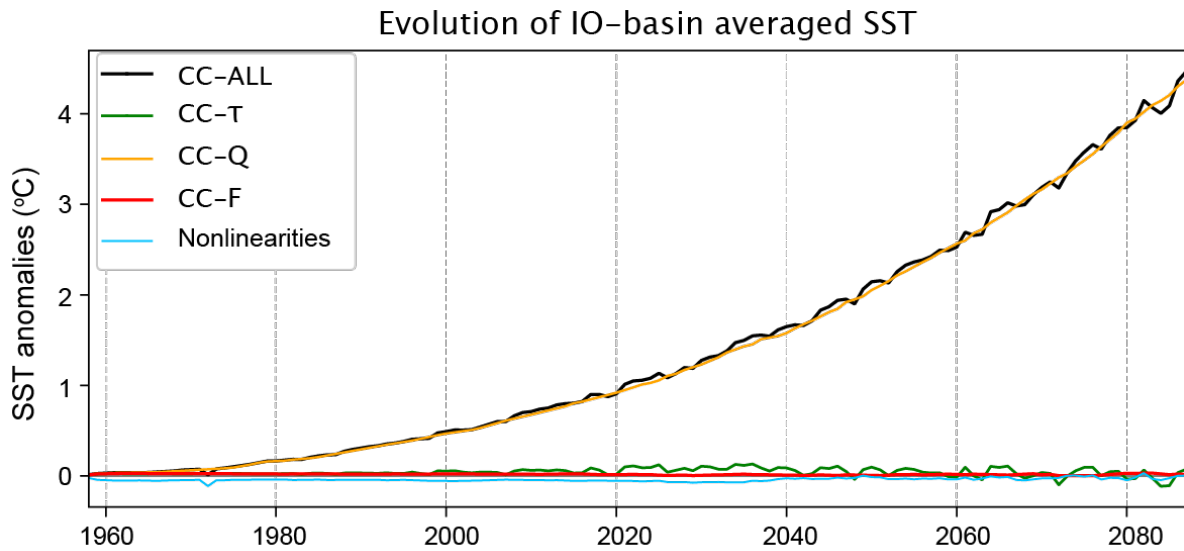


Figure 5.5: Comparison of IO SST evolution in climate change simulations and sensitivity experiments. The figure shows the evolution of the yearly average IO SST for the climate change Full simulation (black), as well as sensitivity experiments with H-only (red), W-only (green), and F-only (orange) forcings and for the nonlinearities (blue).

The statistical analysis performed in Figure 5.1 indicates that the IO basin-averaged warming is primarily driven by net surface heat flux changes, with minimal contribution from ocean dynamics. Fig. 5.5 illustrates the evolution of SST in the climate change Full simulation alongside the CC-Q, CC- τ , and CC-F sensitivity experiments, as well as the nonlinearities, calculated as the difference between CC-ALL and the sum of the three sensitivity experiments. Consistent with the statistical analysis, the Q-CC closely follows the SST basin-averaged warming amplitude of CC-ALL, confirming that surface heat flux remains the dominant driver of IO basin-averaged warming. In contrast, the dynamical component (CC- τ), the freshwater flux (CC-F), and nonlinear interactions do not significantly contribute to the amplitude of IO basin-averaged warming.

5.3.3 The IO warming pattern

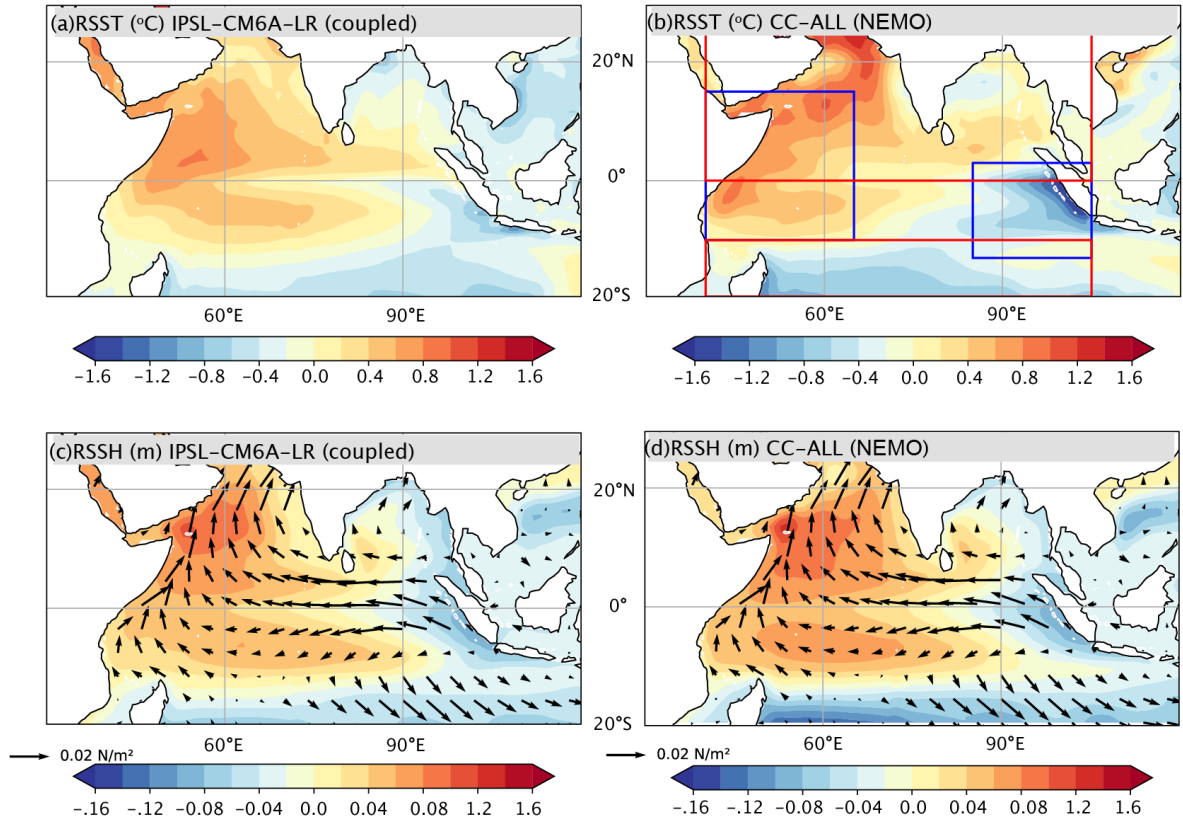


Figure 5.6: Comparison of projected RSST and RSSH changes in IPSL-CM6A-LR and the Climate Change Full simulation. Projected anomalous changes in RSST for (a) IPSL-CM6A-LR and (b) Climate Change Full simulation. (c) and (d) similar to (a) and (b) but show changes in RSSH with wind stress contours overlaid

Figure 5.6 shows the patterns of RSST and RSSH projected by the IPSL model and CC-ALL. Notably, both patterns are qualitatively similar and are reminiscent of an IOD-like pattern, with a relative WEIO warming and thermocline deepening, a relative EIO cooling and thermocline shoaling (Fig. 5.6). Despite this broad agreement, the two simulations display noticeable RSST signals: CC-ALL EEIO relative cooling is larger by -0.33°C compared to the IPSL, the northern Arabian Sea warming is also larger by 0.6°C . In contrast, the IPSL and CC-ALL experiments display very similar RSSH signals.

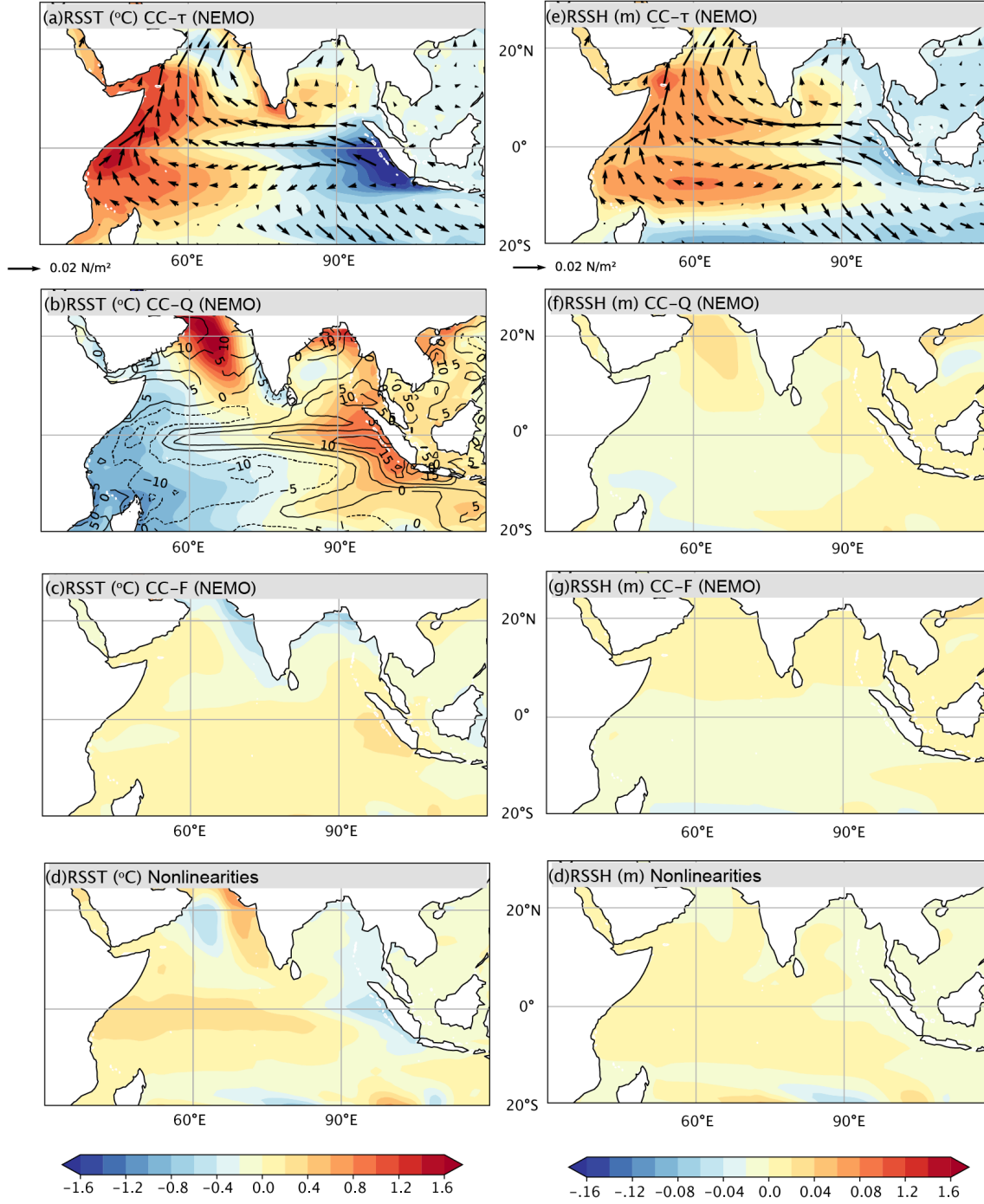


Figure 5.7: Decomposed influences on RSST and RSSH through sensitivity experiments. Same as figure 5.6b but for (a) W-only, with wind stress vectors overlaid, (b) H-only, (c) F-only, and (d) nonlinear effects. (e), (f), (g), and (h) show the corresponding anomalous changes in RSSH for the same experiments as (a), (b), (c), and (d), respectively.

The sensitivity experiments, which isolates dynamical (wind) and thermodynamical (heat and freshwater) components, provides further understanding of the factors contributing to the warming pattern. The IOD-like warming pattern simulated by CC-ALL in RSST (Fig. 5.6b) and RSSH (Fig. 5.6d) is dynamically driven

by

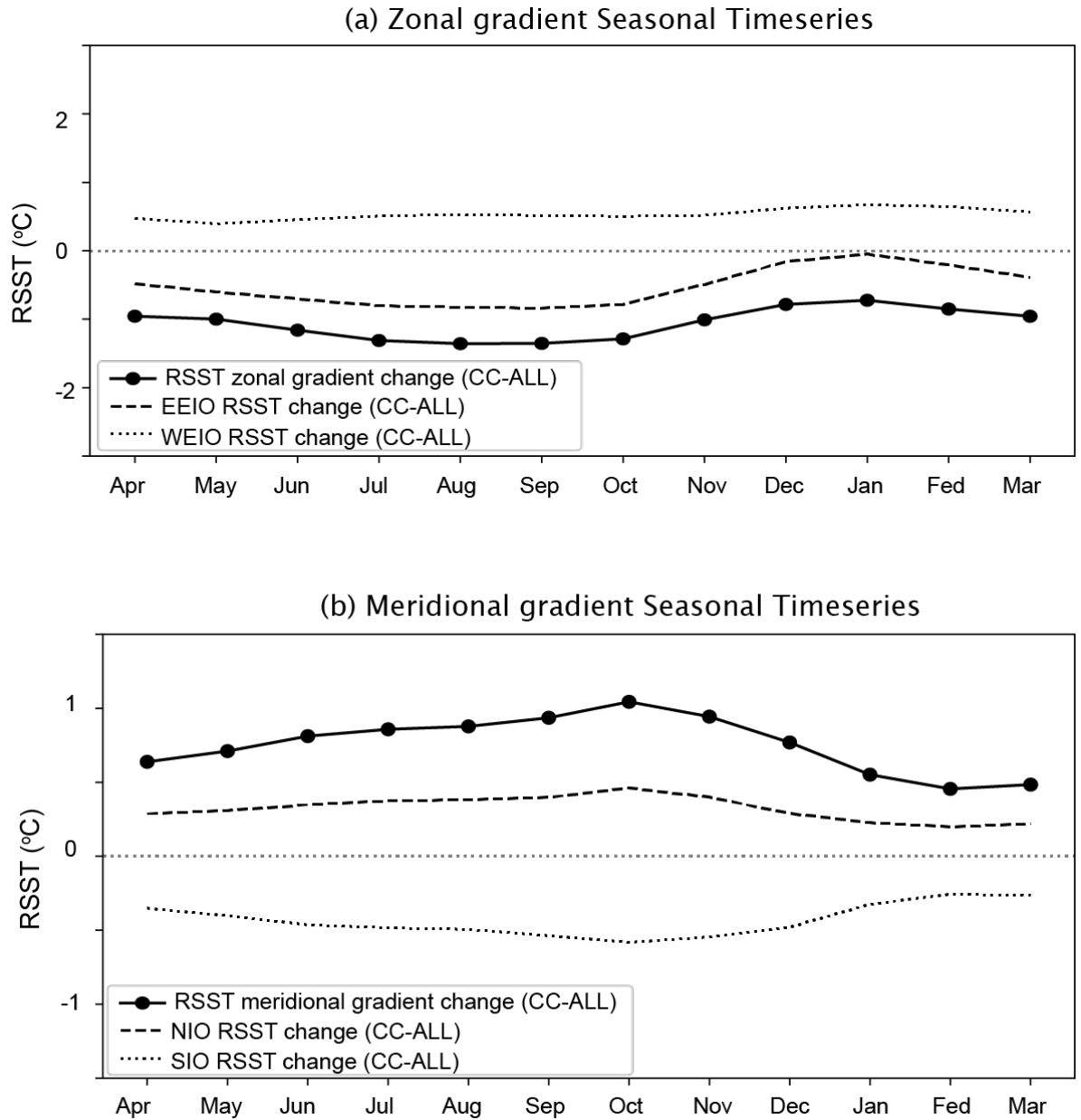


Figure 5.8: Seasonal influence of ZGRAD and MGRAD RSST. (a) Monthly future climatology of RSST changes for the ZGRAD (blue boxes in Fig. 5.8b; same boxes as in chapter 4), showing ZGRAD RSST changes (solid line with dotted markers for each month), EEIO RSST change (dashed line), and WEIO RSST change (dotted line). (b) Same as (a), but for the MGRAD (red boxes in Fig. 5.8b; same boxes as in chapter 4), showing MGRAD RSST changes (solid line with dotted markers), NIO RSST change (dashed line), and SIO RSST change (dotted line).

wind-stress changes (Fig. 5.7a,e), with heat flux changes damping this RSST pattern (Fig. 5.7b). The large relative warming in the northern Arabian Sea (Fig. 5.6b) is driven by heat flux changes (Fig 5.7b). freshwater flux changes does not significantly contribute to the warming pattern (Fig. 5.7c) and non-linearities are small (Fig. 5.7c). RSSH changes are dominate by wind-stress changes (Fig. 5e-h). A more detailed

investigation into the underlying mechanisms will be presented in the following subsections.

Fig. 5.8 shows seasonal time series of ZGRAD and MGRAD for CC-ALL simulation. The ZGRAD is defined as the temperature difference between the EEIO and WEIO (blue box in the Fig. 5.6b), and the MGRAD as the temperature difference between the NIO and SIO (red boxes in the Fig. 5.6c), consistent with gradients definition used in Chapter 4. The seasonality is relatively weak for both gradients, aligning with the simple heat budget analysis from the previous chapter. Therefore, this chapter evaluates the mechanisms using an annual average perspective. The relative cooling in the EEIO and the relative warming in the WEIO contribute nearly equally to the ZGRAD changes. In contrast, for MGRAD, the cooling in the SIO plays a slightly larger role than the warming in the NIO in driving the MGRAD..

The drivers of the IOD-like warming pattern is further examined through a decomposition of thermodynamical and dynamical contributions derived from the sensitivity experiments. Wind-stress emerges as the primary driver of this gradient, via its influence on ocean dynamics, while surface heat flux acts as a damping mechanism. Freshwater fluxes and nonlinear terms contribute minimally (Fig. 5.9a).

An examination of the online mixed layer heat budget indicates that wind-stress induced changes primarily operate through vertical ocean processes, such as upwelling and vertical advection. The modulation of vertical mixing processes can easily be understood by the equatorial thermocline adjustments in response to equatorial easterly anomalies (Fig. 5.7a,e). SSH is indeed characterized by relative increase (decrease) in the WEIO (EEIO), indicative of a thermocline deepening in the west and shoaling in the east (Fig. 5.9d). The eastern IO thermocline shoaling enhances upwelling and the efficiency of vertical mixing processes, which the opposite occurs in the WEIO. The damping by surface heat fluxes is largely due to shortwave radiation changes (Fig. 5.9c). These features are consistent with a Bjerknes-like feedback mechanism shaping the ZGRAD SST and qualitatively agrees with the statistical findings from the previous chapter.

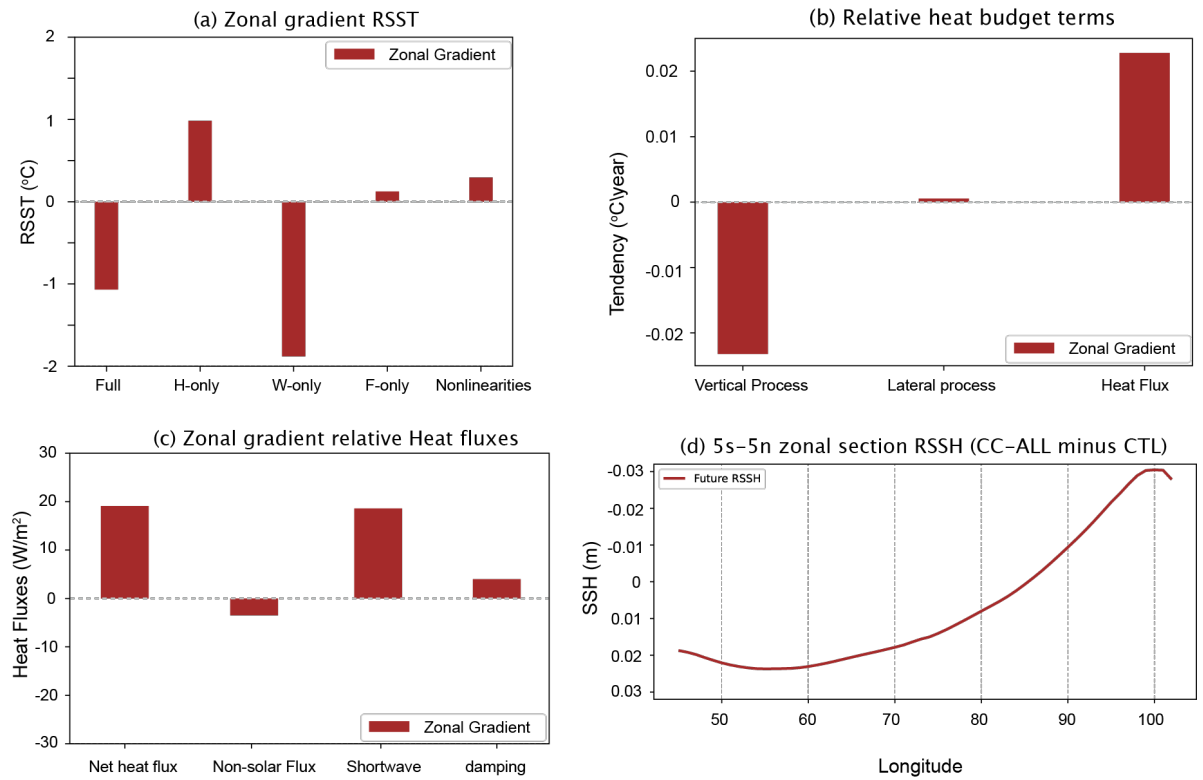


Figure 5.9: Mechanism of ZGRAD RSST changes. (a) Projected future changes in the ZGRAD of RSST for the Full simulation and different scenarios. (b) Future changes in relative mixed-layer heat budget terms, including Vertical processes (comprising vertical diffusion, vertical advection, and entrainment), lateral processes (zonal and meridional advection, and lateral diffusion), and the forcing term. (c) Future changes in heat flux components, including net heat flux, non-solar fluxes (which incorporate the SST-independent components of latent and sensible heat, etc.), shortwave radiation, and the damping (SST-dependent) term. (d) Projected future changes in zonally averaged SSH between 5°S and 5°N.

For the MGRAD, surface heat flux emerges as the dominant contributor, with wind playing a non-negligible role (Fig. 5.10a). The effect of freshwater fluxes is negligible. A breakdown of the heat flux components underscores the importance of SST-dependent damping, primarily through Newtonian evaporative cooling, in shaping the MGRAD (Fig. 5.10b). This highlights the central role of the differential north-south air-sea feedback in setting the north-south temperature contrast, consistent with the earlier heat budget framework.

However, a key difference arises in the role of wind stress. While the statistical heat budget approach suggested a minor damping effect from wind, the dynamical experiments reveal that wind contributes more substantially to the formation of the MGRAD. This contrast suggests that wind-driven oceanic processes may play a larger role than previously inferred from statistical methods alone.

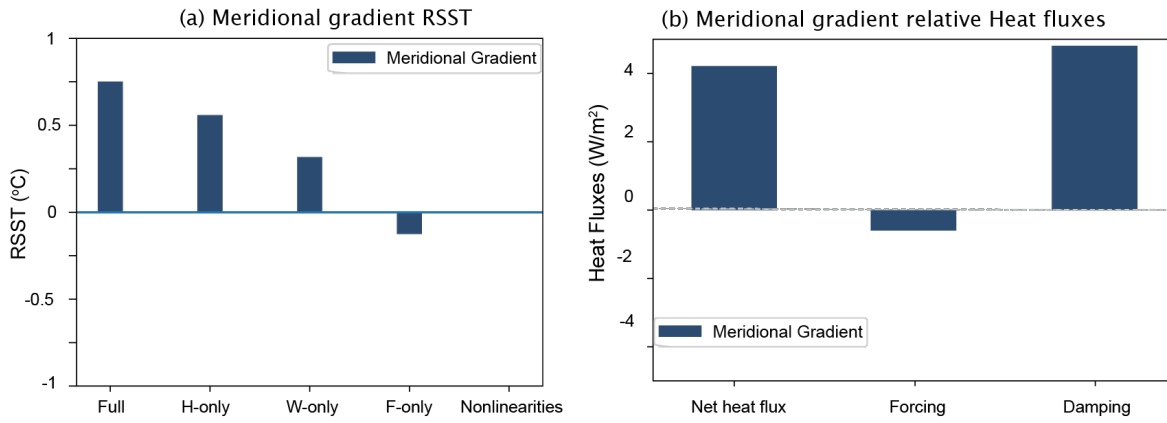


Figure 5.10: Mechanism of MGRAD RSST changes. (a) Projected future changes in the MGRAD of RSST for the Full simulation and different scenarios. (b) Future changes in heat flux components, including net heat flux, the forcing term comprising non-solar flux (SST-independent) component and the shortwave radiation component, and the damping (SST-dependent) term.

5.4 Summary and discussion

This chapter employs a forced ocean modeling framework using the NEMO model to investigate the mechanisms driving IO warming while explicitly accounting for present-day biases typically found in coupled climate models. A bias-reduced control simulation is first performed using observationally derived surface fluxes. Projected changes in wind stress and heat fluxes from the IPSL-CM6A-LR model are then applied, with heat fluxes separated into SST-independent forcing and SST-dependent feedback components. A suite of sensitivity experiments is conducted to isolate and quantify the respective roles of wind stress, surface heat, and freshwater fluxes in shaping the future IO warming pattern.

The modeling strategy effectively reduces several key biases in IPSL-CM6A-LR, including the eastern Indian Ocean warm bias, the Arabian Sea cold bias, the exaggerated eastward extension of the Seychelles–Chagos Thermocline Ridge (SCTR), and overly strong Northern Hemisphere wind stress. Despite these corrections, the impact on IO warming projections remains relatively modest. While there are some differences in the Arabian Sea (increased) and EEIO (decreased) patterns, the overall response remains consistent. This suggests that the present-day mean state biases in this model do not heavily impact its projected warming pattern.

This experimental setup provides deeper insight into the mechanisms be-

hind IO warming. While the previous chapter used a statistical analysis of a simplified upper ocean heat budget across the CMIP5/6 models, this chapter leverages ocean model simulations to investigate these mechanisms in greater detail using IPSL-CM6A-LR CMIP6 model. Before delving into the mechanisms analysis, we verify that IPSL-CM6A-LR is representative of the broader CMIP6 ensemble. This model reproduces both key warming patterns, the IOD-like ZGRAD reduction and the inter-hemispheric SST gradient strengthening, qualitatively matching to that of CMIP5/6 MMe, albeit a larger MGRAD for the IPSL compared to CMIP5/6 MMe. The mechanisms diagnosed using the heat budget framework are also consistent with ensemble results. This confirms IPSL-CM6A-LR as a suitable reference model for exploring IO warming processes.

In line with the statistical analysis presented in the previous chapter, our dynamical framework confirms three key findings:

1. The magnitude of the IO average warming is primarily driven by heat flux changes.
2. The IOD-like warming pattern is shaped by wind stress changes that promotes a shallowing (deepening) of thermocline in the eastern (western) equatorial IO, acting to warm less (more) this region, resulting in SST ZGRAD reduction. This mechanism is consistent with the Bjerknes feedback. While shortwave radiation changes act as the main damping factor.
3. The strengthening of the interhemispheric SST gradient is dominated by the north-south asymmetry in air-sea feedback coefficient, mainly driven by latent heat flux feedback.

Although the mechanism aligns well with most of the findings from the statistical analysis, there is a slight discrepancy regarding the potential role of wind stress in shaping the MGRAD. The results suggest that wind stress may have a greater influence than initially expected. These results strengthen our understanding in the role of both dynamical and thermodynamical processes in shaping future IO warming patterns.

Chapter 6

Summary and Perspective

6.1 Summary

6.1.1 Motivation and objectives

The IO has experienced substantial warming over the past century, which can undoubtedly be attributed to anthropogenic activities (Dong and Zhou, 2014a). Projections from coupled climate models indicate that this warming will intensify in the coming decades, with basin-averaged warming above 3°C in unmitigated emission scenarios. Crucially, this warming is spatially heterogeneous. Both observations and models indicate a larger warming in the western and subdued warming in the eastern equatorial Indian Ocean (Roxy et al., 2015). This spatially heterogeneous pattern has significant climatic consequences. Regions that warm more than the tropical average tend to experience reduced atmospheric vertical stability, which enhances rainfall and increases the likelihood of intense tropical cyclones (Xie et al., 2010). This warming pattern has also been associated with drying over India, raising serious concerns for regional water and food security (Roxy et al., 2015, Roxy et al., 2017). Accurately anticipating changes in the IO warming pattern is therefore of critical importance. However, current coupled climate models struggle to reproduce observed spatial patterns, particularly in the tropical Pacific (e.g. Watanabe et al., 2024), casting doubt on the reliability of future regional projections. This thesis aims to contribute to resolving these uncertainties by improving both the detection and understanding of the IO warming pattern. Chapter 3 addresses the question of whether regional SST warming signals, particularly in the Indian Ocean, can be robustly detected in both observations and models. It introduces a novel methodology, the Time of Detection (ToD), which complements the more widely used Time of Emergence (ToE) approach by focusing on statistical significance rather than signal-to-noise thresholds.

This framework helps evaluate how well models capture observed spatial patterns of climate change. Chapters 4 and 5 focus on understanding the physical mechanisms shaping the IO warming pattern. Chapter 4 uses a simplified upper-ocean heat budget to diagnose the drivers of warming across a large ensemble of CMIP5 and CMIP6 models. Chapter 5 builds on these findings through targeted ocean-only model experiments that isolate the roles of heat fluxes, wind stress, and freshwater forcing. Together, these chapters confirm and clarify the processes responsible for the IO's future warming structure. The chapter 3 results have been published in *Journal Of Climate* (Gopika et al., 2024) and chapter 4 findings have been accepted for publication in *Earth's Future* (Gopika et al., 2025).

6.1.2 Indian Ocean warming pattern detectability

Natural climate variability can mask long-term warming trends: this constitutes a major challenge for detecting climate change signals. A classical tool for estimating when the climate change signal "emerges" from background climate variability is the Time of Emergence (ToE). In Chapter 3 of this thesis, the ToE is estimated for both the Indian Ocean average warming and its spatial pattern, based on 'relative' SST (RSST), defined as SST change minus its tropical average, using historical and future simulations from CMIP5 and CMIP6 models, as well as observational datasets. However, the ToE approach has several limitations. It relies on arbitrary signal-to-noise thresholds and does not formally evaluate statistical significance, making it less suitable for comparing model outputs with observations. To address these limitations, Chapter 3 introduces a new methodology: the Time of Detection (ToD). Unlike ToE, ToD defines the time at which climate change signals become statistically significant, allowing for a more robust assessment of when and where warming patterns can be reliably detected. This method also facilitates more direct comparisons between modeled and observed patterns of warming.

The results show that while basin-averaged SST warming is already detectable in both models and observations, making it suitable for direct comparison, the warming pattern itself, as captured by RSST, emerges much later. This delay occurs

because RSST signals are smaller in amplitude, having removed the dominant basin-average component, and because natural variability (e.g., the Indian Ocean Dipole) is more pronounced at regional scales. These two factors degrade the signal-to-noise ratio, making pattern detection more difficult using traditional methods. ToD, by relying on statistical significance, consistently detects climate signals several decades earlier than ToE, offering a more sensitive metric for evaluating subtle spatial changes. Using this method across CMIP5/6 models and observations, Chapter 3 identifies regions where warming signals are statistically significant in both, thus providing a stronger foundation for evaluating climate model performance.

In the eastern equatorial Pacific, for example, strong ENSO-related variability obscures warming signals. While most models simulate detectable warming in this region, observations do not yet show a clear signal. Across all tropical basins, only two regions show detectable RSST changes with consistent spatial signals in both models and observations: the southeastern tropical Pacific, and the western equatorial Indian Ocean. The Southeastern Pacific experiences subdued cooling relative to the tropical average in both models and observations, likely linked to the poleward extension of the Southern hemisphere Hadley cell in a warmer climate (e.g. Jebri et al., 2020). In contrast, the warming trend observed in the western Indian Ocean has been detectable since the mid-20th century, whereas only 45 of models capture this signal after the 1980s. This mismatch is partly due to a stronger warming signal in observations, attributable to pre-1920 and 1960-70 data uncertainties in this region. The large and early (pre-1970) observed warming in the western IO may therefore be spurious and/or not attributable to anthropogenic forcing. As a result, while models under-represent this trend, it remains difficult to confirm whether the observed enhancement in western IO warming reflects a real climate signal, and therefore a weakening of the IO branch of the Walker circulation. These findings underscore the need for a deeper understanding of the physical mechanisms driving regional IO warming in climate model projections, to establish a firmer scientific basis for the projected spatial patterns, particularly the enhanced warming in the western basin.

6.1.3 Mechanisms of IO warming pattern in CMIP models: A statistical approach

To investigate the future IO warming drivers, Chapter 4 uses a refined version of the heat budget framework originally proposed by Zhang and Li (2014). This framework decomposes surface net air-sea flux future changes into two components: a forcing term that is dependent on SST and feedback term that directly depends on the local SST response. This approach is applied to 18 CMIP5 and 28 CMIP6 models historical and future simulations (RCP8.5 and SSP585 scenario) to investigate the IO warming mechanism. The analysis focuses on both the basin-mean IO warming amplitude and the spatial structure of the warming pattern. Two dominant spatial features are highlighted: (1) the weakening of the equatorial zonal SST gradient, often referred to as an “IOD-like” warming pattern, and (2) the strengthening of the interhemispheric SST gradient between the northern and southern IO, an aspect that has received less attention in previous studies but plays a key role in shaping regional climate responses.

Basin-averaged IO warming is primarily driven by the reduced evaporative cooling, a consequence of weakened surface winds associated with declining summer and winter monsoons, and by increased near-surface atmospheric humidity. In other words, increase in GHGs primarily increase the downward longwave radiation at the surface, but the resulting warming sets up positive feedbacks which primarily control the surface warming through changes in evaporation.

In contrast, the IOD-like pattern is largely shaped by ocean-atmosphere interactions. Both MMM response and its inter-model diversity are both primarily driven by changes in ocean dynamics, are primarily explained by changes in ocean dynamics. These include the positive Bjerknes feedback, in which an initial weakening of the zonal SST gradient leads to a reduction in equatorial easterly winds, a flatter thermocline slope, and consequently a further reduction in zonal SST contrast due to diminished upwelling in the east. While some contribution comes from differential evaporative cooling (particularly stronger damping in the climatologically warmer eastern IO), the dominant effect is this dynamical amplification. Changes in cloud

cover and precipitation patterns, more cloud and rainfall in the west, and less in the east, induce surface net heat flux anomalies that oppose the oceanic feedback, but are insufficient to suppress it. The origin of the feedback loop remains uncertain, though analysis suggests that stronger negative feedbacks in the eastern IO, due to higher mean SSTs, could act as a trigger. Additionally, teleconnections from the tropical Pacific may influence the development of this pattern.

The interhemispheric SST gradient MMM increase and its inter-model diversity are both primarily driven wind-driven. Stronger climatological winds in the Southern Hemisphere enhance evaporative cooling, leading to weaker warming in that region. This results in a strengthened interhemispheric SST gradient in MMM projections. Inter-model diversity is primarily driven by differences across models in cross-equatorial wind changes and their impact on latent heat flux forcing. This interhemispheric gradient strengthening is part of a broader pan-tropical pattern, with similar features in the Pacific and Atlantic Oceans.

Together, these findings illuminate the distinct contributions of thermodynamic feedbacks and dynamic ocean-atmosphere processes in shaping both the magnitude and spatial structure of future Indian Ocean warming. They also provide critical insights into the sources of inter-model uncertainty, offering new guidance for improving the physical realism of climate model projections in this climatically sensitive region.

6.1.4 Mechanisms of IO warming pattern in CMIP models: A dynamical approach

While Chapter 4 provides a robust statistical analysis of Indian Ocean (IO) warming mechanisms using CMIP model heat budget diagnostics, such statistical approaches are inherently limited in their ability to distinguish causality from correlation. To address this limitation and test the robustness of previous findings, Chapter 5 adopts a process-oriented modeling approach using the NEMO ocean general circulation model. This methodology is designed to both validate the conclusions of Chapter 4 and offer a more detailed quantification of the individual contributions of

future changes in heat flux and wind stress to the IO warming pattern. An additional objective of this strategy is to reduce the influence of systematic biases commonly found in fully coupled climate models.

Fully coupled ocean-atmosphere models often exhibit large mean-state biases that can influence their projections (Li et al., 2016a). Instead of relying on a fully coupled climate model, I therefore use a forced ocean modelling framework. A control pre-industrial simulation is first conducted using detrended observational fluxes, reducing systematic present-day biases that usually appear in coupled models. Next, future anomalies in wind stress and surface heat and freshwater fluxes are extracted from the IPSL-CM6A-LR coupled model projections. Following the methodology from Chapter 4, the heat flux changes are separated into forcing and feedback components. These future flux changes are then superimposed on the control simulation, enabling a direct comparison between pre-industrial and future climate conditions. Sensitivity experiments are also conducted in which only one type of forcing, wind stress, heat, or freshwater flux is applied at a time. These targeted experiments provides greater physical insight into the individual contributions of each forcing component than is possible through statistical analysis alone.

The IPSL-CM6A-LR model was selected for this modeling framework because it is in qualitative agreement with CMIP6 MMM, both in terms of present-day biases and projected IO warming trends. The modeling approach successfully reduces several of the IPSL model's well-documented biases, including the eastern Indian Ocean warm bias, the cold bias in the Arabian Sea, weak northern hemisphere wind stress, and the eastward extension of the Seychelles–Chagos Thermocline Ridge. While these corrections improve the realism of the mean state, they have a weak impact on the projected warming pattern, suggesting that the key processes driving future IO warming are not highly sensitive to these biases in this model.

The IPSL-CM6A-LR model projects an IOD-like warming pattern, characterized by a zonal SST gradient reduction and interhemispheric gradient strengthening that closely align with the MMM, both features broadly consistent with the CMIP6 MMM, albeit slightly exaggerated in magnitude. The mechanisms driving these patterns, as diagnosed through the simplified heat budget framework, also align with

those identified in the statistical analysis. The forced ocean simulations confirm that: (1) the IO average warming is primarily driven by heat flux forcing changes, (2) the IOD-like warming pattern is controlled by wind stress changes, which flatten the equatorial thermocline and induce a zonal SST gradient decrease through changes in vertical ocean processes, while shortwave radiation changes act as the primary damping mechanism and (3) the interhemispheric SST gradient strengthening is dominated by latent heat flux changes, with an important contribution from the more efficient evaporative cooling feedback in the strong wind region south of 10°S. In summary, the dynamical modeling framework corroborates the statistical findings of Chapter 4 and provides stronger causal evidence for the physical processes that govern spatially heterogeneous Indian Ocean warming. This dual-method approach strengthens confidence in the robustness of the projected IO warming pattern under continued greenhouse gas forcing.

6.2 Perspectives

6.2.1 Broader Applications of the ToD

The ToD framework introduced in this thesis offers a robust statistically grounded method for determining when climate change signals become statistically significant and distinguishable from natural climate variability. Unlike conventional approaches such as the Time of Emergence (ToE), which relies on arbitrary thresholds of signal-to-noise ratios, ToD uses formal statistical testing to assess detectability. While it has been applied here primarily to SST patterns, its utility extends far beyond. Applying ToD to other essential climate variables could significantly enhance our ability to evaluate climate model performance against observations and build greater confidence in future climate projections.

In Chapter 3, ToD was used to assess the detectability of the relative SST (RSST) pattern, revealing that both the relative cooling in the southeastern tropical Pacific and the relative warming in the western equatorial Indian Ocean were detectable in models and observations, although with caution due to observational uncertainties

in the early part of the Indian Ocean record. RSST is a widely recognized proxy for changes in atmospheric vertical stability, which influences precipitation patterns. Extending the ToD methodology to precipitation data could therefore offer new insights into the detectability of regional rainfall changes. This would be particularly valuable for assessing monsoonal systems, which affect billions of people, and for identifying shifts in large-scale atmospheric circulation, such as changes in the Walker Circulation, which are driven by changes in tropical convection.

A key challenge remains the divergence between observed and modeled trends in the Walker Circulation over the equatorial Pacific. Considering the very strong influence of Walker Circulation shifts associated with ENSO over the entire tropics, and in particular over the Indian Ocean (Schott et al., 2009), this is an important issue to resolve. Most CMIP models suggest an equatorial Pacific zonal SST gradient and Walker cell weakening, while observations suggest a strengthening (e.g., Han et al., 2014; Vecchi et al., 2006; Vecchi and Soden, 2007b; L'Heureux et al., 2013). Some recent studies, such as (Wills et al., 2022), argue that this disagreement is unlikely to be explained solely by internal variability and point instead to deficiencies in the models' representation of the complex processes that govern Pacific SST gradients and associated atmospheric dynamics (Watanabe et al., 2024). However, the results presented in Chapter 3 of this thesis challenge that view. Using the ToD framework and a broader CMIP sample (69 models compared to 16 in Wills et al. (2022)) the findings show that RSST changes in the eastern equatorial Pacific, considered a primary driver of Walker Circulation shifts (e.g., Tokinaga et al., 2012), may not be statistically detectable before the mid-21st century, due to the overwhelming background variability associated with ENSO. This suggests that internal variability remains a plausible explanation for the observed–modeled discrepancies. Differences between these studies could be due to multiple factors, including the shorter time frame used in Wills et al., 2022 (1979–2020) compared to this analysis (1920–2020), and their focus on a subset of models with large ensemble sizes. Further research is needed to reconcile these findings. Applying the ToD framework to additional climate indicators: such as sea level pressure, trade wind speeds, or sea level as a proxy for thermocline depth, could help determine when and where changes in the Walker Circulation become

robustly detectable. This would also allow for a clearer attribution of observed trends and improve our understanding of large-scale tropical atmospheric dynamics.

Beyond atmospheric and ocean dynamics, ToD holds promise for detecting early trends in biogeochemical climate indicators. Oceanic variables such as oxygen concentration, productivity, pH, nutrients, and chlorophyll have profound implications for marine ecosystems (e.g. Bopp et al., n.d.). While ToE has already been applied to such oceanic biogeochemical variables (Frölicher et al., 2016), it is not ideally suited for early detection, especially when observational uncertainty is high or signal amplitudes are modest. Applying the ToD framework to biogeochemical parameters could allow for earlier identification of changes such as deoxygenation, ocean acidification, productivity declines, and nutrient depletion. Moreover, it would help pinpoint regions where model-observation comparisons are most reliable, improving confidence in future ecosystem impact projections and supporting better-informed adaptation strategies.

6.2.2 Towards a better understanding of the warming patterns coupled mechanisms

In this thesis, ocean model simulations were primarily used to reduce biases associated with fully coupled models and to complement the statistical analyses presented in Chapter 4. Due to practical constraints, particularly time limitations, this modeling framework was applied to a single representative CMIP6 model (IPSL-CM6A-LR). While this allowed for meaningful validation of key findings, extending the methodology to a wider ensemble of CMIP models in future studies would provide a more comprehensive picture of how model-specific biases influence future projections and contribute to inter-model spread.

Chapters 4 and 5 both suggest that the Bjerknes air–sea feedback plays a critical role in amplifying the projected weakening of the equatorial zonal SST gradient and Walker circulation in the Indian Ocean. However, the initial trigger of this zonal gradient weakening remains uncertain. Hypotheses include the enhanced negative evaporative feedback in the climatologically warmer eastern Indian Ocean

or the influence of remote teleconnections from the tropical Pacific. Since the Bjerknes feedback involves coupled ocean-atmosphere processes, it is difficult to fully resolve its origin within the framework of an ocean-only model. Future studies using targeted coupled ocean-atmosphere sensitivity experiments could provide crucial insights. For example, suppressing future wind stress changes over the Indian Ocean in coupled simulations would help test the amplifying role of the Bjerknes feedback. Similarly, imposing a uniform SST increase across the Indian Ocean (rather than spatially varying changes) would isolate the impact of differential evaporative cooling on the initiation of the zonal SST gradient weakening. Finally, modifying the atmospheric coupling over the tropical Pacific, so that the atmosphere responds only to basin-mean SST warming would suppress Pacific SST pattern effects and help clarify the role of Pacific teleconnections in driving Indian Ocean changes. These targeted experiments would allow for rigorous testing of the mechanisms hypothesized in Chapters 4 and 5.

The intensification of the inter-hemispheric SST gradient in the IO has been much less studied than the IOD-like pattern. Yet, it is portably a very relevant variable to relate to future changes in the Indian monsoon. The hypotheses formulated in Chapters 4 and 5 could also be investigated using coupled experiments, as discussed above. For instance, we hypothesize a large influence of the differential evaporative cooling related to the stronger southern hemisphere wind stresses to explain the MMM weakening in the interhemispheric gradient. This could probably be tested in a sensitivity experiment in which the future change in latent heat fluxes over the Indian Ocean is computed using a basin-averaged wind speed.

While this thesis has primarily focused on physical mechanisms behind future SST changes, the ocean general circulation model (OGCM) used in Chapter 5 includes a biogeochemical component. Although biogeochemical analysis was beyond the scope of the present study, the simulations produced in this work offer significant potential for future research. The sensitivity experiments, applying wind stress and heat flux changes separately, could be used to disentangle the biogeochemical impacts of increased stratification from those of circulation changes. This is especially relevant for regions such as the Arabian Sea, where upwelling-driven productivity is

highly sensitive to both physical drivers. Future analysis of these simulations could yield new insights into how climate change may alter nutrient availability, primary productivity, oxygen levels, and ecosystem dynamics in the Indian Ocean.

6.3 Closing Remarks

The main objective of this thesis was to improve our understanding of climate change signals in the Indian Ocean, both in terms of their detectability in observational records and the mechanisms shaping their evolution in climate models. This has been achieved through two key contributions. First, the development of the Time of Detection (ToD) metric provides a statistically rigorous method for identifying when climate change signals become distinguishable from natural variability. Compared to conventional approaches, ToD offers earlier and more robust detection. Notably, it confirms that the relative warming of the western Indian Ocean is detectable in both models and observations, supporting the hypothesis that this pattern may reflect a weakening of the Indian Ocean branch of the Walker circulation. The ToD framework also improves model–observation comparisons and highlights where climate models succeed or fail in simulating regional climate change. Second, the thesis provides new insights into the mechanisms driving spatially heterogeneous Indian Ocean warming. Through both statistical analysis and dedicated modeling experiments, it emphasizes the role of thermodynamic feedbacks in controlling basin-wide warming, the influence of the Bjerknes feedback in amplifying zonal SST gradient weakening, and the importance of wind-driven latent heat flux changes in shaping the interhemispheric SST gradient. The latter, though less commonly studied, may have important implications for monsoon dynamics and deserves greater attention in future research.

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List of publications

PAPERS PUBLISHED

- **Gopika, S.,**Lengaigne, M., Suresh, I., Izumo, T., Kwatra, S., Neetu, S. and Vialard, J.(2024), Assessing CMIP Models' Ability to Detect Observed Surface Warming Signals Related to Climate Change, *Journal of Climate*, Volume 37, 6011-6027 .<https://doi.org/10.1175/JCLI-D-24-0102.1>. (IF- 4.8).
- **Gopika, S.,**Sadhvi, K., Vialard, J., Danielli, V., Neetu, S., & Lengaigne, M. (2025). Drivers of future Indian Ocean warming and its spatial pattern in CMIP models. *Earth's Future*, 13, e2025EF006112. <https://doi.org/10.1029/2025EF006112>. (IF- 7.3).

CONFERENCE PAPERS

- **Gopika, S.,**Suresh, I., Lengaigne, M., Vialard, J., Izumo, T., Kwatra, S. and Neetu, S. (2023) Time of Detection vs time of emergence of anthropogenic signals in CMIP models and observations, *Samudra manthan23*, India. (Poster Presentation)
- **Gopika, S.,** Kwatra, S., Vialard, J., Danielli, V., Neetu, S., and Lengaigne, M. (2024) Mechanisms of the tropical Indian Ocean surface warming patterns: simulated by CMIP models, *SOLAS-2024*, India. (Oral Presentation)
- **Gopika, S.,** Kwatra, S., Vialard, J., Danielli, V., Neetu, S., and Lengaigne, M. (2024) Mechanisms of the Indian Ocean surface warming pattern in CMIP5 and 6 models,Geophysical research abstract, *EGU general assembly*, Vienna(Austria). (Oral Presentation)