Increases in Future AR Count and Size: Overview of the ARTMIP Tier 2 CMIP5/6 Experiment

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Key Points:

- Uncertainty associated with AR definition dominates model uncertainty for projections of Pacific and Atlantic landfalling ARs
- Most AR detection algorithms show an increase in AR frequency in future simulations
- AR statistics in CMIP 5-and-6 models compare remarkably well with reanalysis

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Abstract

The Atmospheric River (AR) Tracking Method Intercomparison Project (ARTMIP) is a community effort to systematically assess how the uncertainties from AR detectors (ARDTs) impact our scientific understanding of ARs. This study describes the ARTMIP Tier 2 experimental design and initial results using the Coupled Model Intercomparison Project (CMIP) Phases 5 and 6 multi-model ensembles. We show that AR statistics from a given ARDT in CMIP5/6 historical simulations compare remarkably well with the MERRA-2 reanalysis. In CMIP5/6 future simulations, most ARDTs project a global increase in AR frequency, counts, and sizes, especially along the western coastlines of the Pacific and Atlantic oceans. We find that the choice of ARDT is the dominant contributor to the uncertainty in projected AR frequency when compared with model choice. These results imply that new projects investigating future changes in ARs should explicitly consider ARDT uncertainty as a core part of the experimental design.

Plain Language Summary

Atmospheric rivers (ARs) are a type of weather pattern known to be important for moving water vapor from the warm, moist tropics to the cool, dry polar regions; when they reach midlatitudes in the winter time, they are commonly associated with heavy precipitation. Recent studies that assess the impacts of global climate change on ARs tend to agree that there will be more ARs in a warmer climate, and that ARs will tend to be more extreme. However, it has been increasingly recognized by the AR research community that these results may depend on the method used to identify ARs and the choice of climate model. This study reports results from a controlled experiment, involving an international research community, that aims to show how different AR identification methods and climate models might impact our scientific understanding of ARs in the future. This experiment shows that there will likely be more ARs in the future, and that ARs will generally have a larger spatial footprint. This experiment also shows that uncertainty in these results are large, with the uncertainty from AR identification methods outweighing that of climate models. Future efforts to better understand the physics of ARs may help us reduce this uncertainty.

1 Introduction

Over the past 40 years, research on atmospheric rivers (ARs), filamentary bands of intense water vapor transport that were known as tropical cloud plumes in earlier literature, has increasingly demonstrated their importance for cloud and precipitation variability (Thepenir & Cruette, 1981; McGuirk et al., 1987; Lau & Chan, 1988; Kuhnel, 1989; Kiladis & Weickmann, 1992; Rasmusson & Arkin, 1993; Iskenderian, 1995), the global hydrological cycle (Newell et al., 1992; Zhu & Newell, 1998; Ralph et al., 2017) and regional energy and water cycles (Newell & Zhu, 1994; Neiman, Ralph, Wick, Kuo, et al., 2008; Ralph et al., 2005; Dettinger et al., 2011; Gimeno et al., 2016; Gershunov et al., 2017; Shields, Rosenbloom, et al., 2019). ARs are a main source of precipitation and are frequently associated with hydroclimatological impacts in the midlatitude western margins of North America (Neiman et al., 2002; Ralph et al., 2004, 2005; Neiman, Ralph, Wick, Kuo, et al., 2008; Leung & Qian, 2009; Guan et al., 2010; Warner et al., 2012; Neiman et al., 2013; Ralph et al., 2013; Rutz et al., 2014; Huang et al., 2021), South America (Viale & Nuñez, 2011; Gimeno et al., 2016), Europe (Stohl et al., 2008; Lavers et al., 2012; Lavers & Villarini, 2013; Ramos et al., 2015; Gimeno et al., 2016), and South Africa (Blamey et al., 2018; Ramos et al., 2019). AR impacts on surface heat and water mass balance in polar regions are increasingly evident (Newell & Zhu, 1994; Gorodetskaya et al., 2014; Mattingly et al., 2020; Wille et al., 2019, 2021). Increased understanding of ARs has led to improvements in flood forecasting (Lavers, Waliser, et al., 2016; Lavers, Pappenberger, et al., 2016) and in communication of flood-related risks when intense ARs are imminent (Ralph, Rutz, et al., 2019).

Numerous recent studies have analyzed ARs in future climate scenarios (e.g., Warner et al., 2015; Lavers et al., 2015; Gao et al., 2015a, 2016; Shields & Kiehl, 2016b, 2016a; Polade et al., 2017; Espinoza et al., 2018; Gershunov et al., 2019; Rhoades, Jones, Srivastava, et al., 2020; Rhoades et al., 2021) (see Payne et al. (2020) and references therein). Payne et al. (2020) reviews the related studies over the past 10 years and shows that (1) studies generally agree that global increases in atmospheric moisture will increase the intensity of ARs, and that (2) there is wide uncertainty in the results conveyed in the literature, especially in areas outside the well-studied U.S. west coast. Existing studies generally agree that the frequency and intensity of ARs will increase, and some studies indicate poleward shifts of the AR tracks (Sousa et al., 2020; Shearer et al., 2020). Gershunov et al. (2019) show that intermodel differences in future projections of precipitation are much lower when considering precipitation due to ARs than those when considering changes in bulk precipitation. Given that precipitation is produced by a variety of meteorological phenomena, and that there is no guarantee that the relative proportions of precipitation from various phenomena are the same in models as they are in observations, Gershunov et al. (2019) highlight the importance in using a phenomenon-focused study of precipitation in future climate simulations.

Essentially all of the studies of ARs and future climate (and past climate, e.g., Lora et al., 2017; Kiehl et al., 2018; Skinner et al., 2020; Menemenlis et al., 2021) rely on objective, quantitative methods to discriminate ARs from the background: AR detectors (ARDTs). At present, ARs have a qualitative definition (Ralph et al., 2018), which leaves researchers with the task of implementing a quantitative definition of ARs in specific ARDTs. ARDTs typically consist of a set of heuristic rules (e.g., thresholds and filters) that focus on identifying anomalously high moisture or moisture transport that occurs in contiguous, filamentary structures. The design of ARDTs is guided by understanding gained through decades of observational and model studies (Browning & Pardoe, 1973; McGuirk et al., 1987; Newell et al., 1992; Zhu & Newell, 1998; Lackmann & Gyakum, 1999; Neiman et al., 2002; Ralph et al., 2004, 2005; Bao et al., 2006; Neiman, Ralph, Wick, Kuo, et al., 2008; Neiman, Ralph, Wick, Lundquist, & Dettinger, 2008; Waliser et al., 2012). The number of ARDT algorithms has grown with the number of ARDT studies over the past decade, with new ARDTs often being developed for specialized purposes: e.g., ARDTs for understanding the global hydrological cycle (Zhu & Newell, 1998; Guan & Waliser, 2015), observed hydrometeorological extremes (Neiman, Ralph, Wick, Lundquist, & Dettinger, 2008; Rutz et al., 2014), the cryosphere (Gorodetskaya et al., 2014; Wille et al., 2021), and regional hydroclimate variability (Gershunov et al., 2017). Even though ARDTs are often initially designed with different purposes in mind, Payne et al. (2020) demonstrate that there is overlap in what they are ultimately used to study. The community has recently started to recognize that uncertainty associated with the numerical definition of ARs may have important implications for our understanding of ARs and their changes in a future warmer world (Newman et al., 2012; Huning et al., 2017; Shields et al., 2018; Guan et al., 2018; Rutz et al., 2019; Ralph, Wilson, et al., 2019; Shields, Rutz, et al., 2019; Shields, Rosenbloom, et al., 2019; Lora et al., 2020; O'Brien, Payne, et al., 2020; O'Brien, Risser, et al., 2020)

The Atmospheric River Tracking Method Intercomparison Project (ARTMIP) was launched by members of the AR research community in order to systematically assess the impact of this uncertainty on our scientific understanding (Shields et al., 2018). The First ARTMIP Workshop (Shields, Rutz, et al., 2019) defined a multi-tier experimental design focusing on uncertainty in the observational record (Tier 1; Rutz et al., 2019), and uncertainty in AR variability and change (Tier 2). Two Tier 2 experiments were launched at the Second ARTMIP Workshop (Shields, Rutz, et al., 2019): the Tier 2 C20C+ experiment and the Tier 2 CMIP5/6 experiment. Both experiments are designed to elucidate the effect of uncertainty associated with ARDTs on our understanding of ARs, with the former focusing on uncertainty in regional impacts in a single high-resolution global model, and the latter focusing on the relative roles of model and ARDT-associated uncertainty. A third Tier 2 experiment was launched at the Third ARTMIP Workshop: the Tier 2 Reanalysis experiment, which aims to understand how differences across reanalyses compare with differences across ARDTs. This manuscript overviews the Tier 2 CMIP5/6 experiment.

2 Data and Methods

We use data from the ARTMIP Tier 1 experiment (Shields et al., 2018; Rutz et al., 2019), which provides atmospheric river detections from multiple ARDT algorithms. All Tier 1 ARDTs run on a common set of atmospheric fields (e.g., integrated vapor transport) derived from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al., 2017). A subset of the Tier 1 algorithms have also been run on the Tier 2 input dataset described further on. The subset of algorithms run was determined by the subset of ARTMIP participants who volunteered to run their algorithms on the Tier 2 dataset; these algorithms include `ARCONNECT_v2` (Shearer et al., 2020), `Guan_Waliser_v2` (Guan & Waliser, 2015; Guan et al., 2018), `IDL_rel_future` & `IDL_rel_hist` (Ramos et al., 2016; Blamey et al., 2018), `Lora_v2` (Lora et al., 2017; Skinner et al., 2020), `Mundhenk_v3` (Mundhenk et al., 2016), `PNNL_v1` (Hagos et al., 2015), and `TECA-BARD v1.0.1` (O'Brien, Risser, et al., 2020), and `Tempest` (Ullrich & Zarzycki, 2017; McClenny et al., 2020) (see Table S1). Text S4 describes why choice of reanalysis unlikely affects the qualitative conclusions of this paper.

For the Tier 2 input dataset for ARDTs, we derive integrated water vapor (IWV), and the components of the integrated vapor transport (IVT) vector from outputs from atmosphere-ocean general circulation models associated with the Coupled Model Intercomparison Project (CMIP) 5 (Taylor et al., 2012) and 6 (Eyring et al., 2016; O'Neill et al., 2016) multi-model ensembles (hereafter referred to as CMIP5/6 when both ensembles are jointly discussed). We utilize model output from the historical simulations in both CMIP5 and CMIP6, and we utilize output from the representative concentration pathway 8.5 (RCP8.5, CMIP5) and shared socioeconomic pathways 5-8.5 experiments (SSP5-8.5, CMIP6). We utilize models that provided specific humidity q (`hus`) and wind $\overrightarrow{u}$ (`ua` and `va`) at 6-hourly intervals on the native model vertical grid (the `6hrLev` table); we further restrict the set of models to those which provide model output from the same ensemble member for both the historical and future (RCP8.5 and SSP5-8.5) simulations. We chose to focus on models providing data on the native model vertical grid (either sigma or hybrid-sigma) because this facilitates an accurate calculation of vertical integrals without having to handle below-ground levels as would be necessary if dealing with model output on isobaric surfaces; this choice simplifies interpretation of inter-ARDT differences in continental interiors, where such below-ground levels are common. At the time that the Tier 1 input dataset was constructed (in Summer 2019), we were able to access 6 models from CMIP5 (CCSM4, CSIRO-Mk3-6, CanESM2, IPSL-CM5A-LR, IPSL-CM5B-L, and NorESM1-M) and 3 models from CMIP6 (BCC-CSM2-MR, IPSL-CM6A-LR, MRI-ESM2-0; Xin et al., 2019; Yukimoto et al., 2019; Boucher et al., 2019) that satisfied these constraints (see Table S1): 9 models in total and one ensemble member from each model. We focus on the 1981-2010 time period for the historical reference period, and we calculate trends over the 1951-2099 period (some data are missing due to data availability and corruption issues, and years with these issues are not included in calculations; see Text S3). Examination of the 1951-2099 timeseries at a variety of locations show that changes in AR frequency are close to linear; therefore the trends presented here can be used to infer discrete changes in AR frequency at arbitrary timeperiods (e.g., mid-century and end-of-century). The models selected represent a range of horizontal resolutions (ranging from approximately 100 km to 300 km), and the RCP8.5

and SSP5-8.5 scenarios represent aggressive emission trajectories with large amounts of radiative forcing (nominally 8.5 $\mathrm{W/m^2}$) by end-of-century.

The mass-weighted vertical integrals of water vapor (ρq) and water vapor transport ($\rho \overrightarrow{u} q$) are calculated from all native model levels in the CMIP5/6 output as:

$$\mathrm{IWV} = -\frac{1}{g}\sum_{k=1}^{N} q_k \Delta p_k \tag{1}$$

$$\overrightarrow{\mathrm{IVT}} = -\frac{1}{g}\langle \sum_{k=1}^{N} u_k q_k \Delta p_k, \sum_{k=1}^{N} v_k q_k \Delta p_k \rangle, \tag{2}$$

where index k corresponds to model levels going from the surface ($k = 1$) to the top of the model atmosphere ($k = N$), and Δp_k is the difference in level pressures, estimated at level k. The total vapor transport is calculated as the vector magnitude: $\mathrm{IVT} = \left|\overrightarrow{\mathrm{IVT}}\right|$.

These ARDTs consist of a mixture of algorithms that detect ARs globally (global algorithms) and algorithms designed for specific regions (regional algorithms); see Table S1. We focus most of the analysis in this manuscript on the location of the AR tracks, changes in these tracks, and uncertainty therein. We therefore focus the bulk of the discussion on the global subset of algorithms; the full set of algorithms is discussed in Section 3.3 when comparing the relative magnitudes of uncertainty related to ARDT design and model choice.

2.1 Tier 2 CMIP5/6 Experiment Overview

All Tier 2 CMIP5/6 ARDT contributions use the common dataset of IWV, IVT, and $\overrightarrow{\mathrm{IVT}}$ described in Section 2, which come from 9 models in the CMIP5 and CMIP6 multi-model ensembles. ARDT outputs are regridded to a common 4°x5° latitude-longitude grid. We assess the CMIP5/6 models by comparing annual spatial patterns of AR frequency between the Tier 1 and Tier 2 experiments, for each detection scheme independently, focusing on spatial pattern correlation and spatial variability. Given the 6-hourly frequency of the dataset, we report frequency as 'equivalent' AR days, which we define as 0.25 times the total number of timesteps with AR conditions. We provide details about Tier 2-specific modifications to ARDTs in Text S1 and details about missing data in Text S3.

Grouping algorithms by the type of criteria applied (relative versus absolute thresholds) and degree of restrictiveness (magnitude of thresholds employed, number of criteria involved) can reduce the spread associated with ARDTs (Rutz et al., 2019; Ralph, Wilson, et al., 2019). Here, we group ARDTs into three categories, based on their treatment of thresholds: *absolute* (`ARCONNECT_v2`, `PNNL_v1`, and `Lora_v2`), *fixed relative* (`Guan_Waliser_v2`, `IDL_rel_future`, `IDL_rel_hist`, and `Mundhenk_v3`), and *relative* (`Tempest` and `TECA-BARD v1.0.1`). The categorizations are described and justified in Text S2. A key motivation for this categorization is aggregating ARDTs by their sensitivity to thermodynamic changes in IVT, with the assumption that ARDTs employing absolute thresholds to moisture fields will be the most sensitive, and ARDTs employing time-dependent thresholds will be least sensitive.

3 Results

3.1 Evaluation of Historical Simulations

We show maps of annual average AR frequency from the Tier 1 (MERRA-2) experiments for the 6 global ARDT algorithms in the top row of Figure 1. The ARDTs show broad consistency in the spatial patterns of ARs. All ARDTs identify well-known AR tracks, with distinct maxima in the midlatitude Pacific and the Atlantic, and with a circumglobal maximum in the Southern Ocean; these AR tracks have been described in papers using multiple ARDTs (e.g., Zhu & Newell, 1998; Lavers et al., 2012; Guan & Waliser, 2015; Gimeno et al., 2016; Lora et al., 2020). The ARDTs also identify significant areas with little or no AR activity: the tropics, northeastern Asia, northeastern South America, tropical and subtropical Africa, the subtropical eastern Pacific (near the cold tongue region), as well as interiors of both polar regions (except for with `Guan_Waliser_V2`). The ARDTs differ significantly in the relative frequency of AR conditions. Some of the ARDTs identify AR conditions occurring upwards of 30 days per year (approximately one twelfth of the time) in the main AR tracks, and other ARDTs identify AR conditions occurring fewer than 10 days per year. These results are consistent with previous ARDT comparisons, indicating a wide range of restrictiveness across ARDTs (Ralph, Wilson, et al., 2019; Rutz et al., 2019; Lora et al., 2020). The algorithms also differ in the degree to which the AR tracks penetrate inland and the maximum poleward extension of the AR tracks (poleward non-zero AR boundary), with the `Guan_Waliser_v2` algorithm commonly identifying ARs in continental interiors and polar regions, and `TECA-BARD v1.0.1` rarely identifying ARs in continental interiors and polar regions. The average frequency of ARs (the top-right panel in Figure 1) exhibits a similar spatial pattern to the various ARDTs, with ARs occurring approximately 10 days per year in the core AR track.

Simulated ARs in the Tier 2 CMIP5/6 experiment are remarkably consistent with those in the Tier 1 MERRA-2 experiment. Results from an arbitrary model–MRI-ESM-2-0 from the CMIP6 multimodel ensemble–are shown in the second row of Figure 1, and a similar plot showing results from all possible model-ARDT pairs is shown in Figure S1. The placement of the AR tracks (and opposing gaps in ARs) are very similar when comparing spatial maps for a given ARDT. The algorithm-mean AR frequencies (last column) show very little difference between Tier 1 and 2; this is true for all models analyzed (see Figure S1).

Each ARDT has idiosyncratic spatial patterns that are expressed in both Tier 1 and Tier 2. This suggests that the spatial pattern maps are an emergent property of each ARDT, and that these spatial patterns are relatively insensitive to significant changes in the representation of the underlying atmospheric dynamics. For example, the diffuse spatial pattern associated with the `Guan_Waliser_v2` (GW) algorithm is evident in Tier 1 and in all Tier 2 simulations (Figures S1 and S2), and the multi-model mean for the GW algorithm exhibits a similar spatial pattern. This suggests that there is much more variability in AR frequency across ARDT algorithms than there is across simulations; we quantify this in Section 3.3.

Figure 2a quantitatively shows that CMIP5 and CMIP6 simulations compare well with the MERRA-2 reanalysis when compared within a single ARDT. Spatial correlation coefficients between the AR frequency maps in individual Tier 2 simulations and the corresponding Tier 1 map are above $r = 0.95$ for most ARDT-model pairs (32 out of 52 pairs), and the ratio of spatial standard deviations of AR frequency (Tier 2 divided by Tier 1) is between 0.75 and 1.25 for 40 out of 52 ARDT-model pairs. The Taylor skill scores (Taylor, 2001) are above 0.9 for 37 out of 52 ARDT-model pairs. Variability exists, with some ARDT-model pairs reaching as high as $r \approx 0.97$ and only 5 ARDT-model pairs with correlation coefficients between 0.8 and 0.9 (and skill scores below 0.85); likewise, one combination (`ARCONNECT_v2` and CMIP5 IPSL-CM5A-LR) has variability that is too low by approximately 25%, and one combination (`Tempest` and CMIP5 IPSL-CM5B-LR) has variability that is about 50% too high. Overall, this emphasizes the high degree of similarity between simulated ARs and ARs in MERRA-2, when comparing results using a single ARDT.

Altogether, the various ARDTs portray a similar assessment of model skill, with essentially all of the models analyzed appearing to be ‘fit for purpose’. This is true even for the lowest resolution simulations (e.g., CMIP5 CanESM2 with a nominal 310 km horizontal resolution in the tropics; see Table S1), which have some of the highest correlation coefficients. (Note that the AR detection process was performed at the original model

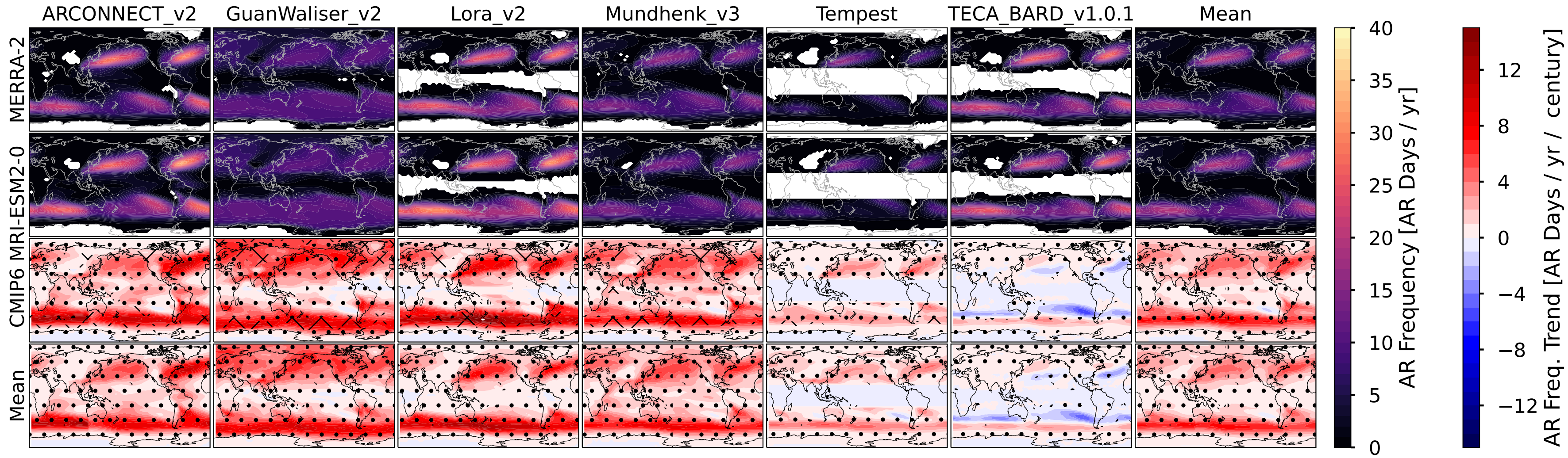

Figure 1. (first and second rows) Maps of AR frequency (shown as average number of days with AR conditions) annually for the 1981-2010 period. Each column corresponds to a global AR detection algorithm, and the last column represents the average across all AR detection algorithms. The top row corresponds to AR detections on the MERRA-2 dataset (the Tier 1 ARTMIP experiment) and the second and third rows correspond to AR detections on the CMIP6 MRI-ESM2-0 simulation. White indicates areas where average AR occurrence is fewer than 1 day. (third and fourth rows) Maps of trends in annual AR frequency in the MRI-ESM2-0 simulation (third row) and all models (fourth row), organized by detection algorithm (columns) from 1951-2099 (with a few exceptions noted in the text). Trends significant at the 90% level (according to a 2-sided t-test) are indicated by stippling, and trends significant at the 95% level are indicated by cross-hatching.

resolution, prior to regridding to a common grid for comparison with reanalysis.). A survey of the literature (Gao et al., 2015b; Hagos et al., 2015; Shields & Kiehl, 2016b; Guan & Waliser, 2017; Payne et al., 2020; Reid et al., 2020; Rhoades, Jones, O'Brien, et al., 2020) indicates a mix of possible resolution effects, with some indication that the effect of resolution may depend on the experimental setup (e.g., coupled vs uncoupled; Guan & Waliser, 2017). We hypothesize that resolution effects may depend on the ARDT used; these effects could be studied more systematically by applying multiple ARDTs to the CMIP6 HighResMIP experiment (Haarsma et al., 2016). The ARTMIP community has discussed the possibility of coordinating a Tier 2 Resolution experiment (O'Brien, Payne, et al., 2020) to explore this more systematically.

Results associated with the `Tempest` algorithm are a somewhat notable exception: five of the models evaluated with `Tempest` have high spatial variability relative to MERRA-2, and relatively low spatial correlations. This may be related to some differences in the implementation of `Tempest` between the Tier 1 and Tier 2 experiments (see Text S1).

3.2 Projected Changes in AR Frequency, Count, and Size

When the ARDTs are applied to the various future simulations described in Section 2, they project a variety of trends in AR frequency. Figure 1 (third row) shows that most ARDTs applied to the MRI-ESM2-0 simulation indicate increases in AR frequency in the main AR tracks. Within each algorithm, the trends from the MRI-ESM2-0 simulation are quantitatively and qualitatively similar to trends from other simulations (see Figure S3), as indicated by the similarity between the MRI-ESM2-0 trends and the multi-model trends shown in the bottom row of Figure 1. The average trend across all model-ARDT combinations (lower right panel of Figure 1) likewise indicates an increase in AR frequency in the midlatitude storm tracks, with increases of $\sim$5 AR days per year per century (an approximate 50% increase). In addition to this increase in AR frequency in the mid-latitude storm tracks, it is also important to note an increase in the areas with historically rare or close to zero frequency of the ARs, such as southern Asia and Africa, the Arctic Ocean and the Antarctic ice sheet. There are essentially no ocean basins where the model-ARDT mean indicates a decrease in AR frequency.

The climatological pattern of AR frequency is primarily controlled by changes in AR size, AR occurrence (count), and AR location. Two ARDTs (`TECA-BARD v1.0.1` and to a lesser extent `Tempest`) suggest poleward shifts in AR location (Figure 1, bottom row, and Figure S3), whereas `ARCONNECT_v2`, `GuanWaliser_v2`, `Lora_v2`, and `Mundhenk_v3` indicate quasi-global increases in AR frequency. We discuss why differences in the quantitative definition of ARs may cause different behavior in future climate simulations and its implications in Section 4. We have run the same analysis for seasonal averages for all four seasons, and the seasonal climatology and seasonal trends are similar to the annual average results presented in Figure 1.

We decompose the changes in AR frequency by changes in AR area A and AR count N; Figure 2b shows the median size of AR objects versus the median number of AR objects counted at any given time. In the historical simulations, the ARDTs appear to cluster along a continuum, with ARDTs typically detecting 5–20 ARs, which is consistent with manual counts of ARs in synoptic maps (Zhu & Newell, 1998; O'Brien, Risser, et al., 2020). `Tempest` is a notable exception, with AR counts ranging from 20–50. In order to aid in interpreting the continuum along which the ARDTs lay in Figure 2b, we add lines of constant global area $A_\oplus$ percentage (calculated as $100\% \cdot A \cdot N / A_\oplus$). These show that algorithms typically detect ARs such that approximately 5% of the Earth's surface is covered in AR objects in the historical simulations. Therefore, we can interpret the relative location of ARDTs in Figure 2b as an indicator of the relative spatial coherence of AR objects: ARDTs on the left detect few, large AR objects and ARDTs on the right detect many small AR objects. This grouping along lines of constant global area fraction is an emergent collective behavior of the ARDTs, and we speculate that it is associated with the tuning process for each algorithm. AR coherence might make a useful measure for objective grouping of AR results in future ARTMIP studies.

Figure 2b shows that four of the ARDTs (except `Tempest` and `TECA-BARD v1.0.1`) tend to detect more ARs and larger ARs in the future simulations. These changes result in increases in the global area coverage of AR objects: changing from ∼5% global area to ∼7% global area. The global count of AR objects does not change in the `TECA-BARD v1.0.1` algorithm, though there are slight increases in AR area in some simulations. In contrast, the `Tempest` algorithm indicates increases in global AR count, with very little change in AR area.

There is an indication that the resolution of the underlying model may affect the characteristics of detected ARs for some ARDTs. The CMIP6 BCC-CSM2-MR, CMIP6 MRI-ESM2-0, and CMIP5 CCSM4 simulations–which are the three highest resolution simulations analyzed (Table S1)–tend to occur on the right side of each ARDT cluster: ARs in these simulations are systematically less coherent. However, the model resolution does not appear to affect the climate change signal evident in Figure 2b. Further, the CMIP5/6 simulations analyzed here do not attempt to control for model resolution; the CMIP6 HighResMIP experiment (Haarsma et al., 2016) could provide a way to examine resolution effects more systematically.

3.3 Sources of Uncertainty in End-of-Century Projections of ARs

The results in Figure 1 indicate that there may be substantial uncertainty in future AR frequency associated with choice of ARDT. Further, it is not clear from the spatial maps in Figure 1 whether the trends in AR frequency evident over the ocean (e.g., the decrease in the southeastern Atlantic) extend to the coastal areas where AR presence matters for western-coastal water cycles and hydrometeorological impacts. We quantify these changes and their uncertainty in Figure 2c,d, which show the mean trend in AR frequency for the Pacific (Figure 2c) and Atlantic west coasts (Figure 2d) from 1951-2099. Figure 2c,d shows trends for all ARDTs listed in Table S1: both regional and global ARDTs.

Figure 2c,d shows that coastal areas in both the Pacific and Atlantic show increasing trends in AR frequency (+2–5 AR days per year per century in the midlatitudes), and the full spread of the blue and light blue shading in Figure 2c,d shows the full range of trends from all ARDTs and all models. There are two areas where `TECA-BARD v1.0.1` indicates weakly decreasing trends (Figure S3 shows the trends by model and by algorithm): southern Chile, near 40°S, and near the entrance of the Mediterranean Sea from 35°N to almost 60°N, which spans the Mediterranean, Iberian Peninsula and British Isles. It is noteworthy that this decrease is compensated by an increase in AR frequency poleward of these regions, indicating a poleward shift in the AR frequency. Otherwise all model-ARDT combinations indicate increasing trends in landfalling AR frequency for both Pacific and Atlantic ARs in both hemispheres.

Large uncertainty appears in the magnitude of the trends, which ranges from just below 0 days/yr/century to over 15 days/year/century, depending on location. There are two main components of uncertainty in these trends: uncertainty associated with choice of model simulation, and uncertainty associated with choice of ARDT. We decompose the uncertainty as $\sigma_T^2 \approx \sigma_A^2 + \sigma_M^2$, where σ_T^2 is the total variance, σ_A^2 is the variance across ARDTs of each ARDT's multi-model mean, and σ_M^2 is the variance across models for each model's multi-ARDT mean. These variances can equivalently be viewed as the variance down the rightmost column in Figure S3 (σ_M^2) and the variance across the bottommost row in Figure S3 (σ_A^2), (excluding the multi-model/multi-ARDT mean in the bottom right corner of Figure S3 and excluding trends from MERRA-2).

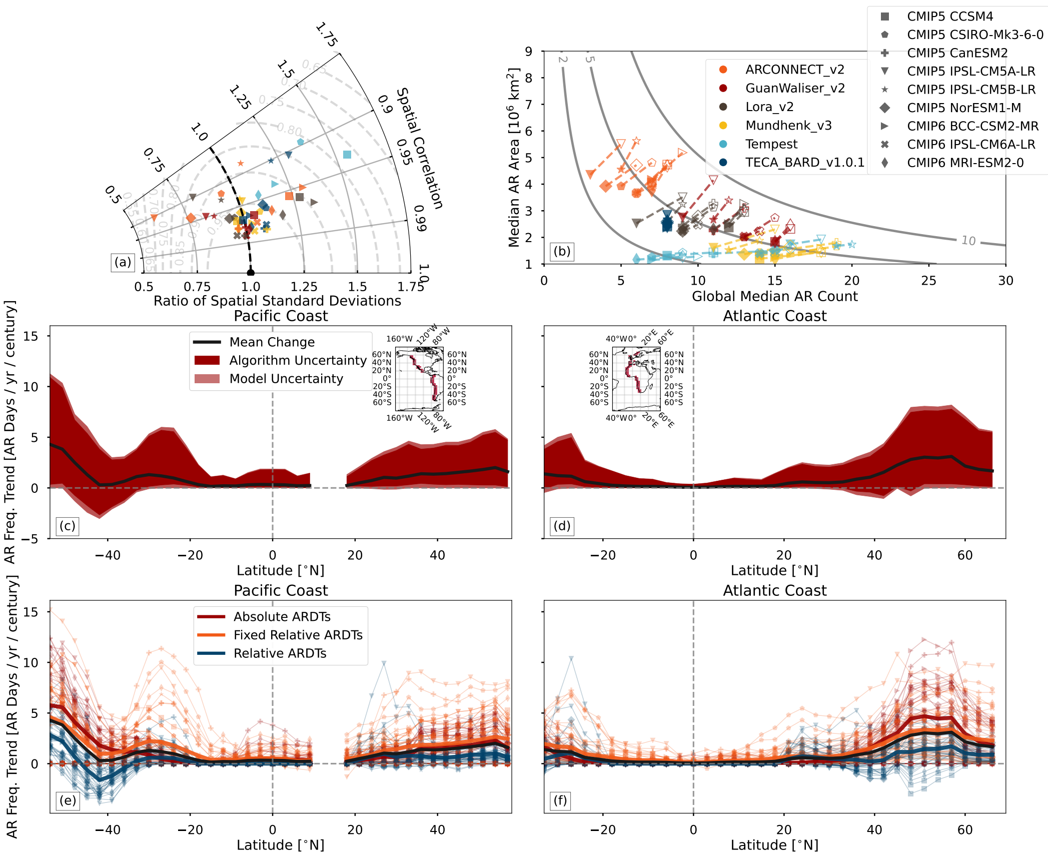

Figure 2. (a) A Taylor diagram comparing the spatial correlation (azimuthal axis) and spatial variability (radial axis) of AR frequency between CMIP5 and 6 simulations (denoted by different symbols) and the MERRA-2 reanalysis. Colors indicate different AR detection algorithms (legend in panel b). Gray dashed lines show lines of constant skill score (Taylor, 2001). (b) Median AR area vs global median AR count for all available combinations of ARDTs (marker colors) and simulations (marker symbols). Filled symbols indicate calculations performed on the 1981-2010 period of each simulation, and open symbols indicate calculations on the 2070-2099 period (two exceptions noted in Text S3). Gray contours show lines of constant fractional areal coverage of ARs (shown as a percentage of Earth's area), calculated as the product of AR area and AR count, divided by Earth's area. (c and d) Trends in AR frequency (black curve) and associated total range of uncertainty (blue and light blue shading) for the west-facing (c) Pacific coastline and (d) Atlantic coastline. Dark blue shading indicates the portion of uncertainty associated with AR detection and the light blue shading indicates the portion of the spread associated with models (across both CMIP5 and CMIP6). The area of dark blue shading is proportional to $\sigma_A^2/\sigma_T^2 \cdot$ (max $-$ min), where 'max' and 'min' are the minimum and maximum trend at each latitude. (e and f) as in (c and d), but showing individual ARDT-model combinations. Markers indicate simulations (legend in panel b) and colors indicate the ARDT classification. Bold lines indicate the mean trend across the ARDT classification. The inset maps in (c) and (d) show the Pacific and Atlantic coast masks respectively.

This decomposition shows that uncertainty associated with choice of ARDT accounts for most of the spread in the climate change signal across all latitudes in both the Pacific and Atlantic coasts. In essence, uncertainty associated with the numerical definition of ARs dominates the combined uncertainty associated with choice of model and choice of model epoch (CMIP5 vs CMIP6). As shown in Figures 1 and 2, comparison against reanalysis shows that most ARDT-model pairs perform well when compared with reanalysis, so this measure of model skill does not provide a way to reduce the uncertainty, since all ARDTs perform equivalently well on average. If there were a standard against which to rank ARDTs, it might be possible to utilize ARDT-weighting approaches to narrow the spread; but such a standard currently does not exist, and so such a weighting approach is not possible.

The spread in the number of detected ARs accounts for some of the spread in trends. If the trends in Figures 2c–f are normalized by the number of ARs detected, the relative magnitude of the ARDT-related uncertainty drops, though it is still large: above 50% of the total spread in the midlatitudes. (Note that this quantity is ill-defined in regions, such as the tropics, where few or no ARs are detected.) As suggested by O'Brien, Risser, et al. (2020), this suggests that constraining the total number of ARs is of central importance to reducing uncertainty about AR variability and change.

4 Discussion and Conclusions

While there have been studies examining future changes in ARs (e.g., Payne et al., 2020) and studies examining uncertainty related to choice of ARDT (e.g., Rutz et al., 2019), no existing study has attempted to quantify the attribution of ARDT uncertainty for climate change by evaluating model uncertainty versus ARDT uncertainty. The ARTMIP Tier2 CMIP5/6 experiment provides a unique opportunity for such a study. The results from this experiment show that most ARDTs project an increase in AR frequency, with mean trends of approximately +2-5 AR days/year per century along the western coastlines of North America, South America, Southern Africa, and Europe (Figure 2c,d). These changes are relatively large, given that the AR frequency in coastal regions is typically between 10-20 AR days per year, though this depends strongly on geographic region and the ARDT used (Figure 1). However, there is considerable spread in the magnitude, with some ARDT-model combinations indicating negative trends (southern Chile and the European west coast from the Iberian Peninsula to the British Isles) with a clear AR shift poleward and other ARDT-model combinations indicating positive trends of ARs in all regions with a magnitude up to $\sim$15 AR days per century. Care must be taken when making general statements about the sign of AR frequency/size/count trends, since this work shows that the sign and magnitude of the trends are linked to choices that ARDT designers make when translating the qualitative AMS definition into a quantitative definition. Specific statements can be made if one settles on a narrow quantitative definition, as is typically done when seeking answers to questions about processes or impacts related to ARs (e.g. orographic precipitation, ice sheet melt, or process drivers).

Globally, all ARDTs indicate either an increase in the total number of ARs, an increase in the areal extent of ARs, or both (Figure 2b). In the historical simulations, the AR area vs size relationship for all ARDTs approximately falls along a line of constant global coverage, with ARDTs in the historical simulations detecting ARs that cover approximately 5% of the global area. This number is somewhat smaller than the 10% global area indicated by Zhu and Newell (1998), which is likely because we are considering the total global coverage, including the tropics, rather than the fraction of zonal circumference in the midlatitudes. It is nevertheless qualitatively consistent in the sense that areas of anomalously high moisture transport occupy a small fraction of the global area. The global areal coverage increases in the future simulations to some degree in all ARDT algorithms, with most indicating a several percent increase in the areal extent of ARs due to increases in both AR size and count.

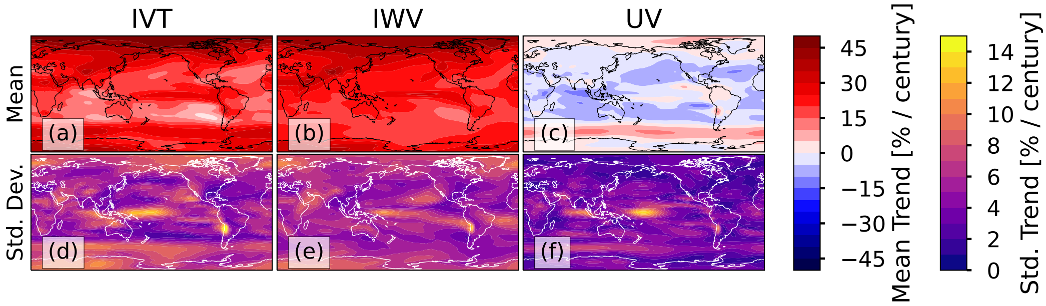

Figure 3. Trends in IVT, IWV, and UV≡IVT/IWV among the CMIP5/6 models, calculated from approximately 1950–2100. Panels (a-c) show the mean trend, and panels (d-f) show the standard deviation of the trends. Trends for each model are shown in Figure S4.

These results further show that future changes in AR frequency can qualitatively differ depending on the type of ARDT used. We aggregate trends by AR classification (see Sections 2 and Text S2) in Figures 2e,f. This aggregation shows that use of any absolute thresholds (*absolute ARDTs*) and time-independent relative thresholds (*fixed relative ARDTs*) tend to produce increases in AR frequency, whereas use of time-dependent relative thresholds (*relative ARDTs*) tend to produce patterns more indicative of a poleward shift. *Absolute ARDTs* and *fixed relative ARDTs*, with thresholds that do not change in time, would be expected to increase the frequency of exceedence of regions above the historical thresholds: more detected AR days in a warmer climate. Such ARDTs are designed to detect increases in occurrence of regions with high IVT, which are important for AR impacts. In contrast, *relative ARDTs* (e.g., `TECA-BARD v1.0.1`) are designed to only account for dynamical–rather than thermodynamical–changes in ARs.

To illustrate the thermodynamic and dynamic changes in IVT, Figures 3a–c shows the model-mean trend in IVT, IWV and the moisture-weighted wind UV $\equiv$ IVT/IWV (it can readily be demonstrated that UV represents the vertically averaged wind, weighted by the specific humidity at each height). The model spread in these trends are shown in Figures 3d–f (Figure S4 shows the trends for each model). Both the IVT and IWV fields increase at a rate of 20–40% per century in the model simulations, whereas the UV field has much smaller changes: decreases in wind of 5–15%/century in most of the tropics and midlatitudes and increases of similar magnitude in the polar regions. Because IVT is the product of IWV and UV, the fractional trend in IVT can be decomposed into a sum of the fractional trends in each quantity:

$$\frac{1}{\mathrm{IVT}}\frac{\partial \mathrm{IVT}}{\partial t} = \frac{1}{\mathrm{IWV}}\frac{\partial \mathrm{IWV}}{\partial t} + \frac{1}{\mathrm{UV}}\frac{\partial UV}{\partial t}.$$

The similarity of the IVT and IWV trend magnitudes implies that most of the trend in IVT is due to the thermodynamic component: the increase in atmospheric water vapor content due to Clausius-Clapeyron (CC) scaling. In contrast, the dynamic change is more indicative of a poleward shift in the magnitude of moisture-transporting winds. It is worth noting that the results presented in Figure 3 are independent of ARDT, though they do help explain some of the differences across ARDTs.

The literature documents two major modes of AR change associated with climate change: (1) a quasi-global increase in IVT associated with CC scaling (thermodynamic; Payne et al., 2020), and (2) a poleward shift in ARs (dynamic; Payne et al., 2020) associated with the poleward shift in the midlatitude storm tracks (Chang et al., 2012).

Poleward shift patterns appear to co-exist to some extent with quasi-global increases in AR frequency in some simulations (e.g., the CMIP5 CSIRO-MK3-6-0 simulation; see Figure S3) for all ARDTs. We argue that *absolute ARDTs* and *fixed relative ARDTs* are more sensitive to thermodynamic changes than *relative ARDTs*. The strongest increase in the *absolute* and *fixed relative ARDTs* compared to *relative ARDTs* explains the sensitivity to ARDT choice especially approaching colder and drier polar regions. The future, much stronger, increase in high latitude temperature associated with polar amplification, compared to other regions, together with hydrological cycle intensification will be more evident in the *absolute* and *fixed relative ARDTs* compared to the *relative ARDTs*.

This categorization of ARDTs does not perfectly explain the spread in trends, as `Tempest` and `TECA-BARD v1.0.1` trends in Figure 1 are qualitatively different; as such the mean trends for the *relative ARDTs* in Figures 2e,f should be interpreted with caution. We hypothesize that they differ due to how the two methods identify relative peaks in the IVT field: `Tempest` uses the Laplacian to find local ridges in the IVT field, whereas the percentile-based approach in `TECA-BARD v1.0.1` seeks out the relatively highest IVT locations in each timestep. It is possible that `Tempest` identifies relatively small, weak ARs that `TECA-BARD v1.0.1` misses because they are weak enough to fall below its relative threshold. If this is the case, it could imply that the contrasting regions, where `Tempest` shows an increase and `TECA-BARD v1.0.1` shows a decrease, are associated with an increase in the occurrence of relatively weak ARs that `TECA-BARD v1.0.1` misses. This is worth studying in a future paper.

It is worth noting here that trend patterns in the MERRA-2 reanalysis are similar across ARDTs (Figure S3), with all ARDTs indicating a poleward shift in ARs. This might suggest that the observed poleward shift in the storm tracks (Fyfe, 2003; Davis & Rosenlof, 2012; Pena-Ortiz et al., 2013; Tilinina et al., 2013; Lucas et al., 2014; Manney & Hegglin, 2018) dominates over quasi-global increases in IVT in the historical record. This should be investigated further as part of the Tier 2 Reanalysis experiment.

The algorithm-wise validation of simulated ARs (Figure 2a) shows that models exhibit spatial patterns of AR occurrence similar to those in reanalysis, as evidenced by high Taylor skill scores for spatial correlations and standard deviations. This is a noteworthy result in the context of the ARDT uncertainty shown here. If only one algorithm is used in a study, such validation could give false confidence in the robustness of results. It therefore seems important to explicitly include ARDT uncertainty as part of evaluation of a model's ability to represent ARs, which, relatedly, points to the utility of appropriate ensemble weighting strategies to help reduce such uncertainty (e.g., Massoud et al., 2019). It also highlights the value of AR-related, but not ARDT-dependent, evaluations of models (e.g., Payne & Magnusdottir, 2015).

Recent work involving manual identification of ARs by experts (Prabhat et al., 2020; O'Brien, Risser, et al., 2020) suggests that the spread in AR algorithm behavior is linked to differences in opinion about what does and does not constitute an AR. O'Brien, Risser, et al. (2020) show that this spread in subjective opinion projects directly on to quantitative differences in the sign of the correlation coefficient between an El Niño index and global AR count. Such differences in subjective opinion likely also play a role in the quantitative choices made by various ARDT designers. Gimeno et al. (2021) add some discussion concerning the diversity of the different meteorological patterns that can be associated with the qualitative definition of ARs, and there is no guarantee that all so-called ARs are associated with the same meteorological patterns. Given this spread in expert opinion, and given that there is no agreed-upon theoretical or numerical definition of what defines an AR, there is presently no way to objectively assess whether one ARDT is better than another.

Somewhat relatedly, the ARTMIP project has established that different AR detectors are designed with different–and equally legitimate–purposes (Shields et al., 2018;

Rutz et al., 2019; Ralph, Wilson, et al., 2019). Some ARDTs intentionally choose to discriminate ARs from the background based on absolute thresholds in IVT (e.g., Rutz et al., 2014), since it is well-established that coastal orographic precipitation is directly linked to IVT magnitude (Neiman et al., 2002; Ralph et al., 2004, 2005; Neiman, Ralph, Wick, Kuo, et al., 2008; Ralph, Rutz, et al., 2019); such a design choice makes it easy to relate ARDT results directly to hydrometeorological impacts. Other algorithms (e.g., Shields & Kiehl, 2016b; O'Brien, Risser, et al., 2020) intentionally use relative thresholds in order to avoid increases in AR detection due to long-term increases in atmospheric water vapor. Both are valid for the purposes for which they were designed: absolute methods detect areas that will likely lead to hydrometeorological impacts–which will increase in a warmer climate–and relative methods seek to focus on the core of regions associated with anomalous vapor transport.

These results suggest that new projects investigating future changes in the statistics and characteristics of ARs should explicitly consider ARDT uncertainty as a core part of the experimental design. This study makes it clear that ARDT design choices can have a major impact on the results of climate change studies, and with dozens of ARDTs in use (Rutz et al., 2019), the uncertainty associated with their varying methods will not be going away soon. Furthermore, using multiple ARDTs can be advantageous. For example, will an increase in ARs and precipitation result primarily from an increase in IWV or an increase in UV wind? Having ARDTs that weigh these variables differently can help answer these questions. The Bayesian, multi-ARDT approach of O'Brien, Risser, et al. (2020) can quantify parametric uncertainty associated with a single ARDT, but it is not yet clear how parametric uncertainty compares to structural uncertainty (i.e., choices in what heuristic rules to employ in the ARDT). There are at least four ARDT codes that are now in the public domain (`Mundhenk_v1`, `Guan_Waliser_v2`, `Tempest`, and `TECA-BARD v1.0.1`; see `https://www.cgd.ucar.edu/projects/artmip/algorithms.html` for a full list of ARDTs that have participated in ARTMIP), and we encourage current and future ARDT designers to likewise enter their codes into the public domain in order to facilitate such uncertainty exploration in future studies.

Ralph et al. (2018) provide a concise, qualitative definition of ARs, and this has been a major benefit to the AR research community. They intentionally chose to "leave specifications of how the boundaries of an AR are to be quantified open for future and specialized developments." The results in this manuscript demonstrate that the choice of how to define AR boundaries–the fundamental job of an ARDT–have a demonstrably large control on the statistics of ARs detected in future climate simulations. These results suggest that the AR research community would further benefit from studies that aim to quantitatively constrain the definition of ARs; e.g., with first-principles analyses that constrain AR properties like size, count, etc. Such constraints could help reduce uncertainty associated with ARDT design choice (and parameter choice), and by extension they could constrain results concerning ARs and future climate change. That said, given that different experiments motivate different ARDT design choices (e.g., absolute vs relative thresholds), it seems unavoidable that some of this uncertainty is irreducible. It is clear, however, that it is imperative for studies to explore and understand the implications of this uncertainty.

This study focuses on a bulk, global perspective of uncertainty associated with ARDTs and simulations in the Tier 2 CMIP5/6 experiment. There are many other types of more detailed analyses that others could take on. For example, this study has not considered the temporal characteristics of ARs, since relatively few existing ARDTs track ARs as they propagate in time; a recent study by Zhou et al. (2021) uses a common temporal tracking algorithm on multiple ARDTs, and such an approach could be applied to the Tier 2 dataset. We encourage others in the research community to utilize this dataset for research on future ARs and climate change (see data availability statement in Acknowledgements). In particular, it seems valuable to revisit past studies of ARs and future climate change in the context of ARDT uncertainty. Payne et al. (2020) review the numerous results concerning the future of ARs that have appeared in the literature in the last decade. There are almost as many ARDTs as there are such results, which makes intercomparison of the results challenging. The Tier 2 CMIP5/6 dataset provides a way to revisit many–if not all–of these previous results within a uniform experimental framework.

Prior to ARTMIP, it was assumed that the various ARDTs in the literature were simply different methods of looking at the same dynamical phenomenon. Recent papers associated with ARTMIP show that that is true for strong ARs (with high IVT, e.g., Rutz et al., 2019; Lora et al., 2020), but that there is disagreement among the various ARDTs for weaker ARs. Further, Zhang et al. (2019) show that approximately 20% of ARs are not associated with a nearby extratropical cyclone (under their ARDT criteria), suggesting that this subset of ARs may have a different dynamical origin. This raises some quesions that remain unanswered. *Are some ARDTs simply missing ARs that other ARDTs are identifying, or is there more than one type of dynamical phenomenon that produces AR-like objects*; *are some ARDTs more sensitive to one dynamical phenomenon and others are more sensitive to another*; and *if there are multiple dynamical causes of ARs, do they have different spatiotemporal responses to climate change?* These questions are likely answerable with the datasets that have been produced by the ARTMIP project.

In summary, this initial analysis of the Tier 2 CMIP5/6 experiment shows that most ARDTs and simulations indicate an increasing trend in AR frequency, size, and number in future simulations with strong radiative forcing. It also shows the critical importance of understanding the implications of uncertainty for AR-related research. Finally, this paper introduces the publicly-available Tier 2 CMIP5/6 dataset, which may be a valuable resource for answering fundamental questions about ARs and about ARs and climate change.

Acknowledgments

The authors thank the multiple reviewers and editors whose feedback and commentary greatly improved the quality and presentation of this manuscript.

This research was supported by the Director, Office of Science, Office of Biological and Environmental Research of the U.S. Department of Energy Regional and Global Climate Modeling Program (RGMA) and used resources of the National Energy Research Scientific Computing Center (NERSC), also supported by the Office of Science of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

The contributions of T.A. O'Brien were supported in part by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research, Climate and Environmental Sciences Division, Regional & Global Model Analysis Program, under Award Number DE-AC02-05CH11231; in part by the Environmental Resilience Institute, funded by Indiana University's Prepared for Environmental Change Grand Challenge initiative and in part by Lilly Endowment, Inc., through its support for the Indiana University Pervasive Technology Institute. Alexandre M. Ramos is supported by the Fundação para a Ciência e Tecnologia (FCT, Portugal) project "Weather Extremes in the Euro Atlantic Region: Assessment and Impacts-WEx-Atlantic" (PTDC/CTA-MET/29233/2017). Alexandre M.Ramos also acknowledges the Scientific Employment Stimulus 2017 from FCT (CEECIND/00027/2017). Irina V. Gorodetskaya thanks FCT/MCTES for the financial support to CESAM (UIDP/500017/2020+UIDB/500017/2020), through national funds, and FCT Project ATLACE (CIRCNA/CAC/0273/2019). Eric J. Shearer is supported by the Ridge to Reef Graduate Training Program funded by NSF-NRT award DGE-1735040.

We acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modelling, coordinated and promoted CMIP6. We thank the climate modeling groups for producing and making available their model output, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF. We thank DOE's RGMA program area, the Data Management program, and NERSC for making this coordinated CMIP6 analysis activity possible.

ARTMIP is a grass-roots community effort and includes a collection of international researchers from universities, laboratories, and agencies. Details on catalogues developers can be found on the ARTMIP website. ARTMIP has received support from the US Department of Energy Office of Science Biological and Environmental Research (BER) as part of the Regional and Global Model Analysis program, and the Center for Western Weather and Water Extremes (CW3E) at Scripps Institute for Oceanography at the University of California, San Diego.

ARTMIP Tier 2 CMIP5/6 catalogues can be found on the Climate Data Gateway: doi.org/10.26024/s4p7-pf13 (`https://go.iu.edu/3ci2`)

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Supporting Information for "Increases in Future AR Count and Size: Overview of the ARTMIP Tier 2 CMIP5/6 Experiment"

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Introduction

This supplementatal information provides additional useful details on ARDTs, their treatment of thresholds, and our grouping of ARDTs into categories. The supplemental figures expand on figures in the main text to show all ARDT-simulation combinations.

Text S1.

Treatment of Thresholds

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We document here choices/specializations (if any) that ARDT contributors made in running their ARDTs on the Tier 2 CMIP5/6 simulations

- `ARCONNECT_v2`: only uses absolute threshold; no Tier 2-specific decisions needed
- `Guan_Waliser_v2`: uses 85^{th} percentile from the historical simulation
- `IDL_rel_future`: uses 85^{th} percentile calculated from the future simulation
- `IDL_rel_hist`: uses 85^{th} percentile calculated from the historical simulation
- `Lora_v2`: uses a time-and-latitude dependent IVT threshold that asymptotes to 225 kg/m/s at the poles; the time/latitude dependence of the threshold is a function of the 30-day running mean and a zonal average of IWV, so no Tier 2-specific decisions are needed
- `Mundhenk_v3`: calculates the mean and seasonal cycle of IVT based on the historical simulation and removes this to determine the IVT anomaly relative to the historical period
- `PNNL_v1`: only uses absolute threshold; no Tier 2-specific decisions needed
- `TECA_BARD_v1.0.1`: uses threshold relative to spatial map of IVT at a given time; no Tier 2-specific decisions needed

The `Mundhenk_v3` algorithm differs from prior published versions (i.e., `Mundhenk_v1`, `Mundhenk_v2`) in its more reliable detection of AR objects that cross the boundary of the dataset's spatial domain.

The `Tempest` ARDT uses an absolute threshold for the laplacian of IVT. The Tier 1 version also utilized an absolute threshold of 250 kg/m/s of IVT, but it was later determined that this threshold had no effect on the ARDT results because regions that satisfied the Laplacian threshold also satisfied the IVT threshold. The minimum latitude for ARs was raised to 20°, from 15°, to filter easterly waves. The stencil radius and magnitude used for the Laplacian depends on the model grid, and this is held constant for the historical and future simulations.

Discussions with the `Tempest` contributing scientists indicate that the algorithm may benefit from further tuning of their method when applied to moderately low resolution data, and efforts are underway to provide a second version of their contribution to Tier 2. Such discoveries and improvements are a benefit of intercomparison projects.

Text S2.

Classification of ARDTs

Building on Rutz et al. (2019), we classify the Tier 2 CMIP5/6 ARDTs into three groups, based on their treatment of thresholds: *absolute*, *fixed relative*, and *relative*. These classifications are indicated as *abs.*, *fix. rel.*, and *rel.* in Table S1. A key motivation for this categorization is aggregating ARDTs by their sensitivity to thermodynamic changes in IVT, with the assumption that ARDTs employing absolute thresholds to moisture fields will be the most sensitive, and ARDTs employing time-dependent thresholds will be least sensitive.

Absolute ARDTs: We define *absolute ARDTs* as utilizing any fixed thresholds (e.g., in IVT) for discriminating ARs from the background. `ARCONNECT_v2` and `PNNL_v1` unambiguously fit in this category. `Lora_v2` uses an IVT threshold that varies with latitude and time, and the threshold asymptotes to 250 kg/m/s at mid-to-high latitudes (the threshold increases toward infinity approaching the tropics). This design effectively imposes an absolute threshold of at least 250 kg/m/s. Because of this, we classify `Lora_v2` as an *absolute ARDT*, while recognizing that this is not a perfect categorization.

Fixed relative ARDTs: We define *fixed relative ARDTs* as those that employ relative thresholds that do not vary with time. For example, `Guan_Waliser_v2` calculates the 85^{th} percentile of IVT from the historical simulations and discriminates ARs from the background where IVT is greater than the local, historical 85^{th} percentile; hence the threshold used in the `Guan_Waliser_v2` algorithm does not change in time. The `IDL_rel_hist` and `IDL_rel_future` ARDTs use a similar approach and are therefore also categorized as *fixed relative ARDTs*. `Mundhenk_v3` calculates IVT anomalies relative to the historical period and identifies ARs that are above the 94^{th} percentile of the historical simulation, so it also fits unambiguously in the *fixed relative* category.

Relative ARDTs: We define *relative ARDTs* as those that employ relative thresholds that vary with time. `TECA_BARD_v1.01` unambiguously fits into this category, since ARs are identified where IVT is above a fixed percentile of IVT, where the percentile is calculated in space (in contrast to time, e.g., for `Guan_Waliser_v2`). `Tempest` uses an absolute threshold applied to the Laplacian of the IVT field, which might warrant its classification as an absolute ARDT. However, the use of the Laplacian removes the mean of the IVT field; therefore `Tempest` identifies areas of IVT that are high relative to nearby areas of IVT at the same timestep. We therefore classify `Tempest` as a *relative ARDT*.

Text S3.

Details on Missing Data All ARDTs detect ARs for the 1951-2099 period for the combined historical and future simulations for each CMIP5/6 model. We analyze output from the entire 1951-2099 timeperiod. There are some exceptions to this: output from the CMIP6 IPSL-CM6A-LR SSP5-8.5 simulation are only available through 2049, there are data corruption issues for the year 2006 in the CMIP5 CSIRO-Mk3-6-0 simulation, and there are data corruption issues for the year 2095-2099 for the `TECA_BARD_v1.01` output applied to the CMIP5 IPSL-CM5B-LR simulation. Years with data corruption issues are marked as missing, and trends and climatologies are only calculated considering non-missing data. The `Guan_Waliser_v2` algorithm did not supply ARDT catalogues for the NorESM1-M and BCC-CSM2-MR simulations due to technical issues at the time.

Text S4.

Comment on the Tier 2 Reanalysis Experiment

The tiered structure of the ARTMIP experiments requires that all participants contribute to the Tier 1 experiment; by design, all ARDTs participating in the Tier 2 CMIP5/6 experiment also have been run on MERRA-2 as part of the Tier 1 experiment. A separate ARTMIP Tier 2 experiment is currently underway, comparing ARDT results applied to different reanalyses. The set of ARDTs participating in the Tier 2 Reanalysis experiment is not identical to the set participating in this Tier 2 CMIP5/6 experiment, so use of multiple reanalyses is not possible for ARDTs. For the sake of uniformity in the experimental approach, we use only the MERRA-2 reanalysis. Preliminary analysis of the Tier 2 Reanalysis experiment (not shown) indicates that the uncertainties associated with choice of reanalysis are small compared to the uncertainties discussed in this paper, and it is therefore unlikely that use of a different reanalysis would change the qualitative conclusions of this paper.

Table S1. (left) ARDT algorithms, and associated metadata, that contributed to the Tier 2 CMIP5/6 experiment. ARDT classifications ('Class.') are described in Text S2. (right) Details of CMIP5/6 models used in the Tier 2 experiment.

ARDTs				Models			
Algorithm ID	Contrib.	Class.	Region	MIP Era	Model Name	Inst.	~Res. [km]
ARCONNECT_v2	Shearer	abs.	Global	CMIP5	CCSM4	NCAR	120
GuanWaliser_v2	Guan	fix. rel.	Global	CMIP5	CSIRO-Mk3-6	CSIRO	207
IDL_rel_future	Ramos	fix. rel.	W. Europe, S. Africa	CMIP5	CanESM2	CCCMA	310
IDL_rel_hist	Ramos	fix. rel.	W. Europe, S. Africa	CMIP5	IPSL-CM5A-LR	IPSL	296
Lora_v2	Lora	abs.	Global	CMIP5	IPSL-CM5B-LR	IPSL	296
Mundhenk_v3	Nardi	fix. rel.	Global	CMIP5	NorESM1-M	NCC	242
PNNL_v1	Sarangi	abs.	W. U.S.	CMIP6	BCC-CSM2-MR	BCC	124
Tempest	McClenny	rel.	Global	CMIP6	IPSL-CM6A-LR	IPSL	198
TECA_BARD_v1.01	O'Brien	rel.	Global	CMIP6	MRI-ESM2-0	MRI	124

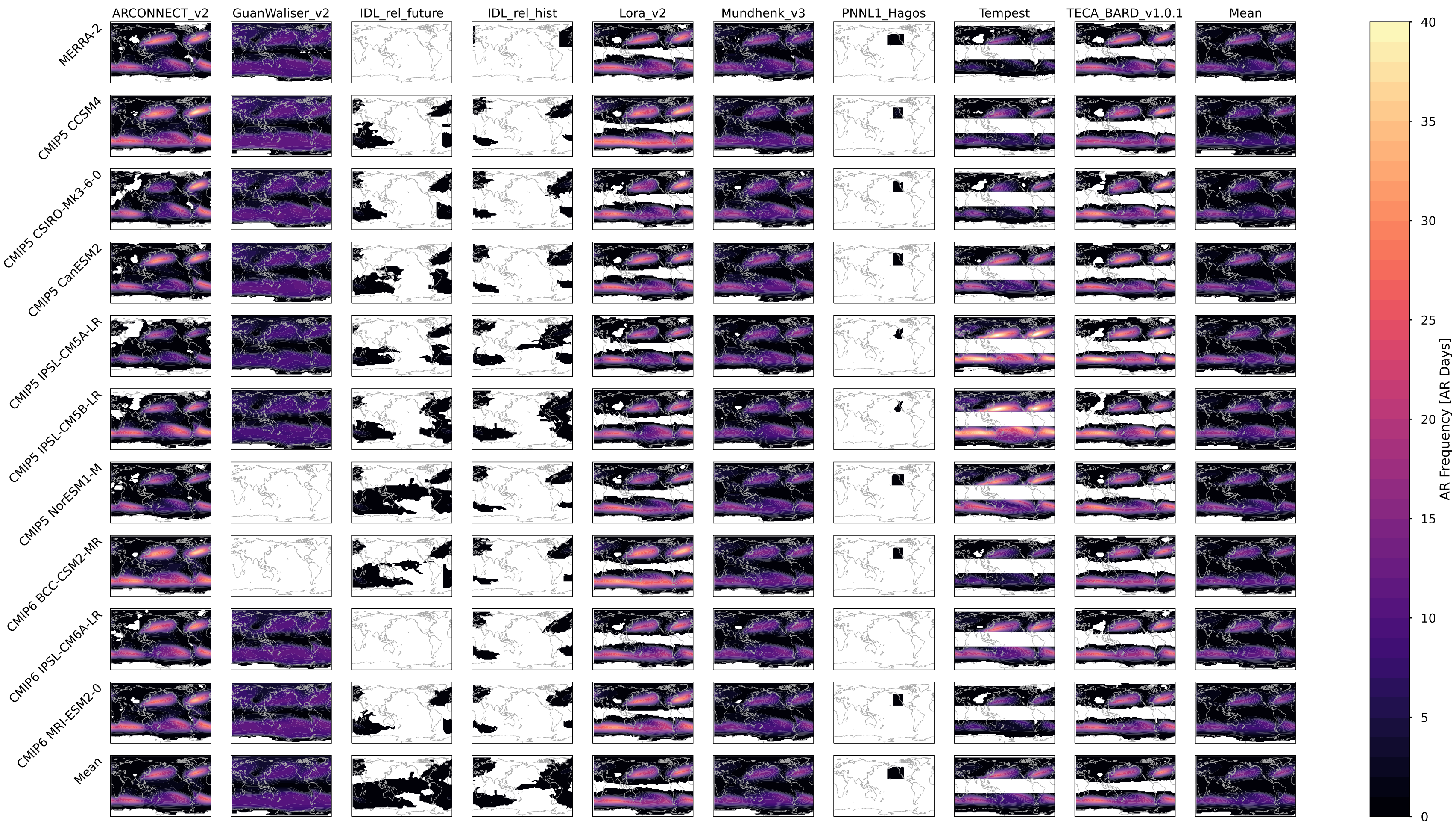

Figure S1. Maps of AR frequency (AR days per year) from 1981-2010. Columns correspond to ARs detected by specific ARDTs, and rows correspond to input datasets (MERRA-2 for the first row and CMIP5/6 for other rows). The rightmost column shows the multi-ARDT mean frequency for each model. The bottom row shows the multi-model mean for each ARDT (excluding MERRA-2 from the mean). The bottom right panel shows the multi-model, multi-ARDT mean frequency (excluding MERRA-2 from the mean).

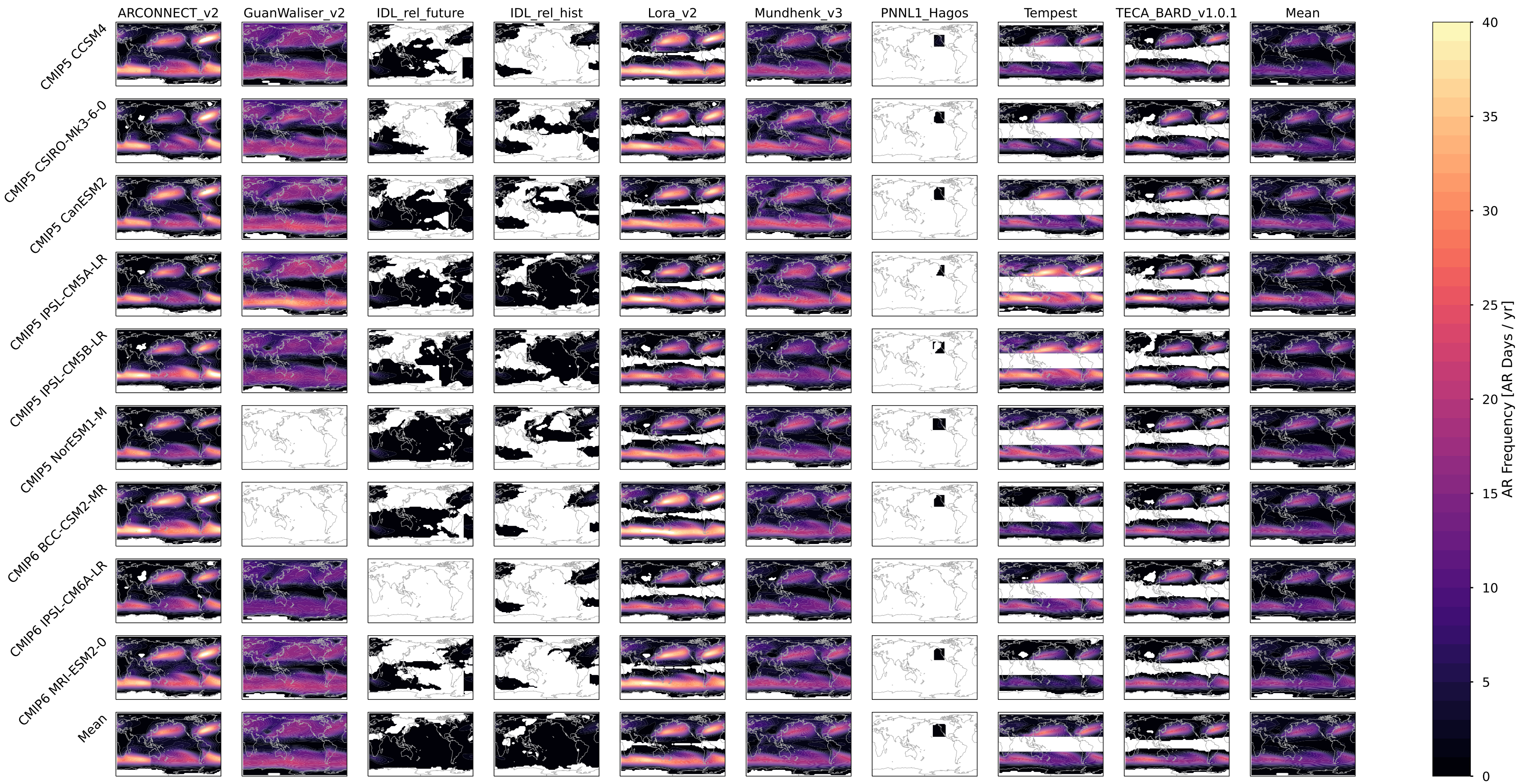

Figure S2. Maps of AR frequency (AR days per year) from 2070-2099. Columns correspond to ARs detected by specific ARDTs, and rows correspond to CMIP5/6 models. The rightmost column shows the multi-ARDT mean frequency for each model. The bottom row shows the multi-model mean for each ARDT. The bottom right panel shows the multi-model, multi-ARDT mean. The CMIP6 IPSL-CM6A-LR row shows the frequency from the last 30 years of available simulation data (2020-2049).

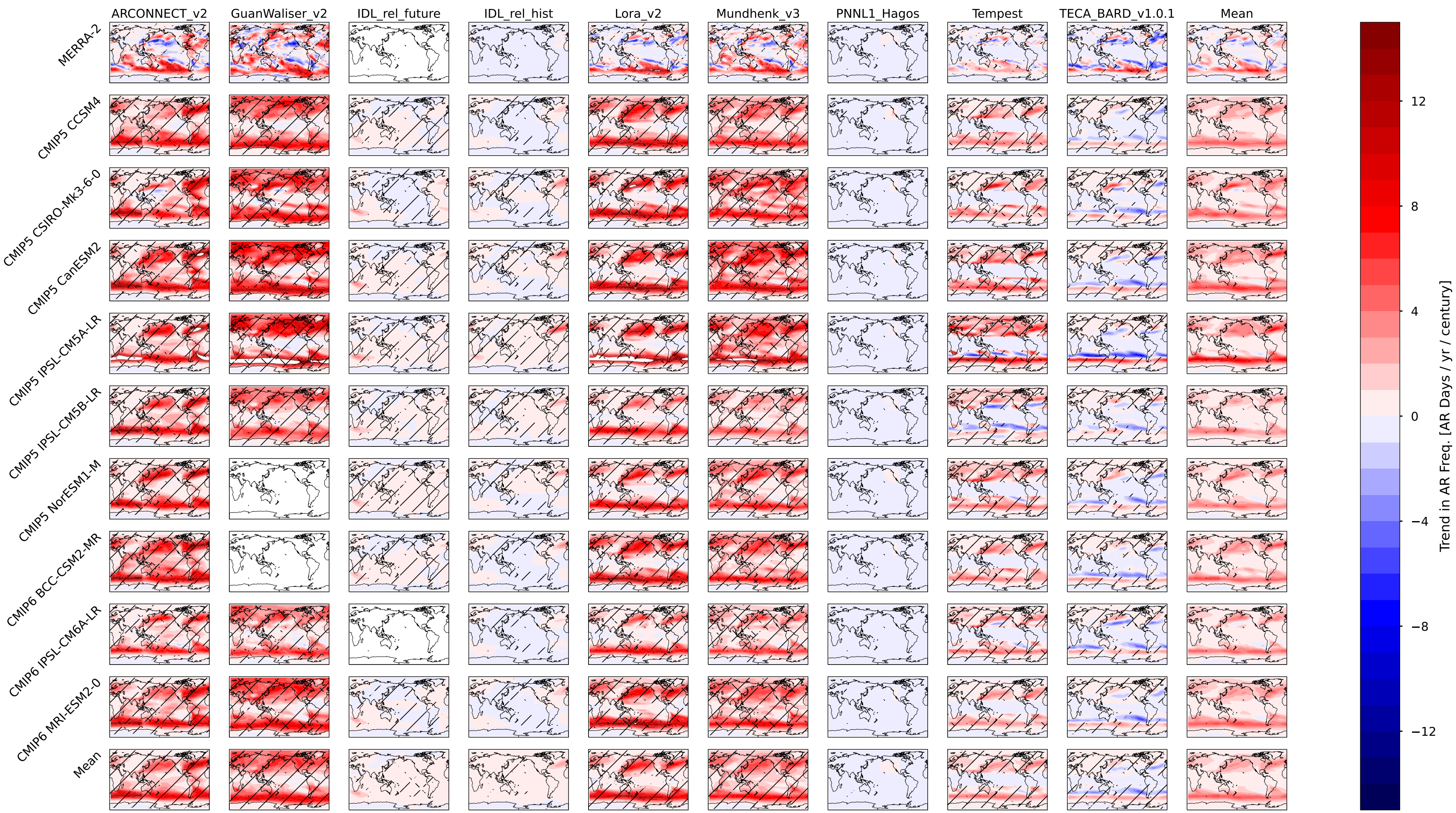

Figure S3. Maps of trends in AR frequency (AR days per year per century) from 1981-2099 (from 1981-2017 for MERRA2). Columns correspond to ARs detected by specific ARDTs, and rows correspond to input datasets (MERRA-2 for the first row and CMIP5/6 for other rows). The rightmost column shows the multi-ARDT mean trend for each model. The bottom row shows the multi-model mean for each ARDT (excluding MERRA-2 from the mean). The bottom right panel shows the multi-model, multi-ARDT mean frequency (excluding MERRA-2 from the mean). Trends for CMIP6 IPSL-CM6A-LR are calculated through 2049.

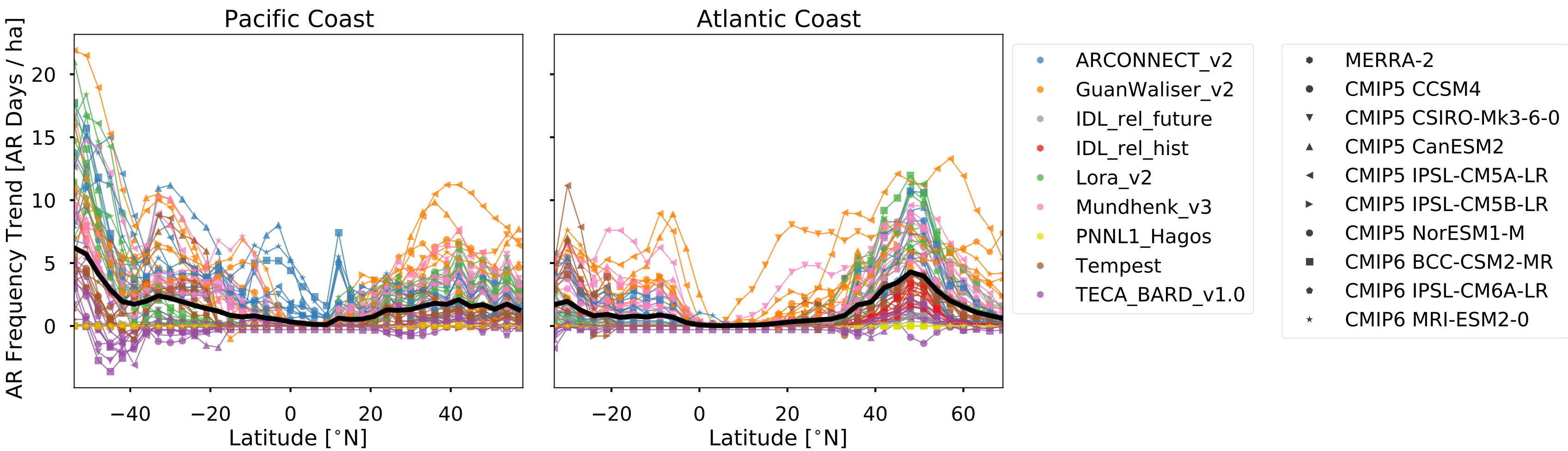

Figure S4. Trends in AR frequency (AR days per year per century) from 1981-2099 for western coastlines along the (a) Pacific and (b) Atlantic oceans. Colors correspond to ARDTs and markers correspond to simulations.

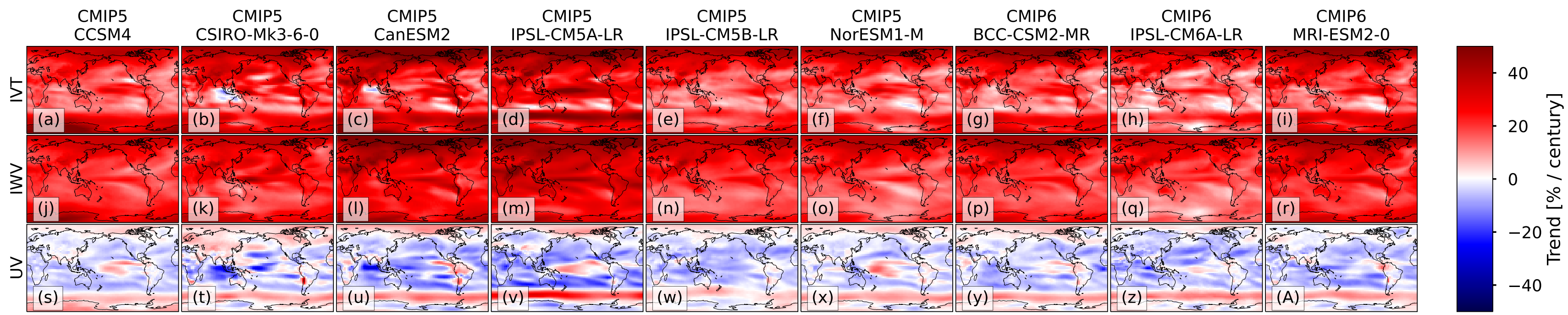

Figure S5. Trends in IVT (a–i), IWV (j–r), and UV≡IVT/IWV (s–A) for each of the CMIP5/6 models, calculated from approximately 1951–2099.