3RD ARTMIP WORKSHOP REPORT

Based on a vision to improve the characterization and predictability of atmospheric rivers (ARs) on both weather and climate time scales, the Atmospheric River Tracking Method Intercomparison Project (ARTMIP) aims to quantify the uncertainty in AR climatology (e.g., frequency, duration, and intensity), precipitation, and related impacts that arise because of different AR tracking methods, and uncertainty in how these AR-related metrics may change in the future. ARTMIP also aims to provide guidance regarding the advantages and disadvantages of different AR tracking methods and which of these methods are best suited to answer certain scientific questions. Finally, ongoing ARTMIP efforts are developing an online repository of data for future use in research. The 3rd ARTMIP Workshop was convened to discuss ongoing ARTMIP experiments and to identify future research priories related to ARs and AR tracking.

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EXECUTIVE SUMMARY

Atmospheric rivers are increasingly recognized globally as an important weather phenomenon associated with extreme precipitation. There is a substantial body of literature indicating that ARs are responsible for a large fraction of wet-season precipitation on western coasts and that they can cause large changes in snowpack (both positive and negative). Individual ARs and collections of ARs can bring large amounts of precipitation that drives floods and other storm-related hazards. ARs are a significant factor for water and associated water systems in the vicinity of western coasts. It is increasingly evident that they have major impacts on the energy and water budgets of the cryosphere: including mountains and high latitude regions. These research advances hinge on technical advances in tracking ARs in observations, reanalyses, and climate model simulations and on understanding uncertainties associated with different tracking methods. In parallel with the recent increase in research activity around ARs, an increasing number of research groups have developed unique methods for tracking ARs.

The Atmospheric River Tracking Method Intercomparison Project was launched in 2016 with the aim of quantifying the uncertainty in AR climatology, precipitation, and related impacts that arise due to differences in AR tracking methods. The first ARTMIP workshop was convened in 2017 to design an experiment that could quantify the uncertainty associated with AR tracking. The concept of a multi-tiered experimental approach, based on tracking ARs across common datasets, resulted from this workshop. The Tier 1 experiment, which is focused on tracking ARs in a modern reanalysis, was launched following the first workshop. The second ARTMIP workshop was oriented around discussion of Tier 1 results and around designing and planning the first set of Tier 2 experiments: the Tier 2 C20C+ experiment and the Tier 2 CMIP5/6 experiment. Both initial Tier 2 experiments are focused on understanding the effects of climate change on AR characteristics, with the C20C+ experiment focusing on a set of high-resolution atmosphere-only simulations, and the CMIP5/6 experiment focusing on a multimodel collection of fully-coupled simulations from the Coupled Model Intercomparison Project.

Following the 2nd ARTMIP Workshop, two unrelated developments motivated the need for developing a large dataset of hand-labeled ARs. Discussions following the 2nd ARTMIP Workshop suggested that differences among AR tracking algorithms might reflect differences in expert opinion about what constitutes the boundary of ARs; resolving this question would require experts to hand-label ARs. Unrelated, but concurrent, advances in Computational Climate Science have demonstrated the utility of modern machine learning methods for tracking weather phenomena. These developments also highlighted the need for high-quality data to train machine learning methods: expert-labeled datasets.

Emerging results from the Tier 1 and 2 experiments, along with the recently identified need to develop a high-quality, hand-labeled dataset of ARs, motivated the ARTMIP Committee to convene the 3rd ARTMIP Workshop, held at Lawrence Berkeley Lab on October 16-18, 2019. The 3rd ARTMIP Workshop was organized around:

- presentation of results from recent and ongoing ARTMIP research: Tier 1 and beyond (with a focus on Tier 2);
- working discussion of current and future ARTMIP experiments and papers; and
- solicitation of expert identification of atmospheric rivers and other weather phenomena for machine learning.

Initial Tier 2 results presented at the workshop show that, while most methods agree, qualitative conclusions about the effect of climate change on ARs can depend on tracking algorithm. These results further motivate exploration of the role of AR tracking uncertainty on other aspects of AR science. Specifications and timelines for three new Tier 2 experiments were defined: Tier 2 Reanalysis, Tier 2 High-Latitude, and Tier 2 paleo-ARTMIP. A future Tier 2 experiment was also discussed, and specifications and a timeline will be developed in future ARTMIP interactions (e.g., teleconferences): Tier 2 MPAS-ENSO. Group and breakout discussions during the workshop identified numerous gaps in understanding and associated research priorities. These gaps and research priorities are a key outcome for the ARTMIP workshop.

Key Gaps and Research Priorities

Gap: Most current AR detection algorithms are primarily based on 2D features, which is partly due to computational considerations and data availability, but ARs have distinct 3D structure.

Research Priorities: Research groups with expertise in, and access to, high performance computing resources should explore detection approaches that leverage the 3D structure of ARs.

Gap: There are a growing number of different AR detection codes reflecting a diversity of quantitative AR definitions. Software differences make the systematic comparison of these definitions difficult.

Research Priorities: Develop open-source computational frameworks to facilitate the implementation of new and existing AR detection methods.

Gap: Existing tracking methods do not consider that there might be different “flavors” of ARs.

Research Priorities: Research is needed to determine whether and how there might be different flavors of ARs (e.g., role of baroclinity, generation mechanisms, etc.), and if so, whether this might lead to different classes of tracking algorithms.

Gap: The physical drivers of AR genesis, development, and dissipation are not completely understood, and this lack of understanding impedes our ability to constrain the quantitative definition, detection, and tracking of ARs.

Research Priorities: There is a need for more basic research on the dynamics and lifecycle of ARs.

Gap: ARTMIP has documented different classes of AR detection algorithm, which partially explains the spread in AR detection results.

Research Priorities: Objective, and physics-informed, clustering approaches could help establish a quantitative vocabulary for explaining differences among AR detection algorithms.

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Introduction

Atmospheric Rivers Defined

The AMS Glossary of Meteorology defines an AR as "a long, narrow, and transient corridor of strong horizontal water vapor transport that is typically associated with a low-level jet stream ahead of the cold front of an extratropical cyclone." This definition was developed following a process described by Ralph et al. 2018, which was marked by open engagement with the atmospheric and geosciences community. However, this elegant definition depends on a qualitative description of ARs, whereas the peer-reviewed literature contains numerous quantitative definitions of ARs, as needed for various applications.

Each method identifies and/or tracks ARs based on meeting criteria selected to address different scientific questions. The first step in developing a method is often the choice of a thresholding variable and magnitude, which serve as the minimum requirements for identifying an AR. The thresholding variable can be integrated water vapor (IWV; e.g., Wick et al. 2013) or, more often, IWV transport (IVT), which accounts for wind speed as well as moisture. IVT is generally preferred for midlatitudes as research has shown that using it extends medium-range predictability for high-impact hydrological events (Lavers et al. 2017). Recent field campaigns have used probabilistic IVT forecasts to determine AR location and intensity (Cordeira et al. 2017). For high latitudes, Wille et al (2019) show that for AR impacts depending both on heat and moisture transport (e.g., melt in Antarctica), the IWV thresholding is more robust. The value of the threshold can be either *absolute* (e.g., IVT ≥ 250 kg m^{-1} s^{-1}; e.g., Rutz et al. 2014) or *relative* (e.g., IVT ≥ 85^{th} percentile of local climatological IVT; e.g., Guan and Waliser 2015, 2019). Once features meeting or exceeding the threshold are identified in a data set, they are examined for geometric parameters such as length, width, shape, axis, and orientation. Temporal requirements may also be chosen (i.e., either AR identification is independent of time [*time slicing*], or it is dependent on criteria being met for a specified duration [*time stitching*]). In addition, machine learning techniques have recently been developed to identify and track ARs (e.g., Muszynski et al. 2019). Figure 1 and Figure 3 depict the variety of AR detection algorithm types.

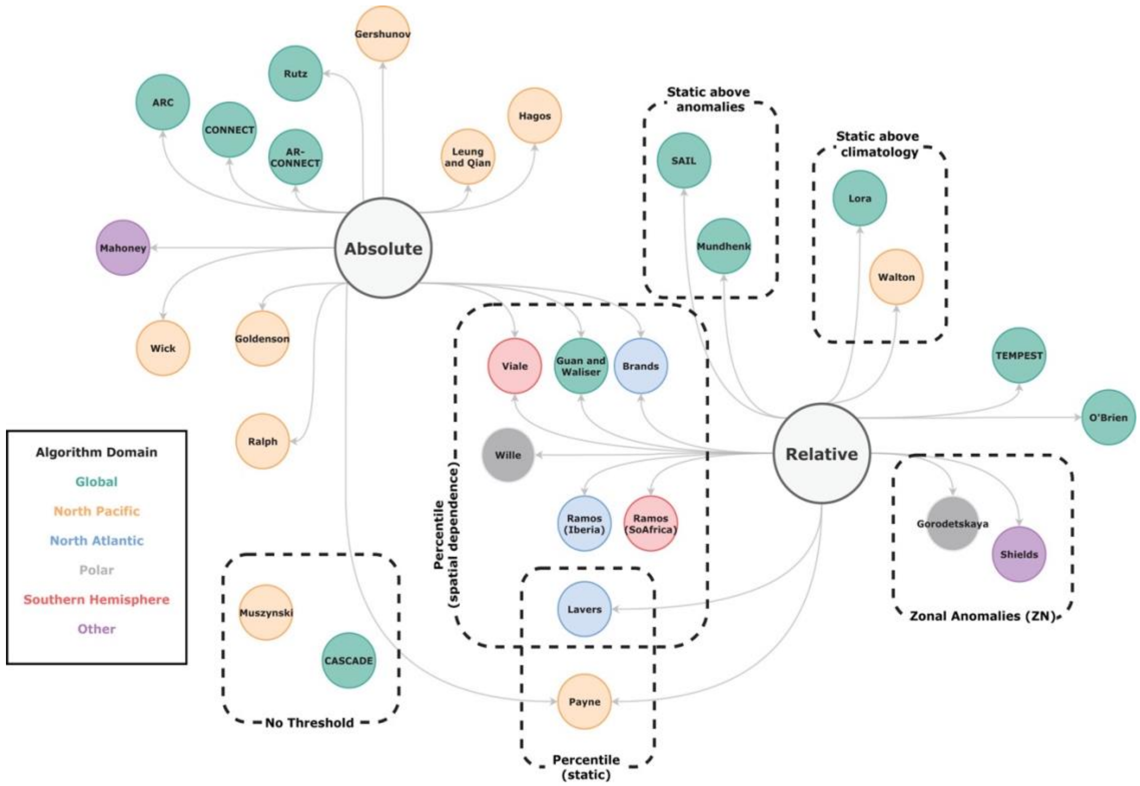

Figure 1: Clustering of ARTMIP algorithm types by algorithm characteristics. (credit, A. Payne)

The different methods used produce different AR climatologies and, hence, different impacts attributable to ARs. These differences lead to uncertainty in operational weather research and forecasting, water management, and climate projections. Figure 2 highlights an example of the differences in AR spatial footprint that can be observed during a single event using a case from 0000 UTC 15 February 2014 (from Rutz et al. 2019). Note that some methods identify an AR only over the greatest values of IVT offshore, others identify an AR making landfall in coastal regions, and some identify an AR extending well into the continental interior. This result has major consequences for understanding the role of ARs in contributing to short-term weather-related impacts and long-term water availability. The goal of the Atmospheric River Tracking Method Intercomparison Project (ARTMIP; Shields et al. 2019; Rutz et al. 2019) is to quantify and understand the uncertainties in AR climatology (e.g., frequency, duration, and intensity), precipitation, and related impacts that arise from different AR identification and tracking methods, and how uncertainties in these AR-related metrics may change in the future.

The path to ARTMIP started in 2016 when colleagues from both weather and climate communities came together at the first International Atmospheric River Conference (IARC 2016) to discuss AR detection and the variety of AR datasets (catalogues) that various groups had produced. It became clear that it is necessary to understand the uncertainties in AR science that originate in the choice of detection algorithm. This in turn is tied to the underlying definition of ARs, which remains theoretically and quantitatively undefined. Hence, ARTMIP was developed to quantify the scientific uncertainty associated with AR detection algorithms.

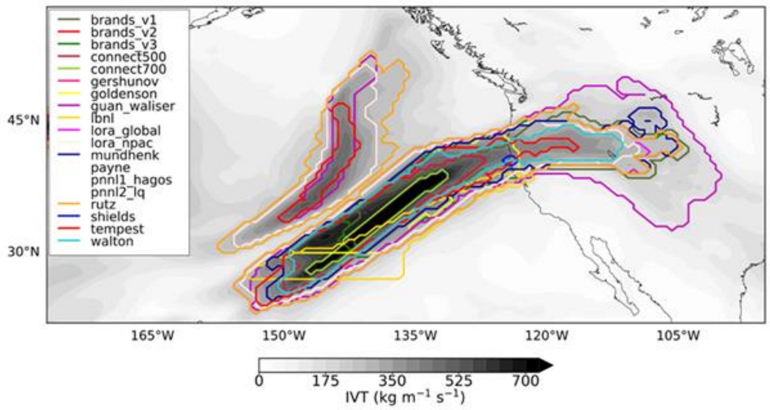

Figure 2: Example of how AR identification and tracking methods differ over the northeastern Pacific, based on MERRA v2 data from 0000 UTC 15 February 2014. Gray shading represents IVT (kg m$_{-1}$ s$_{-1}$), and colored contours represent the spatial regions designated as ARs by the various methods. Note that only algorithms available in this region are shown. Additionally, some methods available for this region do not identify an AR at this time ('payne', 'pnnl1_hagos',and 'pnnl2_hq'). See Figure 3 for more information about methods shown. (credit, J. Lora)

Scientific Motivations for AR Tracking

The development of approaches to identify ARs on climatological timescales emerged from a need to understand the full scope of drivers behind their variability, their impacts on land, and the need to objectively distinguish them from related phenomena, i.e. extratropical cyclones and tropical moisture exports. The AR research community consists of a diverse set of disciplines, and algorithms reflect the range of perspectives, regional perspectivesm, and different applications. Before the development of a formalized AR definition, algorithm choices primarily reflected the focus areas of a diverse research community. There has been an emerging body of research over the last decade focused on AR science and applications, including (but not limited to):

- Assessing prediction skill of operational hindcast systems and statistical models in predicting AR frequency, intensity, and landfall location (Wick et al. 2013; DeFlorio et al. 2018, 2019b,a; Nardi et al. 2018; Baggett et al. 2017; Mundhenk et al. 2018)
- Quantifying insurance losses and linkages between ARs and floods (Ralph et al. 2006; Paltan et al. 2017; Waliser and Guan 2017; Corringham 2018)
- Characterizing the sensitivity of AR statistics to climate change projections (Payne and Magnusdottir 2015; Gao et al. 2015, 2016; Shields and Kiehl 2016; Espinoza et al. 2018; Gershunov et al. 2019)

- Exploring linkages between AR-related water vapor transport and polar hydroclimate (Gorodetskaya et al. 2014; Mattingly et al. 2018; Nash et al. 2018)
- Establishing a connection between the combined effect of the AR-related anomalous heat and moisture poleward transport and major melt events in West Antarctica (Wille et al. 2019)
- Implementing machine learning techniques to improve forecasts of ARs (Chapman et al. 2019)
- Diagnosing the relationship between landfalling AR events and snowpack (Guan et al. 2010, 2013; Huning et al. 2017; Kim et al. 2018; Chen et al. 2019a,b; Huning et al. 2019; Hu and Nolin 2019)
- Identifying dynamical drivers of AR activity (Ryoo et al. 2013; Payne and Magnusdottir 2014, 2016; Hu et al. 2017; Fish et al. 2019)

The underlying conclusions of these scientific investigations depend critically on consistent and precise detection and tracking of AR events over time. At the same time, it is this diversity of scientific questions that has led to existing diversity of AR definitions. One of the major discussions during the workshop concerned the restrictive vs permissive methods in AR tracking. Particularly, focusing on extreme precipitation events over specific regions leads to applying more restrictive methods. In another application, when investigating the role of ARs in the poleward heat and moisture transport affecting the Polar Regions (i.e. traversing 70ºN/S), the definition of "extreme" is no longer the same compared to subtropical and midlatitudes. When AR tracking is done by global algorithms, restrictive methodologies are found to be more efficient in poleward moisture transport compared to more permissive ones. Important differences may arise as a result: e.g., AR duration, landfall location, intensity, and most importantly AR impacts. These issues are even more accentuated when considering AR characteristics and impacts in future climate scenarios.

Summary of Previous ARTMIP Workshops

The first ARTMIP workshop took place in San Diego, at Scripps/CW3E in the spring of 2017. It was at this first workshop that the experimental design and organization structure of ARTMIP were created. One important outcome was the decision to perform a one-month “proof of concept” experiment to test the mettle of the project’s design. The design itself, and the results from the proof-of-concept experiment were published in GMD in early 2018 (Shields et al. 2018a). The ARTMIP design consists of a tiered structure, where Tier 1 operates as a baseline for all ARTMIP intercomparisons. In Tier 1, each developer contributes an AR catalogue using MERRA-2 data from 1980 - June 2017: this is an essential requirement for entry into the project. Tier 2, the second phase of ARTMIP, is divided into different subtopics with the focus of understanding uncertainty in the context of topical scientific questions, such as, explaining how atmospheric rivers will change in a warmer climate. Subtopics addressed thus far include climate change in the context of high-resolution modelling and impacts, such as the relationship between ARs and precipitation; and climate change, in the context of multi-model intercomparisons designed to answer questions related to model uncertainty and climate change trends.

The second workshop, held in Gaithersburg, MD in the Spring of 2018, was held after Tier 1 catalogues were completed and analysis had begun. The purpose of the 2nd workshop was twofold:

(1) to diagnose basic AR metrics computed from the MERRA-2 catalogues, and (2) to design and discuss the details—including analysis goals and timeline—of the Tier 2 climate-change subtopics. A major scientific outcome of the 2nd workshop based on MERRA-2 analysis was the idea to "cluster" algorithms. For example, grouping algorithms by threshold type is one way to approach understanding uncertainty in AR metrics (Figure 3).

Absolute Methods	Relative Methods		
	Latitude-dependent		
	Anomaly above zonal mean	Anomaly above climatology	Percentile based
CONNECT500 CONNECT700 Gershunov Goldenson PNNL1_Hagos PNNL2_LQ Rutz TEMPEST	Gorodetskaya Shields	Mundhenk Walton	Brands_v1 Brands_v2 Brands_v3 Guan_Waliser Ramos teca_bard_v1 Viale Wille
Machine Learning	Latitude-independent		
cascade_ivt cascade_iwv TDA_ML	Lavers Payne Lora_global Lora_npac		

Global Methods	Regional Methods	
cascade_ivt cascade_iwv CONNECT500 CONNECT700 Guan_Waliser Lora_global Mundhenk Rutz teca_bard_v1 TEMPEST	Brands_v1 Brands_v2 Brands_v3 Gershunov Goldenson Gorodetskaya Lavers Lora_npac Payne PNNL1_Hagos PNNL2_LQ Ramos Shields TDA_ML Viale Walton Wille	(Europe, western U.S.) (Europe, western U.S.) (Europe, western U.S.) (western U.S.) (western U.S.) (Polar) (western Europe) (North Pacific) (western U.S.) (western U.S.) (western U.S.) (western Europe, south Africa, adaptable) (western U.S., western Europe, adaptable) (western U.S., adaptable) (southwestern South America) (western U.S.) (Polar)

Figure 3: Tables showing the names of ARTMIP Tier 1 methods grouped into (top) absolute / relative / machine learning clusters and (bottom) global / regional clusters. For the bottom table, the region(s) over which data is used from each method are given in parenthesis following the method name. Note that this is not a comprehensive list of all AR identification and tracking methods found in scientifically relevant literature. (Credit, J.Rutz)

A comprehensive analysis of the uncertainty in AR metrics (frequency, seasonality, duration, footprint) is described by Rutz et al. 2019, which is part of the "Atmospheric Rivers: Intersection of Weather and Climate" AGU special collection.

The second major outcome from the 2nd workshop was the launch of the Tier 2 climate change subtopics, which are described in greater detail in Ongoing ARTMIP Activities. This included defining scientific questions, experimental protocols, and the timeline. Both high-resolution single-model ensembles, and long multi-model climate projections were chosen as foci to answer different science questions. Our 3rd workshop, discussed in this report, was developed to dig deeper into our Tier 2 climate change subtopics, as well as explore future avenues in AR science where ARTMIP can lead the way. Details on the 2nd ARTMIP workshop can be found in a BAMS meeting summary (Shields et al. 2019) and in the published DOE meeting report (Shields et al. 2018b).

To date, six peer-reviewed manuscripts have been enabled by ARTMIP activities (Chen et al. 2018; Shields et al. 2018a; Chen et al. 2019b; Shields et al. 2019; Ralph et al. 2019a; Rutz et al. 2019).

THE 3RD ARTMIP WORKSHOP

ONGOING ARTMIP ACTIVITIES

TIER 1

The cornerstone of ARTMIP Tier 1, the summary paper, was accepted for publication in the month following the 3rd ARTMIP workshop (Rutz et al. 2019). This paper quantifies the uncertainty in observed (1980–2017) AR climatology on a global scale by providing a systematic and global inter-comparison between over 20 different AR identification and tracking methods. Key AR metrics include frequency, duration, seasonality, intensity or efficiency, and related precipitation. There is still work to be done to better quantify the uncertainty in observed AR impacts, particularly precipitation, and analyses of the Tier 1 data are ongoing to provide these results. Furthermore, several separate analyses, such as a comparison between reanalysis data sets, based on the Tier 1 data are planned.

In addition to the summary paper, Tier 1 activities have led to numerous presentations at venues such as the AGU Fall Meeting and the International Atmospheric Rivers Conference. Analysis of the Tier 1 dataset has revealed a number of useful concepts. One of these is the concept of "method restrictiveness", or in other words, the extent to which the criteria of each method limit the potential for AR identification. The benefit of such an approach facilitates comparison between methods. This concept came up several times during the workshop and is referenced frequently in this report. The development of a quantitative restrictiveness measure is an area of future work for ARTMIP, which could lead to better understanding and the recommendation of certain methods depending on the purpose of studies.

TIER 2 – C20C+ EXPERIMENT

The first experiment of the second tier of ARTMIP was initialized in October 2018. The motivating scientific questions for this experiment will be addressed in an overview paper that is to be submitted in late 2019. Generally, these questions surround the uncertainty in methods of comparison between algorithms that incorporate various thresholds (some of which are dependent on the base climate) and an exploration of the robustness of how AR-related impacts will change in the future. A list of questions is included below:

- How do the various treatments for moisture threshold affect climate change signals in ARs?
- How do different methods lead to uncertainty in understanding the thermodynamic and dynamical mechanisms that control how ARs change in a warmer climate?
- With a shifting baseline, what are the appropriate metrics for model evaluation?
- Do we see robust shifts in AR distribution, variability, or frequency? If so, by what mechanisms?
- What is the change in flood potential of future ARs, and how will this affect water management?

The baseline data were sourced from one model participating in the Climate of the 20th Century Plus Detection and Attribution project (C20C+, Stone et al. 2019). Simulations came from the finite volume dynamical core version of the Community Atmosphere Model, run at 25 km horizontal resolution, which was run by LBNL as part of the CASCADE SFA. The experimental design requires catalogues from each developer for the historical period (1979 - 2005) and for end-of-the-century RCP 8.5 (2079 - 2099) to facilitate a comparison of ARs in two climates. Catalogues from two additional historical ensembles (1995 - 2005) and one additional RCP 8.5 ensemble (2079 - 2084) were not required but generally contributed by participating groups. The high spatial resolution and temporal resolution of the simulations, as well as the multiple time slices, introduced an additional level of complexity compared to the original MERRA-2 experiment. This experiment involved 15 catalogues, 12 of which participated in the Tier 1 overview paper. New ARTMIP contributors were required to provide Tier 1 catalogues in order to provide a baseline of comparison to earlier results.

Initial results presented at the workshop (by Payne and Shields) indicate that clustering algorithms by restrictiveness can help explain the spread in how the latitudinal distribution of coastal ARs changes between the historical simulation and the RCP 8.5 scenario (Figure 4).

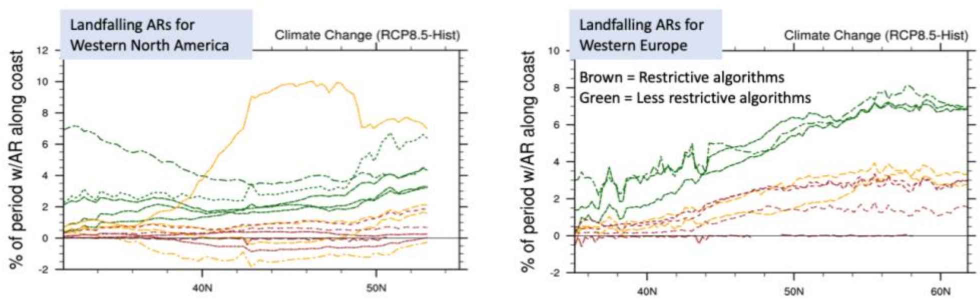

Figure 4: plots presented in the Tier2 C20C+ Overview discussion by Payne and Shields, showing how the latitudinal distribution of landfalling ARs changes between the historical and RCP8.5 C20C+ simulations. The line color indicates the *restrictiveness* of the method (assigned through an experimental, semi-objective method) (credit, C. Shields).

Tier 2 – CMIP5/6 Experiment

The CMIP5/6 experiment was conceived as part of the 2nd ARTMIP Workshop in 2018, and it was officially launched in September 2019 once data from the CMIP5 and CMIP6 experiments were collected. CMIP6 data were gathered as part of a multi-lab DOE effort to mirror large portions of the CMIP6 dataset at NERSC. The goal of the experiment is to provide clarity on several scientific questions:

- How do AR metrics (e.g., intensity, duration, frequency, landfall occurrence, category, etc.) change in future scenarios?
- How does this depend on the algorithm used?
- How does this depend on the region analyzed?
- How does uncertainty in AR tracking compare to model uncertainty?

The first question has been addressed to some extent in existing literature (focused on CMIP5; e.g., Gao et al. 2015; Lavers et al. 2015; Payne and Magnusdottir 2015; Radić et al. 2015; Warner et al. 2015; Ramos et al. 2016), and a key goal of this experiment is to assess the degree to which these results depend on the algorithm used. These questions parallel some of the questions addressed in the Tier 2 C20C+ experiment. The Tier 2 CMIP5/6 experiment complements the C20C+ experiment by focusing on fully-coupled Earth system model simulations. In contrast, the C20C+ experiment utilizes atmosphere-only simulations, with future SST boundary conditions generated by adding projected temperature anomalies to observed SSTs. Additionally, the multi-model aspect of the CMIP5/6 experiment will permit analysis of the relative roles of AR-tracking uncertainty and model uncertainty in future projections.

CMIP5 Model	Simulations	Year Start	Year End
CanESM3	1. Historical 2. RCP8.5	1. 1950 2. 2006	1. 2005 2. 2100
CSIRO-Mk3-6-0	1. Historical 2. RCP8.5	1. 1950 2. 2006	1. 2005 2. 2100
CCSM4	1. Historical 2. RCP8.5	1. 1950 2. 2006	1. 2005 2. 2100
IPSL-CM5A-LR	1. Historical 2. RCP8.5	1. 1950^ 2. 2006	1. 2005 2. 2100
IPSL-CM5B-LR	1. Historical 2. RCP8.5	1. 1950^ 2. 2006^	1. 2005 2. 2100
NorESM1-M	1. Historical 2. RCP8.5	1. 1950* 2. 2006	1. 2005 2. 2100

CMIP6 Model	Simulations	Year Starts	Year Ends
BCC-CSM4-MR	1. Historical 2. SSP585	1.1950+ 2. 2015	1. 2014 2. 2100
IPSL-CM6A-LR	1. Historical 2. SSP585	1.1950 2. 2015	1. 2014 2. 2055
MRI-ESM2-0	1. Historical 2. SSP585	1.1950 2. 2015	1. 2014 2. 2100

Table 1: Models, scenarios, and temporal durations of simulations used in the CMIP5/6 experiments. (top) CMIP5 (bottom) CMIP6.

During the planning phase of the experiment, it was decided to focus on both CMIP5 and CMIP6 for several reasons: inclusion of CMIP5 would allow direct comparison of results from existing papers examining ARs in CMIP5 data, inclusion of CMIP6 would yield results from the latest round of model simulations that will be contributing to IPCC AR6, and comparison between the two would allow assessment of the degree to which next-generation model improvements change the simulation of ARs. The experiment is focused on assessing the difference between AR characteristics in the present climate (*historical* simulations) and future scenarios (*RCP8.5* simulations for CMIP5 and *SSP585* simulations for CMIP6). In the initial CMIP5/6 experiment launch, fields necessary to identify ARs (e.g., IVT) were calculated from six CMIP5 simulations and three CMIP6 simulations (Table 1). The specific simulations were chosen based on a combination of data availability, simulation duration, and availability of historical and future simulations in the same simulation ensemble. The latter constraint ensures that simulations are temporally continuous between the historical and future simulations, which permits trend analysis across the historical and future simulations.

Discussions in the workshop focused on whether to include more CMIP5 and CMIP6 simulations in the experiment. Several CMIP5 simulations were not included because the necessary data were not present at NERSC at the time of processing and re-downloading the data would have substantially delayed the experiment. Additionally, several CMIP6 simulations were not included due to variations in the formatting of model output that will require substantial effort to accommodate the data processing code. Adding more simulations would require additional time to both obtain and process the simulation output and to run the AR tracking algorithms; time was a consideration due to the group's interest in submitting a paper on this experiment in time for it to be included in the IPCC AR6. Ultimately it was determined that the subject of time was somewhat moot since, at the time of the workshop, no groups had yet run AR detection algorithms on the CMIP5/6 data[1]. Also, it was noted that the Working Group 2 volume of AR6, which focuses on climate change impacts, might be an appropriate place for the experiment to be referenced; this would provide more time for data processing. The group did not decide on whether or not to include more simulations.

SYNTHESIS – AR TRACKING UNCERTAINTY

The discussions of the first two days of the workshop centered around activities surrounding Tier 1 and initial results for the C20C+ experiment. At the end of the second day of the workshop, participants broke into small groups to explore the sources and impacts surrounding tracking uncertainty and how our results could inform other tracking intercomparison methods.

IMPACT OF UNCERTAINTY ON OUR SCIENTIFIC UNDERSTANDING

Algorithmic spread: A primary source of uncertainty is the lack of a theoretical, quantitative definition of ARs. The AMS definition defines ARs in a purely qualitative manner, and it does not provide quantitative guidance (Ralph et al. 2018). While workshop participants noted that the AMS definition has important benefits (e.g., providing flexibility for regional variations in defining ARs), the lack of constraint in quantitatively defining ARs has contributed to some of the disagreement across AR algorithms, each of which has been authored with its own concept of AR and ultimate goals for detection in mind. Throughout the ARTMIP effort, we have observed that the characteristics of ARs (such as intensity, duration, and landfalling latitude) vary by detection algorithm: for example, the coastal latitude range of a landfalling AR is likely to shrink when detected by a more restrictive algorithm, as these algorithms tend to pick up the intense AR IWV/IVT core while ignoring surrounding weaker grid points. Disagreement in landfall location then leads to disparities in the attribution of AR impacts (e.g., precipitation, wind extremes), as such attribution will be sensitive to how one defines AR boundaries. It was also noted that differences across algorithms are not limited to the spatial dimensions but can influence the time-stitching of AR conditions into cohesive AR

[1] In the month following the ARTMIP workshop, 6 groups contributed data from their AR detection algorithms.

events; this then results in uncertainty in the duration of landfalling ARs, as well as in the identification of any merging or splitting of AR objects. These uncertainties in AR characteristics ultimately impede our understanding of the dynamics and impacts of ARs from synoptic to centennial timescales. Uncertainties also lead to difficulties in communicating what ARs are and their impacts to the broader science community and the general public.

AR predictability: There was some discussion about the degree to which disagreement in AR detection affects the predictability of ARs across timescales: from synoptic, to subseasonal, to multidecadal. For example, a less restrictive algorithm may capture an AR event earlier or later in its life cycle than a more restrictive one. Such discrepancies (and others) across algorithms then cascade into differences in our understanding of AR dynamics, especially when it comes to the larger dynamical environments and other processes that lead to AR formation, intensification, and/or propagation. In particular, how AR detection uncertainty affects the prediction of AR-related precipitation is a key feature to explore in the future. This topic is especially relevant regarding the needs of local reservoir managers (and the community members they serve), who would benefit greatly from accurate AR landfall and precipitation predictions. Ultimately, this topic raised the question of how uncertainty in AR detection might affect the upper limit of AR predictability.

Climate change: Understanding how ARs might change in a warmer climate is a primary goal for two of the ARTMIP Tier 2 experiments. Under a global warming scenario, an increasing trend in AR frequency is demonstrated in climate projection models (Dettinger 2011; Lavers et al. 2013; Warner et al. 2015). Still, research is needed to quantify the sensitivity of each algorithm to the changing IVT and IWV fields in the future, as some research suggests that ARs are projected to have wider geometric shapes and stronger intensities (Espinoza et al. 2018). Some practical questions were raised: does the algorithm introduce artificial constraints on future climate change results, and should the algorithm tune its parameters to suit the future climate scenario better? Taking detection uncertainty into account when analyzing trends in AR counts is crucial because the trends may be sensitive to changes in parameters (such as length and width) of AR conditions in the future.

Dealing with Uncertainty

Gap: The physical drivers of AR genesis, development, and dissipation are not completely understood, and this lack of understanding impedes our ability to constrain the quantitative definition, detection, and tracking of ARs.

Research Priorities: There is a need for more basic research on the dynamics and lifecycle of ARs.

AR definition: There was considerable discussion during the workshop about the need for refining our theoretical understanding of the AR lifecycle: from genesis to dissipation. Some basic questions were identified that, if answered, could help reduce quantitative uncertainty in the definition of ARs:

1. What causes the genesis of ARs?
2. What controls the frequency of ARs?
3. What controls the duration of ARs?
4. Are ARs always associated with ETCs?

5. Are ARs always associated with some form of baroclinic instability?
6. Are there "flavors" of ARs?

Analysis and intercomparison of the dynamics associated with ARs would be a valuable and logical step toward providing answers to some of these questions. Recent work by Zhou et al., which was presented during the workshop, shows that different phases of the MJO initiate equatorial Rossby and Kelvin waves—in a classic Gill response to tropical heating anomalies—that modulate the frequency and location of AR genesis in the Pacific. This analysis addresses questions 1 and 2, and more analyses of this type would help refine our understanding of the formation of ARs.

It was also postulated that there might be different "flavors" of AR, with different generating physical mechanisms controlling their lifecycle; e.g., if some are associated with transient baroclinic instabilities and others are associated with quasi-stationary geopotential height gradients. Relatedly, there was also discussion about the utility of analyzing the dynamics (e.g., baroclinicity) associated with ARs across different algorithms. This could provide insight into the underlying dynamical processes that influence the evolution of ARs at various stages of their life cycles.

Gap: ARTMIP has documented different classes of AR detection algorithm, which partially explains the spread in AR detection results.

Research Priorities: Objective, and physics-informed, clustering approaches could help establish a quantitative vocabulary for explaining differences among AR detection algorithms.

Leveraging differences in algorithms: The range of features detected by algorithms in existing Tier 1 and 2 datasets is an immediate and ongoing source of uncertainty that has provided challenges for those analyzing ARTMIP output. Aside from relative vs. absolute methods, there is no a priori way—at least that the ARTMIP community has so far identified—to group AR detection methods in a way that helps make sense of the broad range of AR characteristics observed across algorithms.

Despite the focus of the discussion on existing uncertainties in AR detection techniques and impacts on AR science, the group found a cause for cautious optimism: analogous to different physics parameterizations in climate models, different AR algorithms were developed with different goals in mind, and thus may each have distinct applications. This suggests that there exists a logical approach to group and categorize existing AR algorithms to facilitate understanding of how and why AR characteristics and metrics differ among algorithms. The restrictive-vs-permissive categorization (e.g., see Figure 3) is an early attempt at categorizing AR tracking algorithms. The group also discussed the possibility of using statistical methods, such as K-means clustering, to objectively categorize AR detection algorithms. If there are different AR flavors, there is the possibility that different detection methods tend to preferentially identify different AR flavors; objective clustering methods could help clarify this.

Expert Identification of ARs and Machine Learning

A unique component of the 3rd ARTMIP Workshop, relative to previous ARTMIP workshops and to other discipline-focused workshops, is the inclusion of a workshop session devoted to having experts hand-identify ARs. The purpose of the session was twofold: (1) to assess the extent to which differences among algorithms might reflect differences in opinion about what ARs are, and (2) to develop a dataset that can form the basis for machine-learning-based AR detectors.

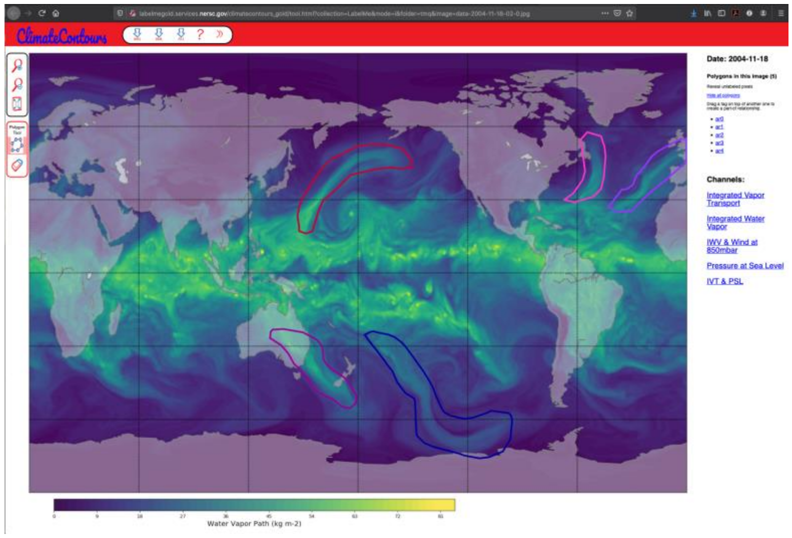

Figure 5: A screenshot of the ClimateNet tool used by ARTMIP participants to label ARs and TCs.

This workshop session took advantage of major investments at LBL in machine learning: it leveraged the development of ClimateNet, which was developed at LBL/NERSC to facilitate the collection of hand-labeled weather datasets (see **Figure 5**). This component of the workshop was substantial: half of a day, out of a 2.5-day workshop, was devoted to this effort. Dr. Karthik Kashinath facilitated the workshop, which included over 15 workshop participants who labeled 660 time slices of data during the session. Interested researchers should contact Dr. Karthik Kashinath.

Early results from the dataset (analyzed in the month following the workshop) suggest that the spread in AR detection algorithms may reflect the spread in expert opinion regarding how ARs should be defined: **Figure 6**. It should be noted that participants were only shown instantaneous meteorological fields (like shown in Figure 5; participants could toggle among several fields, including IWV, IVT at 850 hPa, vorticity, and sea level pressure), and that climatological information was not presented.

The LBL/NERSC group has immediate plans to utilize this dataset to train machine learning methods to emulate expert AR identification. It was decided at the workshop that the dataset would be released publicly, following the publication of a manuscript describing the initial use of this dataset in a machine learning application.

Gap: It is not clear whether differences among expert opinions about AR boundaries are as large as differences among AR detection algorithms.

Gap: Existing machine learning methods for detecting ARs are based on heuristic algorithms.

Research Priorities: Future AR research, especially research using machine learning, should leverage results from the ARTMIP ClimateNet campaign.

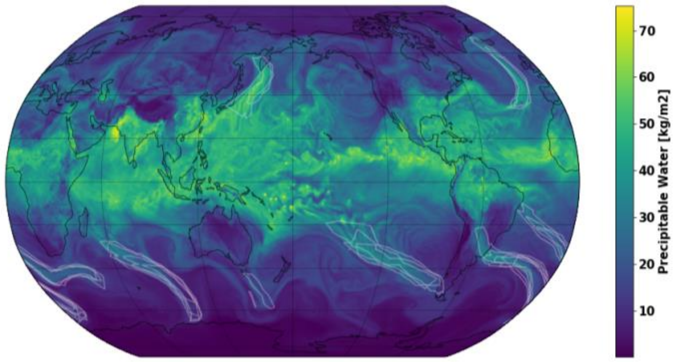

Figure 6: Comparison of expert AR identifications from 06 September 2009 of a 25 km CAM5 AMIP simulation. The background field shows IWV, and the white contours show outlines of ARs identified by 15 ARTMIP participants. (credit, T. O'Brien)

Summary of New Understanding Gained through ARTMIP

Initial results from the Tier 2 C20C+ experiment demonstrate that qualitative conclusions about ARs and climate change can vary, depending on the algorithm used. Figure 4 shows that most algorithms project an increase in the occurrence of landfalling ARs in western North America, while there are a few that project no change—or even a slight decrease.

Workshop participants generally agreed that grouping or classifying algorithms could aid our understanding of the origins of this uncertainty. Intrinsically, algorithms include subjective choices on the importance of various parameters and thresholds in their make-up. Algorithm developers come from a wide range of research communities. As such, their approaches are designed to explore different aspects of ARs (i.e., dynamics or hydrological impacts on land). Results in Tier 1 showed that, generally, algorithms identify similar features. Along the western coastlines of North America and Europe, for example, there are similarities in the seasonality and landfalling latitude of AR conditions. However, differences appear when comparing the spatial footprint of AR grid points in a single timestep and the frequency of occurrence of AR conditions. These differences become especially important when considering the representation of climate change (Figure 4).

AR algorithms that are very restrictive in their approach seem to show little to no climate change signal (Figure 4). This may be because the more restrictive approaches implicitly or explicitly account for the thermodynamic responses of warming. ARs that are less restrictive show a large increase in AR conditions and frequencies. The diversity of these results suggests that guidance should be provided to ensure the appropriate use of AR algorithms available to the scientific community. Future research should seek to understand why and when different algorithms (or classes of algorithms) lead to qualitatively different conclusions. It may also be beneficial to develop AR detection approaches that can explicitly represent the range of possible AR detection characteristics.

KNOWLEDGE GAPS AND PROSPECTS FOR PROGRESS

POTENTIAL FOR ADVANCING AR TRACKING EFFORTS

Gap: Most current AR detection algorithms are primarily 2D, which is partly due to computational considerations.

Research Priorities: Research groups with expertise in, and access to, high performance computing resources should develop detection approaches that leverage the 3D structure of ARs.

Leveraging the 3rd Dimension: Several gaps that may limit the ability of current AR tracking results to improve our understanding and prediction of AR physics and impacts were identified. First, current detection algorithms are all based on two-dimensional horizontal patterns. This choice is partly influenced by the computational resources generally available and by data limitations/availability (e.g., most satellite datasets are 2D). In reality, ARs have complicated three-dimensional structures in nature. The physical features of extra-tropical cyclones likely make simple thresholding methods unfeasible. However, applying detection or tracking algorithms to large, volumetric data is computationally highly complex and requires substantial resources (e.g., memory) that make such work impractical for many. Research groups with sufficient computing resources could advance AR science by developing algorithms that consider the three-dimensional nature of ARs.

Gap: Existing tracking methods do not consider that there might be different types, or “flavors”, of ARs.

Research Priorities: Research is needed to determine whether there might be different flavors of ARs, and if so, whether this might lead to different classes of tracking algorithms.

Considering AR “Flavors”: Second, prevailing tracking methods are based on horizontal moisture fields or moisture transport and have not considered different "flavors" of AR. This includes the ability to distinguish among ARs with different physical characteristics, such as tropical moisture filaments, ARs that originate from extra-tropical cyclones, those encompassing uplifting motions versus not, ARs embedded in steering flow, etc. This is a critical step to enable further understanding, accurate identification, and improved forecasting of ARs and associated physical systems. Ideally, the "flavored" AR tracking methods could incorporate connections to surface precipitation, interactions with synoptic-scale baroclinicity, and interactions with other phenomena such as tropical cyclones and jet streams. It is worth noting that this research priority is closely related to the research priority about basic research on AR lifecycle noted on page 11.

Among these, the apparently missing link to surface precipitation resonates with the needs to better quantify the uncertainty in observed AR impacts in the ongoing Tier 1 plan. AR research is significant in the first place because of its impacts on the environment and society. It is important that the community not lose this focus while advancing theoretical issues. Ultimately, the appropriateness of an AR tracking algorithm is determined by the impacts to be studied or predicted.

Gap: There are a growing number of different AR detection codes reflecting a diversity of quantitative AR definitions. Software differences make the systematic comparison of these definitions difficult.

Research Priorities: Develop open-source computational frameworks to facilitate the implementation of new and existing AR detection methods.

Open-source Feature Detection Frameworks: Lastly, common open-source computational approaches will help broaden and speed up AR-related research. The community can benefit from some open-source codes that make efficient AR tracking for operational tasks or exploratory studies. In addition, open-source codes showing discretization schemes for calculating terms and equations used for AR identification can help ensure consistency across all related physics-driven data analysis studies at the numerical level. The RGMA-funded Toolkit for Extreme Climate Analysis (TECA) may prove to be a useful starting point for developing an open-source ARTMIP framework, as it is designed to facilitate the development of modular data processing pipelines on HPC systems.

Upcoming Areas of Exploration for ARTMIP

Beyond the foundational Tier 1 and 2 applications of ARTMIP tracking algorithms to midlatitude ARs discussed previously, several possible near-term avenues emerged from the workshop discussions that were ripe for deep exploration. These topics had clear leadership and commitment from workshop participants in developing experiments to address associated knowledge gaps; these will evolve into formal ARTMIP experiments over the course of the next year or two. This differs from the general knowledge gaps discussed elsewhere, which remain open topics. These imminent research topics are summarized here, along with their corresponding experimental protocol.

Gap: It is not clear the extent to which uncertainty in reanalyses combines with uncertainty in AR detection methods to impact our understanding of observed ARs.

Comparison of AR character across reanalysis products: The first joint ARTMIP effort in 2017 (Tier 1) focused on the differences between tracking algorithms as applied to the MERRA2 reanalysis. MERRA2 was chosen for this initial study since it was (and remains) a high-resolution, high-quality modern reanalysis product with data available from 1980 through the present. Moving forward, an assessment of tracked ARs and AR characteristics in other high-resolution modern reanalysis products (such as ERA5) will allow us to better understand uncertainties from individual events and within computed AR climatologies, and define comparison metrics across ensembles. This analysis will further provide an opportunity for answering key science questions, including those related to the physical structure of ARs, whether reanalysis is of sufficient quality to evaluate connections between IVT and precipitation, and the statistical relationships that exist in the context of ARs (e.g. connections between extratropical cyclone sea-level pressure and AR IVT, or between IVT and orographic precipitation totals). Multiple ensemble members in the ERA5 product will allow us to assess variability in a single product versus across products.

Even among modern reanalyses, there is a widespread in relevant fields among all available products, with differences in algorithms for data assimilation, spatial and temporal resolution, as well as uncertainty within a single product. Differences are particularly apparent with cloud water (a directly assimilated field) and meridional heat transport in available products. Within a single dataset, there are notable discrepancies as newly assimilated microwave products come online. These differences are also apparent in post-processed fields that emerge from AR tracking, such as a spread in the number of AR days in Washington State. Although climatological differences can be accounted for via retuning of the AR tracker, individual events can often be very different across reanalyses and hence appear different under tracking.

The AR reanalysis project will consist of an analysis of tracked ARs across multiple modern reanalysis products (MERRA2, ERA5, CFSR, JRA55, 20CR). Older reanalyses are not considered because assimilation is poor compared with modern products. Although IVT should be recomputed among these products for consistency with previous efforts, because 3D variables are often not available at the frequency of diagnostic 2D fields, we expect that the reanalysis-provisioned IVT will enable tracking at high temporal resolution. Spatial resolution sensitivity of AR tracking schemes remains an issue in this effort that requires further consideration, with reanalysis products ranging from 0.25 degrees (ERA5) to 1.5 degrees (JRA55). Interested researchers should contact Dr. Allison Collow.

> **Gap:** There is clear evidence that ARs have major impacts on high-latitude energy and water budgets, but it is not clear the extent to which uncertainty in AR tracking methods competes with other sources of uncertainty on basic questions like "what is the relative importance of heat versus moisture transport within ARs that impact high latitudes".

Tracking and character of high-latitude ARs: High-latitude and polar ARs are often not considered alongside their midlatitude counterparts since the integrated water vapor content in these systems usually does not meet the thresholds defined for the midlatitudes. Nonetheless, vapor transport into the Arctic and Antarctic by high-latitude ARs is associated with strong melt events. To date, only two algorithms applicable in polar regions have been assessed as applied to MERRA2 reanalysis (Gorodetskaya et al. 2014; Wille et al. 2019). In general, good agreement was observed between these algorithms, although there were some differences in the shape of the AR objects as they made landfall. There are a number of other algorithms in the ARTMIP project which, although they were not developed for polar regions in particular, do have global coverage and could be included in a more comprehensive intercomparison (e.g., Gorodetskaya et al. 2017).

The high-latitude AR project will consist of an intercomparison of tracking algorithms in high-latitude regions, defined as poleward of 70 degrees latitude. The focus will be on specific case studies of major melt events driven by poleward transport of water vapor. Two tier 2 papers using MERRA2 reanalysis are proposed, one for each of the Arctic and Antarctic. Basic statistics, such as the number of events entering the polar regions, event magnitude, and landfall location will be accumulated and compared among algorithms. The core science questions of this effort include: What is the relative importance of heat versus moisture transport within these systems? What is the relationship between high-latitude ARs and extratropical cyclones? And what are the impacts of effects of ARs on temperature modulation (e.g., are they impacted by / impact Arctic amplification)? Finally, an assessment of AR changes in the future climate will be performed using CMIP6 data to assess changes in the character of high-latitude ARs. Interested researchers should contact Dr. Irina Gorodetskaya.

Gap: ENSO teleconnections may play an important role in modulating ARs, and AR tracking uncertainty may be important in developing and understanding of ENSO-AR interactions.

Sensitivity of ARs to ENSO in a multi-resolution model product: A recent ensemble of global simulations has been developed using MPAS with 15km grid spacing over the northern hemisphere and 60km over the southern hemisphere. The multi-resolution product consists of 10 simulations for March 1st through May 15th of the following year (14.5 months total) from selected historical years covering the range of ENSO phases (from strong La Niña through strong El Niño). Counterpart simulations were conducted under the global pseudo-global warming methodology by adjusting initial conditions and sea-surface temperatures by the CMIP5 future minus historical difference (2079-2099 minus 1979-1999) and applying a corresponding adjustment to sea ice.

The MPAS-based ENSO sensitivity project will consist of an application of AR tracking algorithms from ARTMIP to the multi-resolution model product ensemble. The character of ARs across phases of ENSO will be assessed to understand how AR character and climatological statistics are correlated with ENSO. The character of ARs between future and historical will be assessed to quantify future changes in ARs associated with ENSO conditions. Interested researchers should contact Dr. Allison Michaelis.

Gap: ARs may have differed substantially in past climates, and understanding ARs in paleoclimates may be useful for understanding future AR behavior; this topic remains largely unexplored.

ARs under climatic conditions of the distant past: Two recent studies (Kiehl et al. 2018; Lora et al. 2017) identified a robust change in AR character in response to climatological changes from the PETM and the LGM, respectively. This work demonstrated that past climatologies are useful for understanding potential AR behavior in future or alternate climates. By leveraging paleoclimate records we can constrain climatological conditions in the Earth's past and use these climatologies as a foundation for studying atmospheric rivers under realistic conditions that differ from those of the present day. Because of the substantially different sea-surface temperatures and meteorological conditions present during these periods, this study could enable a better understanding of interactions between ARs and large-scale modes of climate variability like the MJO or ENSO.

The paleo-ARTMIP project aims to apply the ARTMIP suite of tracking algorithms to conditions from the LGM and the last deglaciation. Unfortunately, simulations from PMIP cannot be used for this analysis, as these protocols did not provide IWV or IVT at sufficient temporal resolution (as in PMIP3) or did not produce sufficient output for analysis (as in PMIP4). Consequently, new simulations with CESM are proposed for this project with prescribed forcings from the paleo record. Key science questions addressed would include: Are detection methods robust across climate states? How much of the uncertainty in how AR climatology varies with background climate state is due to differences between methods? And can historical climates inform our understanding of ARs under climate change? Interested researchers should contact Prof. Juan Lora.

Research Priorities: Active participation by new and existing AR research groups in upcoming Tier 2 ARTMIP Experiments: Tier 2 Reanalysis, Tier 2 High-Latitude, Tier 2 MPAS-ENSO, and Tier 2 paleo-ARTMIP.

EMERGING AREAS OF AR RESEARCH

AR research had been restricted to a few areas of the world, with a strong focus on the eastern North Pacific and associated impacts on the contiguous North American west coast. However, in the last decade, special attention has been given to other regions of the world where the AR influence is also important, like western Europe, western South Africa, the South Pacific, and even in the polar regions. Most of the studies in other regions of the world take into account the local climatology and the different AR flavor and their genesis. The AR scale (Ralph et al. 2019b) was originally developed for the US West Coast, which is based on setting a minimum 250 kg/m/s for events. While this threshold is adequate for that region, preliminary results show that for western Europe the threshold is equivalent to ~300 kg/m/s. This motivates taking local climatology into account when developing or adapting ARs detection algorithms.

The spectrum of AR detection algorithms used by ARTMIP can be categorized based on the strictness of criteria that they use to consider a water vapor signature an AR. Less restrictive algorithms have lenient criteria to classify an AR, which lead to frequent and large spatial footprints of AR conditions while more restrictive algorithms have strict criteria, which lead to less frequent and smaller footprints. For example, the Rutz algorithm has relatively fewer criteria can be considered permissive, as its sole criteria are a low IVT threshold of 250 kg/m/s and a minimum length of 2,000 km, while CONNECT700 can be considered very restrictive, as its threshold criteria for IVT of 700 kg/m/s is only exhibited in strong atmospheric rivers. Quantifying algorithm restrictiveness as a basis for comparison and research application is an emerging goal of ARTMIP. This approach allows for intercomparisons between sets of AR detection methods and provides a basis for the recommendation of products. For example, with a scale or score to choose from, the members of ARTMIP can recommend products to use for studies on the impacts of AR-related precipitation. Impacts-focused studies can benefit from algorithms that capture the full range of impacts of overland ARs, even after the IVT signature falls off after landfall. On the other hand, studies on the change in intensity and frequency of extreme ARs from climate change may benefit more from restrictive products.

In addition, the AMS definition (Ralph et al. 2018) states that ARs are defined as a "A long, narrow, and transient corridor of strong horizontal water vapor transport that is typically associated with a low-level jet stream ahead of the cold front of an extratropical cyclone," however the majority of the definitions in ARTMIP do not take into account the analysis of baroclinicity in vicinity of AR (the only exception is the Viale et al. 2018 method for the ARs that hit Chile) nor do they account for the three-dimensional aspect of the moisture transport, which can be important in the regions where the orographic lifting is not the main driver of the precipitation due to an AR.

The reemergence of AR research into the global research community was driven by studies into the impacts of AR precipitation over land, where they have been found to frequently produce the heaviest flooding events in midlatitude coastal regions. Some newly emerging research strongly suggests that precipitation from ARs is also responsible for short-duration high-volume melt events in arctic regions. However, the impacts of AR precipitation onto the ocean's surface has yet to be a focus of research. Questions that can be answered include: how does AR precipitation influence surface sea surface (SS) temperature, SS salinity, or SS chlorophyll production; what do these changes mean for the species that reside in the upper levels of the ocean; and what effects does it have on the mixed layer of the ocean? Investigation into these questions can be undergone with multi-agency efforts that use a multitude of ocean data from satellites, planes, buoys, etc., that can provide valuable information about sea surface interactions during extreme AR precipitation events. Such information can be useful for improving the skill of global ocean and regional downscaling and high-resolution climate modeling. Most observational studies and reconnaissance campaigns are focused on the western U.S., and therefore most AR knowledge outside U.S. is based mostly on remote sensing, reanalyses, and models. There are therefore numerous opportunities for new research in the observational field.

An emerging field in AR research is the study of isotopes in the water vapor and precipitation during ARs to analyze their sources and the transport of water vapor, which can validate studies that use Lagrangian models to investigate water vapor transport. A good example of this is Bonne et al. 2015, where the water vapor isotopic composition using surface in situ observations in Bermuda Island, South Greenland coast, and northwest Greenland ice sheet were compared with Lagrangian moisture source simulation to study the influence of an AR in the arctic melt during the 2012 summer. However, the lack of studies where the heat, energy, and temperature transport to the polar regions due to ARs are analyzed is evident.

ARTMIP GOING FORWARD

The enthusiasm for ARTMIP was evident during the workshop, especially when discussing potential future areas of exploration as described Upcoming Areas of Exploration for ARTMIP. To this end, plans were made to expand the ARTMIP timeline to include two new Tier 2 subtopics, e.g. Reanalysis sensitivity and Paleoclimate.

The comparison of ARTMIP algorithms applied to reanalysis products can be approached either with a focus on differences due to product resolution, differences across the various reanalyses products themselves, and/or the uncertainty within a single reanalysis product (that is, the need for ensembles of each product). To begin, ARTMIP will focus on comparison across different products, such as MERRA-2, ERA-5, 20CR, JRA-55, and CFSR. A model for this approach can be taken from an ARTMIP early start publication (Ralph et al. 2019a) that compared a few reanalysis products and several AR identification methods at one observation point located at Bodega Bay, CA. Plans for a telecon to finalize the experimental design and begin catalogue creation is projected for next year, 2020.

Paleoclimate simulations with a focus on cold climates will be an ARTMIP Tier 2 subtopic. Up until now, only future climate change and global warming has been considered. Now, we will turn our attention to past, cooler climates, specifically the Last Glacial Maximum (LGM) and the Last

Deglaciation. Partnering with Yale and U.Mass, LGM and Last Deglaciation CESM simulations will be provided for ARTMIP participants to contribute catalogues late next year, 2020 into 2021.

ARTMIP will continue to provide the community with AR catalogues across all subtopics with the aim of facilitating scientific discourse and forwarding our understanding of atmospheric rivers. We will accomplish this by continuing our activities (Master ARTMIP Timeline), contributing to the body of scientific literature, and participating in scientific meetings with a short-term goal of proposing sessions at IARC 2020 in Chile, and AGU 2020.

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DAY ONE – Wednesday, October 16, 2019

9:00-9:15am	Welcome and Introduction	*Renu Joseph*

SESSION I

9:15 – 9:40 am	Atmospheric Rivers and Impacts on the Western US	*Jon Rutz*
9:40 – 10:05am	Atmospheric Rivers on the Iberian Peninsula	*Alexandre Ramos*
10:05-10:30am	Importance of Atmospheric Rivers for the Cryosphere	*Irina Gorodetskaya*

10:30-10:45am – Group Discussion, AR Importance – refreshments will be served

10:45 – 11:10am	Atmospheric Rivers and MJO	*Yang Zhou*
11:10 – 11:35am	Summary of Previous ARTMIP Workshops	*Christine Shields*
11:35 – 12:00pm	Tier 1 Status and Summary	*Jon Rutz*

12:00-1:30pm – LUNCH – no host, please return to Wang Hall by ~1:25pm

1:30 – 1:45pm	Tier 2 C20C+ Experiment Overview and Status	*Ashley Payne*
1:45 – 3:00pm	Discussion and Results from Tier 2 C20C+	*Ashley Payne, moderating*

3:00-3:15pm – Group Discussion, Tier 2 C20C+ – refreshments will be served

3:15 – 3:45pm	Tier 2 C20C+ Priming Discussion	*Ashley Payne, moderating*
3:45 – 4:00pm	Tier 2 CMIP5/6 Experiment Overview and Status	*Travis, O'Brien*
4:00 – 4:30pm	CMIP6 Update/Discussion	*Michael Wehner, Sasha Gershunov*
4:30 – 5:00pm	Tier 2 CMIP5/6 Experiment Priming Discussion	*Travis O'Brien, moderating*

5:30–6:30pm POSTER SESSION / Mixer – refreshments will be served

SESSION II – POSTERS

II-a:	Vector-valued spectral analysis of complex flows	*Joanna Swalinska*
II-b:	Influences of Pacific Ocean domain extent on the western US hydroclimatology in variable-resolution CESM	*Alan Rhoades*
II-c:	Western U.S. Hydroclimate Variability	*Christina Patricola*
II-d:	Topological Data Analysis and Machine Learning for AR detection	*Karthik Kashinath*
II-e:	A Bayesian AR Detector for Quantifying Tracking Method Uncertainty	*Travis O'Brien*
II-f:	Impact of Distinct Origin Locations on the Life Cycles of Landfalling Atmospheric Rivers over the U.S. West Coast	*Yang Zhou*
II-g:	Uncertainty in AR contributions to the Iberian Peninsula precipitation	*Alexandre Ramos*
II-h:	Tracking Atmospheric Rivers Globally: Spatial Distributions and Temporal Evolution of Life Cycle Characteristics	*Bin Guan*
II-i:	Creation of AR indices customized for studying surface hydrometeorological impacts	*Chen Zhang*
II-j:	Heat Transport by Atmospheric Rivers	*Christine Shields*
II-k:	Atmospheric River CONNECT-Lifecycle AR detection for object-based analysis	*Eric Shearer*

II-l:	Characterizing the size, lagrangian properties, and coherent structures of ARs	*Héctor Inda Díaz*
II-m:	Atmospheric river climatology in Polar Regions: algorithm comparison ipsum lorem	*Irina Gorodetskaya*
II-n:	Machine learning techniques for tracking of atmospheric phenomena: supervised and unsupervised approaches	*Mikhail Krinitsky*
II-o:	Changes to the frequency of meteorological patterns associated with atmospheric rivers ipsum lorem	*Naomi Goldenson*
II-p:	Divide and Recombine Analysis of Atmospheric Rivers	*Wen-wen Tung*

DAY TWO – Thursday, October 17, 2019

SESSION III

9:00 – 9:45am	Tier 2 C20C+ Discussion Revisited	*Christine Shields, moderating*
9:45 – 10:10am	Tier 2 C20C+ Paper Planning	*Ashley Payne, moderating*

10:10-10:17am – Group Discussion, Tier 2 CMIP5/6 – refreshments will be served

10:17 – 10:45am	Great Shakeout Earthquake Drill	
10:45 – 11:15am	Tier 2 CMIP 5/6 Discussion Revisited	*Michael Wehner, moderating*
10:45 – 11:15pm	Tier 2 CMIP 5/6 Paper Planning	*Travis O'Brien, moderating*

12:00-1:30pm – LUNCH – no host, please return to Wang Hall by ~1:25pm

1:30 – 2:15pm	Tier 2 Reanalysis Paper Discussion	*Bin Guan, Allie Collow, moderating*
2:15 – 3:00pm	Tier 2 Cryosphere Paper Discussion	*Irina Gorodetskaya, moderating*

3:00-3:15pm – Group Discussion, Tier 2 Reanalysis – refreshments will be served

3:15-3:30pm	Tier XX Multi-Resolution MPAS	*Allison Michaelis*
3:30-3:45pm	Tier XX Paleo ARTMIP	*Juan Lora*
3:45 – 4:45pm	Knowledge Gaps and Prospects for Progress	*Alexandre Ramos*
4:45 – 5:30pm	ARTMIP Going Forward	*Jon Rutz, moderating*

5:00–6:30pm SYNTHESIS BREAKOUT GROUPS / Mixer – refreshments served 59-3101

Group I: 59-3049:Impact of uncertainty on our scientific understanding
Group II: 59-3104 Dealing with uncertainty
Group III: 59-3054 Sources of, and prospects for reducing, uncertainty
Group IV: 59-4101 Potential for synergy with non-AR tracking efforts

DAY THREE – Friday, October 18, 2016

9:00 – 10:30am	AR Labeling Tutorial and Working Session	*Karthik Kashinath*

10:30-10:45am – MORNING BREAK – refreshments will be served

10:45 – 12:15pm	Labeling Working Session 2	*Karthik Kashinath*
12:15 – 12:30pm	Closing Remarks and Next Steps	*Travis O'Brien*

Date	Topic	Comment
Oct 16-18, 2019	3rd ARTMIP Workshop	Held at LBNL
Nov, 2019	Tier 1 Overview	Estimated Acceptance Date
Nov 15th, 2019	Tier 2 CMIP5/6 Catalogues Due	Lead Travis O'Brien
Dec 9-13th, 2019	AGU	Spreadsheet of presentations
Dec 31st, 2019	Special Collection Closes	Extension Request Pending AGU journals
Dec 31st, 2019	C20C+, CMIP5/6 Overview Papers Submitted	Leads: Ashley Payne and Travis O'Brien
Jan-Feb 2020	Tier 2 Reanalysis Experimental Design Telcon	Lead: Allison Collow
Mar 2020	AGU Sessions Proposals Due	By ARTMIP Committee
Feb-May 2020	Tier 2 Polar ARs Analysis	Lead: Irina Gorodetskaya

May-Jun-May 2020	Tier 2 Paleo Experimental Design Telecon	Lead: Juan Lora
Jun-Aug 2020	Tier 2 Reanalysis Catalogues Due	Soft Deadline
Oct 2020	ARTMIP Colloquium at IARC?	Pending IARC Plans
Dec 2020	ARTMIP Session at AGU	Pending Session Proposal
Jan-Feb 2021	Tier 2 Paleo Catalogues Due	Soft Deadline

ORGANIZING COMMITTEE

- **Christine Shields**, National Center for Atmospheric Research
- **Jonathan Rutz**, National Oceanic and Atmospheric Administration
- **Michael Wehner**, Lawrence Berkeley Lab
- **Ruby Leung**, Pacific Northwest National Lab
- **Marty Ralph**, CW3E, Scripps, UC San Diego
- **Ashley Payne**, University of Michigan
- [2]**Travis O'Brien**, Lawrence Berkeley Lab

[2] Lead workshop organizer

Left to Right: Zhenhai Zhang, Alison Michaelis, Paul Ullrich, Yang Zhou, Renu Joseph, Christopher Castellano, Alan Rhoades, Jonathan Rutz, Alexandre Ramos, Ashley Payne, Christine Shields, Cody Poulsen, Naomi Goldenson, Travis O'Brien, John O'Brien, Beth McClenny, Eric Shearer, Héctor Inda Díaz, Huanping Huang, Rudong Zhang, Chen Zhang, Mark Risser (Photo Credit: Rosie Davis, LBNL).

Workshop Participants (in person)

1. Arriaga, Sarahi (UC Davis / Lawrence Berkeley Lab)
2. Castellano, Christopher (CW3E, Scripps, UC San Diego)
3. Cleveland, William (Purdue)
4. Collins, Bill (Lawrence Berkeley Lab/ UC Berkeley)
5. DeFlorio, Mike (CW3E, Scripps, UC San Diego)
6. Goldenson, Naomi (UCLA)
7. Guan, Bin (UCLA)
8. Huang, Huanping (Lawrence Berkeley Lab)
9. Inda-Diaz, Héctor (UC Davis, Lawrence Berkeley Lab)
10. Joseph, Renu (Department of Energy)
11. Kashinath, Karthik (Lawrence Berkeley Lab)
12. Kawzenuk, Brian (CW3E, Scripps, UC San Diego)

13. Kim, Sol (UC Berkeley)
14. McClenny, Beth (UC Davis)
15. Michaelis, Allison (CW3E, Scripps, UC San Diego)
16. O'Brien, Travis (Lawrence Berkeley Lab)
17. O'Brien, J.P. (UC Santa Cruz)
18. Paciorek, Chris (UC Berkeley)
19. Patricola, Christina (Lawrence Berkeley Lab)
20. Payne, Ashley (University of Michigan)
21. Poulsen, Cody (CW3E, Scripps, UC San Diego)
22. Ramos, Alexandre (Instituto Dom Luiz, University of Lisbon)
23. Rhoades, Alan (Lawrence Berkeley Lab)
24. Risser, Mark (Lawrence Berkeley Lab)
25. Rutz, Jon (National Weather Service)
26. Shearer, Eric (UC Irvine)
27. Shields, Christine (National Center for Atmospheric Research)
28. Slawinska, Joanna (U Wisconsin, Madison)
29. Tung, Wen-wen (Purdue)
30. Ullrich, Paul (UC Davis)
31. Zhang, Chen (Purdue)
32. Zhang, Rudong (Pacific Northwest National Lab)
33. Zhang, Zhenhai (CW3E, Scripps, UC San Diego)
34. Zhou, Yang (Lawrence Berkeley Lab)

Workshop Participants (virtual):

1. Brands, Swen (MeteoGalicia - Meteorological Instiute of the Galician Government)
2. Collow, Allison (USRA/NASA GMAO)
3. Gorodetskaya, Irina (University of Aveiro, Centre for Marine and Env. Studies)
4. Guan, Bin (UCLA)
5. Krinitskiy, Mikhail (Shirshov Institute of Oceanology, Russian Academy of Sciences)
6. Lora Gonzalez, Juan (Yale)
7. Mahesh, Ankur (ClimateAi)
8. Viceto, Carolina (CESAM, University of Aveiro, Portugal)
9. Wehner, Michael (Lawrence Berkeley Lab)
10. Wille, Jonathan (Université Grenoble Alpes)

Chen, X., L. R. Leung, Y. Gao, Y. Liu, M. Wigmosta, and M. Richmond, 2018: Predictability of Extreme Precipitation in Western U.S. Watersheds Based on Atmospheric River Occurrence, Intensity, and Duration. *Geophysical Research Letters*, **45**, 11,693-11,701, https://doi.org/10.1029/2018GL079831.

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Additional ARTMIP publications will be populated in the AGU special collection "Atmospheric Rivers: Intersection of Weather and Climate" which remains open for submissions until June 30, 2020." This special collection already includes multiple non-ARTMIP papers that cite ARTMIP results.

ACRONYMS

AGU ....American Geophysical Union
AMIP ....Atmospheric Model Intercomparison Project
AMS ....American Meteorological Society
AR ....Atmospheric river
AR6.......................6th Assessment Report (of the IPCC)
ARM ....Atmospheric Radiation Measurement
ARTMIP ....Atmospheric River Tracking Method Intercomparison Project
C20C+..................Climate of the Twentieth Century and beyond (+)
CAM5...................Community Atmosphere Model, version 5
CASCADE ....Calibrated And Systematic Characterization and Attribution of Extremes
CESD ....Climate and Environmental Sciences Division
CMIP ....Coupled Model Intercomparison Project
CW3E...................Center for Western Weather and Water Extremes
DOE ......................U.S. Department of Energy
ECMWF...............European Centre for Medium Range Weather Forecasting
ENSO....................El Niño Southern Oscillation
ERA-5 ....ECMWF Reanalysis, version 5
HPC.......................High Performance Computing
IARC ....International Atmospheric River Conference
IPCC......................Intergovernmental Panel on Climate Change
IVT ....Integrated vapor transport
IWV.......................Integrated water vapor
LBNL....................Lawrence Berkeley National Laboratory
LGM......................Last Glacial Maximum
MERRA-2 ....Modern-Era Retrospective analysis for Research and Applications, version 2
MJO.......................Madden-Julian Oscillation
MPAS ....Model for Prediction Across Scales
NASA....................National Aeronautics and Space Administration
NCAR ....National Center for Atmospheric Research
NOAA...................National Oceanic and Atmospheric Administration
PETM ....Paleocene-Eocene Thermal Maximum
PMIP ....Paleoclimate Model Intercomparison Project
RCP.......................Representative Concentration Pathway
RGMA...................Regional and Global Model Analysis (program within DOE CESD)
SFA ....Scientific Focus Area
SSP........................Shared Socioeconomic Pathway
SST........................Sea-surface temperature
UTC.......................Coordinated Universal Time