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Convectively coupled equatorial waves and their impact on
precipitation

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Abstract

Convectively coupled equatorial waves (CCEWs) and the Madden-Julian oscillation (MJO) are main drivers of tropical rainfall variability, modulating rainfall patterns over large areas. CCEWs comprise several wave types, including Kelvin, equatorial Rossby, mixed Rossby–gravity and inertio-gravity waves, which propagate either eastward or westward.

Despite their importance, global climate models often fail to accurately simulate tropical precipitation due to their coarse spatial resolution and reliance on parameterized moist convection.

In this thesis, I investigate the impact of CCEWs on tropical rainfall variability in both present-day and future climates, using CMIP6 simulations and observational data from GPM IMERG. To accomplish this, I apply a filtering technique based on Kiladis and Wheeler (1999) to isolate individual wave signals. I then quantify their impact on rainfall variability by calculating the squared Pearson correlation coefficient between the filtered wave signals and precipitation anomalies.

Most CMIP6 atmospheric models underestimate the contribution of Kelvin waves and high-frequency waves, like eastward propagating inertio-gravity waves, to tropical rainfall variability in the present-day climate. This is probably due to limited horizontal resolution and deficiencies in convective parameterizations. In contrast, these models tend to overestimate the impact of low-frequency waves, especially equatorial Rossby waves, likely because their slower propagation allows more time for convective schemes to respond to large-scale disturbances (Wang and Chen, 2017), potentially amplifying their simulated contribution.

Under the high-emission scenario SSP585, CMIP6 models project a strengthening impact of Kelvin waves on rainfall variability. In contrast, changes in the contribution of equatorial Rossby waves are modest and slightly negative when averaged across the tropics. For mixed Rossby–gravity waves, a regional increase is projected over parts of Africa. For the Madden–Julian oscillation and high-frequency inertio-gravity waves, no robust changes are projected, which is likely due to a combination of inter-model uncertainties and limited high-frequency wave representation in current climate models.

Overall, the findings reveal significant biases in current state-of-the-art climate models and underscore the importance of accurately capturing CCEW dynamics for accurate climate projections, as these waves influence rainfall variability.

Kurzfassung

Konvektiv gekoppelte äquatoriale Wellen (CCEWs) und die Madden–Julian Oszillation (MJO) sind die Haupttreiber der tropischen Niederschlagsvariabilität, da sie Niederschlagsmuster großräumig modulieren. CCEWs umfassen mehrere Wellentypen, darunter Kelvin-, äquatoriale Rossby-, gemischte Rossby-Schwere- sowie Trägheits-Schwerewellen, die entweder ostwärts oder westwärts propagieren.

Trotz ihrer Bedeutung gelingt es globalen Klimamodellen nicht tropische Niederschläge realitätsnah zu simulieren, aufgrund ihrer geringen räumlichen Auflösung und der Abhängigkeit von parametrisierten Konvektionsprozessen.

Ziel dieser Arbeit ist es den Einfluss von CCEWs auf die tropische Niederschlagsvariabilität im aktuellen und zukünftigen Klima mithilfe von CMIP6 Simulationen und Beobachtungsdaten von GPM IMERG zu analysieren. Dazu wende ich eine Filtermethode nach Kiladis und Wheeler (1999) an, um die einzelnen Wellensignale zu isolieren. Anschließend berechne ich den quadrierten Pearson Korrelationskoeffizienten zwischen den gefilterten Wellensignalen und den Niederschlagsanomalien.

Die Ergebnisse zeigen, dass die meisten CMIP6 atmosphärischen Modelle den Beitrag von Kelvin-Wellen und hochfrequenten Wellen, wie etwa ostwärts propagierenden Trägheits-Schwerewellen, zur tropischen Niederschlagsvariabilität im heutigen Klima unterschätzen. Mögliche Gründe dafür sind die begrenzte horizontale Modellauflösung und Defizite in der Parametrisierung konvektiver Prozesse. Im Gegensatz dazu tendieren diese Modelle den Einfluss niederfrequenter Wellen, insbesondere der äquatorialen Rossby-Wellen, zu überschätzen. Das liegt vermutlich an deren langsamen Ausbreitung, die konvektiven Schemata mehr Reaktionszeit lässt auf großskalige Störungen zu reagieren (Wang und Chen, 2017), wodurch ihr simulierter Beitrag möglicherweise verstärkt wird.

Im SSP585 Szenario nimmt der Einfluss von Kelvin-Wellen auf die Niederschlagsvariabilität deutlich zu. Im Gegensatz dazu, sind die Veränderungen im Beitrag äquatorialer Rossby-Wellen nur gering und über die Tropen gemittelt leicht negativ. Für gemischte Rossby-Schwerewellen wird ein regionaler Anstieg über Teilen Afrikas simuliert. Für die Madden–Julian Oszillation sowie für hochfrequente Trägheits-Schwerewellen werden keine robusten Änderungen gezeigt, was wahrscheinlich auf Modellunsicherheiten und die begrenzte Darstellung hochfrequenter Wellen in aktuellen Klimamodellen zurückzuführen ist.

Meine Ergebnisse zeigen signifikante Biases in aktuellen State-of-the-Art-Klimamodellen und heben hervor, wie wichtig eine realitätsnahe Darstellung der CCEW-Dynamik für präzise Klimaprojektionen ist, da diese Wellen die Niederschlagsvariabilität beeinflussen.

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1. Introduction

1.1. Convective organization in the Tropics

Precipitation in the Tropics is predominantly driven by deep convection and shaped by the interaction of many different processes (Fiedler et al., 2020). Rather than occurring randomly, tropical convection is often organized across multiple spatial and temporal scales—from mesoscale convective systems (MCSs) to planetary-scale phenomena like the Madden–Julian oscillation (MJO). At synoptic scales, tropical rainfall is primarily modulated by convectively coupled equatorial waves (CCEWs) (Cheng et al., 2023; Chen et al., 1996; Mapes and Houze, 1993; Nakazawa, 1988; Kiladis et al., 2009).

These different phenomena can interact. For example, CCEWs can influence the tropical environment in ways that enhance convective initiation and organization (Kiladis et al., 2009; Serra et al., 2020). This influence can increase the likelihood of MCS formation (Mapes et al., 2006; Nakamura and Takayabu, 2022a, 2022b; Yasunaga and Mapes, 2011). Such convective systems are frequently embedded within convectively coupled Kelvin waves (Haertel and Kiladis, 2004) and the MJO (Moncrieff, 2010), and can contribute substantially to tropical precipitation (e.g., Feng et al., 2021; Yuan and Houze, 2010).

Understanding the processes that organize tropical convection is essential, as they modulate both the patterns and the variability of tropical rainfall (Schlueter et al., 2019).

1.2. Tropical rainfall variability and why it matters

Rainfall variability plays an important role in the Earth’s climate system, especially in the Tropics where daily to intraseasonal variations can be profound (Kiladis et al., 2009; Schlueter et al., 2019). While mean rainfall provides valuable climatic context, such as for defining climate classifications (e.g., Köppen, 1936), it is the variability that has a more immediate impact on agriculture and livelihoods, often driving extreme events like droughts and floods (Kolawole et al., 2016). This distinction is particularly vital in vulnerable regions such as Africa (Sultan et al., 2005). In sub-Saharan Africa, for instance, over 96% of cultivated land relies on rain-fed agriculture (FAO, (2016)).

CCEWs and the MJO are main drivers of rainfall variability (e.g., Kiladis et al., 2009; Lubis and Jacobi, 2015; Schlueter et al., 2019). These tropical waves modulate rainfall patterns over large areas (Kiladis and Wheeler, 1999). For instance, Kelvin waves contribute to rainfall variability over the Indian Ocean, the tropical Pacific and the tropical Atlantic, while equatorial Rossby waves are most active over the Asian monsoon region and the northwestern Pacific warm pool (Lubis and Jacobi, 2015).

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Yet, despite their critical importance, global climate models still struggle to realistically simulate tropical precipitation, mainly due to their coarse resolution and the challenges associated with parameterizing moist convection (Fiedler et al., 2020). This highlights the urgent need to improve the representation of tropical waves in climate models, especially CCEWs and their impact on rainfall variability.

1.3. Convectively coupled equatorial waves: Theoretical background

CCEWs are large-scale wave disturbances confined to the tropical atmosphere. They include various wave types, which can propagate eastward or westward (Kiladis and Wheeler, 1999). Their dynamics can be described by the wave solutions for the linearized shallow water equations on an equatorial β -plane (Matsuno, 1966), which represent the motion of a single, shallow layer of incompressible density fluid on a rotating sphere. The wave solutions provide a fundamental framework for understanding equatorial waves under dry conditions. They are based on the following simplifying assumptions:

- (a) The Coriolis parameter f varies linearly with latitude, expressed as $f = \beta y$, where y denotes the meridional distance from the equator. The parameter β represents the rate of change of f with latitude ϕ and is given by $\beta = \frac{2\Omega}{a} \cos(\phi)$, where Ω is the angular rotation rate of the Earth and a is the Earth's radius.
- (b) The flow is shallow enough that the horizontal velocity components are independent of height.

The derivation of the wave solutions begins with the horizontal momentum equations 1 and 2 and the continuity equation 3:

$$\frac{\partial u_l}{\partial t} - \beta y v_l = -\frac{\partial \phi_l}{\partial x}, \quad (1)$$

$$\frac{\partial v_l}{\partial t} + \beta y u_l = -\frac{\partial \phi_l}{\partial y}, \quad (2)$$

$$\frac{\partial \phi_l}{\partial t} + g h_e \left(\frac{\partial u_l}{\partial x} + \frac{\partial v_l}{\partial y} \right) = 0. \quad (3)$$

Here u_l and v_l represent the zonal and meridional velocities, ϕ_l denotes the geopotential, g is the acceleration due to gravity and h_e is the depth of the undisturbed fluid layer. The subscript l indicates that the three-dimensional atmospheric flow has been decomposed into vertical modes. Accordingly, equations (1–3) describe only the horizontal (x, y) and temporal (t) variations of the flow associated with a specific mode l . The parameter h_e

1.3. Convectively coupled equatorial waves: Theoretical background

denotes the equivalent depth corresponding to that mode and must be chosen appropriately.

Matsuno (1966) first derived the full set of zonally propagating wave solutions to these equations by seeking solutions of the form

$$\begin{pmatrix} u_l \\ v_l \\ \phi_l \end{pmatrix} = \begin{pmatrix} \hat{u}(y) \\ \hat{v}(y) \\ \hat{\phi}(y) \end{pmatrix} \exp[i(kx - \omega t)], \quad (4)$$

where ω represents frequency and k is zonal wavenumber. Substituting this form into the governing equations (1-3) and rearranging leads to a second-order differential equation, depending only on $\hat{v}$:

$$\frac{d^2 \hat{v}}{dy^2} + \left(\frac{\omega^2}{gh_e} - k^2 - \frac{k}{\omega} \beta - \frac{\beta^2 y^2}{gh_e} \right) \hat{v} = 0. \quad (5)$$

To obtain physically meaningful solutions, $\hat{v}$ must decay away from the equator as $|y| \rightarrow \infty$. Such solutions are well known and they exist only if the constant term in the coefficient in parentheses satisfies:

$$\frac{\sqrt{gh_e}}{\beta} \left(\frac{\omega^2}{gh_e} - k^2 - \frac{k}{\omega} \beta \right) = 2n + 1, \quad n = \{0, 1, 2, \dots\}, \quad (6)$$

which describes the relationship between wave frequency ω and zonal wavenumber k , with n being a positive integer. The dispersion relation defines the necessary conditions for the wave solutions to exist (Kiladis et al., 2009).

The dispersion relation can be visualized in a dispersion diagram (see Figure 1). The x-axis represents the non-dimensional zonal wavenumber, while the y-axis shows the non-dimensional frequency. Both quantities are scaled with the equatorial Rossby radius of deformation ($R_e = \left(\frac{\sqrt{gh_e}}{\beta} \right)^{1/2}$). Positive zonal wavenumbers indicate eastward propagating waves, whereas negative zonal wavenumbers denote westward propagating waves. The black lines in Figure 1 illustrate the dispersion relation for different wave solutions and various values of n . This diagram also provides information about the energy propagation of each wave type, as described by Wheeler and Nguyen (2015). This can be determined by recalling the equation for the zonal component of the group velocity ($c_g = \frac{\partial \omega}{\partial k}$). The group velocity corresponds to the local slope of the dispersion curves. A positive slope indicates eastward energy propagation, while a negative slope indicates westward energy propagation.

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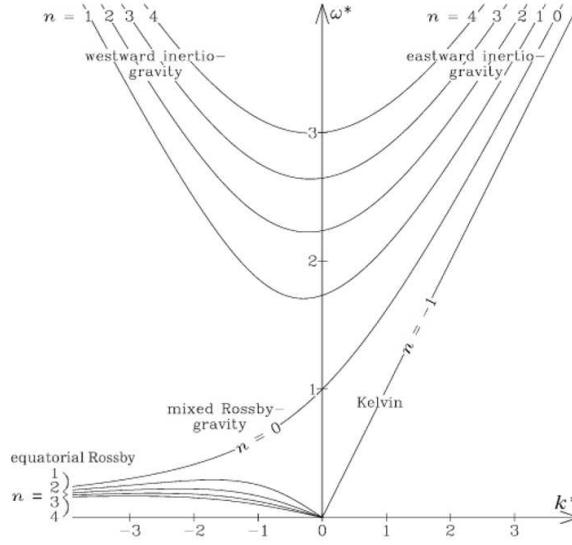


Figure 1: Dispersion relations for equatorial waves (up to $n = 4$) are presented as a function of non-dimensional frequency ($\omega^* = \omega/(\beta\sqrt{gh_e})^{0.5}$) and non-dimensional zonal wavenumber ($k^* = k(\sqrt{gh_e}/\beta)^{0.5}$). The figure has been adapted from Kiladis et al. (2009).

The following descriptions are based on Kiladis et al. (2009) and Wheeler and Nguyen (2015):

- **Equatorial Rossby waves (ER)** occur at low frequencies and only propagate westward, although their energy may propagate eastward or westward depending on their zonal scale. As the zonal wavenumber k increases, the frequency asymptotes to a constant value for all n .
- **Westward and Eastward Inertio-Gravity waves (WIG, EIG)** are high-frequency waves where the last term on the left-hand side of equation 6 becomes negligible. The westward propagating waves may exhibit an eastward group velocity at very low zonal wavenumbers.
- **Mixed Rossby-Gravity waves (MRG)** satisfy the dispersion relation only when $n = 0$. They have mixed properties: the branch with westward phase propagation (Rossby wave) has eastward energy propagation, while the other branch (Inertio-Gravity wave) exhibits both eastward phase and energy propagation.
- **Kelvin waves (KW)** propagate eastward and are a special type of wave because their meridional wind component ($\hat{v}$) is zero. This simplification leads to a unique solution of the shallow water equations that appears as a straight line in the diagram. Although they are not part of the standard set of wave modes ($n = 0, 1, 2, \dots$), their dispersion relation can be obtained by setting $n = -1$ in equation 6.

1.4. Convectively coupled equatorial waves in observations

CCEWs can generally be grouped into low- and high-frequency modes based on their wavenumber–frequency characteristics (Kiladis and Wheeler, 1999; Kiladis et al., 2009). ER waves are considered low-frequency, while WIG and EIG waves represent high-frequency modes. MRG waves fall into an intermediate frequency range and Kelvin waves occur at both low and high frequencies.

1.4. Convectively coupled equatorial waves in observations

Figure 2 displays both the theoretical solutions derived from the shallow water equations and the convective signals associated with the different CCEWs, inferred from the geostationary infrared channel brightness temperature product (T_b) of the GridSat-B1 climate data record (Knapp et al., 2011). The diagram shows the resulting normalized power spectrum of T_b , covering the time period from January 2009 to December 2023, and summing the results over the latitude range from 15°N to 15°S. The shading indicates the strength of observed signals.

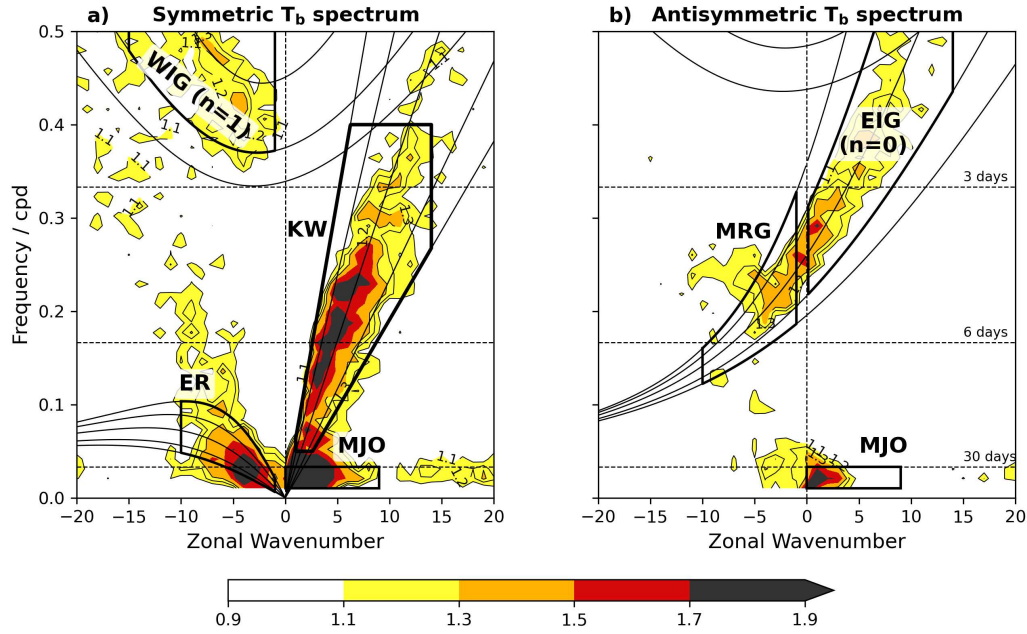


Figure 2: Wavenumber-frequency power spectrum of a) the symmetric component and b) the antisymmetric component of brightness temperature (T_b) from the GridSat-B1 climate dataset. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95% level (Kiladis and Wheeler, 1999). Outlined boxes represent regions of wavenumber-frequency filtering. Frequency is expressed in cycles per day (cpd).

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In contrast to Figure 1, the wavenumber-frequency power spectrum in Figure 2 is separated into symmetric and antisymmetric components with respect to the equator. This distinction is necessary because equatorial waves have characteristic meridional structures (Kiladis and Wheeler, 1999). Symmetric waves, including KW, WIG ($n=1$) and ER waves, are in phase across the equator. Antisymmetric waves, including EIG ($n=0$) and MRG waves, have opposite phases between the Northern and Southern Hemispheres. In the symmetric spectrum, KW show the strongest signal for CCEWs.

Notably, the observed convective signals in both panels of Figure 2 align well with the theoretical solutions derived from the shallow water equations, even though they are based on dry conditions.

Figure 2 also shows a MJO signal, which has no theoretical dry wave solution and therefore is not represented by a dispersion curve (Kiladis and Wheeler, 1999). The MJO is a low-frequency mode. Unlike CCEWs, which are either antisymmetric or symmetric, the MJO can include both symmetric and antisymmetric components (Madden and Julian, 1994).

Additionally, Figure 2a) also shows significant signals in a region associated with tropical depression (TD)-type waves. These disturbances are characterized by frequencies between 0.2 and 0.4 cpd and zonal wavenumbers from -20 to -6 (Lubis and Jacobi, 2015) and are known to contribute substantially to rainfall variability over northern tropical Africa (Schlueter et al., 2019).

1.5. Coupling to convection: Example for a Kelvin wave

Although the discussed wave solutions are for dry conditions and provide a good approximation of the dynamics of CCEWs, these waves can trigger convection through large-scale air movements (Kiladis and Wheeler, 1999). Once convection is initiated, it can modify the wave’s characteristics (e.g., Lubis and Jacobi, 2015; Wheeler and Nguyen, 2015; Yang et al., 2007). This interaction is coupled, meaning that the wave influences the convection, and in turn, the convection alters the wave’s properties, such as its speed. The wave’s speed decreases as convection introduces damping effects, like latent heat release (Kiladis and Wheeler, 1999). Consequently, the observed phase speeds of CCEWs are much slower than their dry counterparts due to this coupling. Figure 3 shows a simplified representation of the phases of convection along an eastward-propagating Kelvin wave.

The following description of the coupling between Kelvin waves and convection is based on Kiladis et al. (2009), Wheeler and Nguyen (2015) and Yang et al. (2007), and refers to a specific point in time. The eastward propagation of Kelvin waves generates alternating regions of divergence and convergence (Figure 3), which influence atmospheric convection. In phase (1), ahead of the trough, divergence prevails at the surface, causing the air

1.5. Coupling to convection: Example for a Kelvin wave

to spread out and sink, thereby suppressing convection. This phase is associated with warm anomalies in the lower troposphere. In phase (2), the transition zone, divergence weakens and low-level convergence begins. Air starts to ascend slowly and temperature anomalies shift from warm to cold. This phase marks the onset of increased convective activity. In phase (3), behind the trough, convergence intensifies. Moist air is rapidly lifted throughout the troposphere, resulting in significantly enhanced convection.

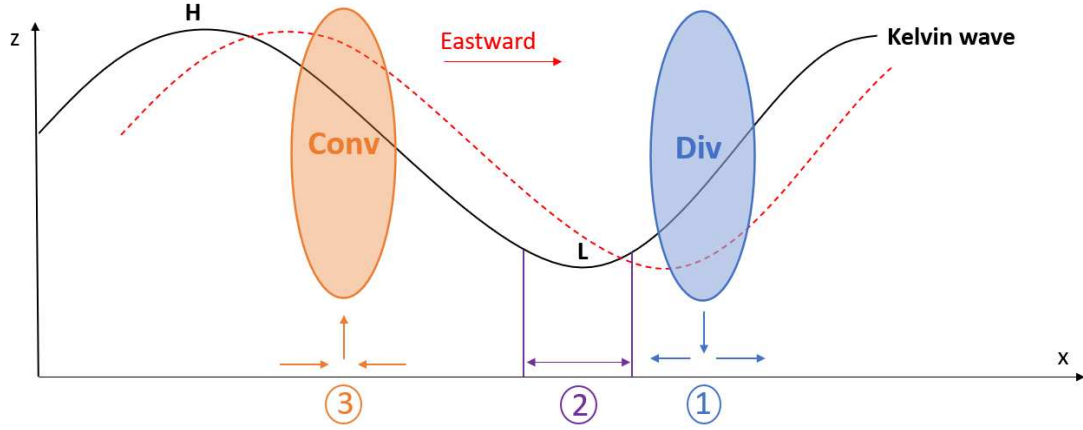


Figure 3: Phases of convection along the eastward-propagating Kelvin wave: (1) divergence suppresses convection, (2) transition initiates convection and (3) convergence enhances convection. The black line shows the idealized vertical structure of the Kelvin wave at an initial time, while the red dashed line represents its eastward propagation. The figure has been adapted from Kiladis et al. (2009).

Unlike the relatively straightforward coupling observed in Kelvin waves, convective coupling is more complex and variable across other equatorial wave types (Wheeler and Nguyen, 2015). MRG and ER waves, for example, often exhibit off-equatorial convection, whereas convection coupled to Kelvin waves is typically centered on the equator (Yang et al., 2007). Additionally, convective coupling depends not only on the wave type but also on environmental factors such as background winds (Zhang and Webster, 1989).

Although the coupling to convection varies across different wave types, most CCEWs exhibit a surprisingly similar vertical structure, as shown by Kiladis et al. (2009). They found that CCEWs typically feature low-level warming ahead of the deepest convection, upper-tropospheric warming near 250 hPa and near-surface moistening followed by rapid deep ascent. However, ER waves deviate from this structure. As demonstrated by Kiladis and Wheeler (1995), they display a more barotropic structure, with temperature and wind anomalies remaining largely in phase throughout the troposphere.

1.6. Convectively coupled equatorial waves in climate models: Challenges and projected changes

The literature on CCEWs in climate models is relatively sparse compared to the extensive studies on the MJO (e.g., Jiang et al., 2022; Lin et al., 2024; Wang et al., 2025). As noted by Kiladis et al. (2009), this is somewhat surprising, as the dynamics of CCEWs are well described by Matsuno’s 1966 linearized shallow water wave theory. The MJO, on the other hand, is harder to explain theoretically (Zhang, 2005). Still, the MJO with its larger spatial scale and lower frequency has a more evident influence on tropical and extratropical weather and was therefore easier to detect in early observations (Kiladis et al., 2009).

Furthermore, global climate models (GCMs) often struggle to accurately represent deep convection due to their coarse resolution and limitations in convection parameterization (e.g., Kiladis et al., 2009; Stevens et al., 2020). A common issue is that the transition from shallow to deep convection often occurs too rapidly (Bengtsson et al., 2019). This leads to insufficient low-level heating and divergent circulation (e.g., Hirons et al., 2013), which limits the models’ ability to accurately represent CCEWs. Linked to this, Spät et al. (2024) found that GCMs with parameterized deep convection tend to underrepresent high-frequency CCEWs, whereas kilometer-scale simulations with explicitly simulated deep convection show better agreement with observations.

There is also a gap in research regarding the impact of climate change on CCEWs. To my knowledge, Bartana et al. (2022) is currently the only published study that investigated projected changes in CCEW activity using data from the Coupled Model Intercomparison Project phase 6 (CMIP6). No comparable analyses exist for any previous CMIP phase. For their analysis, they used outgoing longwave radiation (OLR) and zonal winds at 250 hPa (U250) from historical runs and future scenarios, SSP245 and SSP585. These global warming scenarios are part of the Shared Socioeconomic Pathways (SSPs), with SSP245 indicating a moderate emissions pathway and SSP585 representing a high-emissions future driven by fossil fuels (Meinshausen et al., 2020). They chose OLR because it allows them to compare with observations and has been widely used in previous MJO-related studies (e.g. Le et al., 2021; Raghavendra et al., 2019). They also included U250 due to its link to upper-level divergence, which is important for how the MJO influences midlatitude weather. Bartana et al. (2022) found that the MJO and KW are generally underestimated in the models in the present-day climate, but show an increase under global warming. In contrast, ER waves are overestimated both in the present-day climate and under future warming conditions. They also found that models that better represent the MJO in the historical simulation are more likely to project a stronger intensification in the future and that KW shift toward higher phase speeds. However, their analysis primarily focused on dispersion diagrams, neglecting possible spatial changes.

2. Research questions

The overall goal of my thesis is to evaluate the representation of CCEW-related rainfall variability in CMIP6 models and to investigate changes under global warming in the models. I apply wavenumber-frequency analyses and CCEW filtering, as described in Chapter 3, to address the following two research questions:

1. How accurately do CMIP6 atmospheric models represent the impact of CCEWs on present-day tropical rainfall variability compared to observational data?

CCEWs are major drivers of precipitation variability. While Bartana et al. (2022) studied dispersion diagrams using outgoing longwave radiation and zonal winds at 250 hPa, the impact of CCEWs on precipitation in CMIP models has not yet been analyzed. This thesis fills that gap by evaluating how well 41 atmospheric CMIP6 models capture the observed relationship between CCEWs and tropical rainfall variability. By comparing model simulations with observational data from GPM IMERG, this thesis aims to identify biases and examine regional differences in precipitation variability associated with CCEWs.

2. How does the impact of CCEWs on tropical rainfall variability change under global warming in CMIP6 models?

Despite the importance of CCEWs for tropical rainfall variability, their future impact remains unexplored. To date, Bartana et al. (2022) is the only published study that has examined projected CCEW changes using CMIP6 data, but without considering precipitation. This thesis seeks to fill this gap by providing new insights into how global warming alters CCEW-related rainfall patterns in CMIP6 models. To achieve this, I use global warming simulations from 25 coupled CMIP6 models and compare them to the respective historical runs. I analyze the simulations for SSP245 and SSP585, but mainly focus on the more extreme SSP585 scenario, as CCEW signals become more pronounced under stronger warming (Bartana et al., 2022).

3. Datasets and Methods

In Section 3.1, I present the datasets used for the analysis. Section 3.2 describes the main method, CCEW filtering. Finally, in Section 3.3, I focus on the squared Pearson correlation coefficient, which I use to link precipitation variability to the variability of certain wave types.

3.1. Observation data and CMIP6 models

Generally, I use daily precipitation data conservatively regridded to a resolution of $2.5^\circ \times 2.5^\circ$, focusing on the tropics between 21.25°S and 21.25°N . To answer the first research question, I analyze 41 models from the CMIP6 Atmospheric Model Intercomparison Project (AMIP), covering the period from 1979 to 2014. For each model, I use the ensemble member **r1i1p1f1** and include precipitation data from all months of the year. The model data were downloaded from the ESGF MetaGrid portal (<https://esgf-metagrid.cloud.dkrz.de/search>). Table 1 presents a list of all 41 AMIP models from the CMIP6 dataset along with their native nominal resolutions. The nominal resolution refers to the approximate horizontal grid spacing (in km) (https://pcmdi.github.io/nominal_resolution/html/summary.html), allowing comparison despite differences in native grid types. As an observational reference for daily precipitation, I use the satellite-based and gauge-corrected IMERG version 07 final run (Huffman et al., 2023), which covers the period from 2001 to 2020.

Table 1: Overview of the AMIP models and their corresponding native nominal resolutions.

Model	Native nominal resolution [km]	Model	Native nominal resolution [km]
ACCESS-CM2	250	FGOALS-g3	250
ACCESS-ESM1-5	250	GFDL-CM4	100
BCC-ESM1	250	GFDL-ESM4	100
BCC-CSM2-MR	100	IITM-ESM	250
CAMS-CSM1-0	100	INM-CM4-8	100
CanESM5	500	INM-CM5-0	100
CESM2	100	IPSL-CM6A-LR	250
CESM2-FV2	250	IPSL-CM6A-MR1	100
CESM2-WACCM	100	KACE-1-0-G	250
CESM2-WACCM-FV2	100	KIOST-ESM	250
CMCC-CM2-HR4	100	MIROC6	250
CMCC-CM2-SR5	100	MPI-ESM1-2-HAM	250
E3SM-1-0	100	MPI-ESM1-2-HR	100
E3SM-2-0	100	MPI-ESM1-2-LR	250
E3SM-2-0 NARRM	100	MRI-ESM2-0	100
EC-Earth3-AerChem	100	NESM3	250
EC-Earth3	100	NorCPM1	250
EC-Earth3-CC	100	NorESM2-LM	250
EC-Earth3-Veg	100	SAM0-UNICON	100
EC-Earth3-Veg-LR	250	TaiESM1	100
FGOALS-f3-L	100		

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I address the second research question using 25 models from the future scenarios SSP245 and SSP585, covering the period from 2070 to 2100. Since these models are coupled to the ocean, I also analyze the respective historical runs for comparison. They include the same 25 models as the future scenarios and span from 1980 to 2010. For both the historical and future simulations, I use the ensemble member `r1i1p1f1` and include precipitation data from all months of the year. All data were downloaded from the ESGF MetaGrid portal <https://esgf-metagrid.cloud.dkrz.de/search>. Table 2 provides an overview of all 25 models used in both historical and future simulations, including their native nominal resolutions.

Table 2: Overview of the native nominal resolutions for the 25 models used in both the future scenarios (SSP245 and SSP585) and the historical runs. The resolutions refer to each model’s atmospheric component.

Model	Native nominal resolution [km]	Model	Native nominal resolution [km]
ACCESS-ESM1-5	250	INM-CM5-0	100
BCC-CSM2-MR	100	IPSL-CM6A-LR	250
CanESM5	500	KACE-1-0-G	250
CESM2-WACCM	100	KIOST-ESM	250
CMCC-ESM2	100	MIROC6	250
CMCC-CM2-SR5	100	MPI-ESM1-2-HR	100
EC-Earth3-CC	100	MPI-ESM1-2-LR	250
EC-Earth3-Veg-LR	250	MRI-ESM2-0	100
FGOALS-g3	250	NESM3	250
GFDL-CM4	100	NorESM2-LM	250
GFDL-ESM4	100	NorESM2-MM	100
IITM-ESM	250	TaiESM1	100
INM-CM4-8	100		

3.2. CCEW filtering

My main analysis tool is CCEW filtering, originally developed by Kiladis and Wheeler (1999). It allows me to investigate not only changes in the wavenumber-frequency domain, but also spatial changes in rainfall variability corresponding to the different CCEWs. This wave filtering method has been widely used in tropical wave research, including studies by Bartana et al. (2022), Hung et al. (2013), Kiladis et al. (2009) and others. Figure 2 illustrates the defined filter regions of each wave. These filter regions include their boundaries, meaning that the wavenumber or the frequency at the edge of the region is included in the filtered dataset (Kiladis and Wheeler, 1999). The filter settings for these regions are provided in Table 3 and are identical to those used in Schlueter et al. (2019), except for WIG waves, for which I use the parameters from Kiladis and Wheeler (1999). The table includes the wavenumber, frequency and shallow water depth ranges, based on previous studies on tropical waves. The shallow water depth h is given as a range rather

than a single value because observed wave signals in the wavenumber–frequency domain rarely align with only one dispersion curve (Kiladis et al., 2009).

Table 3: The filter settings for the frequency ω , the zonal wavenumber k and the shallow water depth h to extract certain wave types. The table is based on Schlueter et al. (2019), with adjustments for WIG waves following Kiladis and Wheeler (1999).

Wave type	ω (days)	k	h (m)	Source
Madden–Julian oscillation	30–96	0–9	—	Roundy and Frank (2004a)
Equatorial Rossby wave	9–72	1–10	1–90	Kiladis et al. (2009)
Mixed Rossby–gravity wave	3–8	1–10	8–90	Kiladis and Wheeler (1999)
Kelvin wave	2.5–20	1–14	8–90	Kiladis and Wheeler (1999)
Eastward inertio–gravity wave ($n = 0$)	1–5	4–14	12–50	Yasunaga and Mapes (2012)
Westward inertio–gravity wave ($n = 1$)	<2.7	1–15	12–90	Kiladis and Wheeler (1999)

In simple terms, the wavenumber–frequency filtering process involves applying masks over the corresponding wave signals in the wavenumber–frequency domain and then transforming the masked signals back into spatial coordinates using a double inverse Fourier transformation (Kiladis and Wheeler, 1999). Although originally applied to outgoing longwave radiation, this method has also been applied to precipitation data (Lin et al., 2006). This filtering is implemented using a Python script, which is based on Spät (2024).

Preprocessing steps for wavenumber–frequency filtering

Before performing the wavenumber–frequency filtering, the following four steps are necessary to get to the wavenumber–frequency domain. These steps are based on Kiladis and Wheeler (1999), but I omit the decomposition into symmetric and antisymmetric components for the filtering itself. Following Straub and Kiladis (2002), this avoids splitting the wave signal in regions where convection is confined to one hemisphere and would otherwise project onto both components.

- 1. Detrending the data:** For each grid point, linear detrending is applied to the entire daily precipitation time series to remove or reduce long-term trends from the dataset, ensuring that only fluctuations around the trend are analyzed. This is done by fitting a linear regression line using the least-squares method and subtracting it from the original dataset.
- 2. Removal of the annual cycle:** In this step, frequencies below the cutoff frequency $f_c = \frac{1}{96}$ cycles per day (cpd) are removed from the daily precipitation time series using a high-pass filter. This cutoff frequency corresponds to a window length of approximately three months, which aligns with the time scale of the MJO and captures seasonal variability. The high-pass filter function $M(f)$ is defined as:

$$M(f) = \begin{cases} 1, & |f| \geq f_c \text{ or } f = 0, \\ 0, & 0 < |f| < f_c, \end{cases} \quad (7)$$

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where f is the frequency and $M(f = 0)$ retains the mean value of the time series while removing frequencies lower than the cutoff frequency f_c .

Applying this filter function in the frequency domain yields:

$$x_{\text{HP}}(t, \lambda, \phi) = \mathcal{F}_t^{-1} \{M(f) \mathcal{F}_t\{x(t, \lambda, \phi)\}\}, \quad (8)$$

where $x(t, \lambda, \phi)$ is the daily precipitation data at time t , longitude λ and latitude ϕ . $\mathcal{F}_t$ and $\mathcal{F}_t^{-1}$ denote the discrete Fourier transform and its inverse along the time dimension. $x_{\text{HP}}(t, \lambda, \phi)$ is the resulting precipitation dataset without the annual cycle.

3. **Tapering:** Taper functions are applied because the subsequent Fourier transformation assumes continuous signals in the time domain. To meet this requirement, the ends of the time series are tapered using a "split cosine bell" function. The corresponding taper weight function $w(t)$ is defined as:

$$w(t) = \begin{cases} \frac{1}{2} \left[1 - \cos \left(\frac{2\pi t}{n-1} \right) \right], & 0 \leq t < \frac{n}{2}, \\ 1, & \frac{n}{2} \leq t \leq T - \frac{n}{2} + 1, \\ \frac{1}{2} \left[1 - \cos \left(\frac{2\pi(T-t)}{n-1} \right) \right], & T - \frac{n}{2} + 1 < t \leq T - 1, \end{cases} \quad (9)$$

where T is the total number of time steps in the series ($t = 0, 1, \dots, T-1$) and n represents the total number of tapered points at both ends ($n = 0.1 \cdot T$), which corresponds to tapering the first and last 5% of the time series.

The tapered series $x_{\text{tap}}(t, \lambda, \phi)$ is then obtained as:

$$x_{\text{tap}}(t, \lambda, \phi) = x_{\text{HP}}(t, \lambda, \phi) \cdot w(t), \quad (10)$$

where $x_{\text{HP}}(t, \lambda, \phi)$ is the high-pass filtered precipitation data. The taper function is applied once, smoothing the ends of the precipitation time series.

After completing these three steps, the resulting data represent the precipitation anomalies.

4. **Double Fourier Transformation:** In this step, a double Fourier transformation is applied to the resulting precipitation anomalies ($x_{\text{tap}}(t, \lambda, \phi)$) along the longitude (λ) and time (t) dimensions, separately for each latitude ϕ .

$$X(f, k, \phi) = \sum_{t=0}^{T-1} \sum_{\lambda=0}^{\Lambda-1} x_{\text{tap}}(t, \lambda, \phi) \cdot e^{-2\pi i(k\lambda - ft)} \quad (11)$$

Here, f denotes the frequency and k is the zonal wavenumber. The result ($X(f, k, \phi)$) is the wavenumber-frequency representation of the precipitation anomalies for each latitude, capturing the relevant wave modes as well as certain elements of random or non-periodic events that contribute to the background spectrum (Lin et al., 2006). For the subsequent wavenumber-frequency filtering, the latitude information in $X(f, k, \phi)$ is preserved, which enables the reconstruction of the full three-dimensional precipitation field.

Wavenumber–frequency filtering and inverse Fourier transformation

After completing the preprocessing steps, the wavenumber–frequency filtering is applied to the wavenumber–frequency representation of the precipitation anomalies for each latitude ($X(f, k, \phi)$), following Kiladis and Wheeler (1999). Based on the filter settings in Table 3, masks are created in the wavenumber–frequency domain containing only the corresponding wave signals. The masked signals are then transformed back into spatial coordinates by performing a double inverse Fourier transformation along the frequency and wavenumber dimensions. This step yields the filtered wave variability in physical space $Y(t, \lambda, \phi)$:

$$Y(t, \lambda, \phi) = \frac{1}{T\Lambda} \sum_{f=0}^{T-1} \sum_{k=0}^{\Lambda-1} X(f, k, \phi) \cdot e^{2\pi i(k\lambda - ft)}. \quad (12)$$

Additional steps for the wavenumber–frequency power spectrum

To create the wavenumber–frequency power spectrum (see Figure 2), I apply four additional steps. However, these steps are not part of the wavenumber–frequency filtering process itself and are used solely to visualize the wavenumber–frequency power spectrum, as highlighted by Kiladis and Wheeler (1999). To emphasize this distinction, they are marked with an asterisk. The sequence for computing the wavenumber–frequency power spectrum largely follows the original order, only steps 2.1* and 2.2* are inserted immediately after step 2. The remaining steps proceed as 3 and 4 and then 4.1* and 4.2*.

2.1* Decomposition into symmetric and antisymmetric components: As Matsuno’s wave solutions are either symmetric or antisymmetric about the equator, the gridded precipitation field $P(t, \lambda, \phi)$ is decomposed into a symmetric component $P_s(t, \lambda, \phi)$ and an antisymmetric component $P_a(t, \lambda, \phi)$. This linear decomposition is defined as:

$$P_s(t, \lambda, \phi) = \frac{P(t, \lambda, \phi) + P(t, \lambda, -\phi)}{2}, \quad (13)$$

$$P_a(t, \lambda, \phi) = \frac{P(t, \lambda, \phi) - P(t, \lambda, -\phi)}{2}. \quad (14)$$

2.2* Segmentation into overlapping 96-day windows: Unlike the filtering process, which is applied to the full time series, the wavenumber–frequency power spectrum is constructed using overlapping 96-day segments to better represent the typical spectral characteristics of CCEWs.

4.1* Reordering for wave propagation: After applying the double Fourier transformation to the resulting precipitation anomalies, the data is reordered based on the frequency and wavenumber components to accurately identify westward and eastward propagating waves.

- Westward propagating waves are characterized by positive frequencies and negative wavenumbers, or negative frequencies and positive wavenumbers.

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- Eastward propagating waves are characterized by positive frequencies and positive wavenumbers, or negative frequencies and negative wavenumbers.

After reordering, the wavenumber-frequency representation of the precipitation anomalies ($X(f, k, \phi)$) is summed over the latitude band (21.25°S–21.25°N), yielding the raw power spectra for the symmetric and antisymmetric components.

4.2* Calculating the wavenumber-frequency power spectrum: The final step in generating the normalized wavenumber-frequency power spectrum is to divide each component’s raw power spectrum by a background spectrum. The background spectrum is computed by averaging over the symmetric and antisymmetric components and then smoothing the result with a Gaussian filter. This filter uses the

normalized kernel $K = \frac{1}{8} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$ and is applied iteratively 50 times. This process removes the contribution from random or non-periodic fluctuations. The resulting ratio represents the normalized power spectra for both components and highlights the dominant wave modes in the data.

3.3. Squared Pearson Correlation Coefficient

Calculating the squared Pearson correlation coefficient R^2 between a wave signal and the precipitation anomalies gives the precipitation variability that can be explained by the wave. This coefficient is also known as the coefficient of determination and I calculate it as a percentage as follows (Devore, 2011):

$$\rho_{X,Y} = \left(\frac{\text{cov}_t(X(t, \lambda, \phi), Y(t, \lambda, \phi))}{\sigma_X \sigma_Y} \right)^2 \cdot 100. \quad (15)$$

Here, $X(t, \lambda, \phi,)$ denotes the precipitation anomalies after detrending and removal of the annual cycle, $Y(t, \lambda, \phi)$ is the filtered wave variability in physical space, σ_X and σ_Y are the corresponding standard deviations computed over time. The sum of all R^2 values should be understood as a maximum estimate that can be explained by CCEWs since some modes overlap and wave interactions are not considered (Schlueter et al., 2019). I use the coefficient of determination because it provides an intuitive and direct measure of how much the variability in the precipitation data is explained via the relationship between the two variables. Other measures, such as the Person correlation coefficient, may indicate the strength of the relationship between two variables, while R^2 specifically quantifies the proportion of variance in one variable that can be explained from the other. This makes R^2 particularly useful for evaluating the association between precipitation variability and wave variability.

3.4. Assessing statistical significance

To assess statistical significance throughout my results, I apply a bootstrapping approach. For each model, I generate overlapping subsamples using a rolling window of L consecutive years, starting from the first available year and sliding the window forward by one year for each subsample. Then, for every subsample, I compute the metric of interest, which is either R^2 or the signal over background spectral power and calculate the differences between the models and the corresponding references (GPM IMERG for present-day climate, historical simulations for future projections). A model is considered to show a statistically significant difference if at least 95 % of all subsampled differences share the same sign. For the wavenumber-frequency power spectra, I additionally require that the absolute value of the differences exceeds or equals 0.1. This threshold corresponds to roughly 10% of the value 1.1, which is the conventional cutoff above which spectral power is interpreted as a wave signal (Kiladis and Wheeler, 1999).

Based on these criteria, I also compute a net model score to evaluate model agreement on the direction of significant R^2 changes. The score is defined as the number of models with a statistically significant increase minus the number of models with a significant decrease. Models without a significant difference do not contribute to the score.

4. Results and Discussion

In this chapter, I present and discuss the main findings of my thesis. It is structured into two main parts. In Section 4.1, I examine how well AMIP models represent the impact of CCEWs on present-day tropical rainfall variability compared to GPM IMERG. In Section 4.2, I investigate how this impact is projected to change under global warming, focusing on simulations from the high-emission scenario SSP585. For completeness, I also include results for the more moderate scenario SSP245 in the Appendix.

4.1. Present-day climate

This section is divided into three subsections, each evaluating the performance of CMIP6 models in representing tropical precipitation variability relative to GPM IMERG. In Subsection 4.1.1, I assess the performance of AMIP models in simulating the spatial distribution of precipitation variability. In Subsection 4.1.2, I analyze the ability of AMIP models to represent CCEW activity in the wavenumber–frequency domain using wavenumber–frequency power spectra. Finally, in Subsection 4.1.3, I investigate how much of the tropical rainfall variability can be explained by the variability of individual CCEW types in AMIP models, based on the squared Pearson correlation coefficient (R^2).

4.1.1. Tropical rainfall variability in AMIP models

To assess the impact of CCEWs on tropical rainfall variability in AMIP models, it is important to first evaluate how well these models capture the underlying precipitation climatology, especially its variability. I calculate this variability using the variance of intraseasonal precipitation anomalies, which I obtained by detrending the daily precipitation data and removing the annual cycle. The highest variance in GPM IMERG is located over the Indo-Pacific warm pool region, where values exceed 180 (mm/day)^2 (Figure 4a)). This region is characterized by intense and highly variable precipitation primarily driven by tropical waves, such as the MJO (e.g., Zhang, 2005) and the Indian summer monsoon (e.g., Yadav, 2024). The eastern equatorial Pacific, the equatorial Atlantic and the Amazon basin also exhibit elevated precipitation variance. In contrast, most parts of Africa show comparatively low precipitation variance.

Figure 4b) shows the corresponding precipitation variance from the AMIP multi-model mean. The spatial distribution of rainfall variability is generally well captured by AMIP models, although there are notable differences in amplitude compared to GPM IMERG. These discrepancies become evident in Figure 4c), which displays the difference between the AMIP multi-model mean and GPM IMERG. While model agreement varies regionally (see hatching in Figure 4c)), one common feature among most AMIP models is the underestimation of precipitation variability in regions with high variance in GPM IMERG,

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particularly in the Indo-Pacific warm pool region. According to Ahn et al. (2023), this region is characterized by frequent and heavy rainfall events that contribute strongly to local precipitation variability. They further showed that CMIP5 and CMIP6 AMIP models often underestimate these events mainly due to persistent deficiencies in convective parameterizations already known from earlier model generations (e.g., Dai, 2006). These include, for example, an underrepresentation of intense convective bursts.

Another common feature among AMIP models is a slight overestimation of precipitation variability in southern Africa. As noted by Ahn et al. (2023), this region is dominated by light rainfall events, which are generally overrepresented in AMIP models. Previous studies (e.g., Chen et al., 2021; Ma et al., 2022) have linked this model bias to the so-called “drizzling” bias, where convective parameterizations trigger precipitation too easily, resulting in frequent but weak rainfall events.

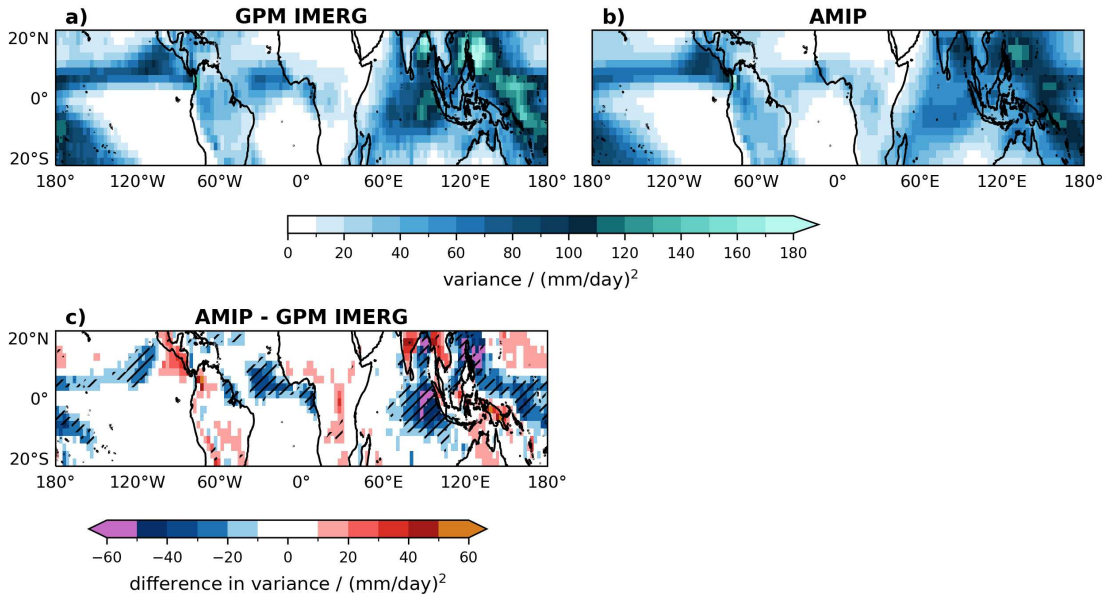


Figure 4: Panel a) shows the variance of intraseasonal precipitation anomalies over the tropics based on GPM IMERG. Panel b) presents the corresponding variance from the AMIP multi-model mean. Panel c) shows the difference in variance between the AMIP multi-model mean and GPM IMERG. The hatching highlights regions where at least 75 % of the 41 AMIP models agree on the sign of the variance difference relative to GPM IMERG.

4.1.2. Tropical wave activity in AMIP models

This subsection examines how well AMIP models represent CCEWs in the wavenumber–frequency domain. The analysis is based on wavenumber–frequency power spectra (see Figure 5), which allow the identification of wave modes based on their spectral characteristics. Following Kiladis and Wheeler (1999), a wave signal in these diagrams is significant above the 95 % level if the spectral power exceeds a value of 1.1. As noted by Hung et al. (2013), significant signals indicate that the variance of a wave mode is higher than the background spectrum, even if its absolute variance is comparatively small.

Symmetric component of the wavenumber–frequency power spectrum

Figure 5 shows that the most pronounced signals in both GPM IMERG and the AMIP multi-model mean appear in the symmetric component of the eastward propagating MJO. This becomes even more evident in Figure 6, which presents a histogram of mean signal over background spectral power across all AMIP models for each CCEW type, with a vertical line indicating the value from GPM IMERG. For the MJO (Figure 6f)), the models simulate relatively high spectral power compared to other wave types. Nonetheless, the GPM IMERG signal exceeds that of every model, and among all wave types, the MJO exhibits the largest difference between GPM IMERG and AMIP models. This is consistent with the fact that the MJO has long posed a major challenge for global climate models, mainly due to difficulties in capturing its vertical heating structure and the interaction between deep convection and large-scale circulation (e.g., Jiang et al. (2015)). In addition, both GPM IMERG and the AMIP model mean display significant MJO-related power at wavenumbers higher than the MJO filter range. According to Salby and Hendon (1994), this extension is caused by the localization of MJO activity to the Eastern Hemisphere.

The second strongest signal in GPM IMERG is associated with eastward propagating KW (Figure 5a)). These signals extend to high zonal wavenumbers and frequencies up to 0.5 cpd, exceeding the boundaries of the KW filter region. Similar to the MJO, all AMIP models underestimate KW activity in the wavenumber–frequency domain (see Figure 6a)).

The ER signal in the wavenumber–frequency domain is well represented in the AMIP model mean, compared to GPM IMERG (Figure 5b)). This is also evident in Figure 6b), which shows that the ER signal in most individual AMIP models is close to the GPM IMERG value, with some models even exceeding it. These results are consistent with the findings of Bartana et al. (2022), who used OLR data and found that all CMIP6 historical models simulate enhanced ER power relative to their background spectrum and that most models slightly overestimate ER activity compared to observations.

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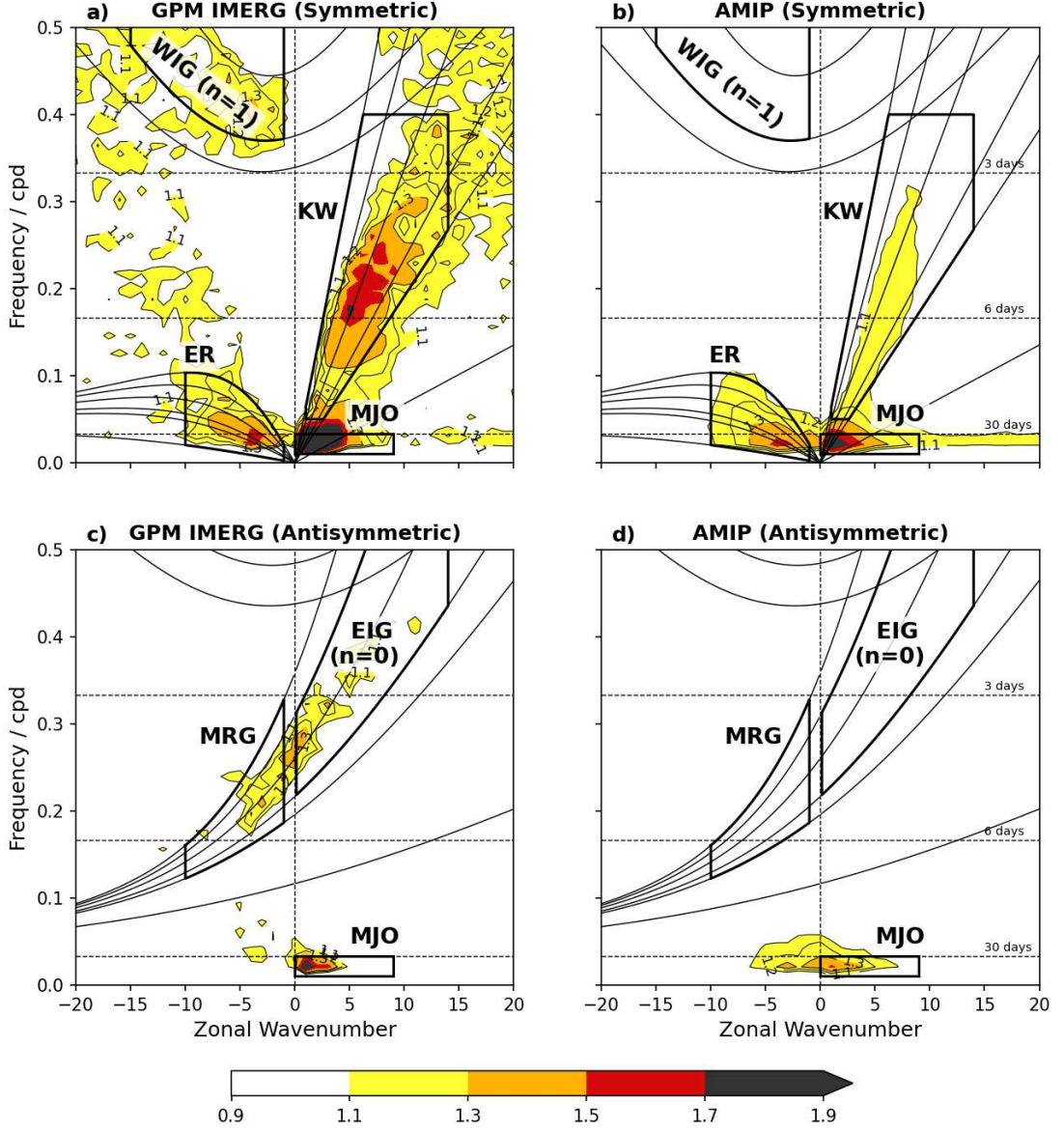


Figure 5: Wavenumber-frequency power spectra of the symmetric (a–b) and the antisymmetric (c–d) component, calculated from precipitation data and plotted as signal over background. Panels a) and c) show observational data from GPM IMERG, while Panels b) and d) present the AMIP multi-model mean. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95 % level (Kiladis and Wheeler, 1999). Thin black lines represent dispersion curves for six equivalent depths (1, 8, 12, 25, 50 and 90 m), while bold black lines indicate the wavenumber–frequency regions used for filtering selected CCEWs.

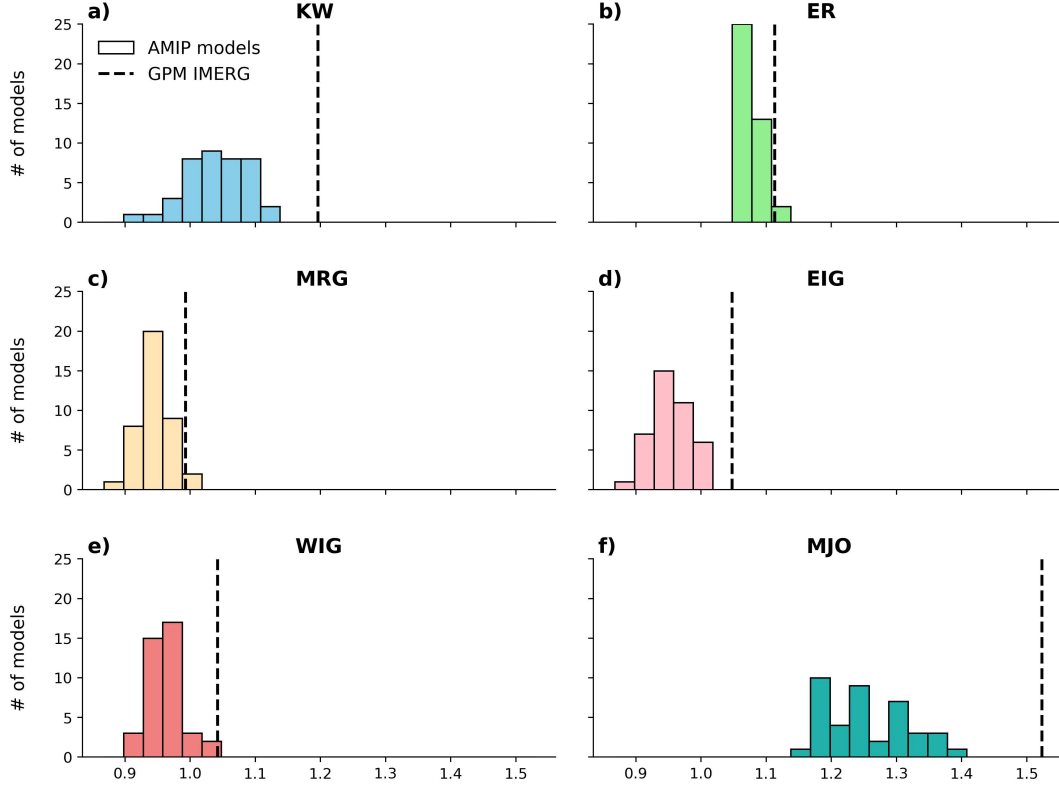


Figure 6: Histograms of mean signal over background spectral power for each of the six CCEW types (Panels a-f)). For each wave type, the signal over background spectral power is averaged over all wavenumber–frequency grid points within the corresponding filter region, including values below the background. This results in one value per AMIP model and wave type (shown as histogram bars with a bin width of 0.02) and one value for GPM IMERG (indicated by a vertical dashed line).

GPM IMERG also shows significant wave activity associated with high-frequency WIG ($n=1$) waves. In contrast, the AMIP multi-model mean does not display significant signals for WIG waves (see Figure 5b)). This is consistent with Figure 6e), which shows that the mean signal over background spectral power of all individual AMIP models remain below the 1.1 significance threshold.

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Antisymmetric component of the wavenumber–frequency power spectrum

Similar to the symmetric component of the power spectrum, the most prominent signals in both GPM IMERG and the AMIP model mean are associated with the MJO, although the signals are weaker (Figures 5c) and d)). A comparison with the OLR based results of Kiladis and Wheeler (1999) shows that the MJO signal in the antisymmetric component of the power spectrum is notably stronger when using precipitation data. Figures 5c) and d) also reveal significant signals for the westward part of the MJO, particularly in the AMIP model mean. However, the reason for the enhanced power in the model mean relative to the observation is unclear, as it has not yet been investigated.

Figure 5c) also shows significant signals associated with MRG and EIG ($n=0$) waves in GPM IMERG, although their mean signal over background spectral power is notably weaker than those of the MJO. In contrast, the AMIP model mean does not exhibit significant power for either wave type (Figure 5d)). This discrepancy is further illustrated in Figures 6c) and d), where nearly all models underestimate the mean spectral power compared to GPM IMERG. Only few models slightly exceed the observed mean spectral power of MRG waves.

Underrepresented wave activity due to model limitations

The results show that AMIP models underestimate the mean signal over background spectral power of several CCEWs, particularly for KW and high-frequency modes such as EIG waves. Although this analysis is based on AMIP simulations, the underlying deficiencies may be related to general limitations in global climate models. One possible reason for this underestimation is the limited horizontal resolution of GCMs, which prevents them from adequately resolving the fine-scale processes and dynamics associated with high-frequency CCEWs (Spät et al., 2024). In addition, GCMs rely on parameterized convection schemes, which introduce further uncertainties. These schemes can distort both the wave signals and the background spectral variability (Lin et al., 2006).

4.1.3. CCEWs and their contribution to tropical rainfall variability

While dispersion diagrams provide insight into the spectral characteristics of CCEWs in the wavenumber–frequency domain, they do not show the spatial contribution of these waves to intraseasonal tropical rainfall variability. To address this, I calculate the squared Pearson correlation coefficient (R^2) between filtered wave signals and precipitation anomalies for each wave type, using GPM IMERG. I then compare these results with the AMIP multi-model mean to evaluate where and to what extent AMIP models overestimate or underestimate the impact of CCEWs on precipitation variability.

To assess whether the differences in R^2 between AMIP models and GPM IMERG are statistically significant, I apply the bootstrapping approach described in Section 3.4. For each AMIP model, I generate 17 overlapping subsamples using a rolling window of 20 consecutive years.

Figure 7 shows that, in GPM IMERG, KW contribute most strongly to tropical rainfall variability with R^2 values reaching up to 30 %, particularly over the tropical oceans, the Amazon basin, the Sahel and the Maritime Continent. Many of these regions are known to be particularly sensitive to wave–convection interactions, which can enhance KW activity. Over the Pacific and Atlantic, KW activity is enhanced by interactions with extratropical Rossby wave trains (e.g., Schreck et al., 2013), while over the Indian Ocean and Africa excitation is primarily linked to mesoscale convective systems, the MJO and latent heating associated with the African easterly jet (e.g., Kim and Alexander, 2013).

The second-largest contribution to rainfall variability is associated with ER waves, especially over the Indian Ocean and the western Pacific, where R^2 values reach up to 21 % (Figure 7b)). This enhanced ER activity is likely driven by westward propagating monsoon gyres (Chatterjee and Goswami, 2004) and by midlatitude Rossby wave trains, which can perturb the equatorial waveguide and generate ER waves (e.g., Roundy and Frank, 2004b).

A notable contribution to tropical rainfall variability is also associated with the MJO, although it is less pronounced than that of KW and ER waves. Elevated R^2 values appear in similar regions as for ER waves, but also extend into the Asian monsoon domain, especially over India. The spatial overlap reflects that both the MJO and CCEWs can co-exist along the tropical rainband. Although CCEWs are not the cause of the MJO, their presence within the same convective envelope allows them to interact. For example, Roundy and Frank (2004b) suggested that ER waves may influence the amplitude and timing of the MJO by modulating convective activity.

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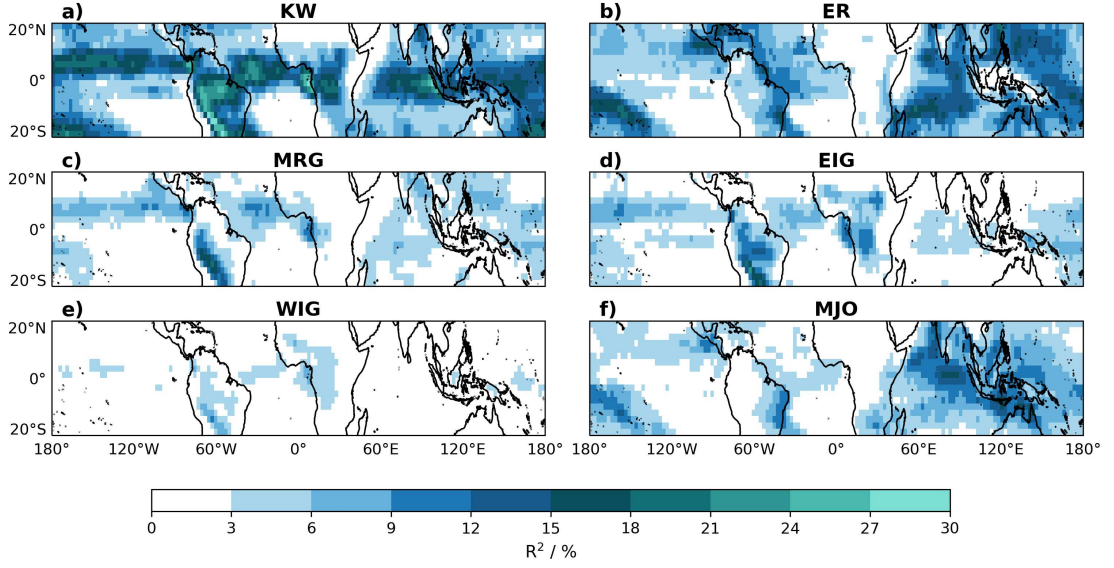


Figure 7: Contribution of CCEWs to tropical rainfall variability in GPM IMERG. Panels a)–f) show the squared Pearson correlation coefficient (R^2) between filtered wave signals and precipitation anomalies.

In contrast to the previously discussed CCEWs, the contributions of MRG, EIG and WIG waves to tropical rainfall variability are generally weaker and more localized (Figures 7c)–e)). MRG and EIG waves contribute most over the Amazon basin, while WIG waves have the weakest impact on rainfall variability among all wave types. These lower contributions are mainly due to the use of daily data, which limits spectral resolution at high frequencies and causes parts of the EIG and WIG spectra to be truncated.

Figure 8 shows the ability of AMIP models to reproduce the contribution of CCEWs to tropical rainfall variability in GPM IMERG. In general, AMIP models tend to underestimate the impact of KW and high-frequency waves and overestimate the impact of low-frequency waves on tropical rainfall variability (left column). This general pattern is supported by the net model score (right column), which highlights areas where the majority of models agree on the sign of the R^2 difference. However, there are also exceptions to this general pattern depending on the region and wave type.

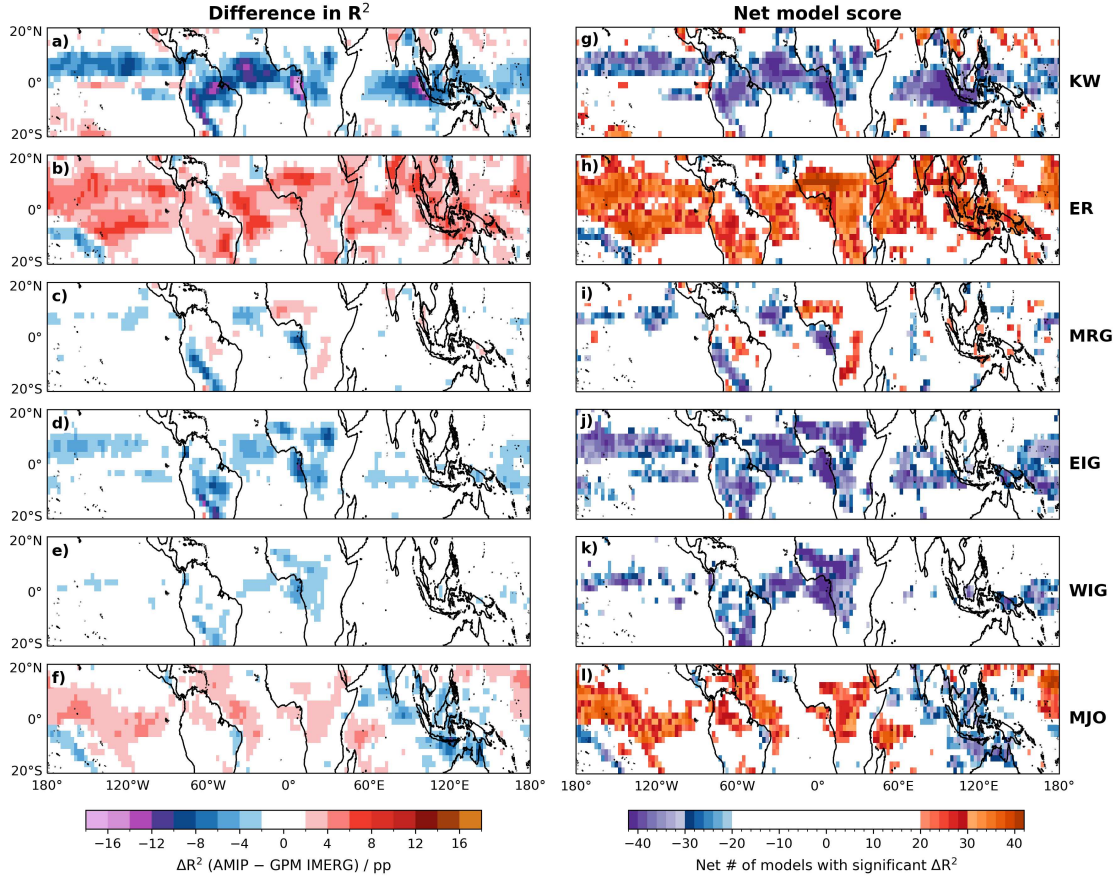


Figure 8: AMIP model performance in representing the contribution of CCEWs to tropical rainfall variability. Panels a)–f) show the differences in the squared Pearson correlation coefficient (R^2) between the AMIP multi-model mean and GPM IMERG for various CCEW types, expressed in percentage points (pp). Panels g)–l) displays the net model score, calculated as the number of AMIP models with a statistically significant increase minus those with a significant decrease for the respective CCEW type.

KW show the most pronounced absolute differences between observed and simulated R^2 values. This is particularly evident over the Amazon basin, the tropical Atlantic and the Indian Ocean warm pool. In these regions, AMIP models underestimate the contribution of KW by up to 18 percentage points, which corresponds to about 60 % of the maximum observed R^2 values. This substantial underestimation aligns with the weaker KW activity simulated by AMIP models in the wavenumber–frequency domain (Subsection 4.1.2).

Similar to KW, AMIP models tend to underestimate the contribution of other high-frequency waves such as EIG, WIG and to a large extent MRG waves. While the absolute differences between simulated and observed R^2 values are generally less pronounced for EIG and WIG waves compared to KW, the relative differences are actually up to 20 % higher than for KW. In the case of MRG waves, AMIP models overestimate their influence

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only in regions where the observed R^2 values are negligible (see Figure 7c)), suggesting that this overestimation does not represent a physically meaningful contribution to rainfall variability.

In contrast, the impact of low-frequency ER waves is generally overestimated in AMIP models, with R^2 differences reaching up to 8 percentage points. One possible explanation for this overestimation is that the slow propagation of ER waves allows more time for convective parameterizations to respond to large-scale atmospheric changes. As shown by Wang and Chen (2017), longer convective adjustment timescales lead to a slower atmospheric response to disturbances. This may enable AMIP models to capture ER waves more effectively, potentially leading to an overrepresentation of their influence on rainfall variability.

Although AMIP models slightly overestimate the MJO's influence in many regions, they underestimate its contribution to rainfall variability over the Indo-Pacific warm pool region. In this area GPM IMERG shows the highest MJO-related R^2 values (see Figure 7f)). This regional underestimation likely reflects the persistent challenges global climate models face in accurately simulating the MJO, as already discussed in Subsection 4.1.2.

4.2. Future climate

After assessing how CMIP6 models represent the influence of CCEWs on tropical rainfall variability in the present-day climate, this section examines projected changes in that influence under future global warming scenarios. It is divided into three subsections. In Subsection 4.2.1, I analyze projected changes in both the mean and variability of tropical rainfall. In Subsection 4.2.2, I assess whether and how CCEW-related precipitation variability in the wavenumber-frequency domain changes. Lastly, in Subsection 4.2.3, I examine how the contribution of CCEWs to tropical rainfall variability is projected to change under global warming.

4.2.1. Projected changes in precipitation under global warming

Numerous studies have shown that global warming will profoundly alter the global water cycle (e.g., He et al., 2023; Douville et al., 2013), affecting not only the mean state of precipitation but also its variability (Pendergrass et al., 2017). These projected changes (see Figure 9) are primarily driven by increased surface temperatures, which increase the moisture-holding capacity of the atmosphere and strengthen evaporation, potentially leading to more extreme events such as floods and droughts (Douville et al., 2021).

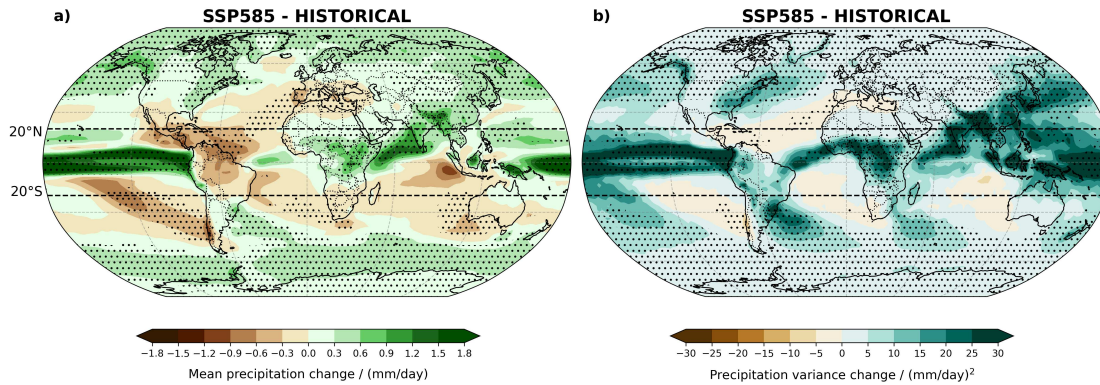


Figure 9: Projected changes in precipitation under the future scenario SSP585 from 2070 to 2100 relative to the historical simulation from 1980 to 2010. Panel a) displays the multi-model and time-mean changes in precipitation, while Panel b) shows the corresponding changes in the variance of intraseasonal precipitation anomalies. The stippling indicates where at least 90 % of models agree on the sign of change. The tropics are marked by black dashed lines at 20°S and 20°N.

As shown in Figure 9a), projected changes in mean precipitation follow a pattern in which wet regions, such as the tropical Pacific and the Maritime Continent, tend to become wetter, whereas dry regions, including the Mediterranean, southern Africa and western Australia, are projected to experience further drying. These patterns are consistent with

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previous studies (e.g., Tebaldi and Arblaster, 2014) and are often summarized by the phrase "dry gets drier, and wet gets wetter" (DDWW), first introduced by Held and Soden (2006). In contrast, changes in precipitation variability do not always coincide with changes in mean precipitation. For example, over the Indo-Pacific warm pool region, mean precipitation is projected to mostly decrease while precipitation variability increases.

Although many projected changes in precipitation are consistent across models, substantial regional differences in model agreement remain (see stippling in Figure 9). High agreement is found over mid-to-high latitudes and parts of the tropical belt, such as the tropical Pacific, while lower agreement occurs over other tropical and subtropical regions, including the Amazon basin, northern Africa and most parts of Australia. According to Zappa et al. (2021), this lower model agreement stems from internal variability that can mask climate change signals and from opposing model responses, with some models projecting drying and others wetting. Their analysis further attributes uncertainty to difficulties in simulating complex processes such as monsoon dynamics and tropical convection, as well as to systematic model biases.

The SSP585 scenario, representing a high-emission future, shows similar patterns in both global mean precipitation changes and variability compared to the more moderate SSP245 pathway (see Figure A.1 in the Appendix). However, the magnitude of the changes is amplified under SSP585. For instance, precipitation variability over the central Sahel, defined here as the region between 5°W-20°E and 10°-20°N following Monerie et al. (2020), more than doubles increasing from approximately 5 (mm/day)² in SSP245 to 12 (mm/day)² in SSP585.

The strongest changes in both mean precipitation and precipitation variability are projected over the tropical Pacific, central Africa and the western Indian Ocean (see Figure 9). These regions coincide with the areas where CCEWs are most active and play a major role in organizing tropical convection (Cheng et al., 2023) and rainfall variability (Schlueter et al., 2019). Furthermore, Pendergrass et al. (2017) found that most models project a larger relative increase in precipitation variability than in the mean.

4.2.2. Changes in the tropical power spectrum under global warming

To determine whether changes in precipitation variability under global warming can be attributed to changes in CCEWs, I first analyze changes in the wavenumber–frequency domain. As already described in Chapter 2, I focus on the more extreme SSP585 scenario, as CCEW signals become more pronounced under stronger warming (Bartana et al., 2022). To assess statistical significance in the wavenumber–frequency power spectra (10 and 11), I apply the bootstrapping approach described in Section 3.4. For each of the 25 models from both historical and SSP585 simulations, I generate 16 overlapping subsamples using a rolling window of 15 consecutive years.

Symmetric component of the wavenumber–frequency power spectrum

Figures 10a) and b) present the multi-model mean signal over background spectral power of the symmetric component for historical and SSP585 simulations, respectively. Similar to the results for the AMIP simulations, the coupled models show significant signals for ER waves, KW and the MJO, with the MJO being the most pronounced. Although Figures 10a) and b) display only the multi-model mean, an analysis of all individual models (see Figures A.2 and A.3 in the Appendix) shows a consistent pattern: all models capture significant signals for ER waves and the MJO, and most also for KW (except for IITM-ESM, INM-CM4-8, INM-CM5-0 and IPSL-CM6A-LR). In contrast, high-frequency WIG ($n=1$) waves are not significantly represented in the multi-model means. Only a few individual models (BCC-CSM2-MR, KIOST-ESM, NorESM-LM and NorESM-MM) show significant signals for WIG waves in both historical and SSP585 simulations (see Figures A.2 and A.3 in the Appendix). A comparison with the native horizontal resolution of each model (Table 2) reveals that resolution alone does not explain these differences. For instance, CMCC-CM2-SR5 (100 km) has the same native horizontal resolution as NorESM-MM but does not exhibit significant high-frequency wave activity. This suggests that beyond resolution, the representation of deep convection is also a critical factor for accurately simulating CCEWs, as previously discussed.

The multi-model mean difference between SSP585 and historical simulations (see Figure 10c)) suggests a strengthening of the KW signal and a shift towards higher phase speeds. This pattern is not robust across the models, as statistically significant changes appear in only about one-third of the models (Figure 10d)). The shift in phase speed is apparent from the concentration of these signals along steeper theoretical dispersion curves associated with KW, which correspond to faster wave propagation as described by the relation $c = \frac{\omega}{k}$ (Kiladis and Wheeler, 1999). Bartana et al. (2022) also found a strengthening of KW when analyzing projected changes between historical and SSP585 simulations using OLR and zonal winds at 250 hPa. They suggested that the intensification of KW may be linked to subtropical forcings. In particular, they proposed that a strengthening of the subtropical jet in a warmer climate could enhance the activity of midlatitude Rossby-type eddies. Since these eddies are known to excite KW (Tulich and Kiladis, 2021), this mechanism may contribute to the projected KW intensification. Bartana et al.

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(2022) also reported an increase in KW phase speeds. They attributed this shift to a more stable tropical atmosphere and stronger warming in the upper troposphere. According to Frierson et al. (2011), these conditions increase gross moist stability and lead to deeper equivalent depths, which correspond to higher phase speeds. Similarly, a recent study by Chien and Kim (2024) investigated the response of convectively coupled KW to surface warming using aquaplanet simulations with the Community Atmospheric Model. They also found a shift toward higher phase speeds under warmer sea surface temperature conditions. However, they explained this change primarily through an expansion of the tropospheric depth with warming, which increases the equivalent depth and thus supports faster wave propagation.

Figure 10c) also shows changes in the symmetric component of the MJO across different zonal wavenumbers. For low wavenumbers from 0 to 2 (indicated by the vertical dashed line in the MJO box), the multi-model mean displays an intensification of the MJO under the future SSP585 scenario compared to the historical simulation. Part of this increase may also stem from KW signals, as Roundy (2020) demonstrated that convectively coupled KW exist over a much broader region of the power spectrum than their normalized peak and overlap with regions typically associated with MJO activity. Nevertheless, only a few models agree on this increase. Bartana et al. (2022) also reported a strengthening of the MJO for low zonal wavenumbers in both OLR and upper-tropospheric zonal wind data. They and others (e.g., Jiang et al., 2020; Maloney et al., 2019) attributed this intensification to enhanced surface latent heat fluxes, stronger low-level moisture convergence and increased vertical advection of moist static energy under global warming. In contrast, the multi-model mean difference between SSP585 and historical simulations shows a weakening of the MJO signal for zonal wavenumbers higher than 3, again consistent with the findings of Bartana et al. (2022). However, this signal is not robust, as only a few models show statistically significant changes at these higher wavenumbers.

Compared to the pronounced changes in KW, the remaining wave types (ER and WIG) do not show significant changes under global warming (Figure 10d)). ER waves exhibit a slight weakening in the multi-model mean under SSP585, in agreement with the results of Bartana et al. (2022). In contrast, the increase in the spectral power for high-frequency WIG waves in the model mean is likely not related to actual wave activity. Instead, it more plausibly results from an overall increase in spectral power under global warming conditions. This increase also appears to be more pronounced at higher frequencies. To my knowledge, no studies have addressed this spectral increase.

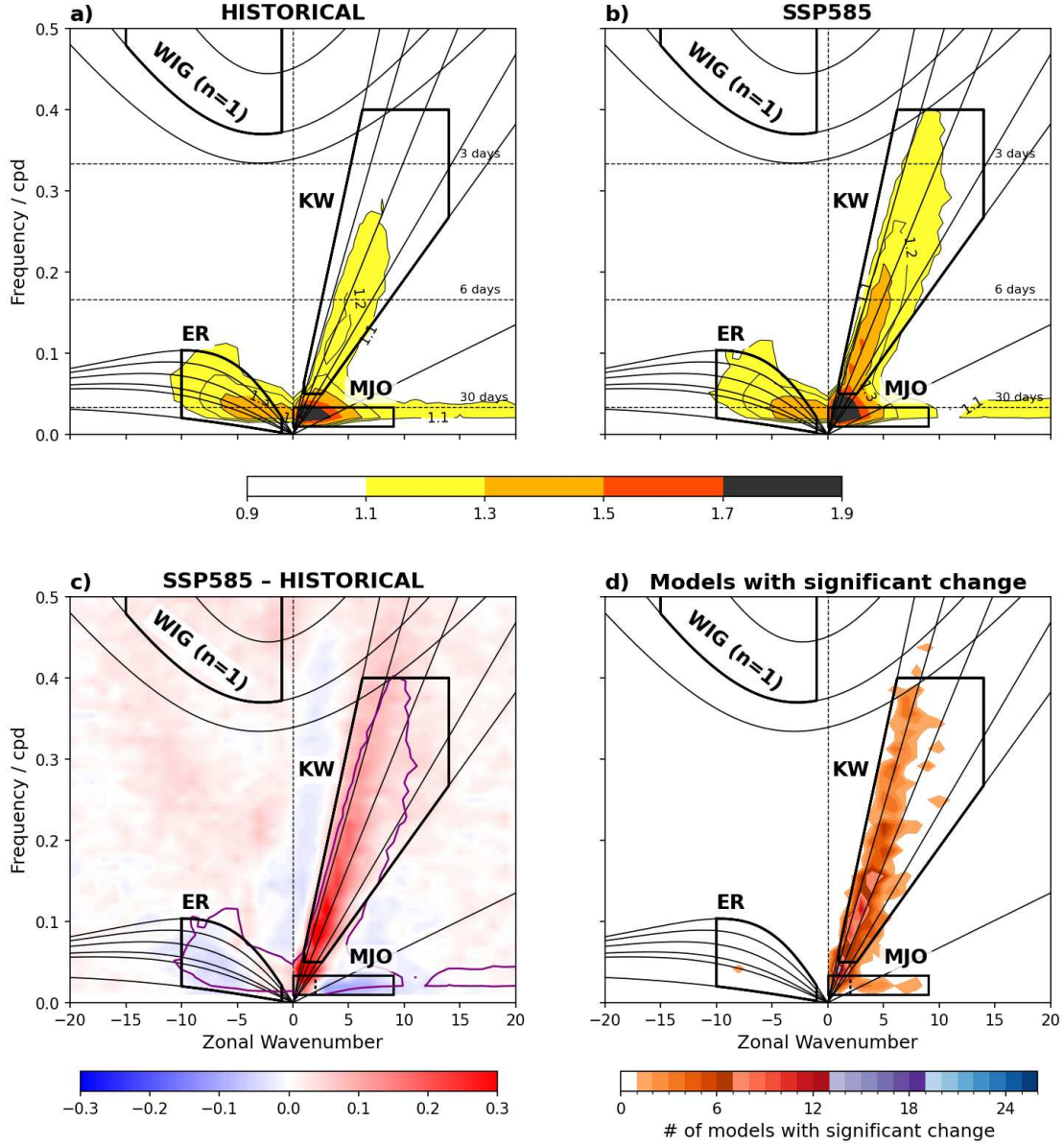


Figure 10: Wavenumber-frequency power spectra of the symmetric component, calculated from precipitation data and plotted as signal over background. Panel a) shows the multi-model mean of the symmetric component of the power spectrum for the historical simulation, while Panel b) shows the corresponding results for the SSP585 scenario. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95 % level (Kiladis and Wheeler, 1999). Panel c) presents the multi-model mean difference between SSP585 and historical simulations. The purple line indicates the 1.1 contour from the SSP585 scenario for reference. Panel d) displays the number of models exhibiting statistically significant changes. Thin black lines represent dispersion curves for six equivalent depths (1, 8, 12, 25, 50 and 90 m), while bold black lines indicate the wavenumber–frequency regions used for filtering selected CCEWs. The vertical dashed line in Panels c) and d) marks the the boundary of the low zonal wavenumber range within the MJO box.

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Antisymmetric component of the wavenumber-frequency power spectrum

Figures 11a) and b) show the multi-model mean signal over background spectral power of the antisymmetric component for historical and SSP585 simulations, respectively. The results are consistent with those from the AMIP simulations: in all models, the most pronounced signals correspond to the MJO, while MRG and EIG ($n=0$) waves exhibit little to no significant power in the multi-model means. An analysis of all individual models (see Figures A.4 and A.5 in the Appendix) reveals that 12 out of 25 models feature significant MRG signals in both historical and future simulations. For EIG waves, only four models show significant wave activity. These results highlight the inter-model variability in the representation of CCEWs, especially for high-frequency modes such as EIG waves. Among all 25 models, only NorESM2-LM and NorESM2-MM show significant signals for all CCEW types in both historical and SSP585 simulations. This may be related to the modified Zhang–McFarlane deep convection scheme used in NorESM2, which was adjusted to eliminate most of its resolution dependence (Seland et al., 2020).

The multi-model mean difference between SSP585 and historical simulations (Figure 11c)) shows no robust changes in the antisymmetric component of the power spectrum for the MJO, MRG and EIG waves. Beyond these wave-specific findings, the antisymmetric component shows a widespread decrease in spectral power under global warming conditions. Similar to the overall increase in spectral power in the symmetric component, this widespread decrease has not been investigated so far.

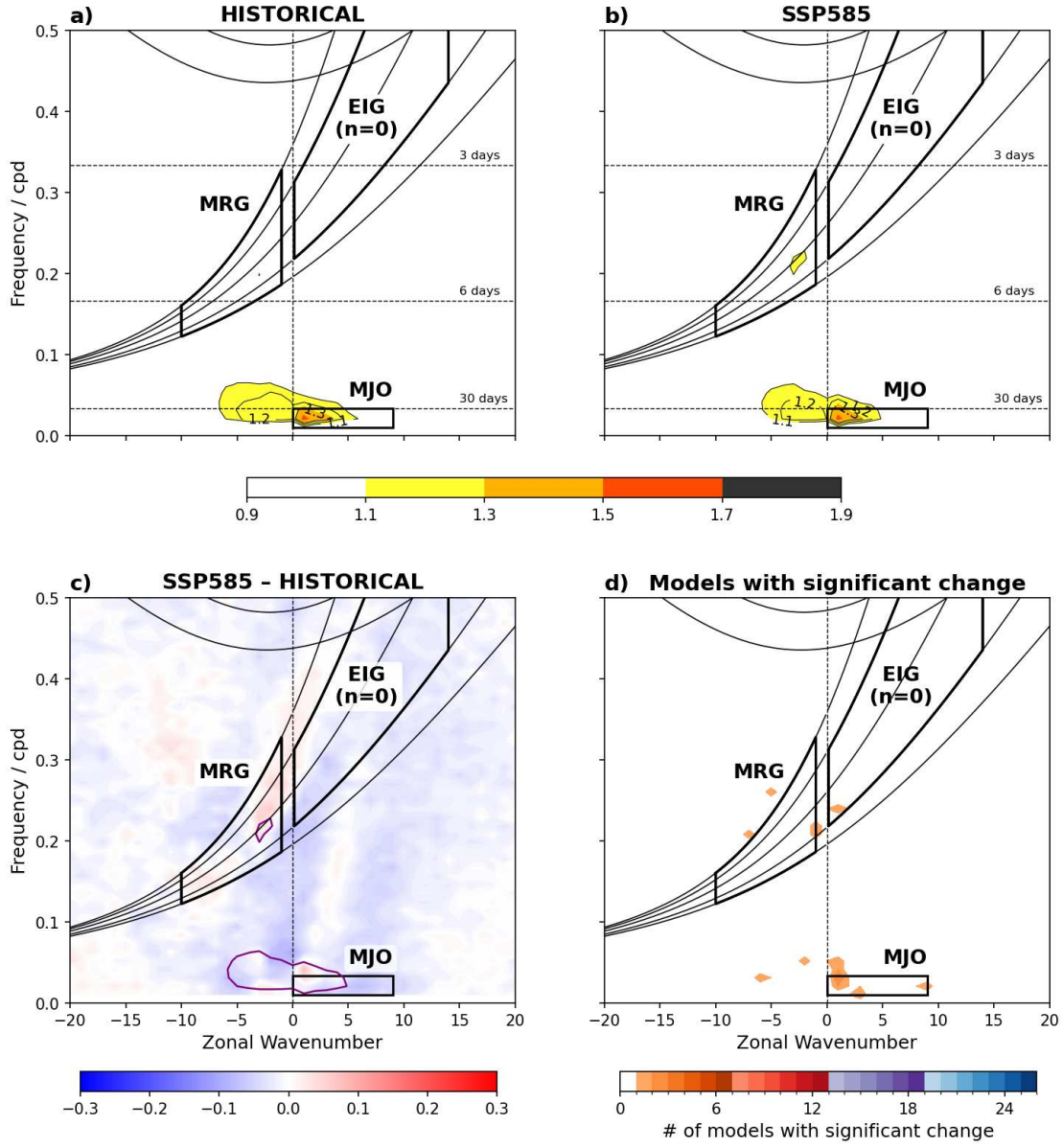


Figure 11: Same as in Figure 10, but for the antisymmetric component of the wavenumber-frequency power spectrum.

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4.2.3. Contribution of CCEWs to future tropical rainfall variability

This subsection examines how the contribution of CCEWs to tropical rainfall variability is projected to change under the high-emission SSP585 scenario, based on the squared Pearson correlation coefficient (R^2). To assess whether the differences in R^2 between SSP585 and historical models are statistically significant, I apply the bootstrapping approach analogous to that used for the wavenumber-frequency power spectra (see Subsection 4.2.2). Based on these results, I also compute a net model score as described in Section 3.4.

Figure 12 shows that the most pronounced changes in the contribution of CCEWs to tropical rainfall variability under global warming occur for KW, especially over the equatorial Pacific, where ΔR^2 values reach up to 7 percentage points. In this region, the KW-related contribution to rainfall variability is projected to nearly double compared to the historical simulation (see Figure A.6a) in the Appendix). This projected increase is robust across the majority of models (Figure 12g)). Robust increases in R^2 are also evident over central Africa, the western Indian Ocean and the Maritime Continent. The increased KW-related contribution to rainfall variability aligns with the enhanced KW activity in the wavenumber–frequency domain under global warming (see Subsection 4.2.2). As previously discussed, the intensification of KW may be linked to enhanced activity of midlatitude Rossby-type eddies under global warming (Tulich and Kiladis, 2021). Notably, the regions with increased KW-contribution to rainfall variability also coincide with areas where precipitation variance intensifies most strongly under SSP585 (see Figure 9b)). This spatial correspondence suggests that enhanced KW activity contributes to the projected increase in tropical rainfall variability.

For ER waves, the projected changes in their contribution to tropical rainfall variability are less pronounced (Figure 12b)). Depending on the region, the ER-related contribution is projected to either increase or decrease. The largest increase of up to 4 percentage points emerges over the central equatorial Pacific and corresponds to an approximate doubling relative to the historical simulation (see Figure A.6b) in the Appendix). In contrast, the most notable decreases in R^2 of up to 4 percentage points occur over the tropical Atlantic and the Indo-Pacific warm pool, indicating a relative decrease of 20 % compared to the historical simulation. According to the net model score, these regional changes are not robust across the models, as only about half of them agree (see Figure 12h)). When averaged across the tropics the overall difference amounts to -0.3 %. This is consistent with the slight weakening of ER activity under global warming, as shown in the dispersion diagrams (Subsection 4.2.2).

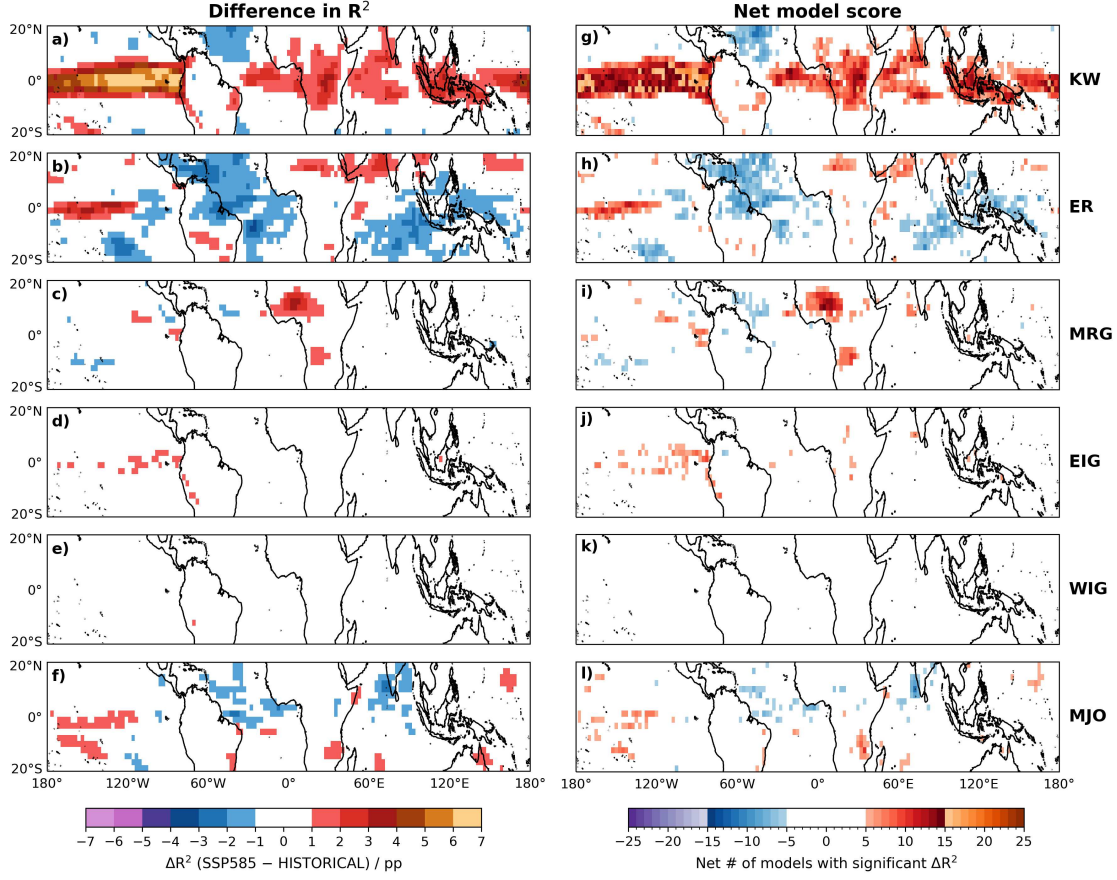


Figure 12: Contribution of CCEWs to projected changes in tropical rainfall variability. Panels a)–f) show the differences in the squared Pearson correlation coefficient (R^2) between the SSP585 scenario and the historical simulation for all CCEWs and the MJO, expressed in percentage points (pp). Panels g)–l) display the net model score, calculated as the number of models with a statistically significant increase minus those with a significant decrease for the respective CCEW type.

In contrast to KW and ER waves, the projected changes for MRG waves are more spatially confined with an increase in R^2 of up to 4 percentage points over West Africa and south of central Africa (Figure 12c)). In these regions, the MRG-related contribution to rainfall variability is projected to approximately double relative to the historical simulation (see Figure A.6c) in the Appendix). The net model score indicates that significantly more models project an increase than a decrease over West Africa, whereas this predominance is smaller over southern central Africa (Figure 12i)). The underlying cause of this regional increase has not yet been investigated.

Projected changes in the MJO-related contribution to rainfall variability are weak and spatially incoherent (Figure 12f)). Slight increases in R^2 appear over the central equatorial Pacific, while decreases in R^2 occur over parts of the Atlantic and the Indian monsoon

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domain. However, the net model score (Figure 12l)) shows that these changes are not robust, as only a few individual models agree on the direction of change. This lack of robustness is consistent with previous findings (e.g., Maloney et al., 2019) that report considerable inter-model variability and uncertainties in simulating the MJO under global warming.

Regarding high-frequency EIG and WIG waves, no changes in their impact on rainfall variability are projected. This outcome is likely related to the already limited representation of these fast, small-scale modes in current climate models. For instance, in the historical simulation the R^2 values for these modes are close to zero across most regions (see Figures A.6d) and e) in the Appendix).

5. Conclusion

This thesis investigates the impact of convectively coupled equatorial waves and the Madden-Julian oscillation on tropical rainfall variability in simulations of present-day and future climates, using CMIP6 simulations. In the following, I revisit the research questions posed in Chapter 2 to conclude on the fidelity of the CMIP6 models in capturing CCEW-related rainfall variability.

1. How accurately do CMIP6 atmospheric models represent the impact of CCEWs on present-day tropical rainfall variability compared to observational data?

To answer this question, I first examined how well AMIP models represent CCEWs in the wavenumber–frequency domain. I then computed the squared Pearson correlation coefficient (R^2) between filtered wave signals and precipitation anomalies for individual CCEW types, using observational data from GPM IMERG and AMIP simulation data. In general, most AMIP models underestimate both the representation of KW and high-frequency waves in the wavenumber–frequency domain and their impact on tropical rainfall variability. Previous work suggested that this model bias is linked to low horizontal resolution (Spät et al., 2024) and the parameterization of deep convection, which can distort wave signals (Lin et al., 2006) and trigger deep convection too rapidly (Bengtsson et al., 2019). Judt and Rios-Berrios (2021) further demonstrated that explicitly resolving convection at kilometer-scale resolution improves the simulation of CCEWs, especially high-frequency modes like WIG waves. The largest underestimations in absolute terms in AMIP models, with ΔR^2 values up to 18 percentage points, occur for KW which also exhibit the highest observed R^2 values. This is especially evident over the Amazon basin, the tropical Atlantic and the Indian Ocean warm pool region. The contributions of other high-frequency modes, such as EIG, WIG and to a large extent MRG waves, are likewise underestimated. Although the absolute differences between simulated and observed R^2 values are smaller for EIG and WIG waves compared to KW, the relative differences are actually up to 20% higher than for KW.

In contrast, AMIP models generally overestimate the impact of low-frequency waves, particularly ER waves, on tropical rainfall variability. This overestimation may result from the slower propagation speed of these waves, which allows convective parameterizations more time to respond to large-scale disturbances (Wang and Chen, 2017), potentially amplifying their simulated contribution. However, an exception to this pattern is the MJO over the Indo-Pacific warm pool region, where AMIP models underestimate its impact despite high observed R^2 values. This likely reflects the long-standing difficulties global climate models face in simulating the MJO.

5. Conclusion

2. How does the impact of CCEWs on tropical rainfall variability change under global warming in CMIP6 models?

Similar to the first research question, I first analyzed changes in CCEWs in the wavenumber–frequency domain based on historical simulations and the high-emission SSP585 scenario. I then calculated the squared Pearson correlation coefficient (R^2) for both simulations. The most pronounced changes in R^2 occur for KW, with a strong increase in their impact on rainfall variability, especially over the equatorial Pacific. In this region, the KW-related contribution to rainfall variability nearly doubles compared to the historical simulation. This increase is consistent with enhanced KW activity in the wavenumber–frequency domain under global warming and may be linked to increased excitation by midlatitude Rossby-type eddies in a warmer climate (Tulich and Kiladis, 2021). Furthermore, regions with increased KW-related contribution to rainfall variability under SSP585 correspond closely to areas where precipitation variance intensifies most strongly. This suggests that enhanced KW activity contributes to the intensification of future tropical rainfall variability.

For ER waves, projected changes in their contribution to tropical rainfall variability are less pronounced than for KW. The largest increase of up to 4 percentage points emerges over the central equatorial Pacific, whereas the most notable decreases in R^2 occur over the tropical Atlantic and the Indo-Pacific warm pool. When averaged across the tropics, the overall change is slightly negative, which is in line with the slight reduction in ER wave activity in the wavenumber-frequency domain under global warming.

For MRG waves, a regional increase is projected over parts of Africa, especially West Africa. The cause of this increase is unclear and requires further investigation.

For the MJO, as well as for high-frequency EIG and WIG waves, little to no change is projected under global warming in either their representation in the wavenumber–frequency domain or their contribution to tropical rainfall variability. This likely reflects their limited representation in current climate models. In the case of the MJO, the absence of robust changes is further compounded by substantial inter-model variability and uncertainties in its response to warming.

In summary, accurately capturing CCEW dynamics is essential for accurate climate projections, due to their influence on rainfall variability. However, the results of this thesis highlight significant biases in current state-of-the-art climate models, particularly in the representation of KW and high-frequency waves. These biases are probably linked to the coarse horizontal resolution and the parameterization of deep convection in these models.

6. Outlook

There are several directions in which this thesis can be extended. Here, I present an overview of the areas that could be explored further.

My results reveal significant biases in CMIP6 atmospheric models, especially in their representation of KW and high-frequency waves, such as WIG waves. These biases are likely related to coarse horizontal resolution and deficiencies in convection. One way to address these shortcomings is to use kilometer-scale climate models, which do not require deep convection parameterization and have shown promising results in representing CCEWs (e.g., Judt and Rios-Berrios, 2021). Alternatively, future research could focus on identifying which specific convection schemes are most effective at representing KW and high-frequency CCEWs.

To my knowledge, this thesis is the first to investigate the impact of CCEWs on future tropical rainfall variability under global warming scenarios. My findings highlight several changes, such as a projected regional increase in the contribution of ER waves over the central equatorial Pacific. However, the underlying mechanisms driving these changes remain unclear and require further investigation.

CCEWs are known to interact with each other. For example, Schlueter et al. (2019) showed that over West Africa, MRG waves tend to be amplified during the convectively active phases of the MJO and ER waves, whereas they are suppressed during convectively suppressed phases. However, wave interactions were not considered in this thesis. Future work could address this by evaluating how the signal of one wave type changes depending on whether another dominant wave is in an active or suppressed phase. Specifically, Schlueter et al. (2019) first identified wet and dry phases of a primary wave based on when the wave-filtered precipitation exceeded ± 1 standard deviation and then analyzed how the presence of a second wave modulated this signal. This approach can help to better isolate the individual contribution of each wave type, especially in regions where several wave modes are active simultaneously.

Finally, seasonal variations in the projected impact of CCEWs on rainfall variability have not been addressed in this thesis. Lubis and Jacobi (2015) demonstrated that wave-related rainfall variability strongly depends on the season, with KW-related variability peaking in boreal spring and ER-related variability in boreal winter. Accounting for such seasonal dependencies in future projections could reveal additional aspects of how CCEWs influence rainfall variability that are not apparent in annual means.

A. Appendix

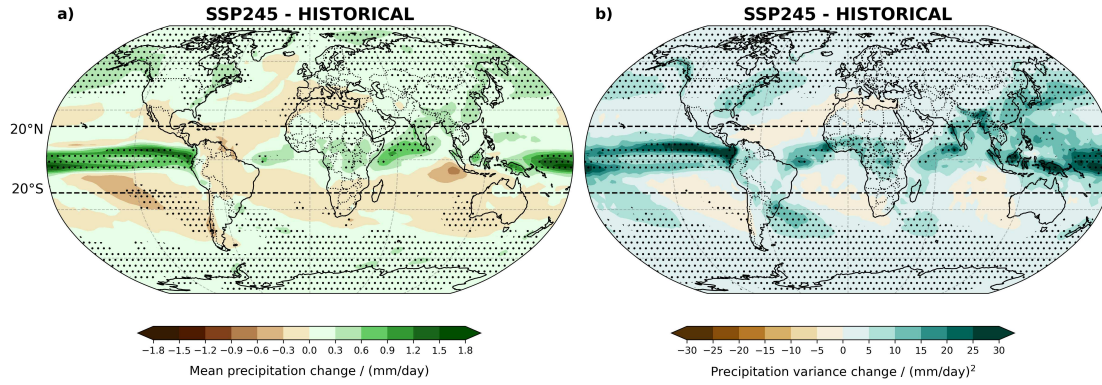


Figure A.1: Projected changes in precipitation under the future scenario SSP245 from 2070 to 2100 relative to the historical simulation from 1980 to 2010. Panel a) displays the multi-model and time-mean changes in precipitation, while Panel b) shows the corresponding changes in the variance of intraseasonal precipitation anomalies. The stippling indicates where at least 90 % of models agree on the sign of change. The tropics are marked by black dashed lines at 20°S and 20°N.

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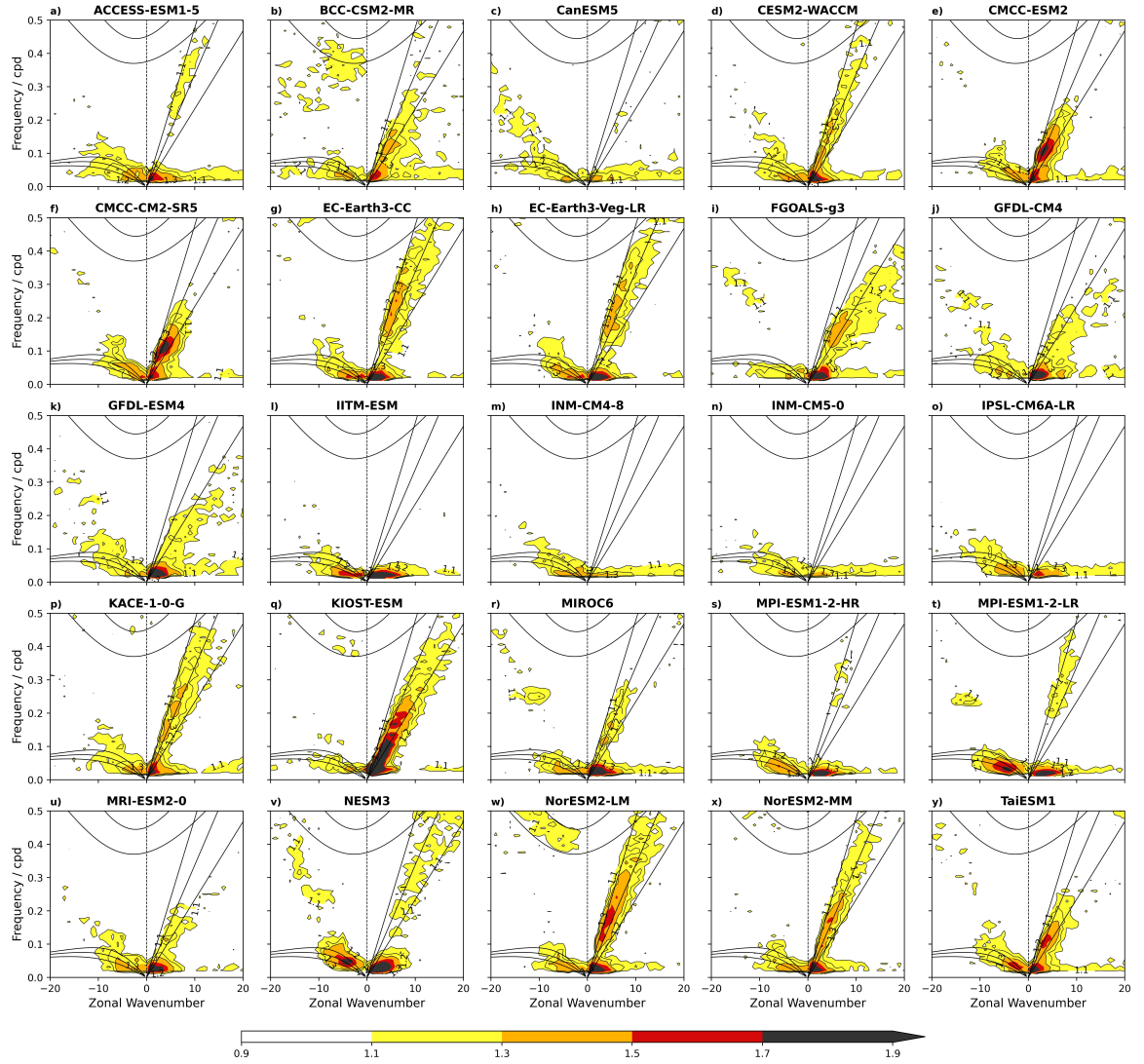


Figure A.2: Symmetric component of the wavenumber-frequency power spectrum for each model of the historical simulations. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95% level (Kiladis and Wheeler, 1999). Black lines represent dispersion curves for three equivalent depths (12, 25 and 50 m).

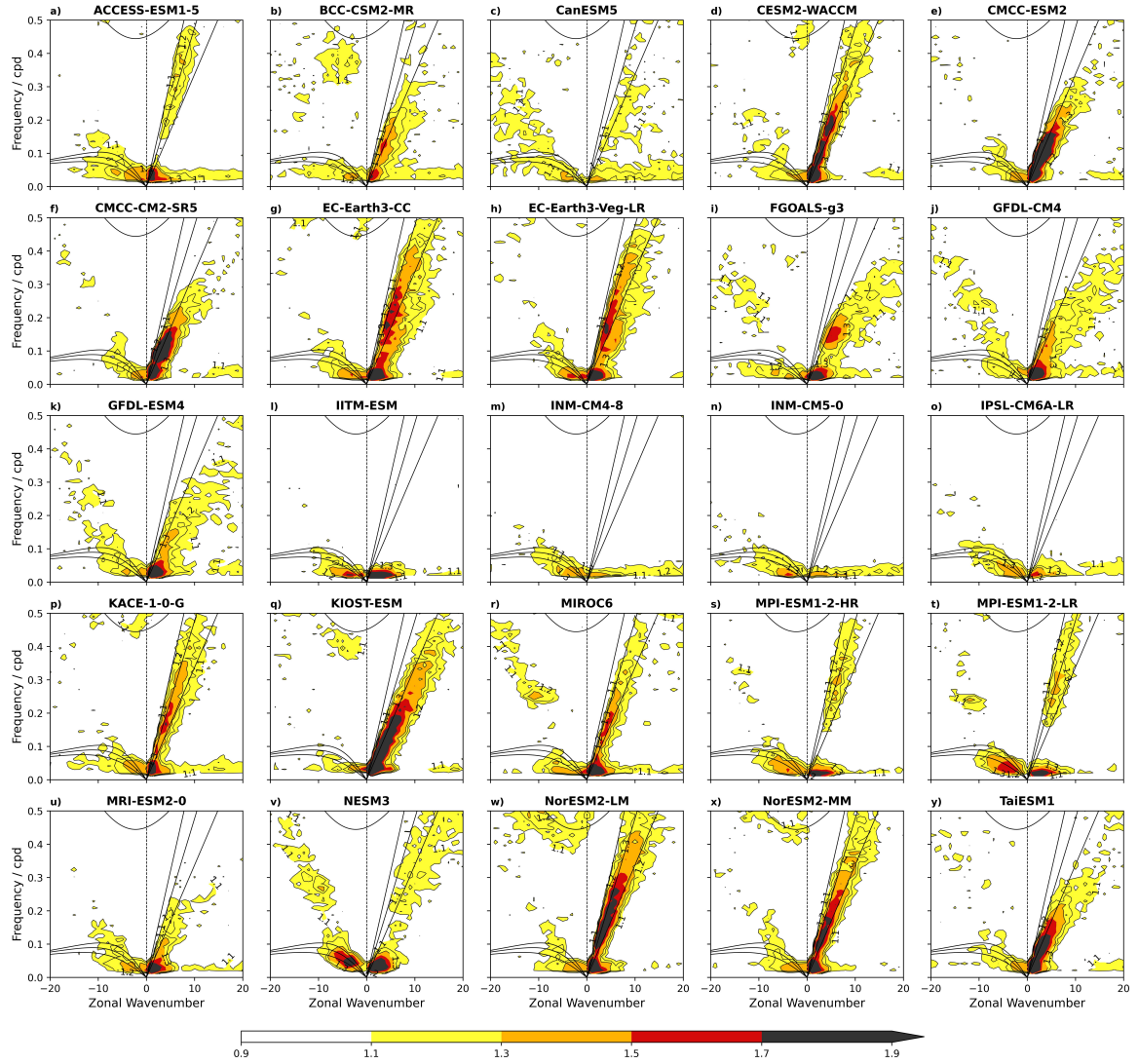


Figure A.3: Symmetric component of the wavenumber-frequency power spectrum for each model in the SSP585 ensemble. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95% level (Kiladis and Wheeler, 1999). Black lines represent dispersion curves for three equivalent depths (12, 25 and 50 m).

A. Appendix

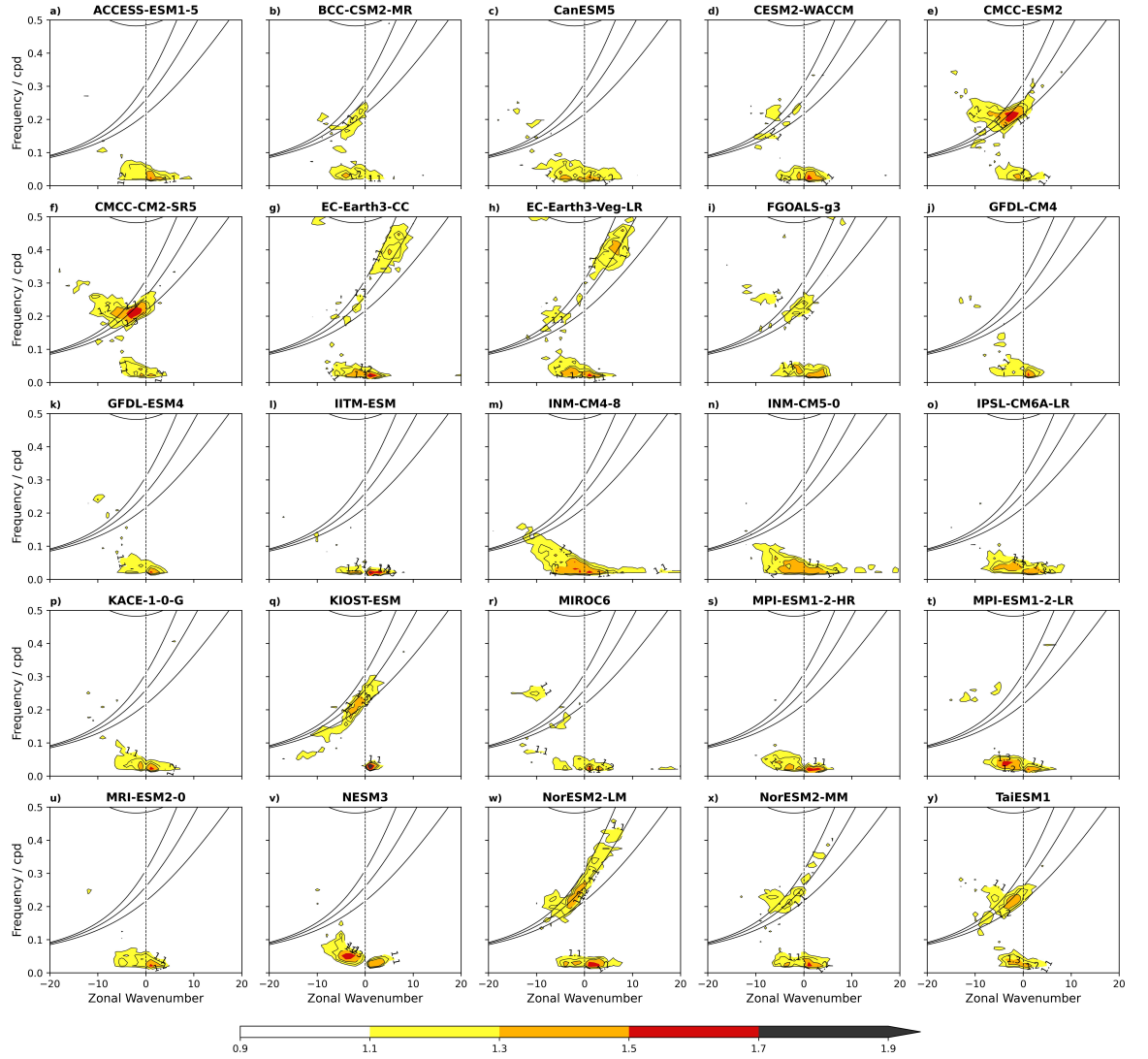


Figure A.4: Antisymmetric component of the wavenumber-frequency power spectrum for each model of the historical simulations. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95% level (Kiladis and Wheeler, 1999). Black lines represent dispersion curves for three equivalent depths (12, 25 and 50 m).

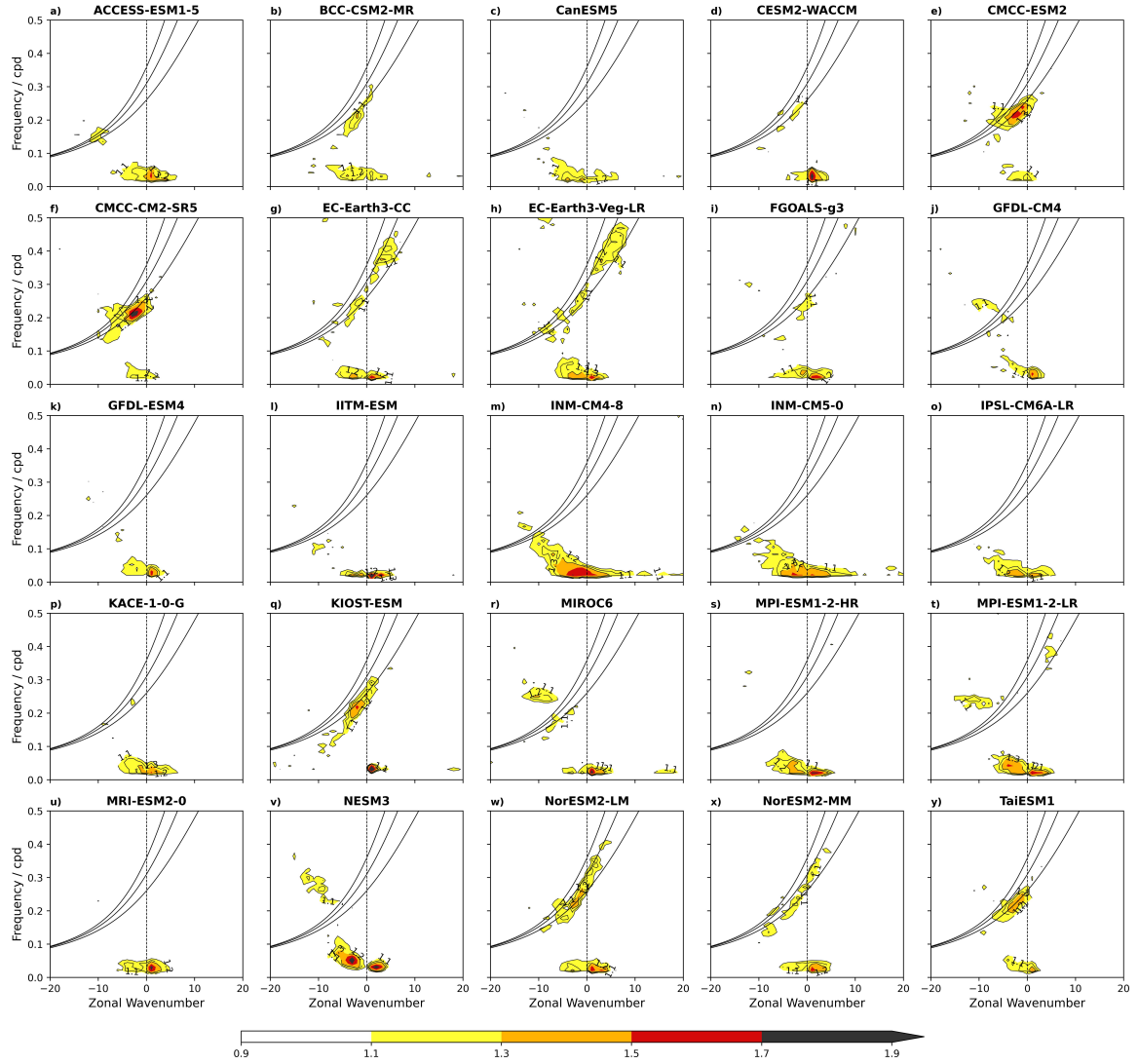


Figure A.5: Antisymmetric component of the wavenumber-frequency power spectrum for each model in the SSP585 ensemble. The contour interval is 0.1 and contours and shading begin at 1.1, where the signal is significant above the 95% level (Kiladis and Wheeler, 1999). Black lines represent dispersion curves for three equivalent depths (12, 25 and 50 m).

A. Appendix

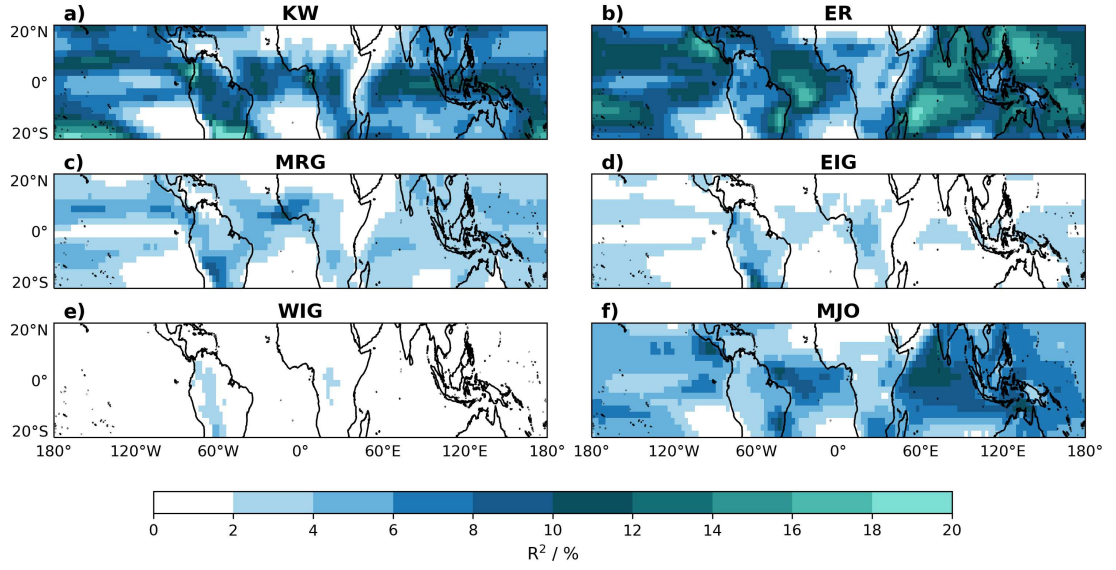


Figure A.6: Simulated contribution of different CCEW types to tropical rainfall variability from the historical multi-model mean. Panels a)–f) show the squared Pearson correlation coefficient (R^2) between filtered wave signals and precipitation anomalies.

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