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Key Points:

- Global storm resolving models underestimate tropical total ice water path (TIWP) in particular in areas of low vertical velocities
- Cloud microphysics and convective detrainment appear to be main reasons for the inter-model variability in frozen fraction of water and TIWP
- Our results suggest that cloud ice converts to precipitating hydrometeors too fast resulting in a too short life time of convective anvils

Supporting Information:

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

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Inter-Model Variability of Tropical Total Ice Water Path Simulated by the Convection Permitting DYAMOND Models

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Abstract Cirrus clouds have a large impact on radiation, yet coarse resolution models struggle to simulate their properties and structure realistically. Employing globally resolutions of below 5 km, the models from the Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) project do not require a parameterization for deep convection. This can be expected to lead to a better representation of cloudiness, particularly in the tropics where most of the total ice water path (TIWP) results from convection. We study the inter-model variability of TIWP simulated by the DYAMOND models during boreal summer, compare to the TIWP from a lower-resolution numerical weather prediction model and evaluate using satellite observations and ERA5 reanalysis data. We disentangle dynamical reasons for the inter-model variability in monthly and daily mean TIWP from reasons connected with the cloud response to convective forcing. As expected, we find that differences in the models' cloud response are mainly responsible for the inter-model variability. The ratio of TIWP to TIWP plus total liquid water path (TLWP), which is controlled by convective de- and entrainment, and the models' microphysical scheme lead to a large inter-model variability in TIWP. Differences in convective dynamics also impact cloudiness with some models compensating a low TIWP in areas of low vertical ascent by an increased probability of large TIWP connected with large vertical velocities. Finally, the spatial distribution of convective events varies with models that parameterize convection simulating a larger fraction of the tropical TIWP in areas of high sea surface temperature.

Plain Language Summary Tropical cirrus (ice) clouds affect Earth's climate by changing how heat and moisture move in the upper atmosphere. Climate models with low resolution cannot directly capture storm-related air flows but instead have to parametrize their effects, which leads to errors in representing cirrus cloud properties. Models with higher resolution, below 5 km, can directly simulate storm-related air flows and are expected to better represent cloudiness, especially in the tropics where majority of TIWP results from convection. We investigate distribution of TIWP and its connection to storm activity over the tropical oceans in high-resolution DYAMOND models and compare them to a lower-resolution NWP model, satellite data, and ERA5 reanalysis data. We find that differences in how the models' clouds react to upward air movement are the main reason for the variability of TIWP between models. Most models underestimate TIWP when the upward air movement is weak. Differences in how environmental air mixes with convective cloud also contributes to this variability of TIWP.

1. Introduction

Cirrus clouds regularly cover about 12%–55% of the globe (Stubenrauch et al., 2013) with more than half of cirrus located within the tropics (Sassen et al., 2008). Clouds play a major role in maintaining the Earth's radiation budget by reflecting shortwave solar and absorbing longwave terrestrial radiation (Schneider, 1972), with cirrus leading to a warming of the atmosphere on average (Gasparini & Lohmann, 2016; T. Chen et al., 2000; Hartmann et al., 1992). The magnitude of shortwave cooling or longwave warming connected with cirrus clouds depends mainly on their microphysical and macrophysical properties (Heymsfield et al., 2017; Stephens et al., 1990; Stephens & Webster, 1981; Zhang et al., 1999). Additionally, properties such as vertical overlap with other clouds and underlying surface characteristics have a large impact. Although frequently occurring thin cirrus clouds have a larger impact on the long wave than short wave radiation and warm the atmosphere, optically thick convective clouds cool (Berry & Mace, 2014).

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Large-scale model simulations display large deficiencies in simulating ice water path (IWP) and liquid water path (LWP) (Waliser et al., 2009; W. Li et al., 2013; J.-L. Li et al., 2023) with inadequate descriptions of processes such as cloud formation and moist convection mainly responsible for climate model uncertainties (Stevens & Bony, 2013). Stevens and Bony (2013) showed that different global climate models (GCMs) simulate dramatically different responses of cloudiness and precipitation to warming, even when using the models in aqua planet configuration, underlining the large uncertainty in simulating processes connected with cloudiness and their importance in climate change simulations. Differences are particularly large in the tropics, where the coupling between water and circulation is disproportionately dependent on the representation of unresolved processes, such as moist convection and cloud formation (Oueslati & Bellon, 2013). Approximately 50% of tropical upper tropospheric cloudiness originates from convection (Luo & Rossow, 2004; Massie et al., 2002; Riihimäki et al., 2012).

Improving the representation of moist convection is necessary in order to simulate important cloud feedback (Bony et al., 2015, 2016; Caldwell et al., 2016) that have a large impact on climate sensitivity. Hectometer scale models allow to resolve the major features of convection by simulating updrafts, downdrafts, precipitation and cloud properties and their development consistently (Rybka et al., 2021) which is challenging to capture within a parametrization (Stevens et al., 2020). But the large computational demand of those models make global simulations required for climate studies currently unfeasible.

Global storm-resolving models (GSRMs) describe convection within the convective gray zone. The development of those convection-permitting (CP) GSRMs, which do not require a parametrization for deep convection and are sometimes also run without a parameterization for shallow convection, allow longer simulations and, therefore, raise hope for improved cloud properties on the global scale. Simulations at storm-resolving scales have been shown to start to resolve the vertical dimension of the atmospheric motion leading to some improvement in the representation of clouds and precipitation compared to lower-resolution models (Stevens et al., 2020). Simulations from GSRMs have been used in machine learning (ML) approaches to set up super-parametrizations (e.g., Rasp et al. (2018); Behrens et al. (2022)) or to coarse-grain simulations and develop a neural-network that can replace the parameterizations (e.g., Bretherton et al. (2022); Henn et al. (2024)) in lower resolution GCMs. Both ML approaches could be shown to reduce biases in low-resolution simulations when compared to high-resolution simulations.

The above approaches to improve global climate models are based on the assumption that high-resolution simulations are substantially more skillful than the low-resolution model simulations. This is not necessarily the case as cloud-radiative biases can be similarly high in the Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) models as in low-resolution models (Bretherton et al., 2022; Stevens et al., 2019). This is since cloud-radiative interaction is strongly affected by the representation of cloud microphysics and turbulence parametrizations. Therefore, our main research question is whether the high-resolution DYAMOND models resolve the processes controlling high cloudiness well enough so that simulated large-scale ice cloud properties scatter around observations or whether significant biases still exist.

In the DYAMOND project, the first intercomparison project of GSRMs, nine models were run on different grid structures with a grid spacing of 5 km or less (Stevens et al., 2019). Since the water budget in the tropical upper troposphere (UT) is controlled by convection, tropical cloudiness should particularly benefit from the increased resolution. Nugent et al. (2022) and Turbeville et al. (2022) examined the tropical convection simulated by the DYAMOND models focusing on the life cycle of deep convection and convective organization and precipitation. Nugent et al. (2022) found that although the cloud structure and precipitation features appear realistic, the different models exhibit significant variability in the partitioning of the total water into the frozen hydrometeors (snow, graupel, and ice) and in their spatial distribution. Turbeville et al. (2022) point out that the models struggle to reproduce the observed convective life cycle, starting as high albedo-low outgoing longwave radiation (OLR) deep convective systems and developing into systems with low albedo- high OLR cirrus shields. Lang et al. (2021) and Roh et al. (2021) analyzed the tropical radiation budget in high resolution DYAMOND models. Lang et al. (2021) showed that despite reduced differences of relative humidity (RH) between the high-resolution DYAMOND models compared to conventional lower resolution atmospheric models, they still show non-negligible spread in the mean tropical clear-sky OLR particularly in the areas that transition from deep convective to subsidence regimes. Roh et al. (2021) showed that over a small domain in

the Atlantic Ocean, where shallow convective clouds were found to be dominant, the DYAMOND models simulate relatively similar OLR, but the net shortwave radiation at the top of the atmosphere varied a lot. They also showed large inter-model variations in cloud ice and liquid water content over the analyzed area.

We focus on evaluating the impact of tropical convection on UT large-scale ice cloud properties in the DYAMOND simulations, expecting a large improvement in the simulations of the large-scale properties due to improvements in the representation of 3D dynamics and, therefore, vertical velocity in storm-resolving models (Stevens et al., 2020). We use ERA5 reanalysis data and observations from active and passive remote sensing in order to evaluate if the DYAMOND simulated large-scale tropical TIWP are close to observations or whether simulations are biased. This is of interest since biases may point at problems originating from the microphysical and turbulence parameterizations and would limit the quality of the parameterizations that can be developed based on the high-resolution simulations for use in lower-resolution GCMs. We investigate the inter-model variability in the large-scale ice cloud properties simulated by the high-resolution DYAMOND models, as this may be a measure for the uncertainty. We study the reasons for the inter-model variability distinguishing between dynamical reasons and reasons connected with the cloud microphysical scheme and convective de- and entrainment. For this purpose we compare the simulated TIWP in vertical velocity space, that is, we determine the mean simulated TIWP within different vertical velocity bins for each model. Moreover, we compare to lower resolution numerical weather prediction (NWP) Deutscher Wetterdienst-Icosahedral Nonhydrostatic model (DWD-ICON) simulations which were run with the same setup as the DYAMOND simulations in order to analyze the impact of the increased resolution on the simulated tropical TIWP.

In Section 2 we give an overview over the simulation, reanalysis and observational data sets and explain the methods. In Section 3 we present the simulated tropical TIWP and its inter-model variability and compare to observations. In Section 3.2.1 we analyze the connection between simulated TIWP and vertical velocity in the high-resolution DYAMOND simulations and its inter-model variability. On a $1^\circ \times 1^\circ$ grid, we evaluate this connection between tropical vertical velocities and the cloud response to convection and compare to ERA5 reanalysis combined with observed TIWP from active and passive remote sensing (Section 3.3.2). In Section 4 we compare the impact of the inter-model variability in vertical velocities with that of cloud response on mean tropical TIWP. We summarize and give an outlook in Section 5.

2. Data and Methods

In our study, we analyze the storm-resolving DYAMOND simulations and compare to DWD ICON, Coupled Model Intercomparison Project phase 6 (CMIP6) GCMs, ERA5 reanalyses, and cloud products derived from both passive and active remote sensing. In order to evaluate the DYAMOND storm-resolving simulations regarding their representation of tropical ice clouds, we compare simulated and observed monthly mean TIWP and its connection to vertical velocity on a $1^\circ \times 1^\circ$ grid. Evaluating the simulated TIWP at a reduced resolution, it is important to keep in mind that good agreement with observational data does not imply that cloud radiative forcing or precipitation is simulated realistically as those quantities are nonlinearly dependent on the TIWP. But any bias in the lower resolution fields has implications for all other dependent processes.

2.1. The DYAMOND Project Model Simulations

Within the DYAMOND project 9 different models performed global simulations over 40 days, beginning on 1 August 2016, using a horizontal grid spacing of below 5 km (Stevens et al., 2019). The GSRMs were initialized with the global (9 km) meteorological analysis from the European Center for Medium Range Weather Forecasts (ECMWF). European Center for Medium Range Weather Forecasts sea-surface temperatures (SSTs) and sea ice concentrations were prescribed. After initialization the GSRMs ran freely for 40 days. The GSRMs were not tuned at high resolution. The models vary in many respects including model grid, resolution, parameterizations and model output (table 1). In some models convection is not parameterized at all, whereas in others shallow convection or both shallow and deep convection were parameterized. All of the models are non-hydrostatic except for ECMWF's Integrated Forecasting System (IFS) model. The GSRMs used single-moment microphysical schemes, and partitioned ice water into 3 frozen hydrometeors — cloud ice, snow, and graupel—except for IFS which does not include graupel. The microphysical schemes of all analyzed models include not only fall velocities for graupel and snow but also for cloud ice. For additional information on the individual microphysical schemes of GSRMs see Seiki et al. (2022).

Table 1
Model Simulations and Observations

Models	Native horizontal grid spacing	Conv. parametrization (D: deep, S: shallow)
ICON (DYAMOND)	2.5 km	None
ARPEGE (DYAMOND)	2.5 km	None
FV3 (DYAMOND)	3.25 km	S
GEOS (DYAMOND)	3.25 km	D,S
NICAM (DYAMOND)	3.5 km	None
MPAS (DYAMOND)	3.75 km	D,S
IFS (DYAMOND)	4 km	S
SAM (DYAMOND)	4 km	None
DWD-ICON (NWP)	13 km	D,S
ERA5 (Reanalysis)	31 km	D,S
Active/Passive Remote Sensing	Grid	Year
DARDAR (active)	1° × 1° (tropics)	2016, 2010
	2° × 2.5° (global)	2016
2C-ICE (active)	1° × 1°	2007, 2009, 2010
MODIS/GEO (passive)	1° × 1°	2016

The available model output varies. Although the three-dimensional (3D) distribution of cloud ice and cloud water is available for all models, only Nonhydrostatic Icosahedral Atmospheric model (NICAM), Goddard Earth Observing System Model (GEOS) and Model for Prediction Across Scales (MPAS) archived 3D distributions of the other hydrometeors. The IWP of individual hydrometeors from NICAM and GEOS simulations had to be calculated from the respective profiles. Model output of the two-dimensional (2D) fields, such as integrated water paths of frozen hydrometeors, is available every 15 min and of 3D fields, such as frozen hydrometeor concentrations every 3 hr. The size of the DYAMOND simulation data set represents a challenge for the analysis. Therefore, different approaches have been taken to analyze the data, either analyzing the simulations in small domains (Nugent et al., 2022; Roh et al., 2021; Turbeville et al., 2022) or/and at lower resolution (mostly in order to compare to observations) (Lang et al., 2021; Turbeville et al., 2022) or with random draws from the simulation data Lang et al. (2021).

We compare the DYAMOND model simulations regarding the simulated TIWP and evaluate them with ERA5 reanalysis data and observations over the whole tropics. For that purpose we transform simulation data to a 1° × 1° grid, the resolution of the remote sensing data sets. Following Stevens et al. (2019), we exclude in our analysis the first 10 days of the simulations removing the model spin-up and the part of the simulation in which simulations from different models are similar due to the common initial conditions. We restrict our analysis to the tropical ocean since the exact height of the model levels, which is dependent on orography, was not available for all DYAMOND models. This is also of advantage when comparing to active remote sensing data. The strong diurnal cycle of convection over land would have posed a problem since the active remote sensing data based on Cloudsat and Cloudsat-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) ceased to provide night time data since the year 2011.

We analyze the connection between vertical velocity and TIWP in the models and ERA5 or a combination of ERA5 and observational data on a common 0.1° × 0.1° or 1° × 1° grid. The model output is horizontally interpolated from each model's native grid to the common regular latitude-longitude grid. As in Lang et al. (2021), this is done using a conservative remapping via the remap function of the Climate Data Operators (Schulzweida, 2020).

2.2. DWD-ICON

We compare the DYAMOND simulations to those of the operational NWP DWD-ICON model (v2.6.5, Oct. 2022) that has a horizontal grid length of 13 km and uses a full set of convection parameterizations (Table 1). This

provides the unique opportunity to compare the same Icosahedral Nonhydrostatic model (ICON) at a storm-resolving and a typical global NWP resolution. For that purpose, two DWD-ICON simulations were performed with graupel as in ICON-DYAMOND and the operational setting without graupel to investigate the sensitivity purely to microphysics. The same ECMWF SSTs and the same starting conditions were used as in the DYAMOND simulations. DWD-ICON determines the cloud-fraction in anvil regions from a balance of convective detrainment and a decay time-scale of 1,500 s. DWD-ICON is mostly tuned to surface radiative fluxes over land and less so for top-of-atmosphere (TOA) radiative fluxes in the tropics.

The vertical velocity within a model that parameterizes convection results from the convection parameterization and the resolved motion. Moreover, at the resolution of the DYAMOND models a large part of the convection can be expected to be resolved, this is not the case within DWD-ICON. In DWD-ICON around 80% of tropical precipitation is connected with the convection scheme and the rest comes from resolved convection. The vertical velocity in lower-resolution models that use convection parametrizations is due to the latent heating that is connected with the condensation and deposition of water vapor calculated within the convection parameterization and from resolved convection that may be triggered if the convective available potential energy is not reduced sufficiently by the convection parameterization. Despite these differences in the vertical velocities from the high-resolution DYAMOND models and the lower resolution NWP parameterized models, in both models vertical velocities are directly related with the water transport into the UT.

2.3. CMIP6 GCMs

In Section 3.1, we compare the DYAMOND simulations to CMIP6 “historical” simulations over the time period August–September 1994–2014. The aim is to investigate whether the average and the spread in simulated cloud ice water path in high-resolution DYAMOND is improved compared to low-resolution GCMs. We use one ensemble member (typically the first member “r1i1p1f1”) per model. We calculated the multi-year multi-model mean (MMM) from the following models: BCC-CSM2-MR (Wu et al., 2019), CAMS-CSM1-0 (Rong et al., 2018), CESM2 (Danabasoglu et al., 2020), NRM-CM6-1 (Voldoire et al., 2019), FGOALS-g3 (L. Li, Xu, et al., 2020), HadGEM3-GC31-LL (Kuhlbrodt et al., 2018), KACE-1-0-G (Lee et al., 2019), MIROC6 (Tatebe et al., 2019), MPI-ESM-1-2-HAM (Mauritsen et al., 2019), MRI-ESM2-0 (Yukimoto et al., 2019), NorESM2-LM (Seland et al., 2020), SAM0-UNICON (Park et al., 2019), UKESM1-0-LL (Sellar et al., 2019), and, additionally, a multi-year mean from the simulations of two high-resolution CMIP6 GCMs, MPI-ESM1.2-HR (Müller et al., 2018), and CNRM-CM6-1-HR (Voldoire et al., 2019). The analyzed variable of cloud ice in CMIP6 models, “clivi,” is defined as ice water mass in the column divided by the column area and includes precipitating frozen hydrometeors only if the precipitating hydrometeor affects the calculation of radiative transfer in the model. Therefore, cloud ice in CMIP6 models can contain snow to some degree if the radiation scheme of the model considers snow. An overview of the CMIP6 models considering snow in the radiation calculations can be found, for example, in J.-L. F. Li, Yu, et al. (2020).

2.4. ERA5 Reanalysis

ERA5 is the fifth generation European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis product (Hersbach et al., 2020) and replaces the ERA-Interim reanalysis. ERA5 reanalysis combines the Integrated Forecasting System (IFS) Cy41r2, which was operational in 2016, with observations using the ECMWF's data assimilation system. We use ERA5 data from the Copernicus Climate Change Service Climate Data Store (CDS). The native horizontal grid length of the ERA5 data is 31 km and is provided by CDS every hour at regular latitude-longitude grid of 0.25°. We use vertical velocity on 500 hPa, vertically integrated cloud ice water, snow, cloud liquid water and rain for the same period as the DYAMOND simulations were ran (table 1). Additionally, we used data from the same time period for the years 2007, 2009, and 2010 in order to investigate the stability of the analysis.

2.5. MODIS/GEO Observations

The global MODIS/geostationary satellite (GEO) ice water path data (table 1) is part of the Clouds and Earth's Radiant Energy System (CERES) synoptic 1° (SYN1deg) Ed4A (Wielicki et al., 1996) Level 3 product provided every hour on a 1° × 1° latitude-longitude grid. For this study, daily ice water path (IWP) averages of the product

(SYN1degDay) were used (NASA/LARC/SD/ASDC, 2017). The cloud properties (e.g., IWP/LWP, cloud area fraction, cloud effective temperature, and cloud visible optical depth) are derived from passive remote sensors and combine data from the GEOs and the MODIS data from the polar orbiting Terra and Aqua satellites. Cloud properties during the MODIS observed hours may differ from the surrounding GEO cloud properties due to their retrieval differences. The product assumes that the MODIS clouds are superior to the GEO clouds, due to MODIS larger number of imager channels, calibration, and image quality. Detailed description of the cloud product retrievals for Edition 4, that were used in this work, Deuts can be found in the work by Minnis et al. (2021).

2.6. DARDAR

Although cloud products from passive sensors excel with their spatial coverage, it is well known that they can miss optically thin clouds (Holz et al., 2008) and are limited in their sensitivity for high IWPs due to the signal saturation (Eliasson et al., 2011). To overcome this observational shortcoming, the ice cloud product raDAR liDAR (DARDAR) (Delanoë & Hogan, 2010) was used which combines the high sensitivity of the Cloud-Aerosol Lidar with Orthogonal Polarization lidar on CALIPSO (Winker et al., 2010) with the cloud profiling radar (CPR) on CloudSat (Stephens et al., 2008) within the sun-synchronous A-Train satellite constellation (Stephens et al., 2002). The DARDAR-Cloud product is based on the optimal estimate framework Varcloud (Delanoë & Hogan, 2008) which derives the ice water content (IWC) and effective radius from the sensitivity of the lidar to the ice particle concentration and the sensitivity of the cloud radar to the ice particle size.

For this study, IWPs were derived from IWCs contained in DARDAR-Cloud with version V3-10 (version details are described in (Cazenave et al., 2019)) for single A-Train orbits and subsequently averaged onto a $1^\circ \times 1^\circ$ grid over the tropics and additionally on a $2^\circ \times 2.5^\circ$ grid globally (Table 1). By that way, a daily and a monthly averaged IWP global product was derived for August–September 2016. In contrast to the CERES SYN1deg Ed4A-Day hourly product, DARDAR is only available during A-Train overpasses at local noon and midnight. Since CloudSat is only available during noon overpasses due to a battery issue in 2011, a corresponding data set was also derived for August–September 2010. To test for diurnal variations, the 2010 IWP was averaged for the noon and midnight overpass separately (appendix A, Figure A1).

2.7. 2C-ICE

2C-ICE (Deng et al., 2010, 2013) is a further ice cloud product, based on the same A-Train data as DARDAR, which we use to compare to DARDAR. It is also based on an optimal estimate algorithm, but using different assumptions and models compared to DARDAR. One important difference is the parameterization of CloudSat signals in lidar-only regions to incorporate the instrument sensitivity of about -29 dBZ (Deng et al., 2015). In addition, 2C-ICE accounts for the hydrometeor attenuation of the radar signal, but assumes a more simplistic factor approach (Platt, 1981) to the multiple scattering correction and a constant lidar ratio. As particle size distribution (PSD), 2C-ICE assumes a modified Gamma PSD instead of a normalized PSD approach (Delanoë et al., 2014). For the mass-size relationship, 2C-ICE uses the habit mixture of Baum et al. (2005) based on the specific ice crystal shapes of Yang et al. (2000), whereas DARDAR relies on the composite in situ data set of Heymsfield et al. (2010). An extensive inter-comparison of both algorithms was done by Deng et al. (2013) which found very close agreement between the products. Differences were found in lidar-only regions where DARDAR retrieved higher IWCs compared to 2C-ICE.

The 2C-ICE and DARDAR cloud ice products are based on several assumptions and limitations which prevent a straightforward distinction between ice and snow. Working with two measurements (lidar and radar backscatter), their ice particle model (soft spheroid) is bound to capture the transition from pristine ice crystals to falling snow flakes using two variables (size and total mass). There are two methods of estimating cloud ice water content from active remote sensing, the flag method (J.-L. F. Li et al., 2008; Waliser et al., 2009) and PSD method (W.-T. Chen et al., 2011), which have been shown to agree well (W.-T. Chen et al., 2011).

This study uses the aggregated data set of 2C-ICE provided by J.-L. F. Li, Yu, et al. (2020). For the time span of 2007–2010, it provides monthly averaged CIWP and TIWP on a $1^\circ \times 1^\circ$ grid (table 1). We exclude the year 2008 from our analysis since there were a high number of CALIPSO errors reported in September 2008 and the comparison with other years showed substantial differences in the mean TIWP for that period.

2.8. Dependence of Simulated TIWP on Convective Strength and Cloud Response to Convection

Our aim is to understand the reasons for variations of tropical TIWP in the high-resolution DYAMOND model simulations. Differences in tropical TIWP could be caused by differences in convective moisture fluxes into the UT or due to differences in the residence time of the water within the convective cell in the UT. We use a framework similar to the one introduced by Bony et al. (2004) that originally aimed at disentangling dynamical and thermodynamical reasons for changes in cloud radiative forcing due to climate change within climate model simulations. We use the framework to study reasons for differences in the tropical upper tropospheric TIWP in different model simulations, distinguishing between reasons associated with the model's representation of vertical velocity at 500 hPa, an indicator for convective dynamics, and with the cloud response, given by convective en- and detrainment and the cloud microphysical scheme. Within the framework we decompose a cloud property C , in our study TIWP, into the mean cloud property for a given value of a predictor variable, in our case for a given vertical velocity at 500 hPa, C_w , multiplied with the probability of the value of this predictor variable, PDF_w . The mean cloud property simulated by an individual model (IM), $\overline{C(IM)}$, can then be calculated by integrating the product of $C_w(IM)$ and $PDF_w(IM)$ over the range of the predictor variable:

$$\overline{C(IM)} = \int_{-\infty}^{\infty} PDF_w(IM) C_w(IM) dw. \quad (1)$$

The benefit of this framework in the context of our study is that we can disentangle the dynamical reasons from the reasons connected with the cloud response to convection that can both lead to differences in the UT cloudiness in the different DYAMOND models. By analyzing the TIWP connected with a certain vertical velocity ($TIWP_w$) we capture the fact that vertical velocity and the connected water transport are to a certain degree coupled to the cloud response. For example, larger vertical velocities often leading to higher reaching convection and colder convective cloud tops which are connected with larger outflow cirrus decks and larger amounts of ice water (Chou & Neelin, 1999; Feng et al., 2012; Machado & Rossow, 1993). This means that an underestimation of convective vertical velocities can lead to an underestimation of the TIWP. This has consequences for atmospheric humidity as larger and longer lived convective anvils and outflow cirrus may lead to a larger moistening of the UT which is controlling clear sky cooling and the descent of the air away from convective centers impacting again dynamics.

Using Equation 1 we calculate the difference in TIWP between the multi-model mean (MM) and a single model (IM).

$$\overline{TIWP(MM)} - \overline{TIWP(IM)} = \int_{-\infty}^{\infty} \delta TIWP_w dw \quad (2)$$

$$= \int_{-\infty}^{\infty} (\delta TIWP_{w,dynamics} + \delta TIWP_{w,cloudresponse} - \delta TIWP_{w,Covar}) dw \quad (3)$$

that results from three different terms. The first term of the integrand in Equation 2 represents the difference in $\delta TIWP_w$ resulting from differences in the model's vertical velocity.

$$\delta TIWP_{w,dynamics} = TIWP_w(MM) * (PDF_w(MM) - PDF_w(IM)) \quad (4)$$

The second term of the integrand in Equation 2 represents the difference in $\delta TIWP_w$ that is due to the difference in the response of TIWP to vertical velocity.

$$\delta TIWP_{w,cloudresponse} = PDF_w(MM)(TIWP_w(MM) - TIWP_w(IM)) \quad (5)$$

The third term of the integrand in Equation 2 represents the covariance between the difference in the TIWP response to vertical velocity and the difference in the PDF of vertical velocity.

$$\delta TIWP_{w,covar} = (PDF_w(MM) - PDF_w(IM))(TIWP_w(MM) - TIWP_w(IM)) \quad (6)$$

If the first term is dominant then we can conclude that despite the fact that deep convection is at least partly resolved, dynamical reasons are still to blame for the variability in TIWP. If the second term should turn out to be more important, the model's cloud microphysical scheme, the moisture flux out of the boundary layer or convective en- and detrainment are to blame for the inter-model variability in TIWP.

We perform our analysis of the DYAMOND simulations on a $0.1^\circ \times 0.1^\circ$ and a $1^\circ \times 1^\circ$ grid and on two different time scales. We analyze the simulation data averaged over all snapshots of a single day or of the whole month, calling, in the following, the analysis a 'daily mean' or 'monthly mean' analysis. Therefore, in the monthly mean analysis, we derive for each model (IM) and for the multi-model mean (MM) the PDF_w from the monthly averaged vertical velocity at 500 hPa and $TIWP_w$ which represents the average monthly TIWP for each bin of the monthly mean vertical velocity. Therefore, in the monthly mean analysis we analyze the spatial variability of TIWP and its dependence on the vertical velocity. The same methodology is applied in the daily mean analysis, except that daily averaged velocities and TIWPs are used instead of monthly averages. We perform the daily mean analysis for the following reason. A single convective updraft may last for about half an hour, but the active convective phase can take many hours. Convectively generated clouds form within deep convective cores and transform into anvil clouds. The convective anvil, resulting from the mass transport within the convective updrafts, has a life time that lasts much longer, often around 15 hr or slightly longer reaching a large spatial extent (Feng et al., 2012; Mace et al., 2006; Massie et al., 2002). During the anvil life time the optical depth decreases (Luo & Rossow, 2004) and the cloud top height of the outflow cirrus may decrease, in particular further away from the convective core, or be maintained by radiative heating (Sokol & Hartmann, 2020; Strandgren, 2018). Maximum life time of the systems, comprising the convective core, the convective anvil and the optically thin outflow cirrus, can be up to a few days (Horner & Gryspeerd, 2023; Luo & Rossow, 2004; Pfister et al., 2001). Although the convective event dies down after several hours, the thin outflow cirrus can persist significantly longer and leads to cloudiness connected with a low TIWP in areas of low vertical velocity. Even though the TIWP of outflow cirrus is low its extent can be significant and, therefore, outflow cirrus can have a significant impact on radiation and on tropical UT moisture. Within the analysis of daily mean TIWP we study the connection between daily mean vertical velocity and TIWP, that is, performing the analysis on approximately the time scale of anvil persistence.

We also perform our analysis on monthly mean data on a $1^\circ \times 1^\circ$ grid. We analyze the connection between monthly mean vertical velocity, which is an indicator for the strength and frequency of convective activity making up the Hadley cell, and the monthly mean TIWP. This analysis enables us to compare to observational data, a combination of ERA5 vertical velocity and TIWP from passive and active remote sensing. When analyzing monthly mean data, differences in monthly mean TIWP depend not only on the reaction of cloudiness to a convective event but also on the spatial distribution and frequency of convective events.

3. Variability in TIWP and Its Connection With Vertical Velocity

In this section we analyze the DYAMOND simulations regarding their spatial patterns of monthly mean tropical TIWP and compare with observations (Section 3.1). Then, in Section 3.2.1, we study convective activity and its impact on daily mean TIWP simulated by high-resolution DYAMOND models on a common $0.1^\circ \times 0.1^\circ$ grid. In order to compare to observations, ERA5 and NWP, we study in Section 3.3 this relationship in monthly mean data on a $1^\circ \times 1^\circ$ grid and compare with ERA5 and DWD ICON simulations. In Section 3.3.2 we evaluate this relationship with the combination of observational TIWP from active and passive remote sensing and ERA5 vertical velocities. The analysis and all the figures, except Figure 1, are limited to ocean-only grid points.

3.1. Spatial Variability of TIWP

Figure 1 shows the total ice water path, TIWP, simulated by the DYAMOND models, ERA5 reanalysis, from passive remote sensing, MODIS/GEO, and active remote sensing, DARDAR for August/September 2016. Additionally the TIWP of the 2C-ICE data set for August/September averaged over the years 2007, 2009 and 2010 is shown (please see Section 2.7 for reasons why the data from 2008 were excluded from the comparison). The active remote sensing data sets are limited to the overpasses of A-Train, the local noon overpass for the DARDAR 2016 data and the local noon and midnight overpasses for 2C-ICE 2007–2010 data, and are therefore noisier than the passive remote sensing product. Beside the different basis years, differences between the

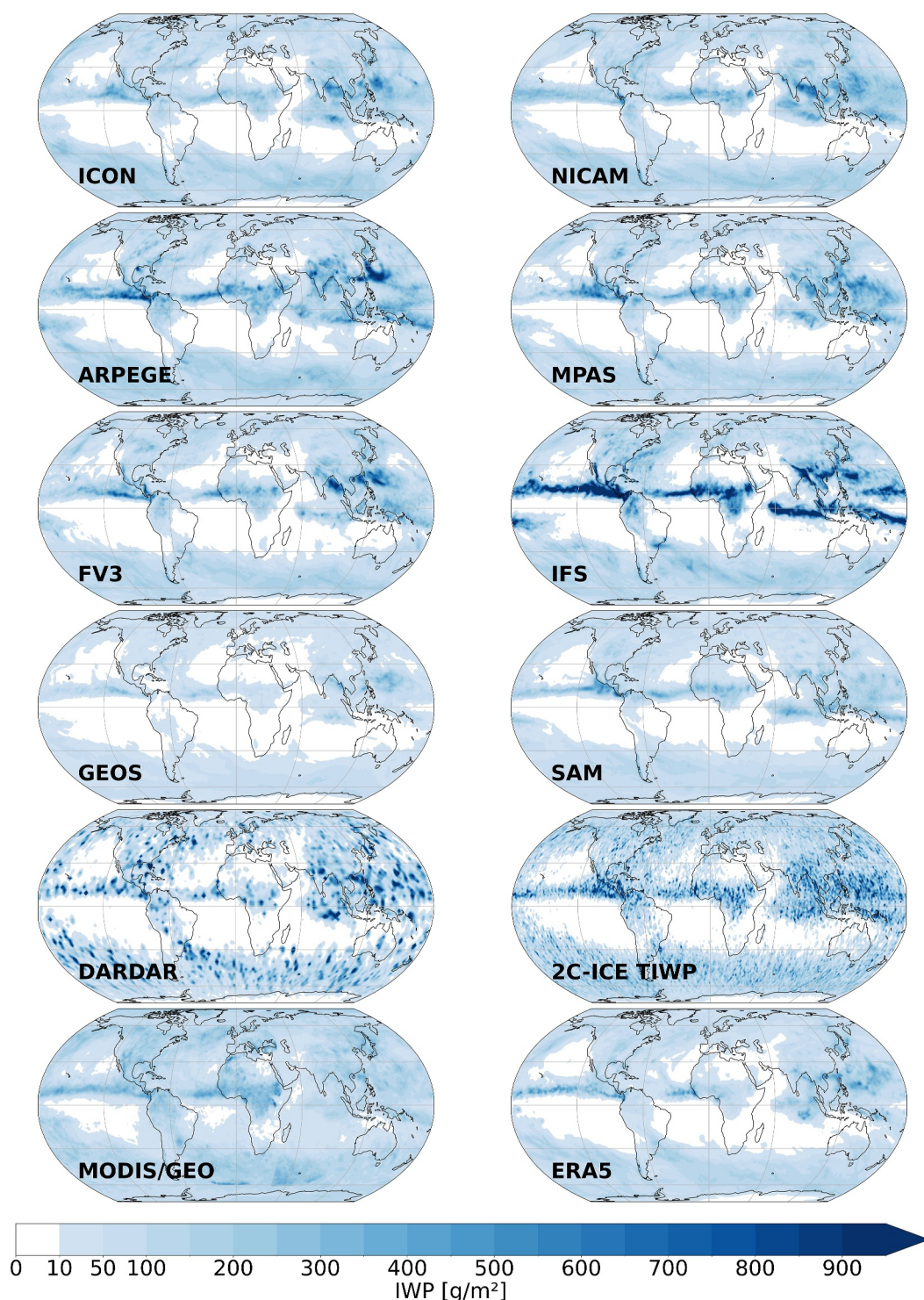


Figure 1. Total ice water path (TIWP) simulated by the high-resolution DYAMOND models, ERA5 reanalysis and MODIS/GEO, DARDAR and 2C-ICE remote sensing data. All figures are for August/September 2016 except for 2C-ICE that shows the average for August/September 2007, 2009 and 2010. All fields are remapped to a $1^\circ \times 1^\circ$ grid. DARDAR data are remapped to a $2^\circ \times 2.5^\circ$ grid due to the sparsity of data. In the remainder of the paper we analyze the frozen water path only over the tropical oceans. The distribution of TIWP for NWP ICON model can be found in the supplemental material (Figure S1 in Supporting Information S1).

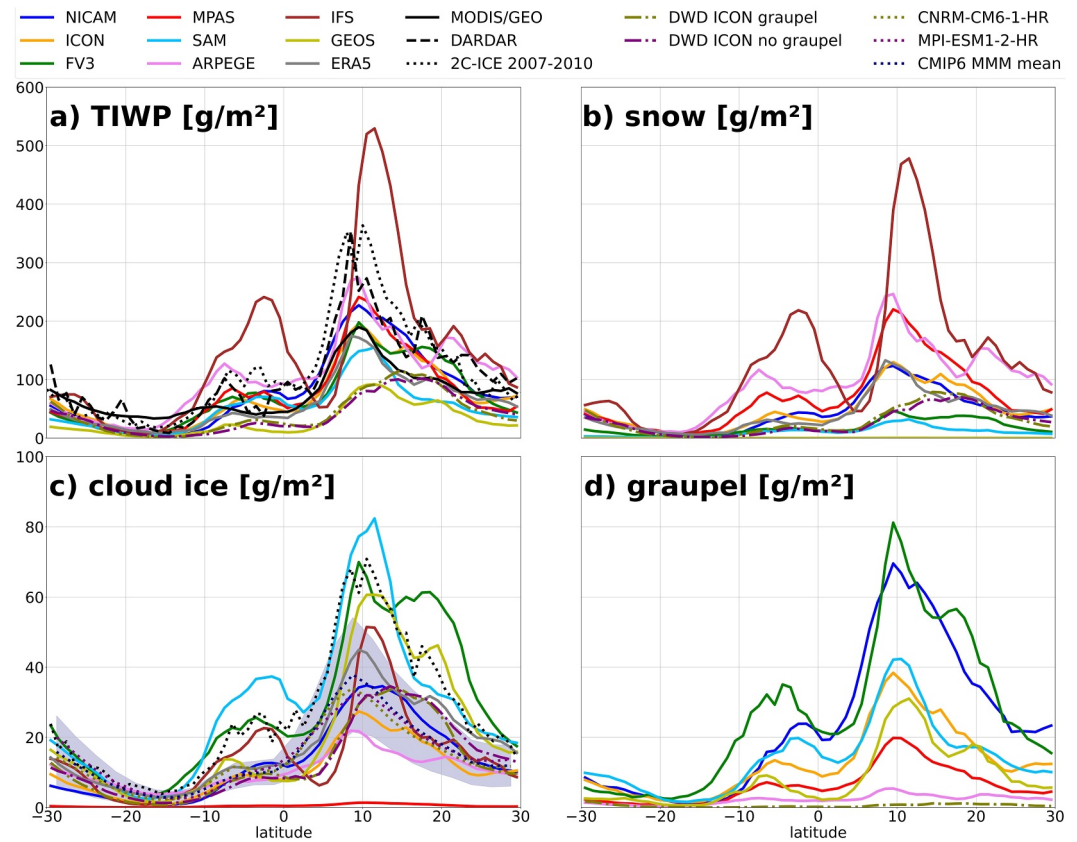


Figure 2. Zonal mean (a) total ice water path and water path of, (b) snow, (c) cloud ice, and (d) graupel over the tropical oceans for August/September 2016. DYAMOND models (colorful solid lines), DWD (NWP) ICON models (dot dashed lines), observations from passive (black solid) and active (black dashed and dotted) remote sensing. All fields are remapped to a $1^\circ \times 1^\circ$ grid. Additionally, the blue dotted line indicates the cloud ice water path of multi-year multi-model mean of 15 CMIP6 GCMs and the shaded area shows their standard deviation. Furthermore, two high-resolution CMIP6 GCMs (CNRM-CM6-1-HR and MPI-ESM1-2-HR) are included. The CMIP6 GCMs are remapped to a common $2.5^\circ \times 2.5^\circ$ grid.

DARDAR and 2C-ICE products are due to differences in the aggregation of the observations onto a grid and the difference in grid box size.

Maxima of the tropical TIWP can be found in the intertropical convergence zone (ITCZ) with absolute maxima over the Western Pacific, Bay of Bengal and a weaker maximum over the Eastern Pacific close to the American continent, consistent with the ascending branch of the Hadley-Walker circulation. DYAMOND simulations display a large variability in the amount and spatial distribution of the TIWP. Although in some models pronounced local maxima of TIWP can be found (e.g., Finite-Volume Dynamical Core on the Cubed Sphere (FV3) or Action de Recherche Petite Echelle Grande Echelle (ARPEGE)), in other models TIWP is more evenly distributed within the ITCZ (e.g., ICON and NICAM). The more homogeneous distribution of TIWP within the ITCZ appears to be more in line with the observational data sets and ERA5 reanalysis data. The large TIWP in the whole tropical ITCZ in the DYAMOND Integrated Forecast System (IFS) model is not supported by observations. It is presumably caused by the overestimation of vertical velocities when using the hydrostatic IFS model at high resolution (Jeevanjee, 2017). The lower resolution DWD ICON models show lower TIWP over most of the ITCZ (Figure S1 in Supporting Information S1). The use of the graupel scheme in the DWD ICON model leads to only a slight increase in TIWP. The TIWP from ERA5 and for example, NICAM, DYAMOND ICON and System for Atmospheric Modeling (SAM) show a good resemblance with the passive remote sensing data over the tropical oceans. In the following, we analyze the distribution of the frozen hydrometeor paths and their connection with vertical velocity only over the tropical oceans.

Figure 2 shows the zonal mean of the TIWP and the water path of snow, cloud ice and graupel over the tropical oceans simulated by the DYAMOND models, the DWD ICON model, CMIP6 GCMs, from the ERA5 reanalysis

and the TIWP from passive and active remote sensing. The TIWP estimate coming from passive remote sensing is significantly lower than the active remote sensing products in areas of large TIWP close to the ITCZ. This is because passive remote sensing saturates at lower TIWP than active remote sensing because it is rather sensitive to the upper part of the clouds and to small ice crystals (Eliasson et al., 2011). Consequently, MODIS/GEO tends to underestimate the mean TIWP in the presence of deep convection, whereas TIWP estimate coming from active remote sensing is expected to be more realistic. Since we do not have 2C-ICE data for 2016 the uncertainty of the TIWP for 2016, coming from the two different retrieval algorithms, cannot be easily determined. But when comparing the DARDAR and 2C-ICE TIWP for 2010 (appendix A, Figure A1), we find that the two active remote sensing data sets agree very well. Furthermore, we find that the fact that TIWP from active remote sensing is only available for the noon overpass since 2011 is not a major obstacle in our evaluation of the tropical TIWP over the oceans.

Most of the models successfully simulate the ITCZ at about 10°N and a minimum in TIWP between 10° and 20° S. Many of the DYAMOND models agree in large parts of the tropics with passive remote sensing data, underestimating TIWP compared to active remote sensing. ARPEGE, and to a lesser degree MPAS and NICAM, simulate a TIWP in the ITCZ that comes close to the observed one from active remote sensing. Those models do so mostly by simulating a large snow path while underestimating the 2C-ICE CIWP significantly. Only NICAM resembles both the observed TIWP and CIWP.

All models, except for FV3, SAM and GEOS, appear to significantly underestimate the CIWP compared to the 2C-ICE CIWP product. As the 2C-ICE cloud ice product is based on a number of assumptions (Section 2.7) the model biases are uncertain. Furthermore, given the problems and model diversity in defining the distinction between different hydrometeors, in particular between cloud ice and graupel, a low CIWP within the DYAMOND models may be compensated by a larger amount of graupel.

Compared to the TIWP in the DWD ICON simulations, the TIWP simulated by the DYAMOND models is significantly closer to observations. The lower resolution DWD ICON model significantly underestimates TIWP and struggles to reproduce the location of the ITCZ. Within the DYAMOND simulations there exists a large variability in the contribution of different hydrometeors to the TIWP. In some models, MPAS, IFS, and ARPEGE, the large TIWP is connected with a large contribution from snow and a low contribution from cloud ice. Total ice water path simulated by SAM and GEOS, on the other hand, is very low but their CIWP resembles closely the 2C-ICE cloud ice product.

The CMIP6 MMM CIWP (clivi) lies over the tropical oceans within the range of the CIWP simulated by the high-resolution DYAMOND models. Nevertheless, the fact that some of the CMIP6 models include radiatively active snow within the cloud ice variable clivi and do not have graupel, point at a significant underestimation of TIWP. The inter-model variability appears to be large in both CMIP6 and DYAMOND simulations. The two high-resolution CMIP6 GCMs (MPI-ESM1.2-HR and CNRM-CM6-1-HR) do not seem to perform better simulating the tropical ice water path than the rest of the CMIP6 GCMs.

The large variability in simulating different hydrometeors may be caused by, for example, differences in conversion rates or in distinguishing between different hydrometeors. Distinguishing between different hydrometeors is not only microphysically but also radiatively important as snow is often assumed to be radiatively inactive or less active due to the larger particle sizes. This means that despite the large TIWP simulated by the IFS model the OLR is well simulated (Nugent et al., 2022).

3.2. Convective Activity and Its Impact on TIWP

Here we analyze the connection between the strength of a convective system and the TIWP of the associated convective anvil in the simulations of the different DYAMOND models on a common $0.1^\circ \times 0.1^\circ$ and $1^\circ \times 1^\circ$ grid. As the anvil TIWP is an integrated quantity which is affected by the vertical velocities over a longer time period, we use the daily mean vertical velocity at 500 hPa as a measure of the strength of convective activity and connect it to TIWP.

3.2.1. Analysis on a $0.1^\circ \times 0.1^\circ$ Grid

The PDF of daily mean vertical velocity at 500 hPa over the tropical oceans and the associated TIWP vary significantly among the DYAMOND models (Figures 3a and 3b). The large positive and negative vertical

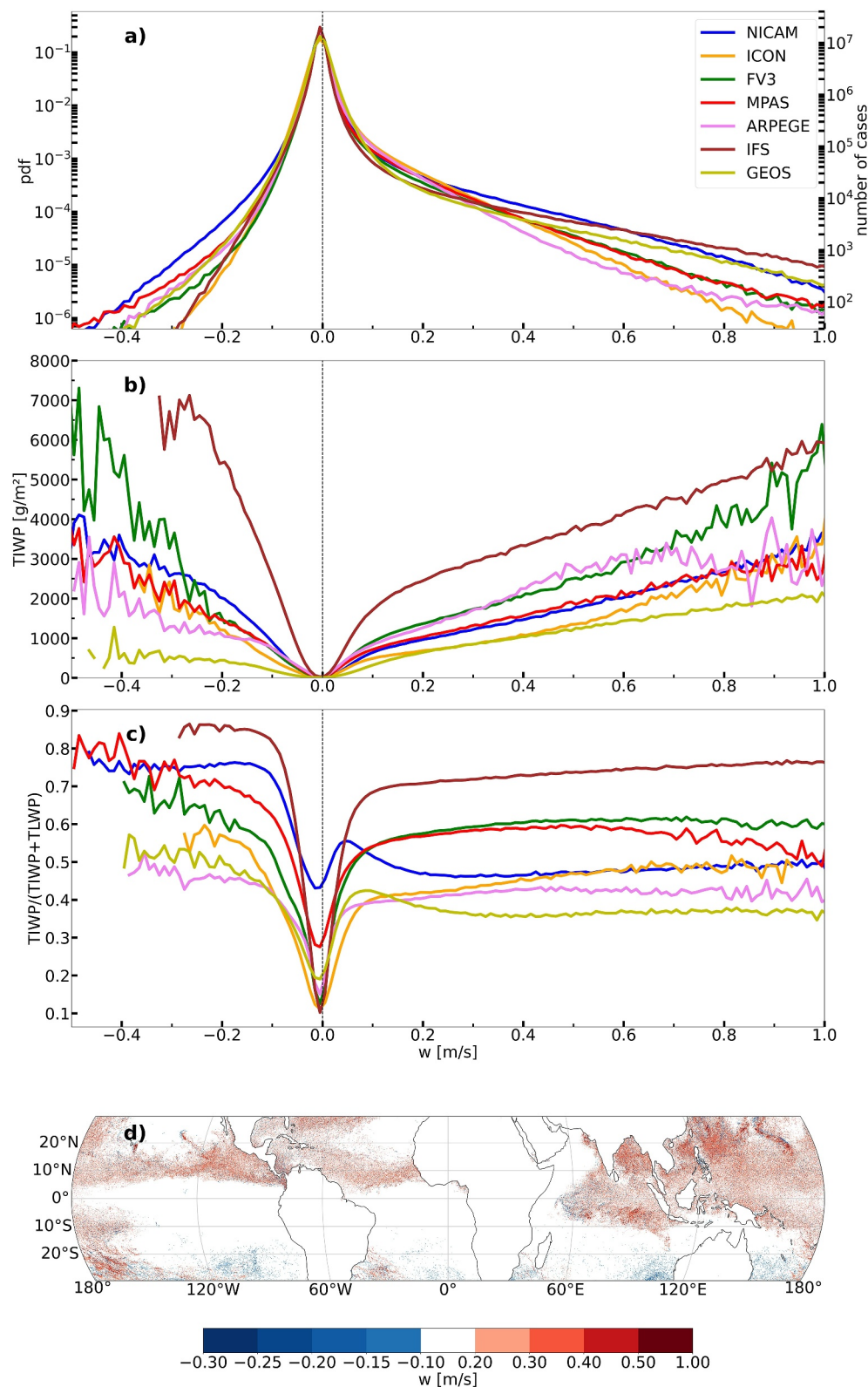


Figure 3. (a) PDF of daily mean vertical velocity (w) at 500 hPa, and (b) total ice water path (TIWP) for different daily mean vertical velocity bins in high-resolution Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) models over the tropical oceans between 30°N and 30°S for August/September 2016. Also shown is, (c) the frozen fraction, $\text{TIWP}/(\text{TIWP} + \text{TLWP})$, and (d) daily mean strongest up- (red pixels) and downdrafts (blue pixels) in DYAMOND ICON. Vertical velocity bins are of the size 0.01 m/s. Diagnostics are based on fields that were remapped to a common $0.1^\circ \times 0.1^\circ$ grid.

velocities indicate strong convective systems with positive vertical velocities indicating convective updrafts and negative vertical velocities indicating downdrafts connected with precipitation. The strong up and downdrafts can be mostly found in the Western Pacific warm pool area and along the ITCZ (Figure 3d) with the distribution changing slightly from model to model. All models simulate an increase of $TIWP_w$ with increasing vertical velocity with similarly large or even larger $TIWP_w$ in convective downdrafts than in updrafts. Most of the models simulate a lower LWP in areas of strong downdrafts than in updraft areas so that the frozen fraction in the downdraft areas is larger.

The analysis shows a large inter-model variability in the simulated $TIWP_w$ originating from differences in the microphysical schemes, differences in the de- and entrainment and/or the moisture flux out of the boundary layer both controlling the TWP_w (Figure S3 in Supporting Information S1). When two models simulate a similar TWP_w for moderate updrafts, such as GEOS, MPAS, and ICON, the frozen fraction indicates that differences in detrainment levels relative to the freezing levels are causing differences in $TIWP_w$. Similarly, models may agree in the $TIWP_w$ but the frozen fraction is very different pointing at the models simulating a similar $TIWP_w$ due to different reasons.

The interpretation of the analysis is limited by the fact that part of the cloud ice within the convective anvil may be transported out of the $0.1^\circ \times 0.1^\circ$ grid box, whereas the convective core remains within the grid box of high vertical velocity. This would lead to a low fraction of the water path that is frozen in strong convective events while the frozen fraction may be larger in areas with little convective activity. This may be one of the reasons for the relatively large frozen fraction in areas of close to zero vertical velocity in NICAM.

Since observational data are available on a grid similar to the native model grid, the comparison of independent PDFs between models and observation is straightforward but the “pixel-by-pixel” association of reanalysis fields with observations carries the risk of mismatches. Matching observed TIWP with ERA5 vertical velocities on a $0.25^\circ \times 0.25^\circ$ grid resulted, therefore, in a $TIWP_w$ that is very noisy due to the spatial mismatches. For this reason, we coarsened the observations and models to the common $1^\circ \times 1^\circ$ grid when creating benchmarks like TIWP (DARDAR) versus w (ERA5).

In the following we analyze the connection between vertical velocity and TIWP on a $1^\circ \times 1^\circ$ grid which not only ensures that the frozen hydrometeors of the convective anvil remain in one grid cell but also enables the comparison with the combination of remote sensing observations and ERA5 reanalysis data.

3.2.2. Analysis on a $1^\circ \times 1^\circ$ Grid

We repeat the above analysis after regridding the simulations onto a $1^\circ \times 1^\circ$ grid. Large upward velocities are an indication for a strong convective system within a grid cell that is connected with a large convective mass flux and that result in maxima of TIWP (Appendix C, Figure C1). When analyzing the dependence of $TIWP_w$ on vertical velocity on a $1^\circ \times 1^\circ$ grid, we find that by averaging over areas with significant convective activity and nonactive areas most of the models display a very similar increase in TIWP with vertical velocity (Figure S2b in Supporting Information S1). Only GEOS and SAM simulate a consistently lower and DYAMOND IFS a larger TIWP. Instead of the close to linear increase seen for the DYAMOND models, the $TIWP_w$ in the DWD ICON simulations is lower for low vertical velocities (between 0.03 and 0.05 m/s), whereas for larger vertical velocities, the $TIWP_w$ in DWD ICON is similar to those of the DYAMOND models. This indicates that the TIWP in the NWP models is to a larger part composed of areas of large TIWP connected with strong convective activity than in the DYAMOND simulations.

Most of the models transition very fast from mostly liquid to a high ice fraction or mostly ice at around 0 m/s (Figure S2c in Supporting Information S1) as at this grid spacing convective events start to be embedded in otherwise quiescent areas.

The models show a large variability in the contribution of particular vertical velocity bins to the TIWP ($PDF_w \times TIWP_w$, Figure S2d in Supporting Information S1). The MM from the DYAMOND models differs significantly from ERA5. At vertical velocities close to 0 m/s, the DYAMOND MM of $PDF_w \times TIWP_w$ is about one and a half times as high as in ERA5 pointing at a slower conversion into precipitating hydrometeors, and, therefore, a longer lifetime of the convective anvils and outflow cirrus in the higher resolution models. It may possibly be also caused by an increased moisture flux from the boundary layer within weak convective systems.

3.3. Spatial Variability in Vertical Velocity and Its Impact on TIWP

Figures 4a and 4b show the PDF of monthly mean vertical velocity at 500 hPa and the associated TIWP over the tropical oceans between 30°N and 30°S for August/September 2016 as simulated by the different DYAMOND models, two versions of the lower resolution DWD ICON model and ERA5. The PDF of vertical velocity is positively skewed with the highest probability for slightly descending motion of a few mm/s which is consistent with the clear-sky radiative cooling rate (Bony et al., 2004). This descending motion can be mainly found in the subtropics and preferentially in the eastern part of the ocean basins. The positive tail of the distribution describes the mean ascent that is mainly resulting from convection. Large vertical velocities are indicative of the strength, size and frequency of convective systems at a given location and are a sign for large convective mass fluxes. Maxima of mean ascent can be found in the ITCZ and in particular over the tropical warm pool in the area of the maritime continent, in the Bay of Bengal and East China Sea. The associated mean connection of the TIWP and total liquid water path (TLWP) (not shown) to the convective mass fluxes shows a steady increase of $TIWP_w$ and $TLWP_w$ with increasing vertical velocity (Figure 4b). The larger the vertical velocity at 500 hPa the more water can be transported into the tropical UT which models successfully simulate.

Despite the fact that all models use the same prescribed SST from ECMWF, the PDF of vertical velocity shows a considerable variability. There does not appear to be any obvious grouping of models that use no convection parametrization (NICAM, ICON, SAM and ARPEGE), only a shallow convection parametrization (FV3 and IFS) or parametrizations for deep and shallow convection (MPAS, GEOS, DWD ICON, and ERA5). Differences in the PDF of monthly mean vertical velocity are at least partly caused by differences in the spatial distribution of convective events. When comparing with Figure 1 there appears to be a slight tendency for models that have a more smoothly distributed TIWP (ICON, NICAM, MPAS, and ERA5) to be connected with a lower probability for large monthly mean vertical velocities whereas models that have larger peaks of TIWP in specific areas (ARPEGE, FV3, IFS and GEOS) tend to simulate larger vertical velocities with a higher probability. Some models, for example, ARPEGE and FV3, are more likely than others to simulate convection close to coast lines which may be due to differences in the boundary layer schemes. Other models may have a larger preference for simulating convection in connection with the cold pool of a prior convective event, whereas others may be more likely to trigger convection as a reaction to a local instability independent of a prior convective event. Large monthly mean vertical velocities are more common and large daily mean vertical velocities less common in the DWD-ICON simulations than in the other model simulations (Figure S2a in Supporting Information S1). This points at resolved convection getting triggered or the convection parameterization being active repeatedly in the same region in the DWD-ICON simulations.

The simulations show large differences in the increase in the mean $TIWP_w$ with vertical velocity (Figure 4b) likely due to differences in the models' cloud and/or boundary layer schemes and in en- and detrainment. DWD ICON simulates, in particular in areas of low vertical velocity, a too low $TIWP_w$ (see also Figures 1 and 2). In areas of large convective activity DWD ICON resembles the other DYAMOND models. Inter-model differences are larger than the variability of TIWPs within a vertical velocity bin simulated by the individual models (appendix B, Figure B1). Despite the large variability in TIWPs within the single vertical velocity bins, we found the connection between the TIWP and vertical velocity in ERA5 to be stable from year to year (not shown).

Even though, in areas with larger vertical velocities, a larger amount of ice water can be observed on average, the probability of those large vertical velocities is too low to have a large impact on the overall tropical TIWP (Figure 4d). A very large part of the tropical TIWP can be found in areas with monthly mean vertical velocities of between -0.005 and 0.02 m/s. The models show a large variability in the contribution of the $TIWP_w$ to the overall TIWP ($PDF_w \times TIWP_w$) with the MM from the DYAMOND models resembling ERA5 (Figure 4d). The $TIWP_w$ contributions to the overall TIWP in the most probable vertical velocity bin is significantly underestimated by the DWD ICON model versions, when compared to the MM of the DYAMOND models or ERA5, and larger than in the other model simulations at larger vertical velocities. That means that, compared to the DYAMOND models, the model tends to make up for a lack of TIWP in the areas of medium high vertical velocity by a large TIWP in areas of large vertical velocity over the warmest part of the oceans. This tendency can be also seen in the parameterized GEOS model.

All models simulate a larger $TLWP_w$ than $TIWP_w$ in areas of subsidence (Figure 4c). This is in line with the common occurrence of lower level liquid clouds in the subtropics. Moving from subsidence to ascent the fraction of the total water path (TWP) that is frozen jumps to higher values and in most models remains constant for

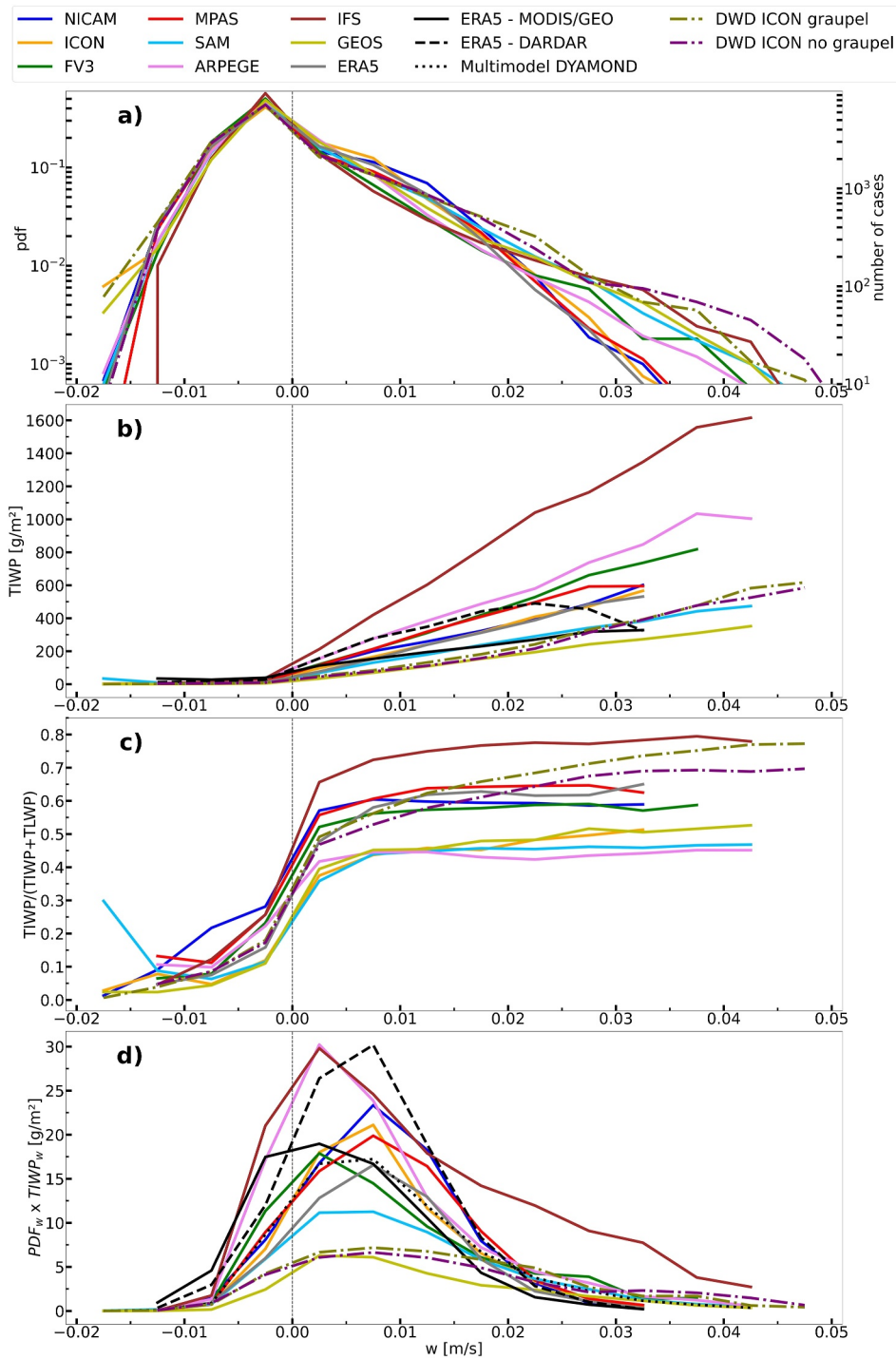


Figure 4. (a) PDF of monthly mean vertical velocity (w) at 500 hPa and, (b) total ice water path (TIWP) for different monthly mean vertical velocity bins in simulations of the high-resolution Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) models, the (numerical weather prediction) DWD ICON model and ERA5 over the tropical oceans. Also shown is, (c) frozen fraction, $\text{TIWP}/(\text{TIWP} + \text{TLWP})$, and (d) contribution of TIWP_w to the overall TIWP ($\text{PDF}_w \times \text{TIWP}_w$). The vertical velocity bins have a size of 0.005 m/s. Lines for individual models are drawn as long as at least 10 realizations belong to a vertical velocity bin. All fields are remapped to a $1^\circ \times 1^\circ$ grid. Multimodel mean DYAMOND is calculated without Integrated Forecasting System.

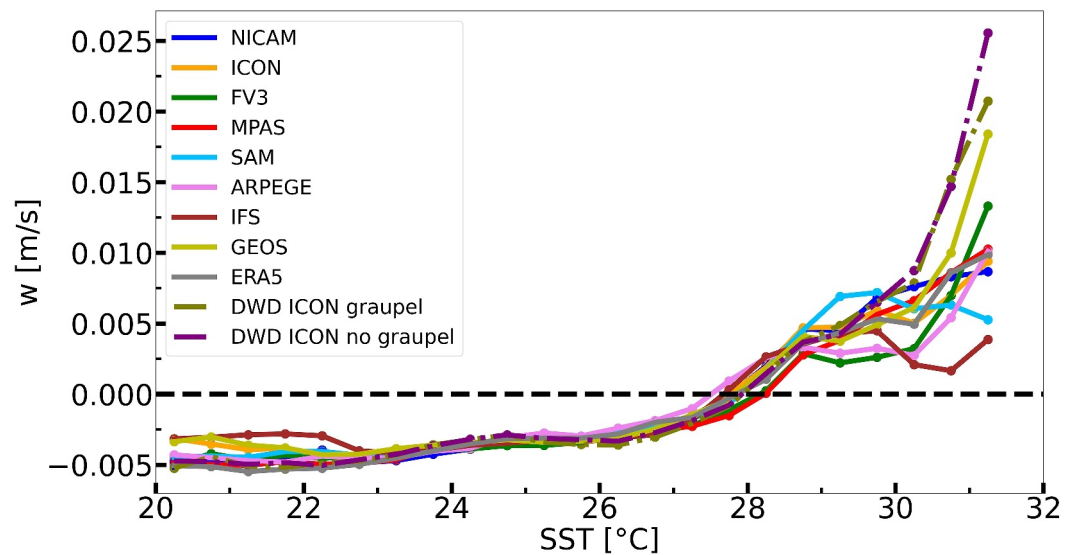


Figure 5. Monthly mean vertical velocity (w) at 500 hPa for different sea surface temperature (SST) bins in simulations of the high-resolution DYAMOND models, the (NWP) DWD ICON model and ERA5 over the tropical oceans. The SST bins have a size of 0.5°C . All fields are remapped to a $1^{\circ} \times 1^{\circ}$ grid.

increasing vertical velocity. This indicates that in areas of mean ascent, the probability of deep convective events is increasing which leads to a more or less sudden increase in the TIWP and, therefore, in the fraction of the water path that is frozen. In areas of strong ascent nearly all models simulate larger TIWP than TLWP indicating that in nearly all models larger vertical velocities lead to a majority of water transported into the UT where droplets freeze. Models for which the frozen fraction is constant while simulating an increasing TIWP with increasing vertical velocity appear to simulate a similar increase in the TLWP, due to shallow convection, cumulus congestus clouds and/or detrainment from deep convection, as the increase in convectively generated TIWP. Models for which the frozen fraction increases, deep convection increasingly dominates the TLWP + TIWP with increasing vertical velocity. The large inter-model variability in the frozen fraction for large vertical velocities is connected with large differences in the amount of lower cloudiness in the respective models. The NWP models simulate a similar $TIWP_w$ to GEOS but $TIWP_w/(TIWP_w + TLWP_w)$ in GEOS is significantly lower which means that either the NWP models form fewer liquid clouds than GEOS or the microphysical scheme is more efficient in converting the liquid water into precipitation, thereby removing more liquid water out of the atmosphere again. The largest difference between $TIWP_w$ and $TLWP_w$ can be found in the DYAMOND IFS simulation with the $TIWP_w$ approximately four times larger than the $TLWP_w$, the largest frozen fraction of all the analyzed models. This large frozen fraction is likely connected with too high cloud top heights resulting from the overestimation of vertical velocity by this high resolution version of the IFS hydrostatic model. DYAMOND IFS does not show a strong resemblance to ERA5 and is in many respects an outlier among the DYAMOND models.

3.3.1. Dependence of Mean Vertical Velocity on Sea Surface Temperatures

Figure 5 shows the distribution of vertical velocity over SST. Although for a wide range of SSTs models simulate on average descending motion, the ascending motion occurs over a narrow range of SSTs. The transition from negative to positive vertical velocities occurs from around 27.2°C for ARPEGE to 28.2°C for MPAS and FV3. In their GCM study, Bony et al. (2004) found this transition from large-scale subsidence to large-scale ascent at around 27°C . Sud et al. (1999) point out that a universal value of this “transition” SST does not exist as it is constrained by the relationship between the vertical profiles of dry and moist static energy in the tropical atmosphere. As expected, the largest mean vertical velocities can be found in the warmest parts of the ocean. The models that parameterize convection, in particular DWD ICON and GEOS, tend to simulate much larger mean vertical velocities in the warmest part of the ocean whereas in the other models this preference is less prominent. As pointed out before, in the case of DWD-ICON this is not due to the model simulating larger vertical velocities but a result of the aggregation of the convective events in the area of highest SSTs. The two lower resolution DWD ICON model versions together with the hydrostatic IFS have the highest probability for large monthly

mean vertical velocities (Figure 4a). In the case of DWD ICON the large vertical velocities appear to be in the western Pacific east of the maritime continent, within the area of largest SSTs, whereas in the case of DYAMOND IFS strong vertical velocities appear to be spread out over nearly the whole ITCZ and are just slightly elevated in areas of warmest SSTs.

3.3.2. Model Evaluation With ERA5 Vertical Velocity and Observed TIWP

We evaluate the connection between the model simulated TIWP and vertical velocity in the monthly mean data by comparing to a combination of ERA5 vertical velocity and observed TIWP from passive and active remote sensing (black solid and dashed lines in Figures 4b and 4d). Considering that the ERA5 data are a reanalysis data set including a full data assimilation system, we expect a reasonable spatial and temporal correlation between ERA5 data and observations on the monthly mean time scale despite the fact that convection is parameterized in ECMWF's IFS model.

Comparing the model simulations with the $TIWP_w$ resulting from the combination of ERA5 and observations from passive remote sensing we find that for larger vertical velocities many models, including ERA5, simulate a larger $TIWP_w$ than the $TIWP_w$ coming from ERA5 and passive remote sensing. This is due to the fact that passive remote sensing quickly saturates in the presence of optically thick clouds. The opposite is true for low and negative vertical velocities, where the combined ERA5 and passive remote sensing $TIWP_w$ is higher than $TIWP_w$ simulated by the models (appendix B, Figure B1). This indicates an underestimation of $TIWP_w$ in areas of mean descend by the DYAMOND models. The fact that passive remote sensing indicates a slightly larger TIWP than active remote sensing in an area of mean descend is surprising since active remote sensing is more sensitive to optically thin clouds and should, therefore, be larger. Differences may well be caused by the low number of samples coming from active remote sensing.

The $TIWP_w$ resulting from the combination of ERA5 vertical velocities and active remote sensing shows a much stronger increase in $TIWP_w$ with increasing vertical velocity. This slight decrease in $TIWP_w$ for the largest ERA5 vertical velocities is likely not statistically significant as the number of overpasses of the A-Train in places of large vertical velocity decreases sharply and the variability of $TIWP_w$ increases significantly. Comparing the DYAMOND and NWP model simulated and ERA5 $TIWP_w$ with the combined ERA5 and active remote sensing $TIWP_w$ we find that most of the DYAMOND models, the NWP models and ERA underestimate $TIWP_w$. However, this comparison should be regarded with caution due to the large variability in $TIWP_w$ from active remote sensing coming from the small sample sizes. Only the simulations of ARPEGE, FV3, and MPAS resemble the combined ERA5 vertical velocity and active remote sensing $TIWP_w$ product.

When comparing to the combination of ERA5 and active remote sensing, most models underestimate the contribution of $PDF_w \times TIWP_w$ to the overall TIWP in on average slowly ascending areas (Figure 4d). This is particularly the case for GEOS and DWD ICON which both have fully parameterized convection. Furthermore, DWD ICON attempts to compensate this underestimation of the contribution of $PDF_w \times TIWP_w$ connected with low vertical velocities to the overall TIWP with a high $PDF_w \times TIWP_w$ for higher vertical velocities.

4. Reasons for Inter-Model Differences in Tropical TIWP

As shown in (Figures 1 and 2), TIWP simulated by the models varies strongly in terms of pattern and size due to, on the one hand, differences in the strength and spatial distribution of convection, and, on the other hand, due to differences in the response of the cirrus to convection (Figure 4 and Figure S2 in Supporting Information S1). Here we want to analyze to which degree the inter-model differences in TIWP are due to differences in vertical velocity, $\delta TIWP_{w,dynamics}$ (Equation 4), a sign for convective activity and its spatial distribution, or the cloud response, $\delta TIWP_{w,cloudresponse}$ (Equation 5), controlled mainly by the models' cloud microphysical scheme, convective en- and detrainment and differences in the moisture flux out of the boundary layer.

Comparing the three terms in Figure 6, it is obvious that the inter-model variability in $\delta TIWP_{dynamics}$ is smaller than in $\delta TIWP_{cloudresponse}$ and that $\delta TIWP_{w,covar}$ is very close to zero. This means that differences within the model's cloud response, in particular the cloud microphysical scheme but also the convective en- and detrainment and/or the boundary layer scheme, are responsible for the large inter-model variability in TIWP (Figure 6). All three terms are larger for the monthly mean than for the daily mean analysis. This is in particular the case for the

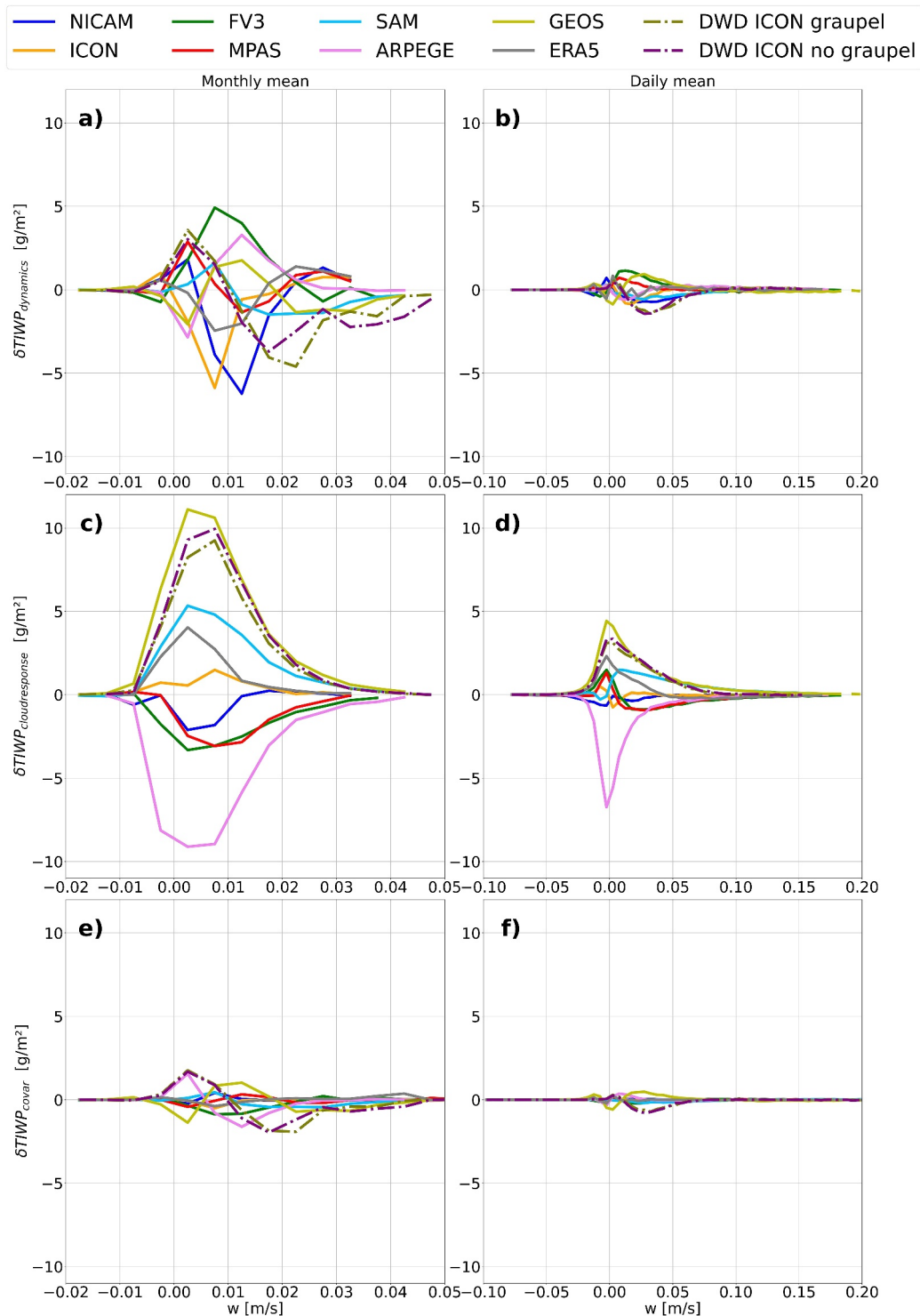


Figure 6. Contribution of (a), (b) the dynamics, $\delta TIWP_{w,dynamics}$, and (c), (d) the cloud response, $\delta TIWP_{w,cloudresponse}$ and (e), (f) the covariation, $\delta TIWP_{w,covar}$ to the inter-model differences in $\delta TIWP_w$ simulated by the Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) models, (numerical weather prediction) DWD ICON and in ERA5 over the tropical oceans. The monthly mean analysis (left) shows the spatial connection of the vertical velocity of the Hadley cell and the associated total ice water path (TIWP). The daily mean analysis (right) shows the temporal dependency of TIWP on vertical velocities. All simulations were remapped to a $1^\circ \times 1^\circ$ grid. Multimodel means were calculated excluding DYAMOND Integrated Forecasting System. Positive $\delta TIWP_w$ indicate an underestimation relative to the MM.

dynamics term (Figure 6a) indicating that differences in the spatial distribution of convection are partly responsible for inter-model differences in the monthly mean TIWP field.

Even though models simulate the highest probability of vertical velocities around 0 m/s, the large inter-model variability in vertical velocity, at around 0.01 m/s, combined with the larger TIWP at those velocities leads to the largest inter-model differences in $\delta TIWP_{w,dynamics}$ at 0.01 m/s. In areas with on average negative velocities, $\delta TIWP_{w,dynamics}$ is small, whereas for large vertical velocities (> 0.02 m/s in the monthly mean), $\delta TIWP_{w,dynamics}$ is relatively large, in particular for NWP ICON due to the high probability of those higher velocities in the NWP simulations (Figure 4a). In the DWD ICON simulations the fraction of the TIWP that is brought into the UT in areas and at times of large vertical velocities is largest.

The peak in the inter-model differences of $\delta TIWP_{w,cloudresponse}$ can be found at vertical velocities close to 0 m/s. The peak remains large over a wide range of vertical velocities pointing at uncertainties in the microphysical schemes. In the daily and monthly mean analysis the cloud response terms (Figures 6c and 6d) are very similar and point at the underestimation of TIWP particularly by DWD ICON and GEOS relative to the MM. As both models simulate also a very low $TLWP_w$ (not shown) this underestimation is likely not due to problems with the convective en- and detrainment but instead due to either the cloud microphysical scheme or a too low moisture fluxes out of the boundary layer. We conclude that the difference between the model's TIWP is mainly caused by the model's cloud scheme and to a lesser degree by the convective scale dynamics.

5. Summary and Outlook

We analyze the simulations of the storm-resolving DYAMOND models with km-scale grid spacing regarding their representation of the tropical TIWP over the oceans and compare to lower resolution NWP simulations, ERA5 and observations from active and passive remote sensing. Storm resolving models that (partly) resolve cloud relevant processes, in particular convection, are assumed to lead to a significant improvement or removal of longstanding problems in climate modeling. Our aim is, therefore, to study the skill of the DYAMOND models in simulating “larger-scale” ice cloud properties and to examine the associated inter-model variability. We focus on tropical UT cloudiness, as it can be expected to particularly benefit from the increased resolution. Our study gives an indication about the remaining biases in TIWP in the CP simulations and in how far the learning from the high-resolution simulations may be dependent on the specific model simulation used. In order to examine the reasons for variations in the tropical TIWP simulated by the DYAMOND models, we use an approach similar to the one introduced for the analysis of GCM simulations by (Bony et al., 2004) attempting to disentangle dynamical reasons for the large variability in TIWP from differences caused by the cloud response to the convective dynamics.

Generally, the simulations by the DYAMOND models mostly display a TIWP that is significantly improved relative to the NWP DWD-ICON simulations and relative to the TIWP in low and high-resolution CMIP6 GCMs. However, despite the fact that the transient dynamics of convective storms are mainly resolved by the DYAMOND models (Stevens et al., 2019), the simulations display a large variability regarding the value and the spatial distribution of tropical TIWP, in line with the large variability of tropical cloud properties described in (Lang et al., 2021; Nugent et al., 2022; Turbeville et al., 2022). We find that most of the DYAMOND models, the lower resolution DWD ICON and ERA5 reanalysis still underestimate TIWP compared to active remote sensing while agreeing in large parts of the tropics with passive remote sensing data, that are known to underestimate TIWP due to the saturation of the signal in the presence of large optical depth connected with, for example, deep convection. Although the location of the ITCZ is, except in the lower resolution DWD ICON simulations, mostly well resolved, the TIWP in the ITCZ is underestimated by most models and the contribution of the different hydrometeors to the TIWP varies strongly. None of the models simulates the TIWP and CIWP consistent with active remote sensing data.

We perform an analysis of the DYAMOND simulations on a $0.1^\circ \times 0.1^\circ$ and a $1^\circ \times 1^\circ$ grid and on two different time scales. The analysis shows a large inter-model variability in the simulated $TIWP_w$ originating from differences in the microphysical schemes, differences in the de- and entrainment and/or the moisture flux out of the boundary layer both controlling the TWP_w . All models capture the increase of both $TIWP_w$ and $TLWP_w$ with increasing vertical velocity but the models vary significantly in the fraction of water path that is frozen in areas of ascending motion pointing at large differences in the vertical profiles of detrainment. Surprisingly, we do not find

clear differences between parameterized and non-parameterized models. We speculate that this is due to deep convection being mainly resolved with the parameterization having only a weak impact.

Analyzing the dependence of $TIWP_w$ on vertical velocity and comparing this relationship to observational data on $1^\circ \times 1^\circ$ grid, we find that $TIWP_w$ is underestimated, in particular, for slow rising and for descending motion by nearly all analyzed models. This underestimation is most emphasized within the NWP simulations. This indicates that models are capable of simulating realistically strong convective events whereas the TIWP of weaker events or aged anvils is underestimated. Although progress is visible when compared to lower resolved NWP models and GCMs, the long-standing challenge of simulating anvil life cycles, as for example, described by Wall and Hartmann (2018), remains an issue in high-resolution DYAMOND GSRMs.

Disentangling dynamical reasons for the inter-model variability in the spatial distribution of TIWP from reasons connected with TIWP response to convection on the larger $1^\circ \times 1^\circ$ grid, we confirm that the inter-model variability in tropical TIWP is mainly caused by differences in the cloud response to convection most likely by the cloud microphysical schemes but also by differences in the detrainment levels. This aligns with Stevens et al. (2019, 2020) who showed that convective scale vertical velocities are much improved within the storm-resolving models. It also agrees with Atlas et al. (2024) who demonstrated a large influence of the cloud microphysical schemes on simulated tropical longwave cloud radiative effects within Global System for Atmospheric Modeling (gSAM) GSRM.

Furthermore, we show that most models that parameterize deep convection (DWD ICONs and GEOS) tend to simulate convection mostly in areas of high SSTs. Those models tend to inject a higher fraction of the tropical TIWP into the UT in the areas of high vertical velocity than the other models apparently making up for the very low TIWP in areas of monthly mean slow ascent. Models that do not use a parameterization for deep convection appear to simulate convection in a larger range of environments including areas with lower SSTs. Most models did not include 3D distribution of all hydrometeors in their output. This did not allow us to analyze the vertical profiles of TIWP and cloud top heights. In the future it would be advantageous to make 3D fields of all hydrometeors available so that cloud profiles and cloud top height can be evaluated. In addition, the higher temporal resolution for 3D fields, in particular of vertical velocities, would allow more detailed studies of individual convective events and their impact on simulated TIWP.

Even at higher model resolution, microphysical schemes will remain a cause of large uncertainty. The GSRMs from the DYAMOND project used single-moment microphysical schemes (see Seiki et al. (2022) for additional information) and include not only fall velocities for graupel and snow but also for cloud ice. Nevertheless, ice crystal habit and sedimentation speeds may differ within the models and microphysical process rates governing the formation of different frozen hydrometeors that are connected with different fall velocities are uncertain. Naumann et al. (2024) showed that overall differences in simulated TIWP resulting from parameter perturbations or switching from one-moment to two-moment schemes are moderate but tend to be larger for individual hydrometeors. Nevertheless, the step toward a microphysical two-moment scheme should lead to an improvement in the simulation of the life cycle of convective anvils due to a more realistic simulation of ice crystal sedimentation. However, this comes at the cost of new uncertainties in ice nucleation pathways which are dependent on aerosol properties that are difficult to constrain with observational data.

Appendix A: Comparison of the DARDAR and 2C-ICE TIWP Data in August 2010

Here we analyze the uncertainty in the zonal mean TIWP from active remote sensing by comparing the 2C-ICE and DARDAR data that use different retrieval algorithms. Furthermore, we determine the uncertainty when using only the day or night or both day and night measurements as an estimate for the TIWP. This is motivated by the fact that after 2011 only day time measurements are available. We compare the TIWP, averaged over the noon and midnight A-Train overpass, from both active remote sensing data sets, DARDAR and 2C-ICE, for August/September 2010 (Figure A1) and find very good agreement. In the time period for which the DYAMOND simulations were performed only the noon overpass is available. Therefore, we show in Figure A1 also the TIWP from DARDAR for only the noon and only the midnight overpass. As our analysis is restricted to the tropical oceans differences between the noon and midnight overpass are small with differences largest in the coastal areas (not shown).

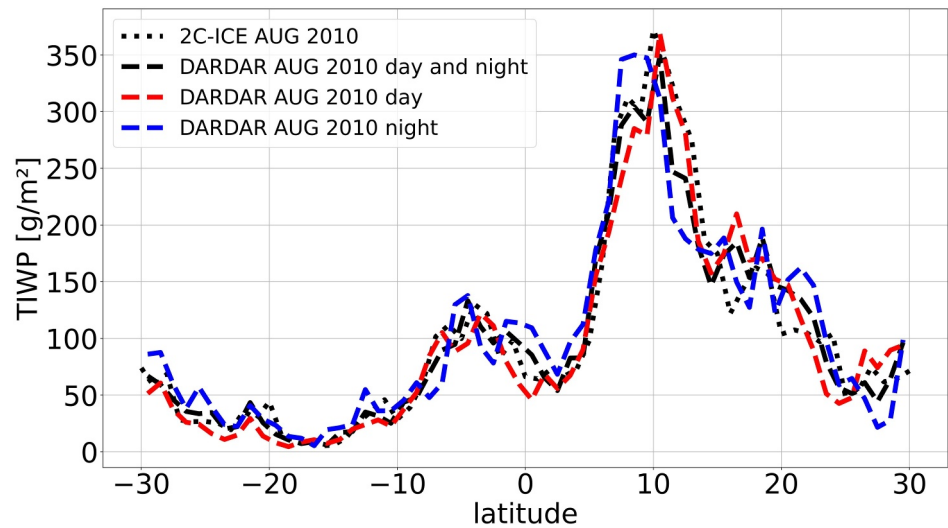


Figure A1. Zonal mean of total ice water path over the tropical oceans in August 2010 from DARDAR local noon overpass (red dashed), midnight overpass (blue dashed) as well as the average over the noon and midnight overpass from both DARDAR (black dashed) and 2C-ICE (black dotted line).

Appendix B: Variability of the Monthly Mean $TIWP_w$

In Section 3.3 we analyzed the mean response of $TIWP$ for given vertical velocity. Here we show the variability of simulated $TIWP$ s within a given vertical velocity bin for the individual models. The analysis is done for a few selected models for which $TIWP_w$ (Figure 4b) is very different. ARPEGE, which has the largest $TIWP_w$, beside the outlier DYAMOND IFS, shows the largest variability for a given vertical velocity bin. GEOS, for which $TIWP_w$ is particularly small, displays the smallest variability of $TIWP$ s within a given vertical velocity bin. The variability range within a particular vertical velocity bin from ARPEGE and GEOS do not overlap. Despite the overall lower $TIWP_w$ in the DWD ICON simulations, the variability of $TIWP_w$ within a velocity bin is so large that the variability ranges of DWD ICON and DYAMOND ICON partly overlap. Moreover, we analyzed $TIWP_w$ using a combination of the ERA5 simulated vertical velocity with the MODIS/GEO observed $TIWP$. Even though ERA5 reanalysis data combines model data with observations the analysis suggests that the observed $TIWP$ and simulated vertical velocity may be not perfectly matched (see Figure B1).

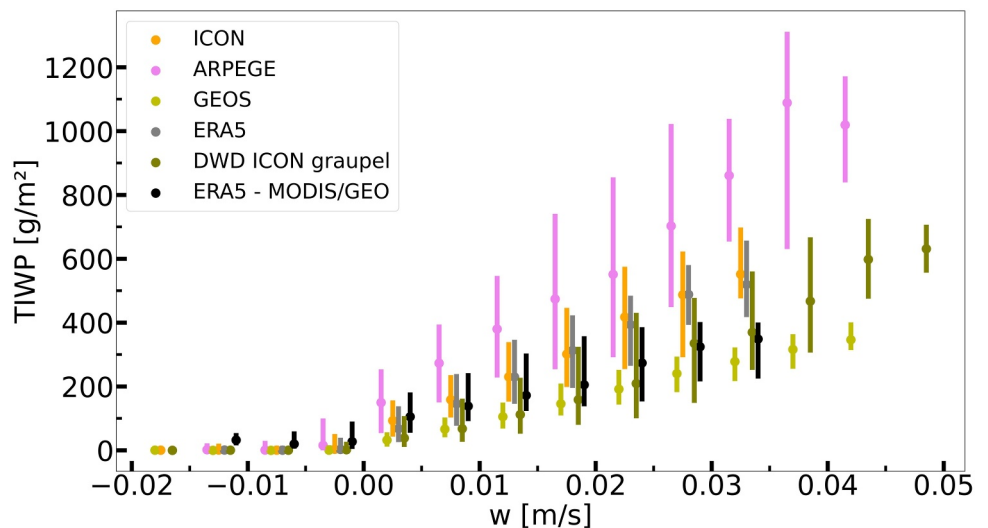


Figure B1. Variability of monthly mean $TIWP_w$ over the tropical oceans. The lines indicate the 10th and 90th percentile with the dots showing the median. The vertical velocity bins have a size of 0.005 m/s. The analysis was performed on the fields remapped to a $1^\circ \times 1^\circ$ grid.

Appendix C: Connection Between Latitudinally Averaged Vertical Velocity and TIWP

Here we illustrate the connection between vertical velocity at 500 hPa and TIWP simulated by the high-resolution DYAMOND ICON model (Figure C1). The Hovmoeller plots show that large positive vertical velocities, which indicate a strong convective mass flux, are connected with a large TIWP. The larger the vertical velocity the larger the TIWP, with maxima of TIWP temporally more extended than maxima in vertical velocity. The largest vertical velocities and TIWPs can be found in the Indian and Pacific Ocean.

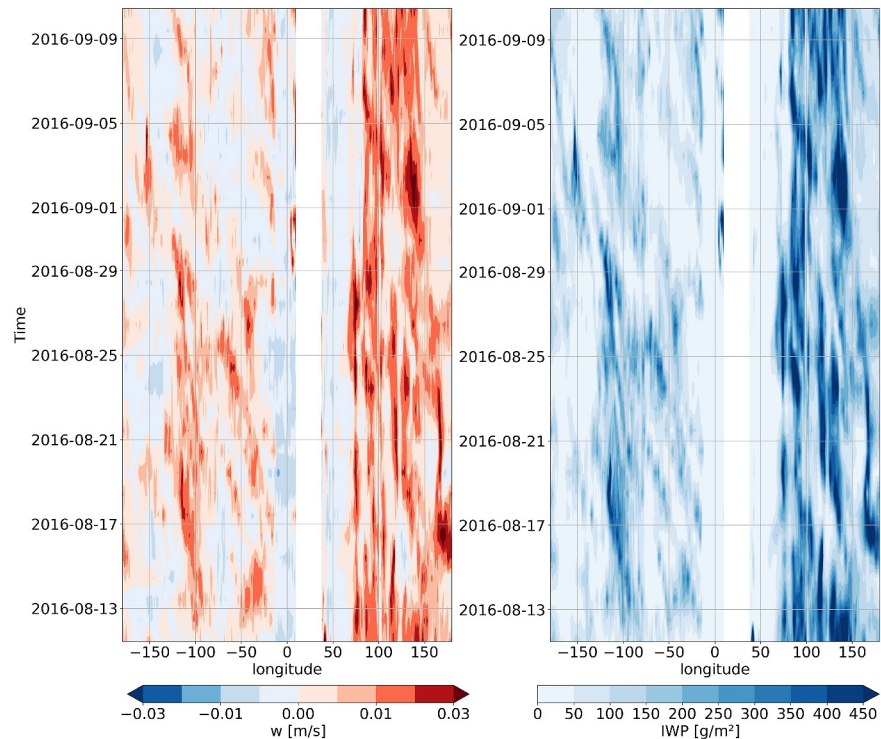


Figure C1. Hovmoeller plots of daily mean vertical velocity at 500 hPa (left) and total ice water path (right) simulated by Dynamics of the Atmospheric general circulation Modeled On Non-hydrostatic Domains (DYAMOND) ICON model over the tropical oceans (0°N - 20°N). Both fields were remapped to a 1° × 1° grid.

Data Availability Statement

The CERES SYN1deg Ed4A, in this work called MODIS/GEO, data were obtained from the NASA Langley Research Center CERES ordering tool at (NASA/LARC/SD/ASDC, 2017). The ERA5 hourly data on single and pressure levels were obtained from the Copernicus Climate Data Store (Copernicus Climate Change Service, 2023). DARDAR V3-10 data (Delanoë, 2023) were obtained from the ICARE Data and Services Center. The 2C-ICE data used in this paper were obtained from (J. Li, 2020). CMIP6 data are available freely and publicly from the Earth System Grid Federation (ESGF). Data and the code for analysis used for the figures can be accessed at (Corko, 2024).

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