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Nellikkattil, Arjun Babu; Lee, June-Yi; Guan, Bin; Timmermann, Axel; Lee, Sun-Seon; Chu, Jung-Eun; Lemmon, Danielle

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Increased amplitude of atmospheric rivers and associated extreme precipitation in ultra-high-resolution greenhouse warming simulations

Arjun Babu Nellikkattil, June-Yi Lee, Bin Guan, Axel Timmermann, Sun-Seon Lee, Jung-Eun Chu & Danielle Lemmon

Atmospheric rivers play an integral role in the global water cycle, but predicting their future changes remains uncertain due to inter-model and inter-detection-method differences. Using ultra-high-resolution Community Earth System Model simulations and a novel detection algorithm based on geometric shape extraction, we quantify global changes in atmospheric rivers and the associated precipitation events in response to doubling and quadrupling of atmospheric CO$_2$ concentrations. We find that, atmospheric rivers are projected to become more frequent and more likely to be associated with extreme precipitation events, increasing their contribution to global mean precipitation. While the water vapor transport within these structures follow Clausius-Clapeyron scaling, the changes in maximum precipitation intensity resemble other saturated atmospheric environments like tropical cyclone cores. The increased amplitude of atmospheric rivers and the associated increase in mean and extreme precipitation have important implications for future water management and adaptation policies.
Atmospheric Rivers (ARs) are narrow, filament-like structures that transport large amounts of water vapor across the globe. They often form ahead of the cold fronts of an extratropical cyclonic circulation accompanied by a low-level jet on the equatorward side and strong convection along the front, constituting large-scale cloud systems with persistent precipitation. ARs undergo vigorous upward motion along topographic barriers like mountains or coastlines where they make landfall, leading to torrential downpours. At any given instant, about four or five ARs per hemisphere provide much of the poleward water vapor transport across the midlatitudes. When time-averaged, over 90% of the total annual poleward water vapor transport in the midlatitudes is controlled by ARs that account for only 10% of the total global surface area. AR genesis and activity also modulate the global mean atmospheric energy budget via sensible and latent heat transports.

Understanding ARs and determining their response to greenhouse warming is extremely important as they play a fundamental role in global and regional hydroclimate. From a global perspective, ARs account for up to 35% of the annual mean precipitation and around 50% of the extreme precipitation and surface wind events in the midlatitudes. Regionally, ARs substantially modulate mean and extreme precipitation along land-falling coastal regions, such as the U.S. west and east coasts, European west coast, South American coastline, and Australasia summer monsoon regions. ARs also influence the intensity of snowfall and snowpack variability over many land-falling regions. The mean hydroclimate over these areas are shaped by ARs in the present as well as past climates. More recently, it has been found that ARs influence the ice melting in the polar regions and glaciers, owing to consistently strong precipitation and long-wave feedbacks associated with AR cloud cover. The complex interplay between ARs, clouds, and ice sheets leads to different outcomes in different regions, such as anomalous snow accumulation over East Antarctica, surface melting over West Antarctica, reduction of sea-ice in both the Antarctic and the Arctic, and extreme melting of Greenland ice sheet. Thus, ARs play an important and intricate role in global and regional climate feedbacks.

Recent modeling efforts have advanced our understanding of the dynamics, forced responses, and impacts of ARs. These studies suggest that the frequency of ARs will increase, and their landfall locations will shift poleward in response to anthropogenic greenhouse warming. Additionally, due to increases in atmospheric moisture, ARs are expected to carry more moisture and increase the associated likelihood of extreme precipitation, particularly over regions with elevated terrain. While considerable progress has been made in the simulation, prediction, and projection of ARs using climate models, coarse-resolution models still have large biases in representing the spatio-temporal characteristics of ARs as well as their interaction with topographic features. These model deficiencies are closely related to biases in the representation of midlatitude storm tracks and jet streams. Although more work needs to be done to definitively conclude whether ARs are better represented in higher resolution models, AR frequencies are suggested to be highly influenced by the horizontal grid resolutions used in climate models. For example, model simulations with higher horizontal resolutions are expected to represent more realistic precipitation patterns and frontal-scale midlatitude air-sea interactions, thus better capturing the interactions between ARs and complex topography. Moving forward in understanding AR dynamics and reliable projections, then, requires reconciling findings from both coarse and high-resolution modeling studies.

While developments in high-resolution modeling have much potential to advance our understanding of ARs, current scientific consensus on new findings is elusive as non-negligible differences in present and projected AR features have been attributed to fundamental differences between AR detection algorithms. The majority of pre-existing ARDTs use absolute or relative thresholds based on climate variables, such as integrated water vapor content (IWV) or integrated water vapor transport (IVT) (hereafter thresholds), along with few shape, size and location constraints to identify ARs in the present climate. Studies on reanalysis data sets that use detection methods with absolute thresholds show a high concentration of ARs along the warm western boundary current region in the global oceans and an asymmetric distribution of ARs between the Northern and Southern Hemispheres. By contrast, reanalysis studies that use thresholds relative to the mean state, as a function of space and time, show a more symmetric distribution of ARs between the two hemispheres and detect considerably more ARs over land. Differences in results obtained between these two methods are likely attributable to the uneven spatial distribution of mean water vapor between hemispheres, which is inherently captured differently by absolute and relative thresholds. Even given the relative consistency between reanalysis data sets in representing present climate, as compared to historical model simulations, building consensus on AR characteristics is difficult as the analysis is extremely sensitive to ARDTs.

The sensitivity of results from AR analysis to ARDTs is even greater when estimating the changes in AR characteristics between various mean climate states, such as between different models and different climate change scenarios. Compared to interpreting AR characteristics in the present climate, analyzing projected AR changes in future climate becomes even more complicated as methods can be based on historical thresholds (i.e., absolute or fixed relative schemes) or based on mean state thresholds (i.e., relative schemes). For example, model studies that use methods based on historical thresholds tend to project ARs as much longer and wider, with small changes in mean strength and precipitation in response to greenhouse gas (GHG) warming. Conversely, model studies using relative mean state thresholds tend to project ARs as greatly strengthened in both IVT and precipitation, with smaller changes in their length and width. The proliferation of the number and type of ARDTs has led to multiplicitous and conflicting interpretations of projected changes, obscuring scientific consensus on AR characteristics in present and future climate.

To simplify the study of present and future AR changes, alternative methods without dependence on climate variable thresholds are being explored by the community, with some studies highlighting the potential benefits of machine learning or image processing techniques. To develop a robust ARDT in mind, we use a methodology that reframes the basis of thresholds away from climate variables like IVT or IWV towards shape-based metrics that are not empirically derived from climate data, and thus may be less sensitive to underlying changes in climate mean states. To analyze present-day (PD), CO₂ doubling (2CO₂), and quadrupling (4CO₂)
ARs in the present climate simulation. Using SCAFET, we compare the 20-year mean spatial distribution of daily AR frequency in the CESM UHR PD simulation with the observed high-resolution counterpart obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Version 5 (ERA5). The CESM UHR PD simulation well captures the observed global distribution of the climatological AR frequency (Fig. 1a, b). The maximum values of the AR frequency are found along the storm track regions in the midlatitudes (contours in Fig. 1a, b). AR frequencies are also high over the warm western boundary currents and the currents’ extensions throughout the year. These AR structures are associated with the frequent moving-extratropical cyclones (ECs) in that region. The integral role of ARs in regulating midlatitude water cycle is likewise expected, as the algorithm does not set a minimum threshold on IVT. AR-like objects are identified from the IVT fields by extracting ridge, and dome-shaped objects within the data. A scale-insensitive, bounded variable called Shape Index (SI) is used to segment the IVT field into various shapes. In essence, regions with SI > 0.375 will be labeled as ARs, given that they are precipitating, large, elongated and have a coherent vapor transport. Although the algorithm sets an absolute (independent of both space and time) threshold, unlike other ARDTs that sets absolute thresholds (Supplementary Figs. 2a–c), we get a hemispherically uniform distribution of ARs similar to ARDTs based on relative thresholds (Supplementary Figs. 2e–g). Thus, although the algorithm cannot theoretically define an AR, it puts forward a unique perspective in its detection. Excitingly, such a framework can be extended to the detection of other climate and weather features.

As observed by recent studies, we find that the spatial pattern of mean AR frequency is largely insensitive to the spatial resolution of the simulations used (see Supplementary Fig. 4). As the parameters used for AR detection in low resolution (LR) datasets are same as that with the high resolution (HR), this also demonstrates the ability of SCAFET to detect ARs from datasets with varying resolution. However, the HR simulations show a more realistic representation of the precipitation and convection characteristics compared to LR counterparts. Consistent with these studies, the CESM UHR PD simulation presented here shows more accurate representation of the AR characteristics as compared to analogous LR simulations (Supplementary Fig. 5). The differences between HR and LR AR characteristics are considerable in the extreme attributes. Since extreme precipitation is an important facet of ARs, HR simulations and resolution-insensitive detection algorithms should be used in future studies into the mechanism and the impacts on extreme precipitation. Whereas the overall patterns in AR frequency between SCAFET and other ARDTs are comparable, SCAFET tends to detect weaker ARs more than most canonical ARDTs and thus detects a higher overall AR frequency (see also Supplementary Figs. 2 and 3). The detection of a large number of weak ARs is expected, as the algorithm does not set a minimum threshold on IVT. AR-like objects are identified from the IVT fields by extracting ridge, and dome-shaped objects within the data. A scale-insensitive, bounded variable called Shape Index (SI) is used to segment the IVT field into various shapes. In essence, regions with SI > 0.375 will be labeled as ARs, given that they are precipitating, large, elongated and have a coherent vapor transport. Although the algorithm sets an absolute (independent of both space and time) threshold, unlike other ARDTs that sets absolute thresholds (Supplementary Figs. 2a–c), we get a hemispherically uniform distribution of ARs similar to ARDTs based on relative thresholds (Supplementary Figs. 2e–g). Thus, although the algorithm cannot theoretically define an AR, it puts forward a unique perspective in its detection. Excitingly, such a framework can be extended to the detection of other climate and weather features.

**Fig. 1 The mean AR statistics in CESM ultra-high-resolution (UHR) PD simulation compared with ERA5 reanalysis.** Fraction of AR days per year (nondimensional) in the CESM UHR PD simulation (a), ERA5 (b), and their difference (c), and the ratio of AR precipitation to annual mean precipitation (nondimensional) in the CESM UHR PD simulation (d), ERA5 (e), and their difference (f). The model climatology is calculated from the daily mean data of the last 20 years of the PD simulation, and the observed climatology is obtained for the 20 years of 2000–2019. The cyan contours in a and b show the column integrated eddy kinetic energy in Mega Joules (MJ).
The most notable difference between ERA5 and the CESM UHR PD simulation is the location of the maximum AR frequency and associated precipitation (Fig. 1c, f). This discrepancy could be due to model biases in the location and extent of the jet streams and associated storm tracks in the simulation (Supplementary Fig. 6). Despite minor inter-data and inter-detection-method differences, there is good agreement in AR characteristics between ERA5 and the CESM UHR PD simulation using SCAFET, and little divergence in this analysis from the other ARDTs (see Supplementary Figs. 2 and 3). The choice of the reanalysis datasets will not affect observed biases as detection of ARs is not sensitive to the absolute values of the IVT and is similar to relative threshold based ARDTs (Supplementary Fig. 7).

The mean climatology of AR frequency exhibits considerable similarity to the means of other synoptic-scale weather systems such as storm tracks, warm conveyor belts (WCBs), Ecs, and atmospheric fronts (AFs). Maximum AR frequencies are manifested on the equatorward side of active storm track regions (Fig. 1a, b contours). Storm track activity is directly proportional to the track density of Ecs, and the starting and ending points of the WCBs match well with the genesis and lysis locations of the cyclones67–69. Also, the distribution of AFs tends to strongly correlate with the AR activity (see Fig. 270). From a cyclone-centered view, ARs can be viewed as vestiges of a poleward moving extratropical storm71,72, with robust co-occurrences and moderate correlations between AR and storm strength73,74. Connecting all these features, ARs are generally formed along the equatorward side of strong cyclonic circulations, extending from WCB genesis locations along with the warm sector of AFs. Importantly, the SCAFET framework well-captures this dynamic link between ARs and synoptic-scale features.

**AR responses to greenhouse warming.** By combining the novelty of both the CESM UHR simulations and the local geometric shape-based detection method, SCAFET, we aim to more reliably quantify the AR responses to GHG forcing. Our results indicate that changes in the 20-year mean of AR frequency under 2CO2 and 4CO2 relative to the PD simulation are highly regional (Fig. 2a, b). Overall, mean AR frequency manifests a robust linear increase in AR frequencies relative to the PD simulation using SCAFET, and little divergence in this analysis from SCAFET (Supplementary Fig. 8c, d). This is because, to detect ARs, TempestExtremes applies thresholds on the Laplacian of the IVT field, which by definition is the divergence of the spatial gradient and is thus fundamentally insensitive to homogeneous mean state increases in IVT. By contrast, ARDTs that use historical or present day IVT or IWV thresholds identifies larger AR areas as they do not account for a future mean state that has ubiquitously higher specific humidity74. By increasing the minimum thresholds for IVT or precipitation in the SCAFET, similar patterns of AR frequency changes can be observed compared to conventional ARDTs (Supplementary Fig. 9). Ultimately, the choice of AR detection method depends on the specific research question being addressed.

Reconciling the patterns of projected AR frequency changes between modeling studies is difficult not only because of different threshold-dependent ARDTs but also because AR projections depend on variable thermodynamic and dynamic physical quantities, like specific humidity and wind speed. Modeling studies have shown that a 1°C increase in global mean temperature corresponds to about a 7% increase in water vapor content and CESM UHR simulations also show that the lower tropospheric mean specific humidity (1000 hPa to 700 hPa) globally increases by about 7.3% and 8% globally per 1°C global warming in 2CO2 and 4CO2 scenarios, respectively75. The changes in wind magnitude and direction are less certain and are dependent on the regional and model characteristics. A combination of these climatological changes modulates the the spatial pattern of IVT, and by extension the spatial pattern of AR frequency. To separate out the influence of humidity increases and wind changes, we split total IVT changes (ΔIVT) into the thermodynamic (∫ \( \nabla q dp \)) and dynamic (∫ \( q \Delta V dp \)) components, hereafter **TIVT** and **DIVT** respectively (see the “IVT decomposition” in “Methods” for complete decomposition of IVT). By separating the thermodynamic and dynamic components, we explicitly show how SCAFET delineates projected AR characteristics from the underlying dynamics and mean state trends that modulate projected changes in AR frequency.

To demonstrate how **TIVT** and **DIVT** affect the mean IVT and hence the distribution of AR frequency, we take the vector projection of **TIVT** and **DIVT** onto mean IVT from PD (Fig. 2e–h). In linear algebra the vector projection of a vector \( \vec{a} \) onto another nonzero vector \( \vec{b} \) is defined as \( a \cdot \vec{b}/|\vec{b}| \). Positive values of the scalar product indicate that the changes act to reinforce the mean circulation in PD while negative values imply that the changes are in the opposite direction of the mean circulation and result in the weakening of the total transport. ARDTs that are based on historical or relative thresholds estimate AR frequency changes that are sensitive to both components, and
thus AR frequency is largely increased following TIVT (Supplementary Fig. 8a, b). However, SCAFET is more responsive to changes in DIVT, similar to other ARDTs that either use a relative or second-derivative threshold (Supplementary Fig. 8c, d). Regions where both TIVT and DIVT act to strengthen the mean circulation show the largest increase in AR frequency, as in the Southern Ocean (Fig. 2e–h). In most regions where the DIVT changes are opposing the TIVT changes, AR frequency often seems to follow the mean DIVT, particularly over the midlatitudes. As the wind response to GHG warming is highly model dependent, mean AR frequencies obtained using SCAFET may vary between models (Supplementary Fig. 10). Examining the zonal and meridional components separately also tells the same story in that AR frequency changes are modulated by DIVT, though the meridional components are inessential in explaining the overall pattern (Supplementary Figs. 11–14). Compared to other ARDTs, AR frequency is more modulated by DIVT in our scheme due to the fact that SCAFET identifies regions with local maxima in IVT regardless of its absolute value. In other words, SCAFET by construct not only identifies regions with high water vapor content but also the low level jet structure associated with it, which is represented by DIVT.

The precipitation changes associated with ARs are consistent with the changes in AR frequency (Fig. 2c, d). Globally, the contribution of AR precipitation to mean annual precipitation increases by 6% (2.4%/°C) and 15% (3%/°C) in 2CO2 and 4CO2 scenarios respectively, which was also seen in previous studies. The greatest increases in AR precipitation occur over high and midlatitudes (Fig. 2c, d), closely following the projected changes in total precipitation (Supplementary Fig. 15).

Fig. 2 Projected changes in AR characteristics, thermodynamic and dynamic components of integrated water vapor transport (IVT). Future changes in the annual fraction of AR days (a, b), AR precipitation to annual mean precipitation ratio (c, d) from 2CO2 (a, c) and 4CO2 (b, d) experiments in comparison to PD. Stippling in a–d denotes significant changes at $\alpha = 0.05$ level in a two-tailed t-test ($n = 20$). The vector projection of thermodynamic (e, f), and dynamic (g, h) components onto the mean IVT from PD are shown as shading.
Additionally, we find that ARs are projected to become stronger by 15%(6%/°C) and 34%(7%/°C) in 2CO2 and 4CO2 simulations respectively, consistent with the Clausius-Clapeyron scaling\(^6\) (Fig. 3a). The mean precipitation within the ARs increases by 4%(1.6%/°C) and 10%(2%/°C) congruent with the hydrological sensitivity estimated from other coupled climate simulations\(^7\) (Fig. 3b) while the maximum precipitation within ARs shows amplification by 12%(5%/°C) and 30%(6%/°C) for 2CO2 and 4CO2 scenarios respectively (Fig. 3c). These changes in maximum precipitation within ARs are similar to responses observed in other saturated atmospheric environments like tropical cyclones\(^8\).

Although the changes in mean AR precipitation is dependent on the AR boundary which in turn is highly sensitive to the choice of ARTD, maximum AR IVT and precipitation are largely insensitive to the detection methods used. AR duration shows an extension of 1.6% and 2.3% in 2CO2 and 4CO2 scenarios (Fig. 3d). Moreover, ARs tend to become 1.5% and 3% longer, bigger, and more elongated in 2CO2 and 4CO2 simulations (Fig. 3e–g). However, these geometric parameters are highly sensitive to the ARDT used. For instance, results obtained using historical thresholds show larger increases in length, width, and area with only moderate changes in mean AR IVT and precipitation\(^9\). Results obtained using mean state thresholds show moderate changes in geometric parameters and a generous increase in IVT, similar to our results\(^5\) . Local shape-based methods like SCAFET have the potential to reduce the ambiguity in projected changes of ARs arising from IWV or IVT threshold-based ARDTs while also successfully capturing the changes in important AR characteristics such as mean IVT and the associated precipitation.

Extreme precipitation associated with ARs. Extreme precipitation (XP) is defined as daily precipitation greater than the 95th percentile of daily precipitation within the CESM UHR PD simulation and ERA5 reanalysis, respectively. In other words, the definition of extreme precipitation does not change between present and future scenarios. To examine the link between ARs and extreme precipitation events, we calculate the conditional probability of extreme precipitation given the presence of an AR, or \(P(\text{XP}|\text{AR})\). As expected, the presence of an AR leads to an increased probability of extreme precipitation everywhere (Fig. 4a, b). Notably, ERA5 and CESM UHR PD identify the same regions for the risk of AR-induced extreme precipitation, although the CESM UHR PD simulation slightly overestimates the probability of AR-induced extreme precipitation. The increased probability is most visible along the coastlines where ARs make landfall and the winds hit perpendicular to regions with a strong topographic gradient (Supplementary Fig. 16a). For example, there are some regions in which the presence of an AR makes precipitation 10 times more likely, such as over the southwestern coast of the U.S., western Greenland, and around the Antarctic coastline (Fig. 4a, b). Other hotspots for AR-induced extreme precipitation are the Iberian Peninsula, the Scandinavian mountains in Norway, the Andes mountains, the Ural mountains, the Hindukush mountains, western Australia, and western South Africa. Expansion of the subtropical dry belt in response to GHG warming leads to a regional reduction of mean precipitation and of AR-induced extreme precipitation in those regions (Fig. 4c–e, Supplementary Figs. 15 and 16). By contrast, the probability of extreme AR precipitation increases substantially on the poleward side of the subsidence regions. The largest increases are seen along the windward side of mountain ranges perpendicular to the large-scale circulation (Fig. 4c–e). To reiterate, ARs and associated mean and extreme precipitation play an important role in ice, precipitation, and cloud feedbacks, and better quantifying the impacts of AR-induced extreme precipitation events on sea ice, ice sheets and permafrost regions will be of paramount importance for future studies in understanding Earth’s hydroclimatic response to GHG warming.

Conclusions

We combined the novelty of CESM UHR simulations and application of a novel, local geometric shape-based ARDT that is independent of IVT or IWV thresholds to estimate and analyze projected changes in AR characteristics. The results are consistent with previous studies indicating an increase in the mean...
frequency (by 6% and 12%) and annual mean precipitation associated with ARs (by 6% and 15%) in response to increased atmospheric CO₂ concentrations (for 2CO₂ and 4CO₂ simulations). The mean precipitation increases within ARs match the mean hydrological sensitivity while the maximum precipitation intensity shows similar changes as in other hydrometeorologically saturated conditions. Owing to the increased atmospheric water vapor content under global warming, we also observe a strengthening of ARs (as measured by mean IVT) by 15%(6%/°C) and 34%(7%/°C) in 2CO₂ and 4CO₂ simulations respectively, approximately following the Clausius-Clapeyron scaling (7%/°C). This leads to a slight enlargement of ARs in warmer conditions, but, this enlargement is much smaller than what is reported in other studies using ARDTs based on historical thresholds.

Defining ARs from historical thresholds in a warmer and wetter world results in the identification of a much larger area of conglomerated AR events, with lower mean AR precipitation and strength compared to the threshold independent or relative or second-derivative threshold based methods. Furthermore, the application of historical thresholds to future warming scenarios corresponds to a reduction in the number of AR-like structures per time step, as multiple AR-like structures are clumped together in a single conglomerate against the backdrop of scoping, basin-wide increases in mean IVT. By comparison, detection methods based on relative thresholds or local-shape indicate ARs slightly increase in area but with a relatively large enhancement in AR strength and mean precipitation. Additionally, they also project a rise in the number of AR events per instant as AR structures are isolated from the elevated background mean state. According to our analysis, changes in AR frequency identified using SCAFET are tightly linked to the mean circulation changes in response to increased GHG forcing. Moreover, the UHR simulations are expected to better resolve the synoptic scale circulation patterns compared to coarser resolution simulations. Our results also appear to capture the interaction of AR circulation systems with the landfalling topography. These aspects of UHR simulations help us to more reliably project and explain AR-associated precipitation characteristics. The accumulated, mean, and extreme precipitation associated with ARs increase in response to increased GHG concentrations. Combining estimated AR frequency and precipitation changes may inform future water management policies as consensus builds on projected changes under global warming.

Importantly, the lack of coherence between IVT and IWV threshold-dependent detection methods fundamentally stems from the lack of a quantitative definition for ARs, though this is difficult to systematically apply globally and in perpetuity. To address the ambiguity in defining thresholds for ARs, we develop SCAFET and use the local geometric shape of IVT magnitude to detect strong local maxima and coherence within water vapor transport to identify AR-like conditions. Detection algorithms for cyclones, AFs, and other phenomena may encounter comparable challenges when attempting to estimate future changes in their frequency and the associated precipitation. This is because they are also expected to be responsive to variations in the mean state, which presents exciting opportunities for further investigation and improvement. When analyzing synoptic-scale dynamics that overlie different mean states, especially between present and increased CO₂ scenarios, using a local shape-based feature extraction algorithm could be useful for building scientific consensus going forward. The ARDT introduced in this study is now expanded into a general feature extraction and tracking method framework allowing us to more objectively quantify (background-state independent) future changes in synoptic-scale phenomena.

**Methods**

**ERA5 reanalysis.** European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis Version 5 (ERA5) data is used to validate the capability of the CESM UHR PD simulation in capturing AR characteristics and associated precipitation in the present climate. We use daily mean data of zonal velocity (U), meridional velocity (V), and specific humidity (Q) from 1000 hPa to 300 hPa for calculating integrated water vapor transport (IVT) and daily mean precipitation (PRECT) for 20 years (2000–2019) with a horizontal resolution of 31 km and 37 vertical levels. IVT is a vector quantity given by,

\[
IVT_z = -\frac{1}{g} \int_{1000 \text{hPa}}^{300 \text{hPa}} q \cdot U \, dp
\]
Scalable Feature Extraction and Tracking (SCAFET). Although there is a wide variety of peer-reviewed ARDTs, this study uses a novel local geometric shape-based method to identify ARs, with broader applications for extracting synoptic-scale features for different background states. As discussed in the main text, the aim of the new method is to rethink how the thresholds are used for feature extraction. In contrast with many existing ARDTs, we use local geometric shape of a field to extract AR structures instead of applying IVT or IWV thresholds directly. The method uses Shape Index (SI), a measure of the local shape of the surface as follows:

\[ SI = \frac{1}{\pi} \tan^{-1} \left( \frac{k_1 + k_2}{k_2 - k_1} \right) \]  

Where \( k_1 \) and \( k_2 \) are the two eigenvalues satisfying \( k_1 \geq k_2 \) for the Hessian matrix of \( [\text{IVT}] \) given by:

\[ \mathcal{H} ([\text{IVT}]) = \begin{bmatrix} \frac{\partial^2 \text{IVT}}{\partial x^2} & \frac{\partial^2 \text{IVT}}{\partial x \partial y} \\ \frac{\partial^2 \text{IVT}}{\partial y \partial x} & \frac{\partial^2 \text{IVT}}{\partial y^2} \end{bmatrix} \]  

The SI is a unitless, bounded quantity between -1 to 1, independent of the absolute magnitude or resolution of the scalar field. This invariance is crucial as it ensures that the SI focuses solely on the nature of curvature, independent of its magnitude or size. A traditional ARDT may use the absolute magnitude of the field or its curvature to identify AR-like structures while SI would characterize all ridge structures on the [IVT] as ARs. The basic philosophy of SI can be summarized as "all circles are circles regardless of its radius". The SI provides a single-value representation that captures different shapes: values close to -1 represent concave surfaces, values near +1 indicate convex shapes, and the intermediate range corresponds to transitional shapes like flat or saddle-shaped regions. This intuitive interpretation makes the SI an effective tool for characterizing and analyzing local shapes across a wide range of applications. To obtain AR-like structures, the SI threshold of 0.375 is chosen to extract local shapes such as ridges, caps, and domes. Additionally, points where the IVT deviates by more than 45° from the local ridge are also removed to ensure coherence in the transport direction. The local ridge is aligned in the direction of the eigenvector corresponding to \( k_2 \).

3. Filtering: A variety of geometric and physical characteristics of the objects obtained from the previous step are estimated. Later, weak structures are removed by fixing a minimum mean precipitation of 1mm/day for each object. Other filters are applied to eliminate small (area < 2 x 10^6 km^2), short (length < 2000 km) and circular (eccentricity < 0.75) structures. AR-like structures associated with the Inter-Tropical Convergence Zone (ITCZ) are removed by masking out objects centered between 20°S and 20°N.

4. Tracking: The distance between filtered objects for each adjacent timestep is calculated based on their centroids. The closest objects among them are identified as the progression of one AR. If the distance traveled is greater than 4000 km per day, the object is considered to be separate. Objects with a duration of less than two days are removed from the analysis.

IVT decomposition. IVTx is decomposed into mean and anomaly as follows:

\[ \text{IVTx} = -\frac{1}{8} \int_{p_1}^{p_0} (\bar{q} + \bar{q}') (\bar{u} + \bar{u}') dp = -\frac{1}{8} \int_{p_1}^{p_0} \bar{q} u + \bar{q}' u' + \bar{q} u' + \bar{q}' u dp \]  

Where \( \bar{u} \) and \( \bar{q} \) are the monthly mean zonal velocity and specific humidity respectively and \( \bar{u}' \) and \( \bar{q}' \) are anomalous zonal velocity and specific humidity with respect to monthly means. The pressure levels are integrated from \( p_1 = 1000 \) hPa to \( p_2 = 300 \) hPa. The same pressure bounds are also chosen for the IVT calculation in AR detection.
For a particular mean state, the time averaged IVTx is calculated as,

$$ IVT_x = \frac{-1}{g} \int_{P_0}^{P_f} \left( \overline{qu} \Delta u + \overline{qg}^d u + \overline{qg}^e \right) dp $$

(7)

The change in IVTx between two mean states is calculated as,

$$ \Delta IVT_x = IVT_x^2 - IVT_x^1 $$

$$ = \frac{-1}{g} \int_{P_0}^{P_f} \left[ \overline{q_i u_i} + \Delta \overline{u_i} + \overline{q_i} \Delta u_i \right] dp $$

(8)

Substituting $\overline{u_i} = \overline{u_i} + \Delta \overline{u_i}$ and $\overline{q_i} = \overline{q_i} + \Delta \overline{q_i}$ in Eq. (8).

We identify the dynamic, thermodynamic, and eddy terms as follows.

$$ \Delta IVT_x = IVT_x^2 - IVT_x^1 $$

$$ = \frac{-1}{g} \int_{P_0}^{P_f} \left[ \overline{q_i u_i} + \Delta \overline{u_i} + \overline{q_i} \Delta u_i \right] dp $$

(9)

Similarly, IVTy is decomposed into dynamic, thermodynamic, and eddy terms as

$$ \Delta IVT_y = IVT_y^2 - IVT_y^1 $$

$$ = \frac{-1}{g} \int_{P_0}^{P_f} \left[ \overline{q_i v_i} + \Delta \overline{v_i} + \overline{q_i} \Delta v_i \right] dp $$

(10)

Noting that for both zonal and meridional components, thermodynamic term > dynamic term > eddy term, we can neglect the eddy terms. Now isolating thermodynamic and dynamic terms, we can write,

The thermodynamic component of IVT changes is formulated as,

$$ TIVT = TIVT_x + TIVT_y $$

$$ = \frac{-1}{g} \int_{P_0}^{P_f} \overline{q_i u_i} dp + \frac{-1}{g} \int_{P_0}^{P_f} \overline{q_i v_i} dp $$

(11)

The dynamic component of IVT changes is formulated as,

$$ DIVT = DIVT_x + DIVT_y $$

$$ = \frac{-1}{g} \int_{P_0}^{P_f} \overline{q_i u_i} dp + \frac{-1}{g} \int_{P_0}^{P_f} \overline{q_i v_i} dp $$

(12)

Finally, to express the TIVT and DIVT with respect to the PD mean IVT, we calculate the vector projection of each component onto IVT. This approach simplifies our analysis by illustrating the impact of each component on the mean IVT in the PD. Negative values indicate opposing effects on the PD IVT, whereas positive values signify strengthening of the mean IVT in the PD due to the specific vector being examined.

The vector projection of thermodynamic component (TIVT) onto IVT is calculated as,

$$ TIVT \cdot IVT \over |IVT| $$

(13)

Likewise, the vector projection of dynamic component (DIVT) onto IVT is calculated as,

$$ DIVT \cdot IVT \over |IVT| $$

(14)

Data availability

The data from the CESM UHR simulations are available on the IBS Center for Climate Physics climate data server (https://climatedata.ibs.re.kr/) and upon request (https://ibsclimate.org/research/ultra-high-resolution-climate-simulation-project/). Sample high resolution datasets and data used for making all the main figures and most of the supplementary figures can be found at https://doi.org/10.5281/zenodo.8166542. The ERA5 reanalysis dataset is freely available from Copernicus Climate Change Service (C3S) (https://cds.climate.copernicus.eu/cdsapp#!/dataset). The codes used for downloading the ERA5 data is also provided within the repository. Outputs from various Atmospheric River Detectors (ARDTs) are downloaded from https://www.earthsystemgrid.org/search.html?Project=ARTMIP. The CMIP5 and CMIP6 data are available at https://esgf-node.llnl.gov/search/cmip5/and https://esgf-node.llnl.gov/search/cmip6/.

Code availability

The CESM source code and the standard setup files for the ultra-high-resolution model simulation can be obtained from http://www.cesm.ucar.edu/models/cesm1.2/. For more details regarding the simulations and the PE layout for a Cray XC50 computer refer to https://ibsclimate.org/research/ultra-high-resolution-climate-simulation-project/. All the data analysis was done using python. The latest version of Python source codes for SCAFET is available at https://github.com/obhunin/SCAFET. The codes used for AR detection and for producing the figures in this manuscript are available at https://doi.org/10.5281/zenodo.8166542.

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Author contributions

A.B.N., J.-Y. L., and A.T. designed the study. A.B.N. conducted the data analysis and prepared the figures. S.-S.L. conducted the CESM UHR simulations. D.L. designed the IVT decomposition method which was implemented with assistance from A.B.N. and J.-E.C. B.G. supervised the development of the feature detection method and provided useful benchmarks. A.B.N., J.-Y. L., and D.L. wrote the initial manuscript draft. All authors contributed to the interpretation of the results and to the improvement of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Arjun Babu Nellikattil or June-Yi Lee.

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