



RESEARCH ARTICLE

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Key Points:

- A method is presented to effectively adjust Kelvin wave amplitudes in simulations with parameterized convection
- This method can identify two-way convective coupling in Kelvin waves and has potential use in attributional work on their impacts
- The failure of numerical models to simulate a strong Kelvin wave motivates future work on the predictability of individual wave events

Supporting Information:

Supporting Information may be found in the online version of this article.

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The Representation of Convectively Coupled Kelvin Waves in Simulations With Modified Wave Amplitudes

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Abstract Convectively coupled Kelvin waves (CCKWs) are important drivers of tropical weather and may influence extreme rainfall and tropical cyclone formation. However, directly attributing these impacts to CCKWs remains a challenge. Numerical models also struggle to simulate the convective coupling of CCKWs. To address these gaps in understanding, this study examines a set of global simulations in which CCKW amplitudes are modified in the initial conditions. The Model for Prediction Across Scales—Atmosphere is used to simulate a time period in which several CCKWs coexisted around the globe, including an unusually strong CCKW located over the Atlantic. Prior to running the simulation, Kelvin-filtered fields are identified in initial conditions and used to either amplify or dampen the initial wave amplitude. This method is effective at robustly changing the strength and structure of simulated CCKWs and can illuminate their convective coupling. Rainfall intensity within simulated CCKWs is shown to be partially controlled by column saturation fraction and deep convective inhibition. Despite the accurate depiction of most CCKWs during this time period, however, these experiments fail to simulate convective coupling in the strong Atlantic CCKW. This is true even after amplifying this wave at initialization. The cause of this failure is unclear and motivates additional work into the modeling and predictability of CCKW events. Overall, this study demonstrates that modifying CCKW amplitudes can serve as a useful tool for understanding CCKWs. This method may also be useful for future attributional work on the influence of CCKWs on other phenomena.

Plain Language Summary Convectively coupled Kelvin waves (CCKWs) are large waves in Earth's atmosphere that travel along the equator and can influence other weather features, like rainfall and tropical cyclones. However, it has been difficult to directly prove how CCKWs impact these other weather features. Weather forecasting models also struggle to accurately simulate CCKWs. To address these challenges, this study investigates a set of modeling experiments in which the strength of CCKWs has been changed. The Model for Prediction Across Scales—Atmosphere is used to produce simulations of a period for which several CCKWs existed around the world. The strength of these CCKW is changed in the initial conditions prior to running these simulations. Results show this adjustment method is effective at changing the strength and structure of simulated CCKWs. This is useful for identifying the connections between a wave's wind structure and rainfall. However, these experiments fail to accurately simulate a strong CCKW over the Atlantic. The cause of this failure is unclear, motivating additional work into modeling CCKW events. This study demonstrates how a method for changing CCKW strength could serve as a useful tool for understanding CCKWs and their influence on other weather features.

1. Introduction

Convectively coupled Kelvin waves (CCKWs) are eastward-propagating equatorial waves that are important drivers of tropical weather. These waves contribute significantly to the variability of tropical rainfall and convection, including over the Maritime and African continents (Cheng et al., 2023; Lubis & Jacobi, 2015; Mekonnen et al., 2008; Mounier et al., 2007; Sakaeda et al., 2020; Schlueter et al., 2019). They also influence high-impact weather events (Ferrett et al., 2020; Latos et al., 2021; Lawton et al., 2022; Lawton & Majumdar, 2023; Mantripragada et al., 2021; Peyrillé et al., 2023; Schreck, 2015; Ventrice, Thorncroft, & Janiga, 2012; Ventrice, Thorncroft, & Schreck, 2012). Given their importance, understanding the predictability, dynamics, and downstream impacts of CCKWs—along with their representation in numerical modeling systems—has been a topic of much inquiry over the past few years (e.g., Bengtsson et al., 2019; Dias et al., 2018; Gehne et al., 2022; Janiga et al., 2018; Judt & Rios-Berrios, 2021; Rios-Berrios, Davis, & Martinez, 2023; Yang et al., 2021).

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CCKWs in the real atmosphere are well documented. In the troposphere, CCKWs move eastward at speeds of 10–20 m/s and have wavelengths that range from 3000 to 7000 km (Gruber, 1974; Kiladis et al., 2009; Straub & Kiladis, 2002; Takayabu, 1994; Wheeler & Kiladis, 1999). These observed waves bear many similarities to their theoretical Kelvin wave counterparts, which were first derived by Matsuno (1966) and expanded upon in more advanced treatments thereafter (Kiladis et al., 2009 and references therein). However, the presence of a moist atmosphere and a variable mean state result in the deviation of observed tropospheric CCKWs from theory (e.g., Dias & Kiladis, 2014; Kiladis et al., 2009; Tulich & Kiladis, 2021). For example, CCKWs tilt westward with height in the troposphere, and are often shifted slightly poleward of the equator with the intertropical convergence zone (ITCZ; Kiladis et al., 2009; Mayta et al., 2021; Mounier et al., 2007; Straub & Kiladis, 2002). Regional differences in CCKW activity and phase speed have also been observed, often attributed to changes in the mean state (Roundy, 2008, 2012; Tulich & Kiladis, 2021; Yang et al., 2007). However, the cause of this regionality is still not fully understood. Most importantly, these waves are coupled with atmospheric convection, which plays a role in wave growth and causes them to propagate slower than they would otherwise (Herman et al., 2016; Kiladis et al., 2009; Weber et al., 2021; Wolding, Dias, Kiladis, Ahmed, et al., 2020; Wolding, Dias, Kiladis, Maloney, & Branson, 2020).

The mechanisms driving convective coupling in CCKWs are still debated. Adames et al. (2019) proposed that CCKWs are best classified as gravity-wave-type waves, with their dynamics responding primarily to thermal fluctuations. Supporting this are studies indicating that deep convective inhibition (DCIN) is the primary mechanism controlling the onset of CCKW-related precipitation (Fuchs et al., 2014; Herman et al., 2016). Changes to DCIN within the wave envelope are thought to be driven primarily by adiabatic motion and its control on thermodynamics, which encourages the development of convection through a reduction of static stability (Herman et al., 2016). Other studies, however, have emphasized that the column moisture—often represented by column saturation fraction (CSF)—still plays a non-negligible role in setting the amount of precipitation within a CCKW's convective envelope (Weber et al., 2021; Wolding, Dias, Kiladis, Maloney, & Branson, 2020). These studies do not dispute the role of DCIN in setting the onset of CCKW precipitation but do emphasize that CSF may still have some contributions to rain rate.

An incomplete understanding of CCKW convective coupling may compromise the representation of these waves in numerical models. A plethora of research has demonstrated that CCKWs are often poorly represented in medium-range and subseasonal forecast systems (Bengtsson et al., 2019; Dias et al., 2018, 2023; Gehne et al., 2022; Janiga et al., 2018; Schreck et al., 2020; Yang et al., 2021). For example, CCKW forecast skill in a recent version of the NOAA Global Forecast System was limited to only 1–2 days (Gehne et al., 2022), and CCKWs in subseasonal forecasting systems are often poorly represented and add minimal forecasting skill (Dias et al., 2023; Janiga et al., 2018; Schreck et al., 2020). These errors have often been attributed to the use of convective parameterization schemes, which may reduce the effectiveness of how well models represent coupled tropical systems like CCKWs (e.g., Dias et al., 2018). However, there is also the possibility that the predictability of CCKWs is intrinsically limited. For example, Li and Stechmann (2020) used Tropical Rainfall Measuring Mission (TRMM) data to show that the typical predictability of CCKW rainfall only extends for 2–3 days.

Some numerical models show more skill in simulating CCKWs than others. This may be tied to how these models represent tropical convection and their coupling to the atmosphere. The Model for Prediction Across Scales—Atmosphere (MPAS-A; Skamarock et al., 2012), is one modeling system that has shown relatively high skill in the representation of CCKWs. MPAS-A experiments using realistic input conditions (Judt & Rios-Berrios, 2021), aquaplanet configurations (Hagos et al., 2013; Rios-Berrios et al., 2020, 2022; Rios-Berrios, Davis, & Martinez, 2023; Rios-Berrios, Judt, et al., 2023), and for an individual case study (Weber et al., 2021) have all demonstrated realistic CCKW structure and behavior. Furthermore, Judt (2020) found that CCKWs in storm-permitting MPAS-A simulations exhibited limited error growth over a 20-day period. While many of these improvements are attributed to the storm-permitting resolutions of many of the simulations (~3 km), coarser experiments with parameterized convection still fare well. For example, Judt and Rios-Berrios (2021) investigated the global contributions of equatorial waves to rainfall in 40-day simulations with varying horizontal resolutions. They found that CCKWs contributed nearly the same percentage of rainfall variance in coarse parametrized experiments (~15 km, ~120 km) as they did for storm-permitting runs (~3.75 km) and observational data. Meanwhile, Weber et al. (2021) used MPAS-A to simulate a single CCKW event over the Indian Ocean. While they found that storm-resolving resolutions (~3 km) more completely captured the magnitude of the CCKW signal, a parameterized 15-km experiment was still able to simulate the main details of CCKW

structure and evolution, including its vertical tilt and progression of cloud features. However, Weber et al. (2021) also noted that these 15-km experiments underestimated the amplitude of the wave's rainfall, likely due to an inaccurate linear relationship between moisture and precipitation. Finally, Rios-Berrios, Davis, and Martinez (2023) found that MPAS-A aquaplanet simulations produced realistic CCKW structures at both parameterized and convection-permitting resolutions. The evidence showing that MPAS-A can accurately simulate CCKWs motivates our use of this model for this study.

Despite this previous research, there also exists a gap in our understanding of the predictability of *individual* CCKW events. Most studies have opted to look at how these waves are *collectively* represented in forecast systems across a large sample (e.g., Dias et al., 2023; Gehne et al., 2022; Judt & Rios-Berrios, 2021). Only a few recent studies have focused on high-impact CCKW events and their predictability (Doyle et al., 2023; Senior et al., 2023; Weber et al., 2021). This may serve as a limiting factor for our understanding of the representation and predictability of CCKWs in forecast models. For instance, it is unknown if CCKWs are better represented in different regions, under the influence of certain large-scale atmospheric regimes, or whether their strength at initialization contributes to a model's ability to accurately predict its evolution. A detailed documentation of notable failures or successes for individual CCKW cases could provide a framework for answering these questions, and can illuminate areas in which future, more systematic studies should be targeted.

The need for such work is elevated by evidence that individual CCKW events can have significant ramifications on the prediction of high-impact weather in the tropics. Recent research has demonstrated that CCKWs may aid in the amplification of African easterly waves and encourage tropical cyclone formation (Lawton et al., 2022; Lawton & Majumdar, 2023; Mantripragada et al., 2021; Schreck, 2015; Senior et al., 2023; Ventrice, Thorncroft, & Janiga, 2012). While several hypotheses have been presented to explain the influence of CCKWs on these phenomena, the relative importance of each mechanism remains unclear (Lawton & Majumdar, 2023; Mantripragada et al., 2021; Schreck, 2016; Ventrice, Thorncroft, & Schreck, 2012). Such attributional work is challenging in observational and reanalysis data sets, where the exact contribution of CCKWs to a given outcome can only be inferred. This motivates the development of a method to modify CCKWs in modeling systems, which could allow for attributional questions to be more directly addressed.

This study aims to advance our understanding of CCKWs and their impacts by modifying the amplitude of CCKWs in MPAS-A simulations with parameterized convection. We focus these experiments on a period in September 2021 in which there were several propagating CCKWs around the globe, including a historically strong CCKW in the Atlantic that was linked to the formation of Tropical Storm Victor. The purpose of this study is twofold: (a) to demonstrate the usefulness of amplitude modification in investigating CCKW coupling and filling the gap in attributional work, and (b) to illustrate an example of a poorly forecasted CCKW with ramifications on high-impact weather. We will argue that the results from this study strongly motivate follow-up work on the predictability of individual CCKW events, and that this modification method could assist future attributional studies focused on equatorial waves.

The layout of the paper is as follows. Section 2 describes the model configuration and the CCKW amplitude modification method. Section 3 presents results from these simulations in comparison with reanalysis and observational data. Section 4 details the implications of this study to future attribution and predictability work. Finally, Section 5 concludes with a summary of our findings.

2. Materials and Methods

2.1. Data Sets

Several data sets are utilized for the comparison to, and initialization of, MPAS-A experiments. All data are obtained August–October 2021, overlapping the time period of the 8-day MPAS-A simulations. Reanalysis fields are obtained from the global fifth-generation ECMWF reanalysis (ERA5; Hersbach et al., 2020) on a $0.25^\circ \times 0.25^\circ$ grid. Satellite brightness temperature data are obtained from the NOAA GridSat-B1 data set (Knapp et al., 2011). The late stage run of the Integrated Multi-satellite Retrievals for GPM (IMERG) data set is used for estimates of observed precipitation (Huffman et al., 2019). We also leverage data from the Integrated Forecasting System (IFS), an operational system run by the European Centre for Medium-Range Weather Forecasts (ECMWF). The data used here are from the 47r2 IFS upgrade cycle, primarily consisting of the high-resolution forecast system (HRES) and ensemble forecast system (ENS). Both have 137 vertical levels, with HRES having

an atmosphere resolution of near 9 km and ENS members having an atmospheric resolution of near 18 km. These IFS fields are obtained on a $0.125^\circ \times 0.125^\circ$ grid for initialization of the MPAS-A system. More information on this IFS cycle is provided by Maass (2021).

2.2. Equatorial Wave Identification

To modify and analyze CCKWs in these experiments, we must utilize a method of objective equatorial wave identification. Numerous identification methods have been developed, each with distinct advantages and disadvantages (Knippertz et al., 2022). A potential complication of this study is the short 8-day duration of our simulations, which could affect spatio-temporal filtering (Kiladis et al., 2009; Knippertz et al., 2022). As such, we follow the recommendation of Knippertz et al. (2022) by employing a combination of spatio-temporal filtering and spatial projections methods for our analysis. Results using each of these methods largely complement each other, giving us confidence in our identification of CCKWs and their related fields. Below we provide a description of both methods and briefly address their caveats.

2.2.1. Spatio-Temporal Filtering

The primary technique of CCKW identification used for this study is frequency-wavenumber filtering as developed by Wheeler and Kiladis (1999). In this method, a fast Fourier transform (FFT) is used to filter input data in space and time, allowing for the isolation of signals associated with a desired equatorial wave type. Here, we use the Kelvin-band bounded by a temporal period of 2.5–20 days, a zonal wavenumber from 1 to 14, and equivalent depth of 8–90 m. These bounds follow those used in several studies (Lawton et al., 2022; Lawton & Majumdar, 2023; Roundy, 2008; Ventrice, Thorncroft, & Janiga, 2012). While a 2.5–20 days temporal period is slightly larger than the 2.5–17 day period used in other applications (Straub & Kiladis, 2002), it is unlikely that this choice substantially alters the results presented here.

One disadvantage of this method is that it is not time-independent and has reduced accuracy for short data sets with abrupt starts and ends (Kiladis et al., 2009; Knippertz et al., 2022). As such, we apply 30 days of zero-padding to data sets prior to filtering, as has been done for real-time equatorial wave identification (Wheeler & Weickmann, 2001). While this method can be used on any variable, here it is primarily used to isolate CCKW signals prior to model initialization (via wind, temperature, and moisture) and for the analysis of convective signals in observations and simulation output (via brightness temperature and rain rate).

2.2.2. Filtering Using Spatial Projections

We also utilize another identification method that projects atmospheric fields onto parabolic cylindrical functions (PCFs; Yang et al., 2003). These PCFs represent theoretical solutions for equatorial waves on an equatorial β -plane (Matsuno, 1966). For this study, the meridional trapping scale for the PCFs is set at 6° . Wind and geopotential height fields are transformed and projected onto the theoretical PCFs separately for each level, and then are transformed back to physical space. Prior to the spatial projection, an FFT filter still must be used to separate eastward and westward propagating disturbances. However, this filter is much broader than that used in the spatio-temporal method, spanning a period of 3–30 days and zonal wavenumbers 2–20.

As discussed in detail by Knippertz et al. (2022), the PCF projection method has a few advantages. It is less susceptible to edge effects due to short simulation lengths and does not assume relationships in height or time. However, existing theory only provides support for isolating a CCKW's wind and geopotential height fields using this method. This precludes us from identifying CCKW-associated convection using these PCFs. As such, this method is used in conjunction with the spatio-temporal method discussed previously.

2.2.3. Meridional Averaging

To summarize changes in the propagating CCKWs over time, meridional averages are taken of both the PCF-filtered and FFT-filtered fields. In the Atlantic basin, the convective envelope of CCKWs often shifts northward and away from the equator with the ITCZ (Mounier et al., 2007). This influenced our decision to use 0 – 10°N for meridional averaging of FFT-filtered convective fields. However, testing was done using an equatorially centered 10°S to 10°N averaging range, which did not change the results presented here. Meanwhile, CCKW dynamic fields are often more equatorially constrained, despite the poleward shift in convection (Mounier

et al., 2007). Furthermore, the PCF-filtering method employed here produces filtered fields that are *by definition* centered around the equator. As a result, PCF-filtered fields are meridionally averaged from 5°S to 5°N.

2.3. Model Configuration

MPAS-A is used to generate the simulations used for this study. MPAS-A is a global non-hydrostatic model that uses a C-grid staggered Voronoi mesh (Skamarock et al., 2012). One of the advantages of this mesh is its ability to be “stretched,” allowing for variable resolution meshes with smooth transitions between cell sizes. Data from these MPAS-A experiments are saved every hour and remapped to either a $0.25^\circ \times 0.25^\circ$ or a $1^\circ \times 1^\circ$ latitude-longitude grid, balancing the need for computational efficiency. Most multiple-level variables are remapped to a $1^\circ \times 1^\circ$ latitude-longitude grid using barycentric interpolation. However, rain rate, single-level fields, and other variables utilized for detailed quantitative analysis are remapped to a $0.25^\circ \times 0.25^\circ$ latitude-longitude grid using a conservative remapping method. Additionally, multi-level variables are linearly interpolated from model levels to 26 pressure levels from 100 hPa to 1,000 hPa matching those in ERA5 reanalysis.

All MPAS-A experiments presented here are run using the same dynamical core and model physics. Simulations are run on 55 vertical levels and utilize Thompson microphysics (Thompson et al., 2008), RRTMG radiation (Iacono et al., 2008), and MYNN boundary layer schemes (Nakanishi & Niino, 2006). Two horizontal meshes are employed. One is a uniform mesh with ~30-km cell spacing, and the other is a stretched mesh with a ~15-km cell spacing in an outer grid and ~3-km cell spacing in an inner grid. This inner grid is centered over the northern Atlantic Ocean basin (see Figure 1a), in part due to the tendency of a CCKW's convective envelope to be shifted to the north with the ITCZ (Mounier et al., 2007). The variable resolution of the 15-3 km mesh necessitates the use of a scale-aware version of the Tiedtke convection parameterization scheme (Wang, 2022), which is utilized in all experiments for consistency. As the 15-km and 30-km resolutions are not storm-resolving, most of the rainfall in these experiments is produced via the convection parametrization scheme (Figure 1b). Within the inner mesh of the 15-3 km simulation, however, nearly 90% of rainfall is directly resolved (Figure 1b). This is comparable to the 3.75 km MPAS-A simulations produced by Judt and Rios-Berrios (2021), which was able to resolve 88% of simulated precipitation.

All of the experiments are initialized on dates near 24 September 2021, and integrated until 00Z on October 2nd, approximately eight days. Initial conditions for these experiments originate from IFS analysis fields. IFS was chosen instead of a reanalysis data set in part due to the availability of existing simulation data from a series of real-time MPAS-A experiments produced by NSF NCAR in 2021. Those real-time simulations were initialized from IFS and accurately captured the genesis of Tropical Storm Victor, motivating us to emulate their model configuration.

A summary of the MPAS-A experiments is presented in Table 1. There are three categories of simulations analyzed here: control simulations initialized at 00Z on 24 September 2021, control simulations initialized at slightly different times (from the 23rd to the 26th), and “modified” simulations in which CCKW amplitudes have been adjusted at initialization. The modified simulations have either their dynamic fields (U and V wind; labeled as “Wind”) or their dynamic *and* thermodynamic fields (U, V, temperature, relative humidity; labeled as “All”) changed. These fields are either amplified or dampened. These groupings are selected to illuminate how initial changes to a CCKW's wind fields could impact their eventual convective coupling, especially in comparison to experiments in which the initial thermodynamic fields were also modified. Other groupings were tested in which only moisture or temperature are changed; however, the resulting experiments were insufficiently different from the control run and are thus not evaluated here. To fit within computational restraints and the goal of making this method useful for attributional work, we are motivated to design experiments in which CCKWs were noticeably different than those in the control run.

2.4. Modification of Kelvin Wave Signal

In these experiments, we modify the amplitude of CCKWs in the initial conditions provided to the MPAS-A system. It is anticipated that these initial changes will persist for a non-negligible amount of time. The step-by-step process for doing so is as follows:

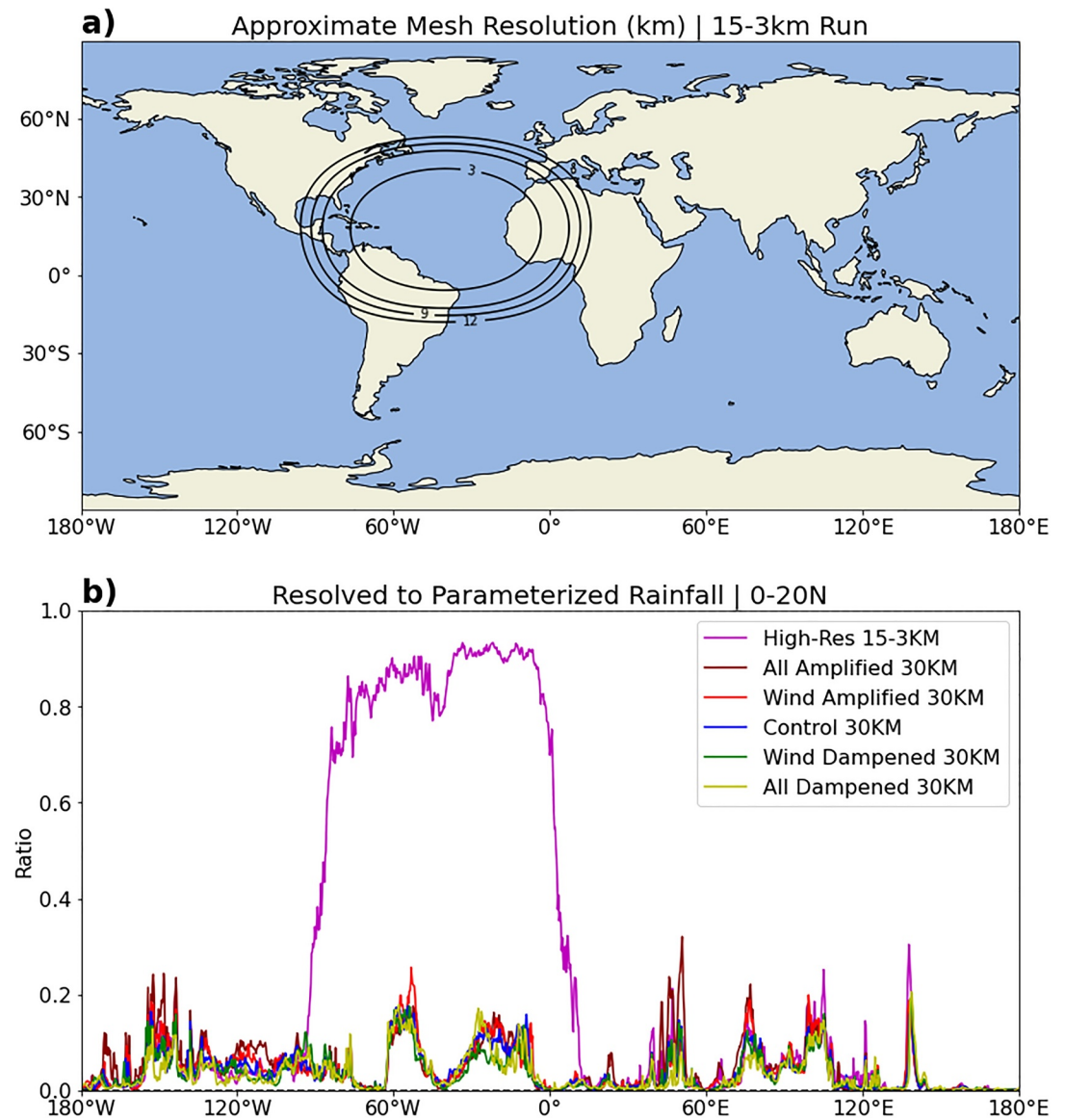


Figure 1. (a) The approximate mesh resolution of the 15-3 km Model for Prediction Across Scales–Atmosphere simulation (solid black contours; km). (b) The ratio of model-resolved to total rainfall, averaged in a 0 to 20°N band at each longitude through the simulation length. 0 to 20°N is chosen because it encompasses most of the 3 km mesh in the Atlantic.

1. IFS analysis fields for wind, water vapor mixing ratio, and temperature are obtained on a $0.125^\circ \times 0.125^\circ$ grid for the dates August 24th through 24 October 2021. This encompasses a 2-month period surrounding the primary date of interest. 30 days of zeros are appended to both ends of this data set.
2. The FFT filtering method is run on each of these variables at every IFS model level (137 levels total) to isolate their CCKW-related component. Filtering is done after the IFS data is remapped to a $1^\circ \times 1^\circ$ resolution to improve computational performance and smooth the data.
3. These FFT-filtered fields are trimmed to extend from 20°S–20°N and tapered in latitude using a Tukey window. This limits the impacts of mid-latitude systems that erroneously get isolated during the filtering process.
4. Finally, these trimmed FFT-filtered fields are remapped back to a $0.125^\circ \times 0.125^\circ$ grid. They are then either added to, or subtracted from, the original IFS analysis fields. Subtracting fields leads to an initial dampening of the CCKW amplitude, while adding fields leads to amplification. When just the wind fields are changed, it is

Table 1

Summary Table of the Model for Prediction Across Scales–Atmosphere Experiments Analyzed in This Study

Run name	Grid spacing	Initialization time	CCKW modification direction	Modified fields
High-Res (15-3 km) Control	15 km outer 3 km inner	2021-09-24 00Z	N/A	N/A
Original Control	30 km	--	--	--
All-Amplified	--	--	1× addition	U, V, T, RH
Wind-Amplified	--	--	1× addition	U, V
Wind-Dampened	--	--	1× subtract	U, V
All-Dampened	--	--	1× subtract	U, V, T, RH
<i>Control Member 1</i>	--	<i>2021-09-23 00Z</i>	<i>N/A</i>	<i>N/A</i>
<i>Control Member 2</i>	--	<i>2021-09-23 12Z</i>	--	--
<i>Control Member 3</i>	--	<i>2021-09-23 18Z</i>	--	--
<i>Control Member 4</i>	--	<i>2021-09-24 06Z</i>	--	--
<i>Control Member 5</i>	--	<i>2021-09-25 00Z</i>	--	--
<i>Control Member 6</i>	--	<i>2021-09-26 00Z</i>	--	--

Note. Italicized runs are of unmodified control members initialized at varying times.

denoted as a “Wind” modification. When thermodynamics are also adjusted, we call this an “All” modification.

We anticipate that at least two preconditions must be true for this method to work properly. For one, the CCKW of interest must exist at the time of modification; otherwise, it is unlikely that the modification method will change the CCKW's amplitude. Second, there must be adequate convective coupling. Otherwise, initial changes may not be reinforced by the CCKW, causing the modifications to not persist.

To highlight the implementation of this methodology, Figure 2 presents differences between the 30-km All-modified simulations and the control simulation at the time of model initialization (amplified Figures 2a and 2b; dampened Figures 2c and 2d). The largest magnitude differences in upper-level wind (Figures 2a and 2c) and low-level relative humidity (Figures 2b and 2d) exist over South America and the Atlantic Ocean basin. This corresponds to the position of a strong CCKW at the time of model initialization. As expected, changes to the amplified and dampened simulations are exactly opposite one another. The influence of CCKWs in other regions (i.e., Indian Ocean, Western Pacific) can also be seen. While the Wind-modified experiments (not shown) have identical changes to zonal wind as in these plots, they do not share the adjustments to relative humidity.

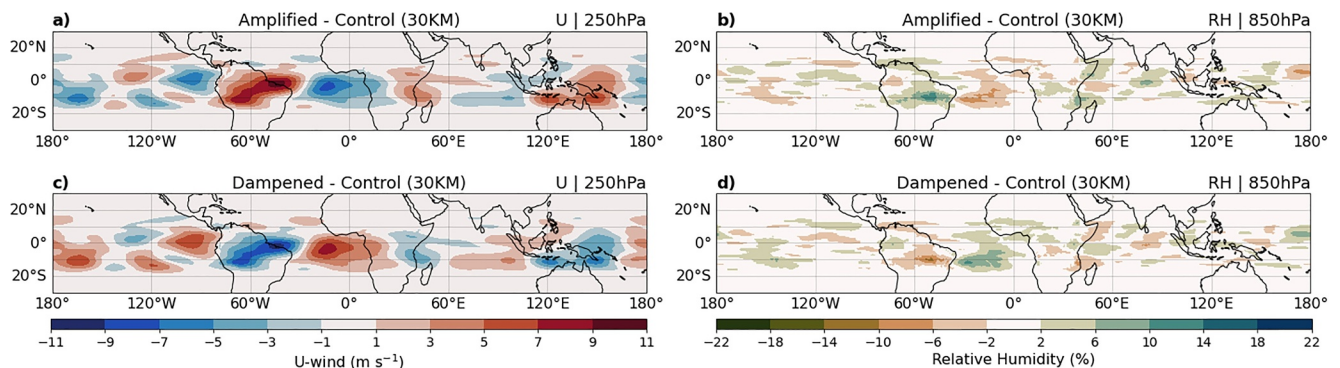


Figure 2. Comparisons of key model fields at the time of model initialization: 2021-09-24 00Z. These diagrams show differences between the (a)–(b) 30 km All-amplified and control simulations and differences between the (c)–(d) 30 km All-dampened and control simulations. The left column (a), (c) is of 250 hPa zonal wind (U), and the right column (b), (d) is of 850 hPa relative humidity.

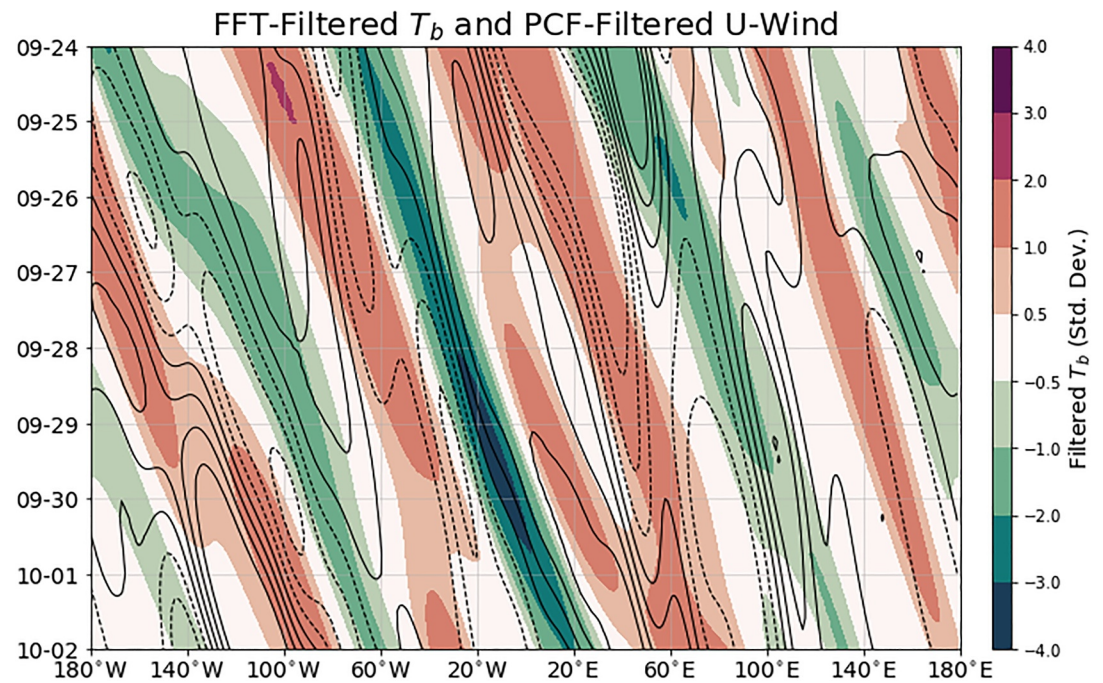


Figure 3. Time versus Longitude (Hovmöller) diagram of FFT-Filtered GRIDSAT T_b (shading) averaged between 0 and 10°N, and PCF-filtered 250 hPa zonal wind (contours) averaged between 5°S and 5°N. T_b is plotted in standard deviations, relative to the 1981–2019, July–September climatology presented in Lawton et al. (2022; their Figure 1b). PCF-filtered wind contours are spaced every 1 m/s, except for the lowest contour, which is 0.5 m/s. Filtering here is done using a full month of data as opposed to only the times shown here, in order to limit edge effects.

2.5. CCKW Tracking

CCKWs are tracked in these simulations and in IMERG data using the Kelvin band FFT-filtered total rain rate. Rain rate is filtered using the FFT method and averaged between 0 and 10°N prior to tracking. To identify the wave tracks, we find local maxima in this filtered rain rate at each timestep (corresponding to the convectively active phase) and connect these points in time to maxima at previous timesteps. The connected signals must last for at least one day to be considered a stand-alone CCKW track.

3. Results

3.1. Observed CCKWs

We first describe observations for late September 2021 to contextualize the period for which the MPAS-A experiments are run. From September 24th through October 2nd, multiple CCKWs existed simultaneously around the globe. These CCKWs can be seen in a Hovmöller diagram of FFT-filtered brightness temperature (T_b) and PCF-filtered 250 hPa zonal wind (Figure 1). On September 24th, three convectively active CCKWs (negative filtered T_b) had a strength of at least one standard deviation from climatology. As these CCKWs primarily propagate over the Eastern Pacific, Atlantic, and Indian Ocean basins during this period, they will henceforth be identified by these basin names. In between the active phases are convectively suppressed phases (positive filtered T_b). Plotted contours of PCF-filtered wind suggest the presence of large scale upper-level divergence in phase and slightly west of the T_b minima, in agreement with previous CCKW observational studies and theory (Kiladis et al., 2009).

The strongest CCKWs during the period of interest are in the Atlantic and Indian Ocean. Of these two, the active phase of the Atlantic CCKW is by far the highest in magnitude, peaking in absolute strength from September 28–30th at over three standard deviations from climatology (Figure 3). This is not its only unique characteristic; ERA5 and GridSat-B1 data suggest that this CCKW may have interacted with an African easterly wave (AEW) that subsequently resulted in the genesis of Tropical Storm Victor (2021). This interaction can be seen in basinwide snapshots of CCKWs and AEW position in the Atlantic (Figures 4a, 4c, and 4e). As the CCKW

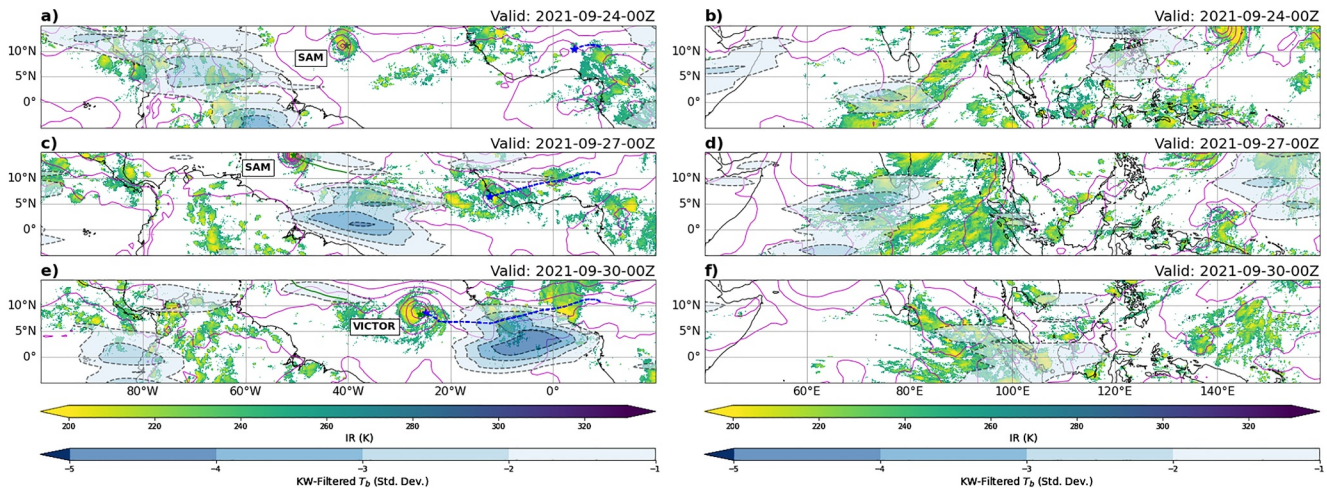


Figure 4. Sequence of events prior to the development of Tropical Storm Victor in 2021. Three snapshots in time are shown: (a) 9-24-2021 00Z, (b) 9-27-2021 00Z, and (c) 9-30-2021 00Z. (d), (e), and (f) are for the same times, but centered on the Indian Ocean basin. Brightness temperature (T_b) (green—yellow shading) is overlain with the FFT-filtered T_b (blue shading with dashed contours), with only *negative* values of at least 1 standard deviation shown. For the non-filtered fields, only values of T_b below 260K are plotted. 700 hPa geopotential height (magenta lines) is contoured every 100 m. The track of the pre-Victor African easterly wave (AEW) is also plotted (blue dashed line and star). The AEW track is from the Lawton et al. (2022) data repository, and the tropical cyclone best track from the HURDAT database.

propagates through the Atlantic basin, its filtered T_b anomalies grow in magnitude (e.g., Figures 3 and 4c). Meanwhile, a westward propagating AEW passes through this convectively active CCKW phase between September 28th–29th (Figures 4c and 4e). Tropical cyclogenesis shortly follows, with the system designated as a tropical depression at 12Z on September 29th (Stewart, 2021). Meanwhile, the depiction of the Indian Ocean CCKW (Figures 4b, 4d, and 4f) largely matches that of Figure 3, demonstrating that it did not reach nearly the same magnitude as the Atlantic CCKW and began weakening much earlier. The Pacific Ocean CCKW (Figure 3, clearer in Figure S1 in Supporting Information S1) also remains relatively weak, though there are some indications it begins to amplify as it reaches the South American continent.

These observations motivate a modeling study focused on the late September 2021 period. The existence of widespread CCKW activity means that multiple CCKWs can be analyzed, allowing for comparisons between regions with different base states. Furthermore, the presence of a historically strong Atlantic CCKW event is a unique opportunity to investigate the consistency and skill of model forecasts for a high-impact CCKW, and to evaluate how these forecasts change if the initial wave amplitude is altered.

3.2. Structure of Modified CCKWs

We now explore the impacts of amplitude modification. All of the experiments presented in this section, including those that are modified, are initialized on 24 September 2021 at 00Z. To provide spatial context, a basin-wide comparison of FFT-filtered rain rate and PCF-filtered upper-level zonal wind is shown at 00Z on 28 September 2021 for IMERG/ERA5 observations, the two controls, and the two All-modified experiments (Figure 5). Other timesteps were also analyzed and yielded similar interpretations (e.g., Figures S2 and S3 in Supporting Information S1). Observations demonstrate the presence of convectively active CCKWs over the Atlantic and Indian ocean basins (Figure 5a). For both CCKWs, positive values of FFT-filtered rain rate are co-located with a region of upper-level divergence. While both controls and the modified simulations show upper-level winds consistent with the observed CCKW over the Atlantic, there is not a corresponding signal in the filtered rain rate fields in any of the 30 km runs (Figures 5c–5e). In the 15–3 km run, in which convection is directly resolved in this region, a slightly more pronounced CCKW-like signal can be seen in the open Atlantic spanning 30°W to 0°W (Figure 5b). Overall, it is clear that the MPAS-A experiments fail to accurately depict the Atlantic CCKW's rainfall. This is in stark contrast to the Indian ocean basin, where the CCKW is more accurately simulated. There, an upper-level CCKW signal is collocated with the FFT-filtered rain rate, implying there is anomalous upper-level divergence over areas with enhanced rainfall (Figure 3). Yet despite the more pronounced depiction of the CCKW's convection in the Indian Ocean, the simulated PCF-filtered upper-level wind there is

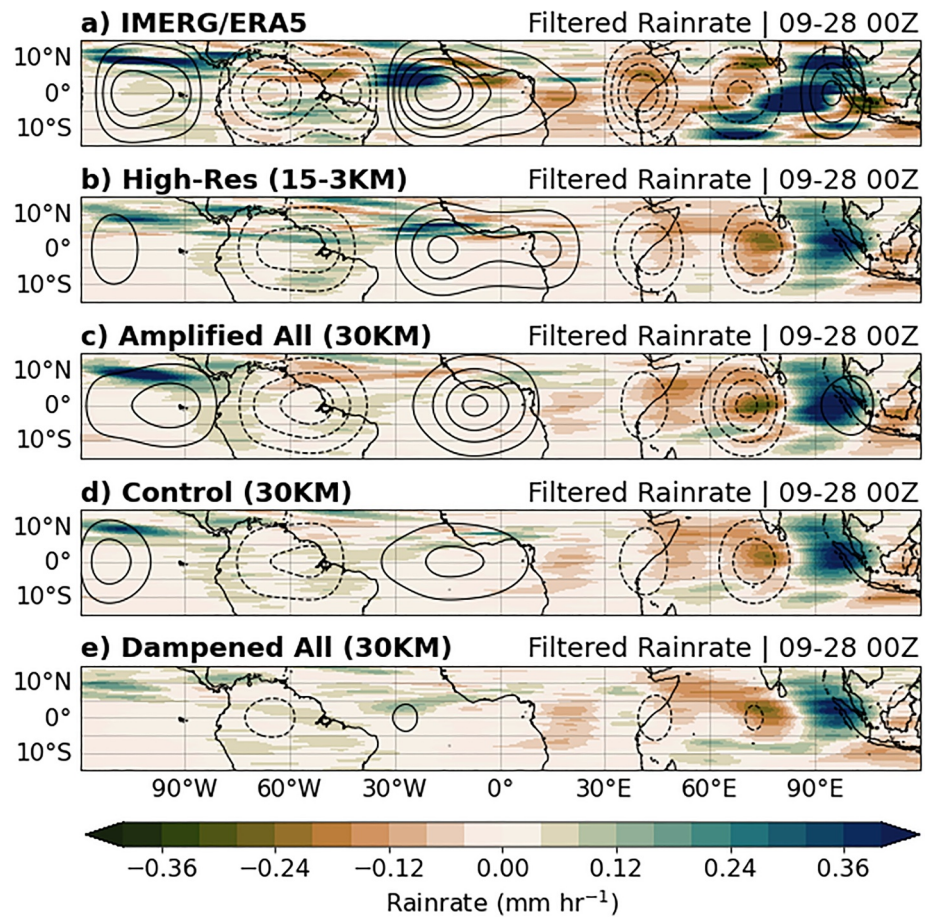


Figure 5. Comparison of the FFT-filtered rain rate (shading) and PCF-filtered upper level wind (250 hPa; contours with 0.5 m/s increments) between several of the Model for Prediction Across Scales–Atmosphere experiments, centered on the Atlantic basin at 00Z on 9-28-2021. (a) Is IMERG (rain rate) and ERA5 (250 hPa winds), (b) is the 15-3 km control, (c) is the All-amplified experiment, (d) is the 30 km control, and (e) is the All-dampened experiment.

still significantly weaker than in the Atlantic. This implies there could be significant differences in the convective coupling between these regions.

Figure 5 also hints at differences in CCKW-related fields between the All-modified experiments and the 30 km control. In general, the All-amplified experiment yields stronger wind and rainfall than the 30 km control, and the All-dampened experiment yields weaker wind and rainfall, suggesting the modification method was at least partially successful.

To better elucidate how the CCKW wave structure is represented in these experiments, longitudinal cross sections are built using 5°S–5°N averages of PCF-filtered wind and its divergence (Figure 6). These are plotted for a few key timesteps and compared with ERA5 reanalysis data. Because PCF-filtering produces fields that are, by definition, symmetric around the equator, comparisons in Figure 6 are not sensitive to the meridional range used. A classic CCKW vertical structure is evident for both the Atlantic (left green box) and Pacific (right green box) waves in the ERA5 data (Figures 6a–6c), with upper-level divergence within the 100–300 hPa layer overlaying that of convergence below it. This region of large-scale convergence extends to near the surface and tilts westward with height, reminiscent of previous observational studies (e.g., Kiladis et al., 2009; Mayta et al., 2021). Both the 30 km (Figures 6d–6i) and 15-3 km (not shown) experiments are able to recreate this observed vertical structure in the Indian Ocean and the Pacific Ocean. However, there is a stark difference in the representation of the simulated Atlantic CCKW in these experiments versus ERA5. Not only is the CCKW's upper-level signature weaker in the experiments, but there is also a complete lack of lower-level convergence. Departures in the simulated low-level convergence (red shading) from that of ERA5 data can especially be seen at 700 hPa on September 29th, located

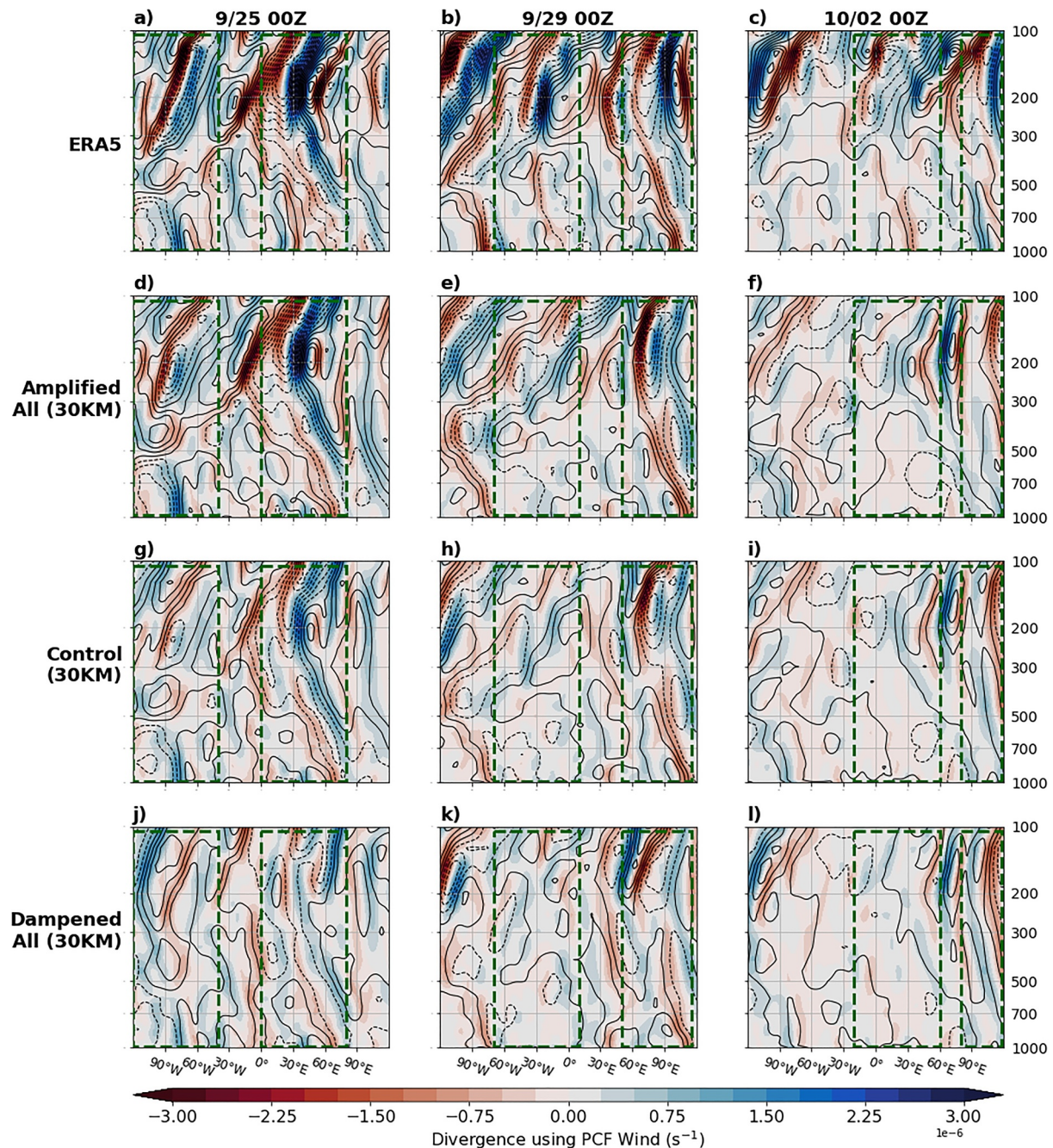


Figure 6. Vertical cross-sections of 5°S – 5°N averages of PCF-filtered zonal wind (0.5 m/s contours; dashed for negative, solid for positive) and divergence (shading). The box overlay (green dashed contours) indicates the regions of focus for the Atlantic and Indian Convectively coupled Kelvin waves (CCKWs), respectively. The Pacific CCKW is also visible at later timesteps to the left of the Atlantic CCKW box. Plotted data sets are of (a–c) ERA5, (d–f) the 30 km All-amplified experiment, (g–i) the 30 km control experiment, and (j–l) the 30 km All-dampened experiment. Each column is for a different snapshot in time. These times are, from left to right: 00Z on 25 September 2021, 00Z on 29 September 2021, and 00Z on 2 October 2021. To be comparable, all simulations are cut down to the same time length (September 24th–October 2nd) and padded identically prior to filtering.

near 30°W (c.f. Figures 6b, 6e, 6h, and 6k). This suggests a failure of MPAS-A to simulate the full vertical structure of the Atlantic CCKW. This failure was persistent across the 30 km experiments, occurring in every 30 km simulation that was run (not shown).

Nevertheless, the vertical structures shown in Figure 6 provide evidence that the CCKW modification method was effective at changing CCKW strength. For the three CCKWs of interest, the All-amplified experiment shows

enhanced amplitudes of zonal wind and divergence compared to the control (Figures 6d–6f). Similarly, the All-dampened experiments result in reduced magnitudes for these same fields (Figures 6j–6l). Differences in these simulated fields persist at least halfway through the simulations, and in some cases last the entire 8 days. The modification method even changed the Atlantic CCKW's wind fields, though changes to this wave were confined to upper levels.

There are two additional details important for the interpretation of the modified MPAS-A experiments. First, the All-modified experiments were not the only ones that showed success in changing the CCKW's wind structure; we find that Wind-modified experiments exhibit similar success (see Figure S4 in Supporting Information S1). This suggests that the depiction of wind fields at initialization may be important for the accurate representation of CCKW structure later in the simulations. Second, amplifying the CCKW signal at initialization did not appear to remedy errors in the low-level structure of the Atlantic CCKW. This could indicate that the modeling inaccuracy shown for these experiments does not directly stem from the initial representation of the CCKW.

We now shift to considering the behavior of individual CCKWs. The longitude tracks of CCKWs are identified in each experiment and for IMERG data using the local maxima in FFT-filtered rain rate (Figure 7a). In general, CCKW propagation in MPAS-A experiments is similar to observations. One exception is the location of the Atlantic CCKW at the start of the experiments, which is significantly to the west of the observations (Figure 7a). Given that the FFT-filtering method is not time-independent, this could be a result of deviations in CCKW-filtered fields later in the simulations.

CCKWs in the MPAS-A simulations slightly differ in phase speed from observations, in part due to variations in their starting longitudes (Figure 7b). For example, the simulations temporarily accelerate the Atlantic CCKW after an erroneous starting position to the west of observations (c.f., Figures 7a and 7a). The difference in phase speed for the Indian Ocean CCKW, however, appears to be more consistent. The simulations propagate this wave faster than in IMERG data through the entire simulation period (Figure 7a). This trend is consistent across all the experiments. For the other CCKWs, the average phase speed was relatively similar across the experiments.

These CCKW wave tracks can be used to build wave-following vertical composites, which allow a more complete exploration of their dynamic and thermodynamic properties (Figure 8). Vertical composites are built over the entire simulation period and importantly *do not* involve any wave filtering. Instead, they are built using variable anomalies taken from the time mean across the length of each experiment. This provides confidence that differences between the MPAS-A experiments are not artifacts of wave filtering. Here we focus on the Atlantic and Indian Ocean CCKWs, the two strongest CCKWs seen in observations during this period.

Composites of ERA5 fields for the Indian Ocean CCKW—and to a lesser extent, the Atlantic CCKW—demonstrate close similarities to previous studies of CCKW observations (Figures 8a–8d). There is a confluence of zonal winds near the center of the active phase (denoted by 0°) that is tilted westward with height (i.e., Figures 8a and 8b). Aloft are zonal winds of the opposite sign, representative of large-scale divergence, which are also in phase with the active phase (Figures 8a and 8b). Anomalies in both temperature (Figures 8a and 8b) and water vapor mixing ratio (Figures 8c and 8d) also tilt westward in the troposphere, with positive values at and east of the CCKW's convectively active phase. The depicted CCKW structure is consistent with longitudinal cross-sections of PCF-filtered wind and divergence (Figure 6), and with observational results from previous studies (e.g., Kiladis et al., 2009; Mayta et al., 2021).

However, there is a notable difference between the structure of the Atlantic (Figures 8a and 8c) and the Indian (Figures 8b and 8d) CCKWs in the ERA5 data. In general, the Atlantic CCKW exhibits a much more pronounced upper-level wind and temperature signal than that of the Indian CCKW, but a weaker low-level signature in these fields and for low-level moisture. This differs from the satellite observations, which suggest that the Atlantic CCKW had a more comparable convective signature to that of the Indian CCKW (Figures 3 and 4). Enhanced convective activity would *imply* the existence of higher magnitude moisture and convergence anomalies at low levels, unlike what is shown by ERA5 data. This may indicate disagreement between satellite and ERA5 reanalysis data in the depiction of this event.

Nevertheless, these composites illustrate that the amplitude modification method is successful in changing temperature, zonal wind, and water vapor mixing ratio within the Indian Ocean CCKW. For this CCKW, anomalies are strongest in the All-amplified experiment (Figure 8f), followed by the 30 km control experiment (Figure 8j) and the 30 km All-dampened experiment (Figure 8n). In fact, temperature and wind anomalies are

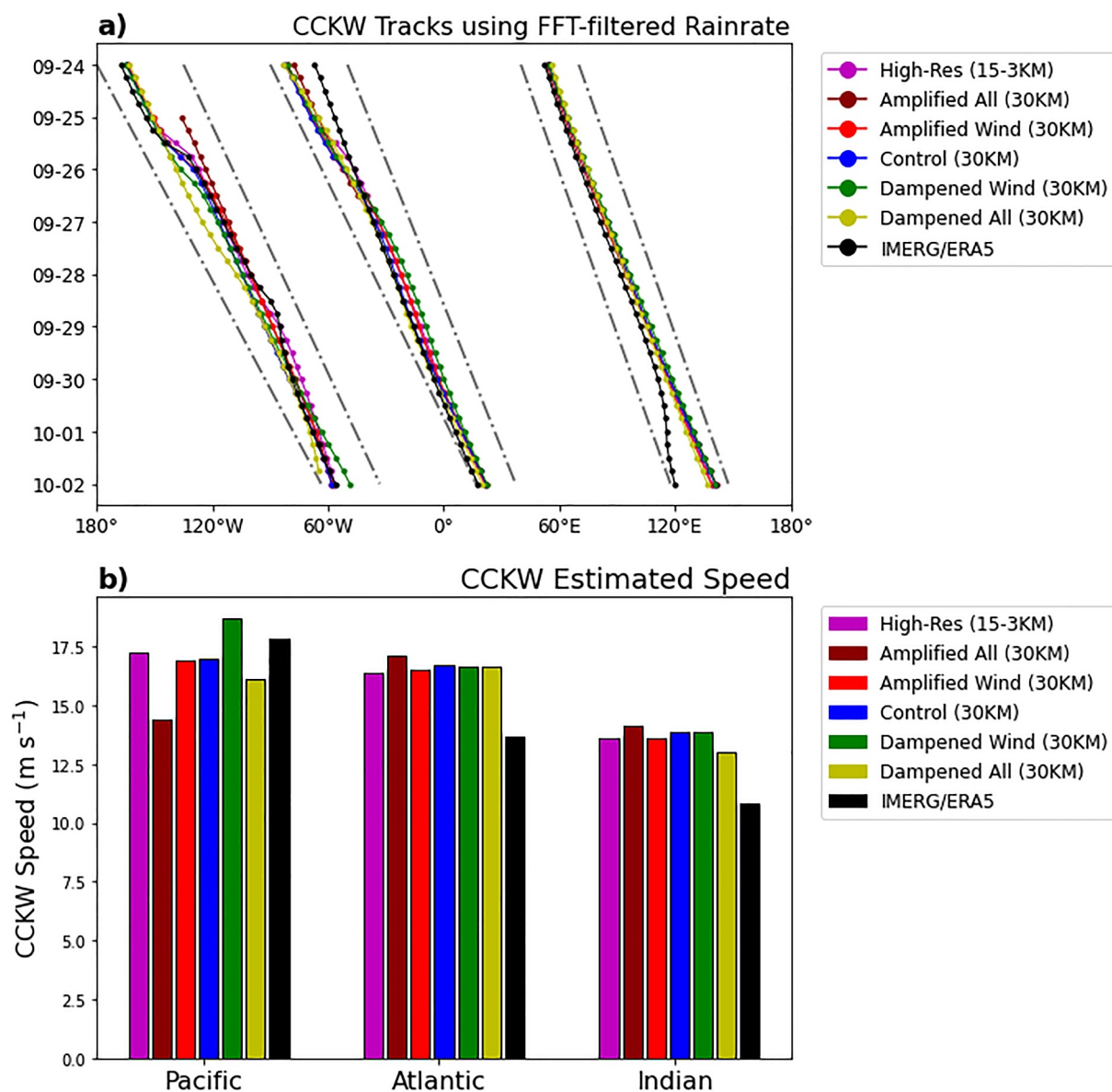


Figure 7. (a) Longitude tracks of the convectively active phase of three CCKWs, with colors representing each experiment, and (b) a comparison of the average longitudinal phase speed of CCKWs in these experiments. IMERG tracks are included for comparison (black line). Only tracks for three CCKWs of focus (Pacific, Atlantic, and Indian) are shown; these are defined within the regions denoted by the gray dash-dot lines. CCKW tracks for plot (a) are found by finding local maxima in 0–10°N average FFT-filtered rain rate. Phase speed for plot (b) is calculated by applying a linear best-fit line to the longitude points.

higher in magnitude for the All-amplified experiment than in ERA5 data (compare Figures 8f and 8h to Figures 8b and 8d). Similar successes are found for the Wind-modified experiments, though those simulations lack notable differences in moisture, as expected (Figure S5 in Supporting Information S1).

The Atlantic Ocean CCKW also experiences changes to its temperature and zonal wind fields across experiments, but *only* at middle- and upper-levels. Unlike that of the Indian Ocean CCKW, lower-level anomalies in temperature and zonal wind for the Atlantic CCKW are largely the same across experiments (Figures 8e, 8i, and 8m). There are also minimal differences in the water vapor mixing ratio (Figures 8g, 8k, and 8o). Results for the Wind-modified experiments are similar (Figure S5 in Supporting Information S1). This further suggests that CCKW amplitude modification is most successful when the CCKW of interest is accurately represented in the control simulation.

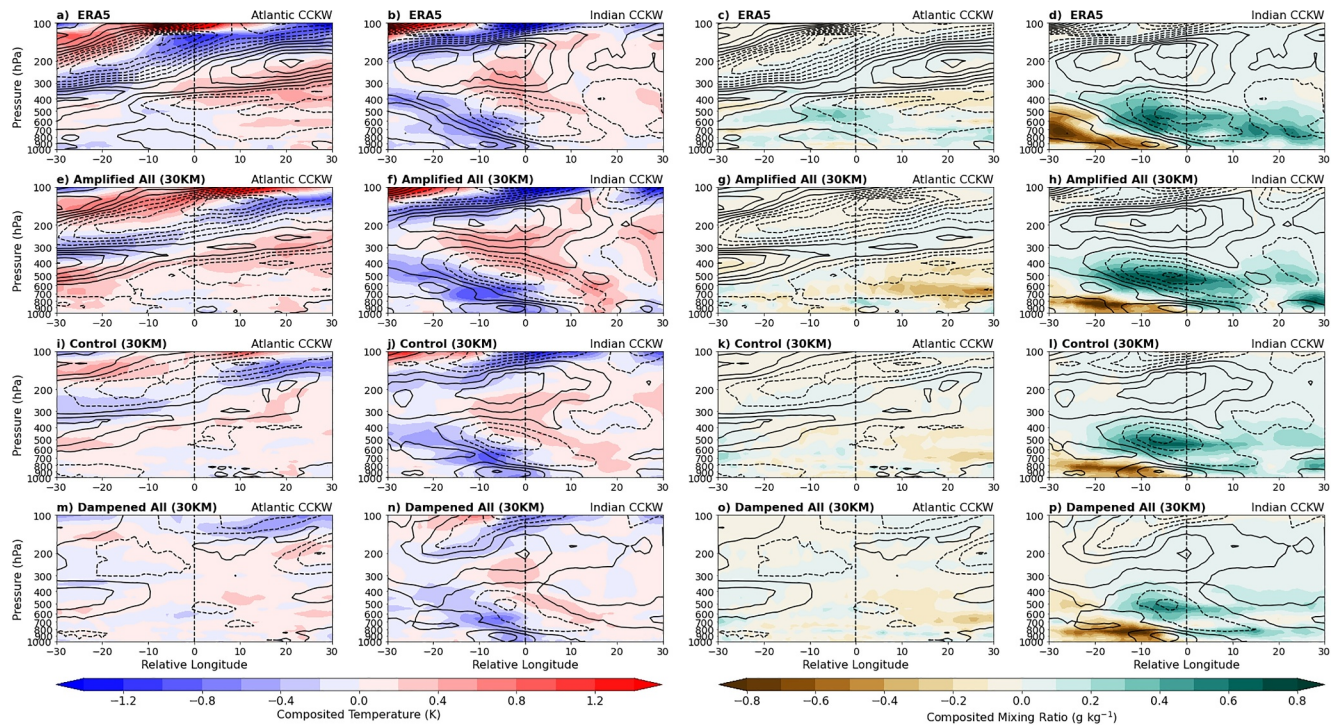


Figure 8. Vertical composites of the Atlantic Ocean and Indian Ocean CCKWs. The top row (a–d) is of ERA5 data, the second row (e–h) is of the 30 km All-amplified simulation, the third row (i–l) is of the 30 km control simulation, and the fourth row (m–p) is of the 30 km All-dampened simulation. Data are composited across the entire simulation period (2021-09-24-00Z to 2021-10-02-00Z) and from 5°S to 5°N using the CCKW tracks shown in Figure 7a. The vertical dashed line at 0° represents the compositing point—each CCKW's maximum rainfall anomaly—with the relative longitudes composited along the x-axis. In the left two columns, temperature anomalies are shaded; in the right two columns, water vapor mixing ratio anomalies are shaded. Zonal wind anomalies are overlain on all simulations (contours; 1 m/s intervals).

3.3. Simulated Convective Coupling

So far it has been shown that the amplitude modification method successfully alters the wind and thermodynamic structure of CCKWs, and that the structure of the Atlantic CCKW may have been poorly simulated in the 30 km MPAS-A experiments. We now shift to an evaluation of CCKW convective coupling to illustrate how the amplitude modification method can be leveraged to reveal two-way feedbacks between CCKW dynamics and convective activity.

Hovmöller diagrams of meridionally averaged FFT-filtered rain rate are shown for IMERG and the All-modified 30 km experiments in Figure 9. The failure of these 30 km experiments to simulate the Atlantic CCKW's convective signal immediately stands out (Figures 9b–9e vs. Figure 9a; signal from 60°W–20°E). This lack of a coherent convective signal persists for most of the CCKW's propagation over the open Atlantic (Figures 9c–9e). Even the 15-3 km experiment, which captures the CCKW's filtered rain rate slightly better than the 30 km simulations, deviates significantly from IMERG (Figure 9b vs. Figure 9a). Amplifying the CCKW at initialization does little to remedy this lack of coupling (Figures 9c–9e).

In contrast, both the Indian Ocean (Figures 9f–9j) and the Pacific Ocean CCKWs (Figures 9a–9e; 100°W to 50°W) have convective signals generally matching the observations. For these CCKWs, initial adjustments by the All-modified experiments successfully change the CCKW's filtered rain rate. Compared with the control, the Pacific CCKW's filtered rain rate anomalies are stronger in the All-amplified experiment and weaker in the All-dampened experiment across most of the simulation period (Figures 9c–9e). The same is true for the Indian Ocean CCKW, though only through the first 4 days (Figures 9h–9j). Note that experiment-driven differences exist in both the positive (convectively active) and negative (convectively suppressed) anomalies. The changes to convective activity by the modified experiments closely match their impacts on the CCKW's wind and thermodynamic structure (Figures 6 and 8). This suggests that MPAS-A is able to simulate the convective coupling for both the Indian and Pacific CCKWs.

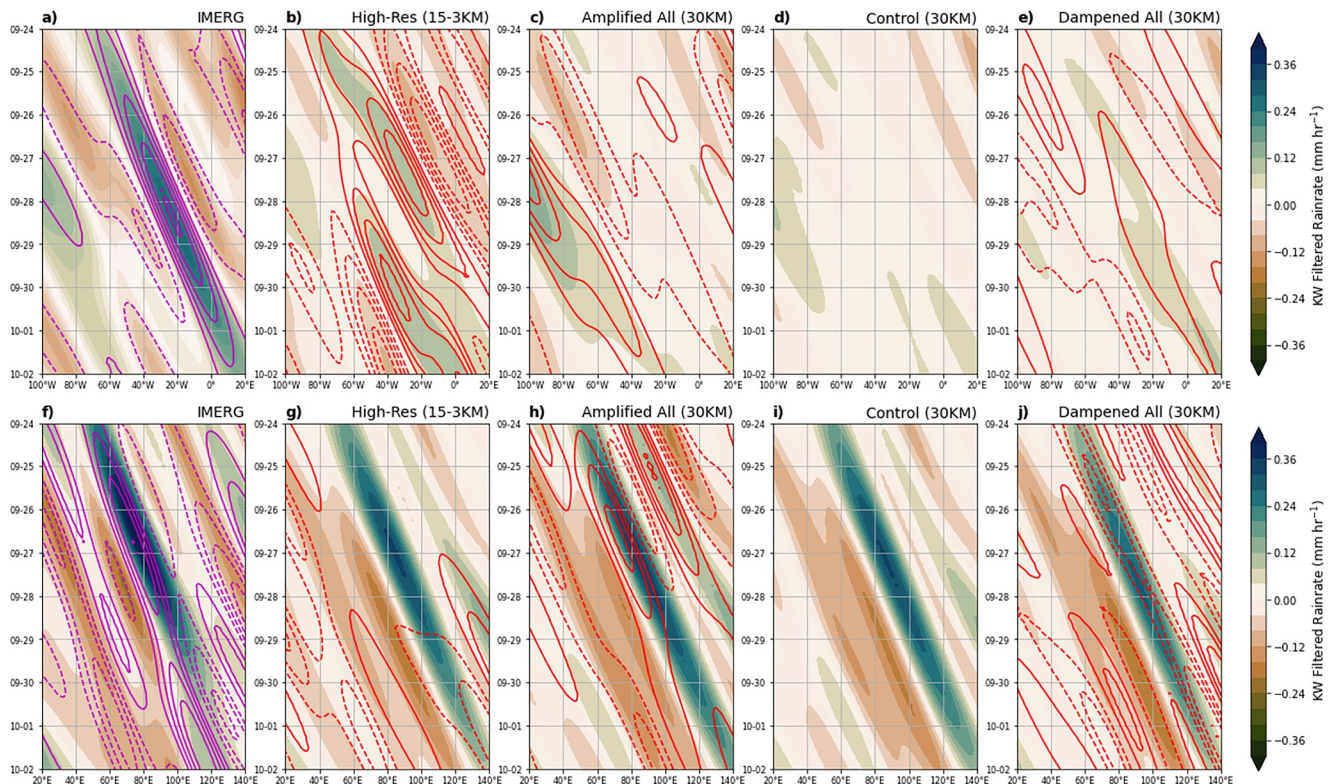


Figure 9. Hovmöller diagram of 0–10°N averaged FFT-filtered rain rate (mm/hr; shading) centered on the (a)–(e) Atlantic Ocean in the first row and the (f)–(j) Indian Ocean in the second row. Diagrams are of (a), (f) IMERG data, (b), (g) 15–3 km simulation, (c), (h) the 30 km All-amplified simulation, (d), (i) the 30 km control simulation, and (e), (j) the All-dampened simulation. Differences between each simulation and the 30 km control are overlain (red contours) in 0.02 mm/hr increments, with positive values as solid lines and negative values as dashed lines. In the IMERG Hovmöller (a) and (f), contours are magenta and in 0.05 mm/hr increments.

Similar diagrams for the Wind-modified CCKW experiments provide additional evidence that MPAS-A accurately simulates this convective coupling (Figure 10). Despite only adjusting the CCKW-associated wind fields at initialization, both the Pacific and Indian Ocean CCKWs generally have higher rain rates in the Wind-amplified experiment and lower rain rates in the Wind-dampened experiment compared with the 30 km control. These differences are not as high in magnitude as for the fully modified experiments and are also slightly lagged in time from the start of the simulation (c.f., Figures 9 and 10). The time lag is likely a result of the CCKW's convective signal “adjusting” to differences in CCKW structure, indicative of a coupling between dynamics and convection.

To summarize the changes in wave structure and convection for these experiments, CCKW-following averages of filtered rain rate and upper-level strength are presented for the three major CCKWs in Figure 11. Results here largely confirm what is illustrated by Figures 6–10; that is, adjusting the wave amplitudes at initialization leads to long-lasting changes in the amplitude of upper-level winds in all three CCKWs (Figures 11a, 11c, and 11e), as well as significant changes in the rain rates for the Pacific and Indian Ocean CCKWs (Figures 11d and 11f). For the most part, 30 km simulations underestimate the convective coupling and upper-level winds of CCKWs, though amplifying CCKW signals at initialization appear to bring these measures closer to observations in the Pacific and Indian oceans (Figures 11a, 11b, 11e, and 11f). This figure also further elucidates the convective-coupling present in these MPAS-A simulations. The largest perturbations in the upper-level strength and filtered rain rate occur when the wind, temperature, and moisture are all modified at initialization (Figures 11a and 11e; All-amplified and All-dampened). This suggests that adjusting the CCKW's moisture—and by extension, convective activity—has an influence on the CCKW's vertical wind structure. At the same time, adjusting just the wind fields at initialization *also* influences the rain rate within CCKWs (Figure 11f; Wind-amplified and Wind-dampened). This is further evidence of two-way convective coupling between the CCKW's dynamical fields and convection. However, this coupling was not apparent for the Atlantic CCKW, which was poorly captured by all 30 km simulations and even by the 15–3 km simulation.

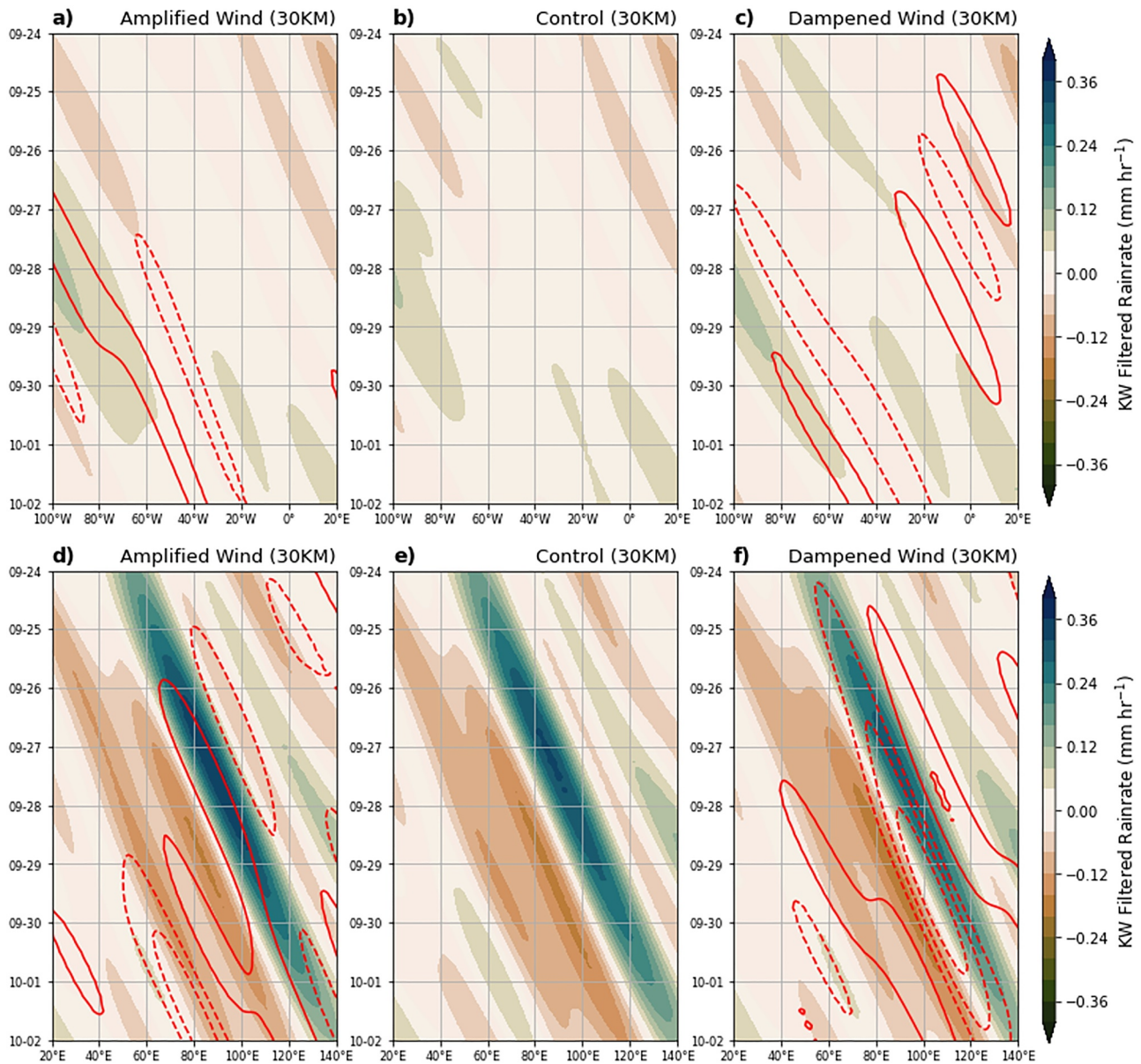


Figure 10. Here (a–c) are as in panels (c–e) in Figure 9, except now the 30 km Wind-amplified, 30 km control, and 30 km Wind-dampened simulations are shown. (d–f) Are as in panels (a–c) in this figure but centered on the Indian Ocean.

3.4. Tropical Diagnostics and Sources of Atlantic Ocean Forecast Errors

Throughout this paper, we have demonstrated that the Atlantic CCKW was poorly simulated by the MPAS-A experiments, despite it being a historically strong case. Though the 15-3 km experiment was able to better capture some of the CCKW's convective envelope, it still differed significantly from IMERG data (Figures 9a, 9b, and 11d). This motivates further investigation into the drivers of convection and its coupling to dynamics with these experiments.

Previous studies have emphasized the roles of DCIN and CSF in the maintenance of equatorial waves (e.g., Herman et al., 2016; Weber et al., 2021; Wolding, Dias, Kiladis, Ahmed, et al., 2020; Wolding, Dias, Kiladis, Maloney, & Branson, 2020). Gravity wave-type equatorial waves, like CCKWs, are thought to be driven more by temperature perturbations and adiabatic ascent (reflected by DCIN) than water vapor fluxes (reflected by CSF and surface fluxes), though the relative contributions of each are still unknown (Adames et al., 2019; Herman

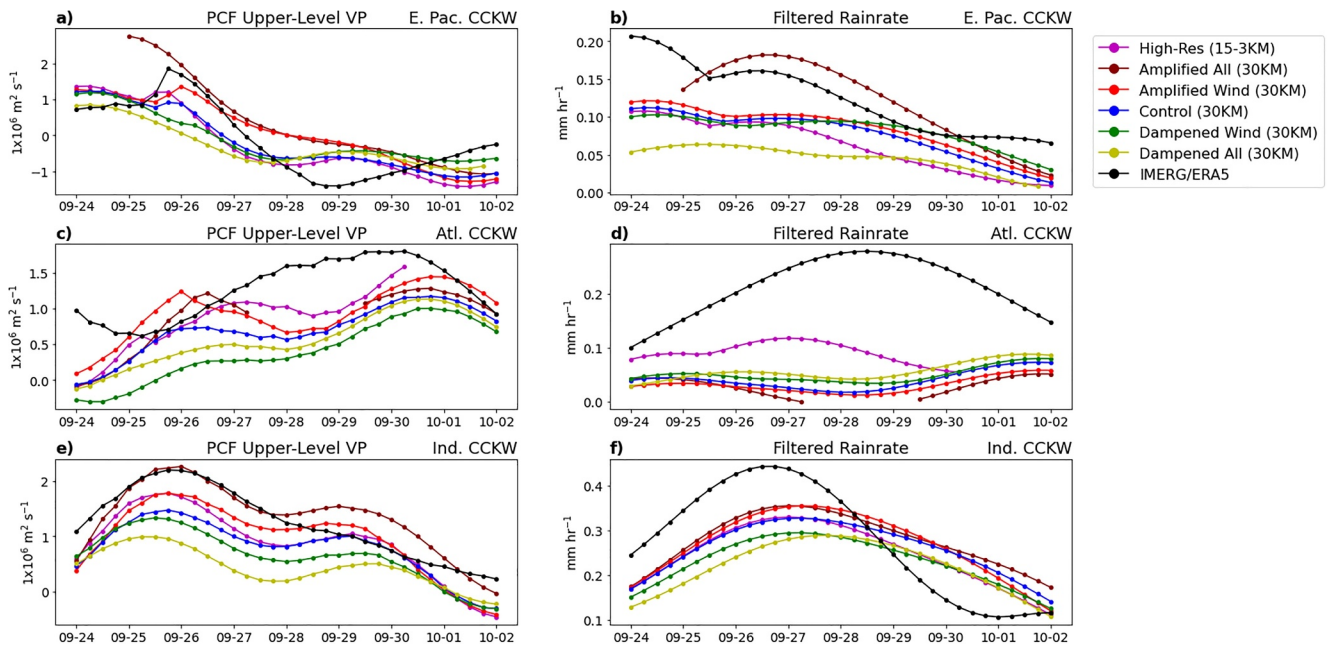


Figure 11. Summary of Convectively coupled Kelvin waves (CCKWs) characteristics following three major CCKWs in the 9-24-00 00Z initializations of the Model for Prediction Across Scales—Atmosphere experiments, built using the tracks of Figure 7a. (a) Shows CCKW-following averages of PCF-filtered velocity potential averaged between 250 and 300 hPa, and (b) shows CCKW-following FFT-filtered rain rate, both for the Pacific CCKW. (c) and (d) are as in panels (a) and (b), but following the Atlantic CCKW. (e) and (f) are as in panels (a) and (b) but following the Indian CCKW. All experiments are shown as a different colored line, with the corresponding ERA5 (PCF-filtered VP; left column) or IMERG (FFT-filtered rain rate; right column) data shown in black. Note that, by definition, the tracking methodology used here is unable to follow CCKWs that do not have a pronounced convective signal. As such, there is a roughly 2-day gap for the Atlantic CCKW track in the All-amplified simulation (c), (d).

et al., 2016; Wolding, Dias, Kiladis, Maloney, & Branson, 2020). As such, we will compare these variables in the MPAS-A experiments. DCIN is computed following Fuchs et al. (2014) and Weber et al. (2021), and is defined as:

$$\text{DCIN} = s_t^* - s_b \quad (1)$$

s_t^* is the saturated moist entropy of a layer from 800 to 750 hPa, and s_b is the moist entropy of the boundary layer, here defined as below 850 hPa. DCIN provides a measure of environmental stability for convection originating in the boundary layer. CSF, meanwhile, is simply the fraction of vertically integrated precipitable water to the theoretical value of precipitable water if the column was fully saturated.

Simulated anomalies in rain rate, CSF, and DCIN are composited relative to tracked CCKWs and compared with IMERG and ERA5 data (Figure 12). As discussed by Weber et al. (2021), longitude composites such as these can be interpreted as having time on the x -axis and increasing toward the left, due to the eastward propagation of CCKWs. There is a pronounced peak in IMERG-derived rain rate near the tracked center of both CCKWs (Figures 12a and 12b). Unsurprisingly, the MPAS-A simulations do not capture this anomalous peak in rain rate for the Atlantic CCKW (Figure 12a). This is true even in the 15-3 km simulation (i.e., Figures 9b and 11d), which had previously demonstrated some skill in capturing filtered signals. These composites of unfiltered rain rate largely confirm what has been shown using filtered data.

The observed covariance of CSF and DCIN within the CCKW's convective envelope, as depicted by ERA5 and IMERG data, are consistent with previous research. There is a pronounced increase in CSF and a decrease in DCIN that is mostly in phase with the IMERG rain rate anomalies (Figures 12a, 12c, and 12e). It can be argued that the values of DCIN ever so slightly lead the peak in CSF and rain rate, alluding to the potential role of DCIN in driving the onset of CCKW precipitation (i.e., Fuchs et al., 2014; Herman et al., 2016). Overall, these results align with those generated by Weber et al. (2021) for another CCKW case.

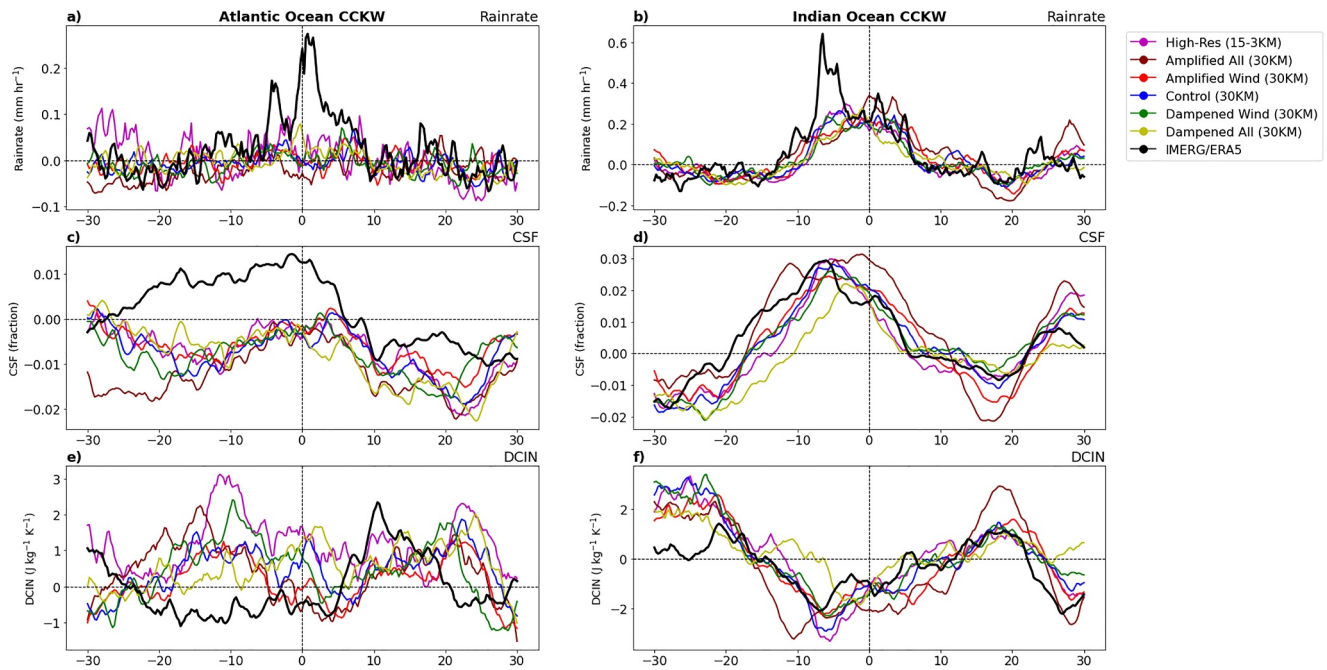


Figure 12. Diagrams showing Convectively coupled Kelvin wave (CCKW)-following composites of (a)–(b) rain rate, (c)–(d) column saturation fraction, and (e)–(f) deep convective inhibition. Data are composited across the entire simulation period (2021-09-24-00Z to 2021-10-02-00Z) and from 0° to 10° N using the CCKW tracks shown in Figure 7a. The left column (a, c, e) are composites following the Atlantic CCKW, and the right column (b, d, f) are composites following the Indian CCKW. Colored lines are of different Model for Prediction Across Scales –Atmosphere experiments, which are compared to the IMERG (a), (b) and ERA5 (c)–(f) data (black lines). The vertical dashed line at 0° represents the compositing point—each CCKW's maximum filtered-rainfall anomaly—with relative longitudes composited along the x -axis.

The ability of MPAS-A to accurately simulate these convective parameters again breaks down by region. These experiments fail to capture the observed progression of CSF and DCIN in the Atlantic CCKW (Figures 12c and 12e). In contrast to observations, simulated anomalies in DCIN and CSF do not exhibit a clear pattern; in fact, many of the MPAS-A experiments lack any negative values of anomalous DCIN within the Atlantic CCKW. Given the lack of a clear signal of DCIN or CSF within simulations of the Atlantic CCKW, the absence of any associated convective coupling or rainfall comes as no surprise.

In contrast to that of the Atlantic CCKW, the depiction of rain rate, CSF, and DCIN within the Indian Ocean CCKW are generally well-represented by the MPAS-A experiments (Figure 12b). CCKW-centered anomalies in CSF and DCIN (Figures 12d and 12f) largely match their behavior in ERA5 and are mostly in-phase with rain rates. Unsurprisingly, there exist higher amplitude deviations in rain rate within the amplified experiments as compared to the dampened experiments (Figure 12b). These differences in anomalous rain rate appear connected to modifications to CSF and DCIN, with amplified simulations generally showing higher magnitude anomalies in CSF and DCIN as compared to their dampened counterparts (Figures 12d and 12f). Notably, the highest magnitude differences in rain rate, CSF, and DCIN exist between the All-amplified and All-dampened experiments. That modifications to CSF are associated with changes in rain rate supports previous work highlighting a connection between CSF and precipitation rate in CCKWs (Weber et al., 2021; Wolding, Dias, Kiladis, Ahmed, et al., 2020; Wolding, Dias, Kiladis, Maloney, & Branson, 2020). However, DCIN also varies across the modified MPAS-A experiments (Figure 12f), and thus could also play a role.

It remains unclear why the Atlantic CCKW was so poorly simulated in these experiments. As illustrated in an earlier section, amplifying this CCKW in initial conditions failed to improve its representation in the simulations (i.e., Figures 9a–9e). This suggests that the problem may not be with the initial depiction of the wave. One possibility is that discrepancies in the depiction of rainfall and its relationship to other parameters could hinder the convective coupling of CCKWs in these simulations. For example, work by Weber et al. (2021) suggests that the Tiedtke cumulus scheme—which is used for these experiments—may result in an overdependence of rain rate on DCIN. Judt and Rios-Berrios (2021) also found that coarse resolution MPAS-A simulations have trouble

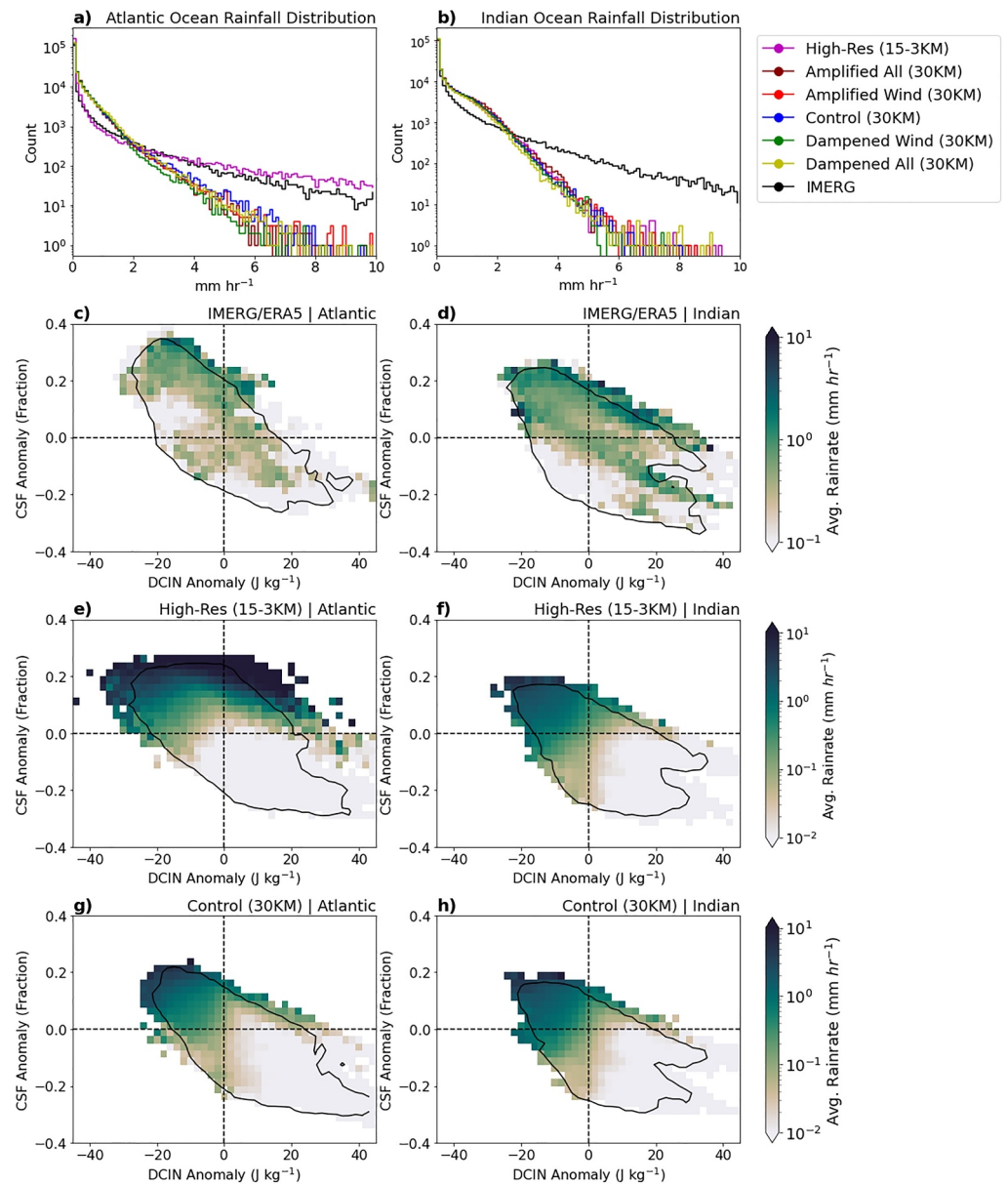


Figure 13. (a)–(b) are of basin wide distributions of rain rates over the entire simulation length (9–24–2021 00Z through 10–02–2021 00Z) for the Atlantic and Indian ocean, respectively. These distributions are plotted on a logarithmic scale. (c)–(h) Are of the average rain rate binned by deep convective inhibition (DCIN) and column saturation fraction (CSF) anomalies, again computed over the entire simulation length. Rain rates are jointly binned by DCIN in $2 \text{ J kg}^{-1} \text{ K}^{-1}$ increments, and by CSF in 0.025 increments, with the average rainfall in each bin calculated and shaded. Note that the shaded range is also on a logarithmic scale and differs between the IMERG/ERA5 subplots (c)–(d) and the Model for Prediction Across Scales – Atmosphere subplots (e)–(h). The black contour indicates bins containing at least 25 values, and grid points over land are excluded. All data in the left column (a, c, e, g) are computed for the north Atlantic basin, defined as a box from 60°W – 20°W and 0 – 10°N . Data in the right column (b, d, f, h) are computed for the north Indian basin, defined as a box from 60°E – 100°E and 0 – 10°N .

representing extremes in rainfall intensities. To explore whether these findings could impact our simulations, we compute the distributions of rainfall intensity for MPAS-A experiments and observations (Figures 13a–13b). These distributions demonstrate that the 30 km simulations with parameterized convection are unable to fully simulate the extreme rain rates seen in IMERG observations in both basins (Figures 13a and 13b). In contrast, the storm-permitting 15–3 km simulation more accurately captures the full distribution of rainfall intensity in the Atlantic, especially at high intensities. The distribution of the 15–3 km simulation closely follows those of the

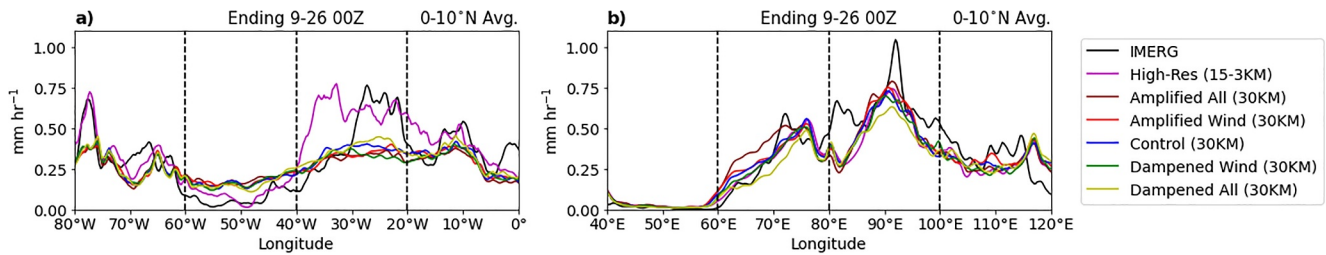


Figure 14. Meridionally (0–10°N) and temporally averaged rain rate through 9–26–2021 in the (a) Atlantic and (b) Indian Ocean basins, as a function of longitude. Colored lines represent averages taken in each Model for Prediction Across Scales –Atmosphere experiment, with IMERG data plotted in black for comparison.

30 km simulations for the Indian Ocean, as its mesh is coarser in this region and requires convective parameterization (i.e., Figure 1b).

IMERG rain rates binned by CSF and DCIN (from ERA5) demonstrate a strong dependence of rain rate on CSF (Figures 13c and 13d). In both basins, the highest rain rates are associated with the highest CSF anomalies and appear to have a lesser dependence on DCIN. The combined IMERG/ERA5 plots, however, are peculiar in their depiction of a region of high rain rates associated with anomalously low CSF and high DCIN. In contrast, similar plots by Weber et al. (2021) (see their Figure 13) depict a much clearer relationship between TRMM data and ERA5 and show a pronounced cutoff in DCIN above which rainfall magnitude was largely minimized. This may suggest a disconnect between the ERA5 reanalysis and IMERG observations for this event. Nevertheless, a dependence of rain rate on CSF (when DCIN is below a certain threshold) is well established in the literature, giving us little reason to believe otherwise (e.g., Weber et al., 2021; Wolding, Dias, Kiladis, Ahmed, et al., 2020).

Meanwhile, regions for which convection is parameterized (Figures 13f–13h) have rain rates controlled *both* by the values of CSF and DCIN, suggesting an overdependence on DCIN. In these regions, the average rain rate increases as DCIN decreases and CSF increases. There also appears to be a DCIN threshold near $0 \text{ J kg}^{-1} \text{ K}^{-1}$, above which average rain rates are extremely low. In the Atlantic, the 15–3 km storm-resolving simulation fares much better (Figure 13e). There, the rain rate appears to vary primarily as a function of CSF, as suggested by observations and previous work. While DCIN does appear to act as a thresholding value, high average rain rates are still occasionally seen with high DCIN values *if* CSF is also high.

Nevertheless, the diagnostics presented in Figure 13 illustrate that neither inaccuracies in the representation of extreme rainfall nor an overdependence of rain rate on DCIN can sufficiently explain failures in simulating the Atlantic CCKW. This is because the overall distribution of rainfall intensity (Figures 13a–13b) and the dependence of rain rate on DCIN and CSF (Figures 13g–13h) was largely similar for the Atlantic and Indian basins. Furthermore, these results suggest that the observed model deficiencies aren't automatically solved by increased model resolution. Recall that the storm-permitting 15–3 km MPAS-A experiment still struggled to fully represent the Atlantic CCKW's rainfall and associated parameters, despite its more accurate depiction of extreme rainfall and its relationships here (Figures 12a, 12c, and 12e).

Another possible source of model error may be the environment ahead of the Atlantic CCKW. Figures 14a–14b show meridional averages of rainfall in the MPAS-A experiments and IMERG through 26 September 2021. This period was chosen as it is just *prior* to when the convectively active CCKW enters the eastern Atlantic (40°W–20°W; Figures 9a–9e). IMERG data (averages in Figure 14a; spatial plots in Figure S6 in Supporting Information S1) demonstrates that there was scattered convection in the Eastern Atlantic ITCZ during this window of time. However, the 30 km MPAS-A experiments struggle to simulate this convection and rainfall (Figure 14a). In contrast, the convection-resolving 15–3 km simulation better captures the extent and magnitude of the ITCZ, though it slightly over-simulates the total rainfall. This discrepancy may be related to the failure of the Tiedtke parameterization scheme in capturing extreme rain rates (i.e., Figure 13a). Given the tendency for CCKW signals to project onto the ITCZ, an under-simulation of ITCZ convection ahead of a propagating CCKW could reduce the efficiency of convective coupling. Perhaps not coincidentally, MPAS-A simulations appear to better capture rainfall in the Indian ocean where CCKW activity is also better represented (Figure 14b). Yet this explanation may still not fully explain observed model deficiencies. After all, despite its adequate simulation of the Atlantic ITCZ, the 15–3 km simulation still failed to fully resolve the associated CCKW (Figures 11d and 12a).

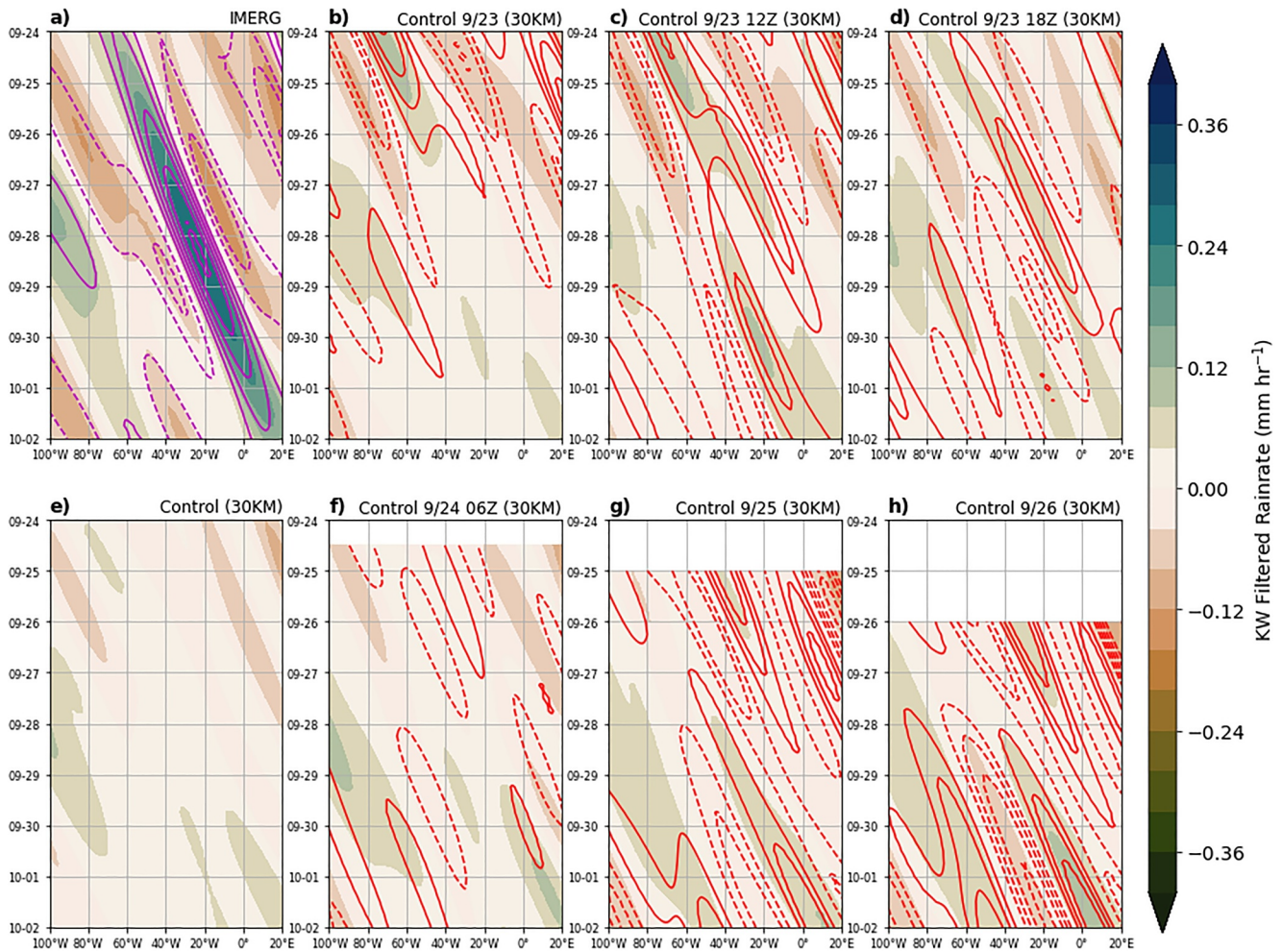


Figure 15. (a) is identical to Figure 9a. (b)–(h) Are plotted identically to Figures 9b–9e, but for 30 km simulations with different initialization times. These runs are initialized on (b) 9/23/2021 00Z, (c) 9/23/2021 12Z, (d) 9/23/2021 18Z, (e) 9/24/2021 00Z (original control), (f) 9/24/2021 06Z, (g) 9/25/2021 00Z, and (h) 9/26/2021 00Z. Differences plotted in red (magenta in panel (a)) are from the original control shown in panel (e).

The mixed results from these diagnostics make interpreting the precise sources of error for the Atlantic CCKW challenging. However, it is worth noting that these errors are not just confined to simulations at this particular initialization time (24 September 2021, at 00Z). Several other 30 km control simulations were run at initialization times varying from September 23rd to September 26th (Table 1; control members 1–6). The filtered rain rates from these experiments, and their differences from the original 30 km control, are shown in Figure 15 for the Atlantic Ocean. This figure illustrates the significant variability in the CCKW's rainfall signal, even at initialization timesteps differing by only 6 hours (i.e., Figures 15b–15e). While the magnitudes of Atlantic CCKW signals increase at later initialization times (Figures 15f–15h), the resulting CCKW pattern (active and suppressed phases) more resembles the 15–3 km experiment (i.e., Figure 9b) than IMERG observations (Figure 15a). It should be mentioned that the other waves, including the Indian and Pacific CCKWs, also exhibit some variability in their amplitudes across the controls (Figure 15; Figure S7 in Supporting Information S1). However, these CCKWs still mostly retain their overall characteristics, unlike the Atlantic CCKW.

It is also possible that errors in the initial conditions could have degraded the simulation of the Atlantic CCKW. Here we show that ECMWF's operational IFS system (HRES), from which these experiments are initialized, also depicts erroneously weak convective coupling for the Atlantic CCKW. Figures 16a–16b show 24-hr precipitation overlain with FFT-filtered outgoing longwave radiation (OLR), for two different initializations of IFS. Data are plotted at 00Z on 29 September 2021, near the time of the peak amplitude of the Atlantic CCKW in observations (Figure 3). In these IFS runs, there is a clear bifurcation in CCKW outcome for simulations initialized prior to and

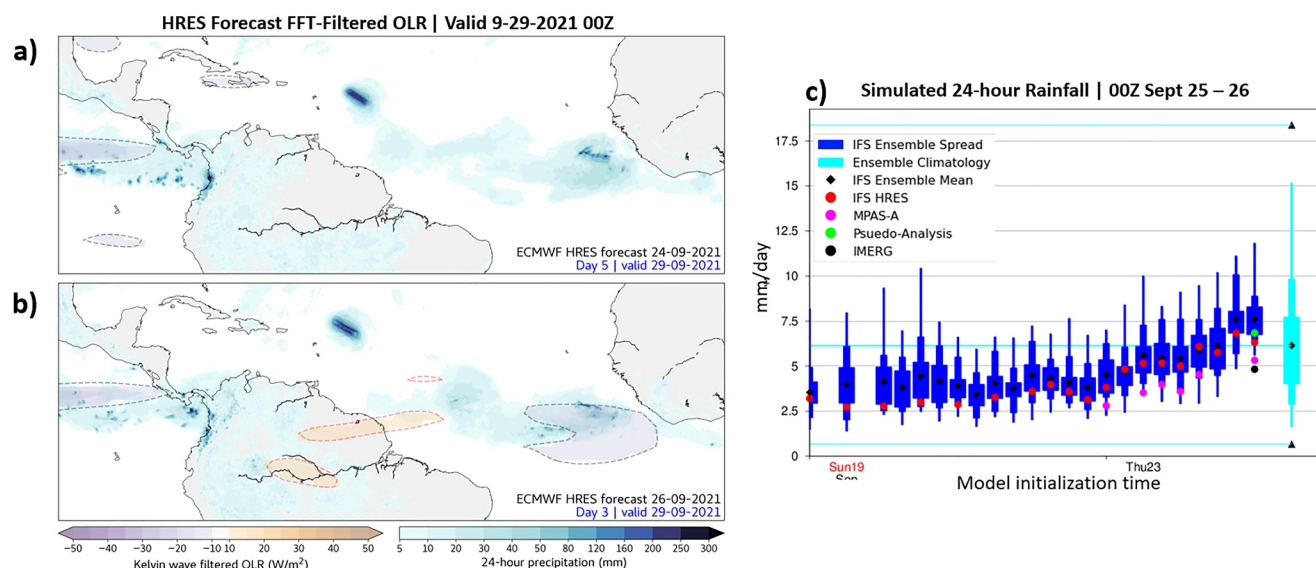


Figure 16. The left two panels show FFT-filtered outgoing longwave radiation (OLR) valid at 00Z on 29 September 2021 from two different initializations of IFS: (a) the 00Z initialization on September 24th, and (b) the 00Z initialization on September 26th. The blue shading is of the total 24-hr precipitation, whereas the purple to orange hatching is of FFT-filtered OLR. (c) The right panel is comparison of 24-hr rainfall averaged in a box spanning 0–10°N and 40°W–20°W across different model initialization times, which are spread in 6-hr increments. For the bar and whisker plots (blue, cyan boxes), the large box is the 25th–75th percentile, small box is the 10th–90th percentile, and the whiskers are the 1st–99th percentile. Integrated Forecasting System deterministic output (HRES, red dot) are compared to output from the various initializations of 30 km Model for Prediction Across Scales –Atmosphere simulations (30 km runs, magenta dot), the 6-hr forecast (pseudo-analysis; green dot), and IMERG (black dot) for the valid date.

after September 25th. In the runs initialized on September 24th (Figure 16a) and 25th (not shown), there is almost *no* indication of an Atlantic CCKW in the filtered OLR fields. Yet in the run initialized on September 26th (Figure 16b), a CCKW signal is readily apparent. This run-to-run variability illustrates IFS's lack of forecast skill for this particular CCKW, largely mirroring the MPAS-A experiments.

Like the MPAS-A simulations (i.e., Figure 14), the ECMWF system also greatly underestimates rainfall in the Eastern Atlantic ITCZ ahead of the Atlantic CCKW. Figure 16c shows IFS (blue boxes, red dots) and MPAS-A (magenta dots) forecasts of the 24-hr precipitation from September 25th - 26th within a 0–10°N and 40°W–20°W box (c.f., Figure 14a). In both the MPAS-A and ECMWF systems, enhanced ITCZ precipitation in the Eastern Atlantic was only captured in forecasts initialized 1–2 days beforehand. As also found for the filtered OLR signal (Figures 16a and 16b), September 25th is a clear inflection point in these rainfall forecasts. These results demonstrate that IFS initializations with a more accurate simulation of ITCZ rainfall are better able to capture the Atlantic CCKW's convective signal (Figures 16a–16b). It is also clear that changes in rainfall between 30 km MPAS-A initializations qualitatively follow changes in the corresponding IFS HRES forecasts (Figure 16c; magenta and red dots). This could suggest that errors in the MPAS-A experiments may originate from IFS analysis fields, from which the experiments are initialized. Because the ERA5 reanalysis data set is also based upon the IFS system (albeit a previous version, cycle 47r3; Hersbach et al., 2020), it is possible that the noted discrepancies in ERA5 from IMERG (Figures 8, 13c, and 13d) could also be connected to errors in IFS analysis. Another possibility for errors in the Atlantic CCKW could be related to the model physics. Preliminary experiments (not shown) based on a test version of a more recent IFS cycle, 47r3, suggest that the introduction of an improved physical basis for moist processes in the IFS resulted in an improvement of the representation of this CCKW. While intriguing, more work is needed to confirm the role of the model physics scheme in modifying CCKW dynamics, which is beyond the scope of this study.

Interestingly, the MPAS-A simulations (red dots) appear to produce less total rainfall than that of the IFS system for this region and period. However, MPAS-A rainfall is more in line with that of IMERG (black dot). The cause of this difference is unclear. Nevertheless, qualitative trends in MPAS-A rainfall across the included initialization times generally follow those of the IFS simulations.

4. Discussion

4.1. Implications for CCKW Predictability

Results from these MPAS-A experiments elucidate the significant hurdles that remain in our understanding of CCKW predictability. These simulations failed to capture a very strong CCKW event in the Atlantic, despite accurately representing CCKWs in other parts of the world. We showed that a multitude of factors may have played a role, including shortcomings in the simulation of the Atlantic ITCZ (Figure 14a), inaccurate initial conditions provided by the IFS system (see discussion of Figure 16), and an erroneous depiction of CSF, DCIN, and other environmental conditions (Figure 12). It seems unlikely that the strength of the CCKW in initial conditions was entirely responsible, given that amplifying these signals at initialization did not improve the forecast (Figure 11d).

While we are not the first to document the limited forecast skill of CCKWs (e.g., Dias et al., 2023; Gehne et al., 2022), this study is unique in its focus on an individual, poorly forecast CCKW event. In fact, the Atlantic CCKW was not just poorly predicted, but it was hardly represented in the modeling system *at all*. On the surface, this seems to contrast previous MPAS-A experiments demonstrating good skill in their representation of CCKWs (Judt, 2020; Rios-Berrios et al., 2020, 2022; Rios-Berrios, Davis, & Martinez, 2023; Rios-Berrios, Judt, et al., 2023; Weber et al., 2021). However, other CCKWs in our simulations were still well captured, and the IFS system also struggled to capture the same CCKW event (Figure 16). This may indicate that errors in the IFS analysis fields, from which the MPAS-A simulations were initialized, played the biggest role in the erroneous model response. Another interpretation could be that this was an inherently low-predictability CCKW event, resulting in failures across modeling platforms. This may explain the inter-run variability seen for filtered rain rate across the set of MPAS-A simulations with varying initialization time (Figure 15). Either scenario would suggest that the failure to simulate this CCKW may not entirely be a result of the modeling systems themselves.

There is also the possibility that the initial amplitude and lifecycle stage of the CCKWs may have affected how well they were captured by the modeling systems. Satellite data indicates that the Atlantic CCKW may have been newer and further from its peak intensity than the Indian CCKW at the simulation start (Figure 3). Furthermore, the more accurate IFS and 30 km MPAS-A experiments were those initiated at later timesteps, when the Atlantic CCKW was *closer* to its peak intensity (Figure 15). Research into another large-scale tropical phenomenon, the Madden-Julian Oscillation (MJO), has found that the MJO's initial amplitude *and phase* at model initialization significantly influences forecast skill (Kim et al., 2014, 2018; Lim et al., 2018). While it is unclear whether a similar relationship exists for CCKW forecasts, this hypothesis may be worthy of future study.

No matter the cause, this case raises important questions. Is such a large CCKW forecast failure a common occurrence? Why was the Atlantic CCKW so poorly simulated as compared to the Indian and Pacific CCKWs, and is it connected to regionality in CCKW predictability? The existing literature offers insufficient evidence to answer these questions with confidence. Previous work has focused on the collective forecast skill of CCKWs, not individual events (Bengtsson et al., 2019; Dias et al., 2018, 2023; Gehne et al., 2022; Janiga et al., 2018; Schreck et al., 2020; Yang et al., 2021). Furthermore, research on the regionality of CCKWs has primarily focused on wave characteristics and propagation speed, not forecast skill or predictability (Dias & Kiladis, 2014; Tulich & Kiladis, 2021). As such, it is hard to directly contextualize the evolution of this case. However, a recent study by Li and Stechmann (2020) on the *intrinsic* predictability of CCKWs offers some relevant insights. Using TRMM rainfall observations, they found that CCKW rainfall may have very limited intrinsic predictability (2–3 days), supporting our suggestion that CCKW events with low forecast skill could be common. They also found that the predictability of CCKWs did not vary by location, suggesting that the errors found here may not be connected to wave location. But as with the other collective CCKW studies, it remains unclear if these results directly translate to individual CCKW events.

We argue that this case serves as a strong motivation for future work investigating the predictability and forecast skill of *individual* CCKW events. There is widening evidence that individual CCKWs play a role in initiating high-impact weather events like tropical cyclones and extreme rainfall (Latos et al., 2021; Lawton & Majumdar, 2023; Mantripragada et al., 2021; Ventrice, Thorncroft, & Janiga, 2012). How CCKWs and their predictability could influence the forecast skill of these phenomena still remains relatively unknown. Elucidating this connection will require a systematic analysis of CCKW skill centered on individual events.

4.2. Caveats and Future Use of CCKW Amplitude Modification

This study has also demonstrated the effectiveness of a method to modify CCKWs in numerical simulations with parameterized convection. Our testing illustrates two factors that could compromise the success of this amplitude modification. For one, modifying just the wind fields appears less effective than jointly changing wind, temperature, and moisture. Second, this method appears to work best when the CCKW of interest already exists at the time of initialization *and* is properly represented in the unmodified simulation. We suggest that those conducting future work using this method take these considerations into account.

There remain several other unknowns with this procedure. It is unclear if this method also works for simulations at finer horizontal resolutions, especially those in which most rainfall is explicitly simulated (storm-permitting). Preliminary work by the authors (not shown) suggests that this modification method may still be effective for 15–3 km MPAS-A simulations, but this requires further evaluation. Additionally, it is unknown if this method could work in modeling systems other than MPAS-A, especially since they often differ in their representation of CCKWs (e.g., systems produced by NOAA (Gehne et al., 2022), the UK Met Office (Yang et al., 2021), and ECMWF (Dias et al., 2018)). Similar uncertainty exists for other model physics schemes and for other CCKW cases or time periods. We speculate that the relative simplicity of the adjustment method presented here, in which changes are made to the strength of CCKWs in initial conditions, should make it robust to differences in the modeling system or case of interest.

Another consideration is the equatorial wave identification. Filtering for these waves is a nuanced process, with each method having potential disadvantages that could limit our methodology (Knippertz et al., 2022). For example, FFT filtering can mistakenly filter signals that are not associated with CCKWs. This could be because of noise or due to other wave signals erroneously projecting onto the Kelvin-band, such as those of the MJO. It is possible that these factors could change the amplitude modification. For example, mid-latitude features near the boundaries of our CCKW-modification window (20°S–20°N) could erroneously project onto filtered data and change the amplitude modification. Nevertheless, we do not believe these factors had a significant impact on our results. Zero-padding was used to reduce the impacts of edge effects while adjusting the initial conditions and filtering data for analysis. Furthermore, two different filtering methods were used throughout our analysis, and data sets were cut to the same length prior to filtering. This should reduce the impact of these factors on comparisons shown here. Results from the composites of *unfiltered* fields also largely confirmed the results found in our *filtered* fields (i.e., Figures 8 and 12). Finally, that the amplitude modification itself was largely successful suggests that errors in the initial identification of CCKWs did not have significant consequences.

We argue that amplitude modification could be a powerful tool for better understanding the role of CCKWs and other equatorial waves. One of the main advantages of this method is the ability to adjust CCKWs in realistic experiments that encompass the complexities of Earth's atmosphere and its interactions. This could complement previous studies on CCKW interactions and better attribute their influence. For example, previous work on CCKWs, AEWs, and tropical cyclogenesis has found it challenging to directly assess cause-and-effect between these phenomena using existing observational frameworks (Lawton et al., 2022; Lawton & Majumdar, 2023; Schreck, 2016; Ventrice, Thorncroft, & Schreck, 2012). The CCKW amplitude modification discussed here could be one way to better attribute tropical wave and cyclone outcomes to CCKW amplitude. We also envision that this modification method could be expanded to other equatorial wave types. Both equatorial Rossby waves and mixed Rossby-Gravity waves have important impacts of their own on rainfall, waves, and tropical cyclones (i.e., Feng et al., 2023; Latos et al., 2021, 2023; Yang et al., 2018). Applying an amplitude modification framework to these wave interactions could help better attribute their impacts and driving mechanisms.

5. Conclusions

This study examined a set of MPAS-A experiments in which CCKW amplitudes were modified at initialization. These experiments are run for a period in late September of 2021 in which several CCKWs co-existed around the globe. To modify the amplitude of these waves, a Kelvin band FFT-filter is applied to IFS analysis fields of wind, temperature, and moisture. Select FFT-filtered fields are either added or subtracted to the initial conditions prior to running each experiment, resulting in “amplified” and “dampened” CCKW-fields at the model start. Modified simulations are compared to a control experiment at the same resolution (~30 km), a storm-permitting simulation (15–3 km), and to a set of 30 km simulations run at different initialization times.

We showed that this amplitude modification method is effective at changing the strength and structure of simulated CCKWs. These changes were reflected in both the wind and rainfall structure of these waves and persist anywhere from 4 days to the end of the experiments (8 days). The resulting differences in CCKW amplitude across the simulations allowed convective coupling and its driving processes to be more readily identified. For example, experiments for which only wind is modified (Wind-modified) depicted lagged changes to CCKW-associated rainfall that appear coupled to changes in wind structure. Relatedly, adjusting wind, temperature, and moisture (All-Modified) led to higher magnitude changes in the CCKW's wind structure than only adjusting the wind. These results demonstrate the intrinsic connection between the CCKW's dynamics and convective activity, and the ability of the MPAS-A system to capture this coupling. Perturbations to wave amplitude in these experiments also demonstrate that changes to rain rate within CCKWs are closely tied changes to CSF and DCIN (Figures 12d and 12f). The relationship with CSF was especially clear (Figure 12d), supporting previous work indicating that CSF partially controls CCKW rainfall (Weber et al., 2021; Wolding, Dias, Kiladis, Ahmed, et al., 2020; Wolding, Dias, Kiladis, Maloney, & Branson, 2020).

However, the MPAS-A experiments failed to accurately simulate a historically strong CCKW propagating over the Atlantic, despite accurately capturing CCKWs in other parts of the world (Figure 11). In fact, most of these simulations hardly resolved the convective signal for the Atlantic CCKW at all, and its wind signature is erroneously confined to the upper-troposphere in all of the experiments. Such a failure is remarkable, especially given that satellite observations indicated that the magnitude of this event was over three standard deviations the background climatology. Amplifying the CCKW signal at initialization failed to improve the model performance, suggesting the initial wave strength was not a primary cause. Increasing the horizontal resolution (to 3 km over the Atlantic) also did not fully rectify these problems; while this simulation produced a CCKW with a slightly stronger filtered rain rate signal, its representation of CCKW strength and structure was significantly diminished compared with data from IMERG and ERA5.

While a multitude of factors may have played a role in the inaccurate representation of this CCKW, two are emphasized here. The first is the possibility of errors in the initial IFS analysis fields used to initialize the MPAS-A simulations, which could have affected the representation of the environment ahead of the CCKW. This is supported by evidence that the IFS system itself struggled to resolve this Atlantic CCKW event. The ITCZ was also poorly resolved by the MPAS-A simulations ahead of the Atlantic CCKW, perhaps related to IFS analysis errors, which could diminish the effectiveness of the convective coupling. On the other hand, the commonality of errors in both MPAS-A and IFS could indicate that this was an intrinsically low-predictability CCKW event. This is supported by the pronounced run-to-run variability in the CCKW's rainfall signal for MPAS-A and IFS simulations at different initialization times. Previous studies have indicated that many modeling systems, including IFS, still struggle with resolving and propagating CCKWs (Gehne et al., 2022; Yang et al., 2021). Moreover, recent work by Li and Stechmann (2020) indicates that CCKWs themselves may have a low intrinsic predictability, perhaps no greater than 2–3 days.

These results illustrate that modifying CCKW amplitudes can serve as a useful tool for understanding the convective coupling and sensitivity of these waves in numerical simulations. This method could also be used in the future to better *attribute* the suspected impacts of CCKWs, such as their interactions with other tropical waves and cyclones. This study motivates additional work investigating the predictability of individual CCKW events. Previous research has primarily focused on the collective predictability of these waves around the globe. As such, it remains unclear if this forecast error seen in these simulations was an outlier, or if it has any connections to regionality. We recommend future work focus on a systematic investigation into the predictability of individual CCKW events, especially those that are particularly strong or impactful. Follow-up work could also test if this CCKW amplitude modification method is effective using other horizontal resolutions, modeling systems, and equatorial wave types. This could include a complementary study expanding a CCKW forecast error analysis to additional basins and CCKW cases. Finally, we suggest future studies focus on CCKWs in the Atlantic and over Africa, as these locations are understudied compared to other regions (Liebmann et al., 2009; Mayta et al., 2021).

Data Availability Statement

Post-processed MPAS-A output files necessary for the replicability of these results are publicly accessible in an online repository (Lawton et al., 2024; <https://doi.org/10.7910/DVN/5OCYBR>). GridSat-B1 data is available at

<http://doi.org/10.7289/V59P2ZKR> (Knapp & NOAA CDR Program, 2014). IMERG data is available from <https://disc.gsfc.nasa.gov/>, with details on the IMERG methodology provided by Huffman et al. (2019). ERA5 data was obtained via the Copernicus Climate Data Store at <http://cds.climate.copernicus.eu>, and the reanalysis methodology is described by Hersbach et al. (2020). ECMWF data is available via the operational archive; see the following for more information: <https://www.ecmwf.int/en/forecasts/access-forecasts/access-archive-datasets>.

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