

1 **Detection Uncertainty Matters for Understanding Atmospheric Rivers**

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ABSTRACT

71 **The 3rd ARTMIP Workshop**

72 **What:** Over 30 participants from multiple universities and research insi-
73 titutions met to discuss new results from the Atmospheric River Tracking
74 Method Intercomparison Project.

75 **Where:** Lawrence Berkeley National Lab, Berkeley, CA, USA

76 **When:** 16-18 October 2019

77

78 Atmospheric rivers (ARs) are increasingly recognized globally as an important weather phe-
79 nomenon associated with extreme precipitation. There is a substantial body of literature indicating
80 that ARs are responsible for a large fraction of wet-season precipitation on western coasts (Rutz
81 et al. 2019) and that they can cause large changes in snowpack (both positive and negative; Guan
82 et al. 2010; Chen et al. 2019). Individual ARs and collections of ARs can bring large amounts of
83 precipitation that drives floods and other storm-related hazards (Ralph et al. 2006, 2019a). ARs
84 are a significant factor for water and associated water systems in the vicinity of western coasts
85 (Gao et al. 2016; Ralph et al. 2019b). It is increasingly evident that they have major impacts on
86 the energy and water budgets of the cryosphere: including mountains (Chen et al. 2019) and high
87 latitude regions (Gorodetskaya et al. 2014). These research advances hinge on technical advances
88 in tracking ARs in observations, reanalyses, and climate model simulations and on understanding
89 uncertainties associated with different tracking methods. In parallel with the recent increase in
90 research activity around ARs, an increasing number of research groups have developed unique
91 methods for tracking ARs (Shields et al. 2019).

92 The Atmospheric River Tracking Intercomparison Project (ARTMIP) was created to design a set
93 of experiments that could quantify the uncertainty associated with AR tracking (Shields et al. 2018;
94 Rutz et al. 2019). The concept of a multi-tiered experimental approach, based on tracking ARs
95 across common datasets, resulted from the 1st ARTMIP workshop in 2017. The Tier 1 experiment
96 is focused on tracking ARs in a modern reanalysis (MERRA2). The 2nd ARTMIP workshop
97 (Shields et al. 2019) was oriented around discussion of Tier 1 results and around designing and
98 planning the first set of Tier 2 experiments: the Tier 2 C20C+ experiment and the Tier 2 CMIP5/6
99 experiment. Both initial Tier 2 experiments are focused on understanding the effects of climate
100 change on AR characteristics, with the C20C+ experiment focusing on a set of high-resolution

101 atmosphere-only simulations, and the CMIP5/6 experiment focusing on a multimodel collection
102 of fully-coupled simulations from the Coupled Model Intercomparison Project.

103 Following the 2nd ARTMIP Workshop, two separate developments motivated the need for de-
104 veloping a large dataset of hand-labeled ARs. Discussions following the 2nd ARTMIP Workshop
105 suggested that differences among AR tracking algorithms might reflect differences in expert opin-
106 ion about what constitutes the boundary of ARs; resolving this question would require experts
107 to hand-label ARs. Unrelated, but concurrent, advances in Computational Climate Science have
108 demonstrated the utility of modern machine learning methods for tracking weather phenomena
109 (Mudigonda et al. 2017; Muszynski et al. 2019; Kurth et al. 2018). These developments also high-
110 light the need for high-quality data to train machine learning methods: expert-labeled datasets.

111 Emerging results from the Tier 1 and 2 experiments, along with the recently identified need
112 to develop a high-quality, hand-labeled dataset of ARs, motivated the ARTMIP Committee to
113 convene the 3rd ARTMIP Workshop¹, held at Lawrence Berkeley Lab on October 16-18, 2019.
114 The meeting included a substantial virtual component, with 25% of attendees attending virtually;
115 the meeting included several presentations from remote attendees. The 3rd ARTMIP Workshop
116 was organized around:

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

¹Funded by the U.S. Department of Energy

122 Initial Tier 2 results presented at the workshop show that, while most methods agree, qualita-
123 tive conclusions about the effect of climate change on ARs can depend on tracking algorithm.
124 These results further motivate exploration of the role of AR tracking uncertainty on other aspects
125 of AR science. Specifications and timelines for three new Tier 2 experiments were defined: Tier
126 2 Reanalysis, Tier 2 High-Latitude, and Tier 2 paleo-ARTMIP. A future Tier 2 experiment was
127 also discussed, and specifications and a timeline will be developed in future ARTMIP interactions
128 (e.g., teleconferences): Tier 2 MPAS-ENSO. Group and breakout discussions during the work-
129 shop identified numerous gaps in understanding and associated research priorities. These gaps
130 and research priorities are a key outcome for the ARTMIP workshop. Those interested in more
131 information about the workshop should refer to the full workshop report, which is available at the
132 Department of Energy website.

133 **1. Key Gaps and Research Priorities**

134 *a. Basic Research on AR Lifecycle*

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

138
139 **Recommendation:** There is a need for more basic research on the dynamics and lifecycle of ARs.

140
141 There was considerable discussion during the workshop about the need for refining our theoret-
142 ical understanding of the AR lifecycle: from genesis to dissipation. Some basic questions were
143 identified that, if answered, could help reduce quantitative uncertainty in the definition of ARs:

- 144 1. What causes the genesis of ARs?
- 145 2. What controls the frequency of ARs?
- 146 3. What controls the duration of ARs?
- 147 4. Are ARs always associated with ETCs?
- 148 5. Are ARs always associated with some form of baroclinic instability?

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

156 *b. Flavors of ARs*

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

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

161
162 It was also postulated that there might be different “flavors” of ARs, with different generating
163 physical mechanisms controlling their lifecycle; e.g., if some are associated with transient baro-
164 clinic instabilities and others are associated with quasi-stationary geopotential height gradients.

165 Relatedly, there was also discussion about the utility of analyzing the dynamics (e.g., baroclinic-
166 ity) associated with ARs across different algorithms. This could provide insight into the underlying
167 dynamical processes that influence the evolution of ARs at various stages of their life cycles.

168 Prevailing tracking methods have not considered this possibility. Such methods might require an
169 ability to distinguish among ARs with different physical characteristics, such as tropical moisture
170 filaments, ARs that originate from extra-tropical cyclones, those encompassing uplifting motions
171 versus not, ARs embedded in steering flow, etc. This is a critical step to enable further understand-
172 ing, accurate identification, and improved forecasting of ARs and associated physical systems.
173 Ideally, “flavored” AR tracking methods could incorporate connections to surface precipitation,
174 interactions with synoptic-scale baroclinicity, and interactions with other phenomena such as trop-
175 ical cyclones and jet streams.

176 *c. Classes of AR Algorithm*

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

179 **Recommendation:** Objective, and physics-informed, clustering approaches could help establish
180 a quantitative vocabulary for explaining differences among AR detection algorithms.

181

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

187 Despite the focus of the discussion on existing uncertainties in AR detection techniques and
188 impacts on AR science, the group found a cause for cautious optimism: analogous to different
189 physics parameterizations in climate models, different AR algorithms were developed with differ-
190 ent goals in mind, and thus may each have distinct applications. This suggests that there exists
191 a logical approach to group and categorize existing AR algorithms to facilitate understanding of
192 how and why AR characteristics and metrics differ among algorithms. The group also discussed
193 the possibility of using statistical methods, such as K-means clustering, to objectively categorize
194 AR detection algorithms. If there are different AR flavors, there is the possibility that different de-
195 tection methods tend to preferentially identify different AR flavors; objective clustering methods
196 could help clarify this.

197 *d. Leveraging 3D Structure*

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

200 **Recommendation:** Research groups with expertise in, and access to, high performance comput-
201 ing resources should explore detection approaches that leverage the 3D structure of ARs.

202

203 The group identified several gaps that may limit the ability of current AR tracking results to
204 improve our understanding and prediction of AR physics and impacts. First, current detection
205 algorithms are all based on two-dimensional horizontal patterns. This choice is partly influenced
206 by the computational resources generally available and by data limitations/availability (e.g., most
207 satellite datasets are 2D). In reality, ARs have complicated three-dimensional structures in nature.
208 The physical features of extra-tropical cyclones likely make simple thresholding methods unfea-
209 sible. However, applying detection or tracking algorithms to large, volumetric data is computa-

210 tionally highly complex and requires substantial resources (e.g., memory) that make such work
211 impractical for many. Research groups with sufficient computing resources could advance AR
212 science by developing algorithms that consider the three-dimensional nature of ARs.

213 *e. Common Software Infrastructure*

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

217 **Recommendation:** Develop open-source computational frameworks to facilitate the implemen-
218 tation of new and existing AR detection methods.

219

220 Common open-source computational approaches will help broaden and speed up AR-related re-
221 search. The community can benefit from some open-source codes that make efficient AR tracking
222 for operational tasks or exploratory studies. In addition, open-source codes showing discretization
223 schemes for calculating terms and equations used for AR identification can help ensure consistency
224 across all related physics-driven data analysis studies at the numerical level. The RGMA-funded
225 Toolkit for Extreme Climate Analysis (TECA)² may prove to be a useful starting point for de-
226 veloping an open-source ARTMIP framework, as it is designed to facilitate the development of
227 modular data processing pipelines on high-performance computing systems.

228 *f. Expert-Labeled AR Dataset*

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

²<https://github.com/LBL-EESA/TECA/>

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

232 **Recommendation:** Future AR research, especially research using machine learning, should
233 leverage results from the ARTMIP ClimateNet campaign.

234

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

240 This took advantage of major investments at LBL in machine learning: ClimateNet³. ClimateNet
241 was developed at LBL/NERSC to facilitate the collection of hand-labeled weather datasets. This
242 component of the workshop was substantial: half of a day, out of a 2.5-day workshop, was devoted
243 to this effort. This effort included over 15 workshop participants who labeled 660 time slices of
244 data during the session (Figure 1).

245 2. Conclusions

246 The enthusiasm for ARTMIP was evident during the workshop, especially when discussing
247 potential future areas of exploration (e.g., new Tier 2 experiments). To this end, plans were made
248 to expand the ARTMIP timeline to include two new Tier 2 subtopics, e.g. Reanalysis sensitivity
249 and Paleoclimate. ARTMIP will continue to provide the community with AR catalogues across
250 all subtopics with the aim of facilitating scientific discourse and forwarding our understanding
251 of atmospheric rivers. We will accomplish this by continuing our activities (Master ARTMIP

³<https://www.nersc.gov/research-and-development/data-analytics/big-data-center/climatenet/>

252 Timeline), contributing to the body of scientific literature, and participating in scientific meetings
253 with a short-term goal of proposing sessions at IARC 2020 in Chile and relevant society meetings.

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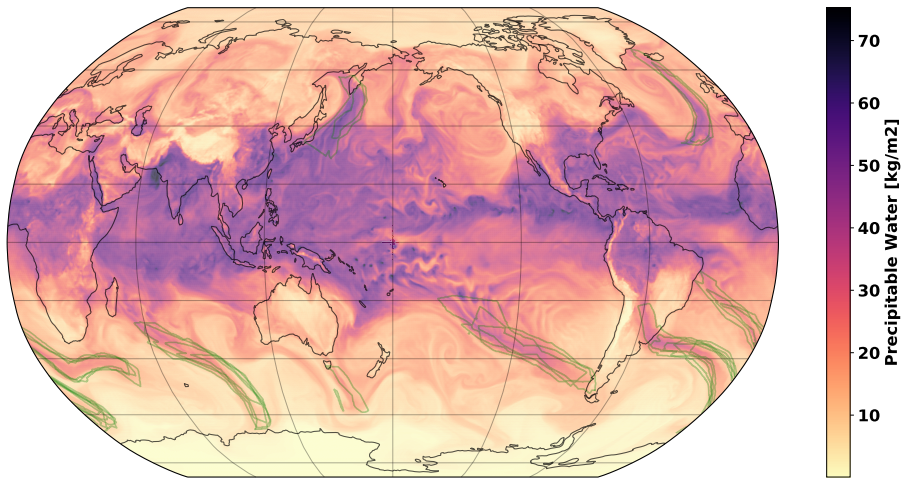
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315 **LIST OF FIGURES**

316 **Fig. 1.** Comparison of expert AR identifications from 06 September 2009 of a 25 km CAM5 Atmo-
317 spheric Model Intercomparison Project simulation. The background field shows integrated
318 water vapor, and the green contours show outlines of ARs identified by 15 ARTMIP partic-
319 ipants. 18



320 FIG. 1. Comparison of expert AR identifications from 06 September 2009 of a 25 km CAM5 Atmospheric
321 Model Intercomparison Project simulation. The background field shows integrated water vapor, and the green
322 contours show outlines of ARs identified by 15 ARTMIP participants.