Seasonality of Atmospheric River Frequency Depends on Location, Year, and Detection Algorithm

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Abstract

Understanding the regional and temporal variability of atmospheric river (AR) seasonality is crucial for preparedness and mitigation of extreme events. Previously thought to peak mainly in winter, recent research reveals that ARs exhibit region-specific seasonality. However, AR analysis is heavily influenced by the chosen detection algorithm. Our study examines how AR seasonality varies based on both location, year and algorithm selection. We investigate the link between year-to-year consistency of peak AR activity and the presence of a dominant seasonal pattern. We categorize regions based on their year-to-year seasonality characteristics, including consistent patterns (e.g., India, Central Asia), patterns with occasional outliers (e.g., British Columbia coast, Gulf of Alaska), and regions lacking a clear dominant season of peak AR frequency (e.g., South Atlantic, parts of Australia). Hence, not all regions exhibit a consistent seasonal cycle of AR activity. Additionally, different algorithms may detect a consistent seasonal pattern for the same region but disagree on the exact dominant season. This is exemplified by the conflicting results obtained for China. Integrated Vapor Transport (IVT) often corroborates consistent or inconsistent patterns across regions. In conclusion, this study suggests that variations in the consistency of seasonal patterns are related not only to the detection technique but also to atmospheric circulation, synoptic and low-frequency anomalies. Understanding the variations in the consistency of seasonal pattern in areas like Britain remains challenging due to algorithmic and physical differences. These findings emphasize the need for a multi-faceted approach to AR research, considering not just detection methodologies but also regional characteristics and atmospheric processes. Understanding the specific reasons for inconsistent seasonal patterns is an important next step for future research to improve forecasts and preparedness.
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Key Points:

• Atmospheric river seasonal patterns vary by location and exhibit temporal variations in some regions.
• The variations in seasonal patterns can be so vast across the temporal scale that identifying a dominant season of peak activity becomes difficult for some regions.
• Inconsistency in the seasonal pattern may not be solely due to the design of the detection algorithm, but could also be linked to changes in moisture transport, which influence AR activity.
Abstract

Understanding the regional and temporal variability of atmospheric river (AR) seasonality is crucial for preparedness and mitigation of extreme events. Previously thought to peak mainly in winter, recent research reveals that ARs exhibit region-specific seasonality. However, AR analysis is heavily influenced by the chosen detection algorithm. Our study examines how AR seasonality varies based on both location, year and algorithm selection. We investigate the link between year-to-year consistency of peak AR activity and the presence of a dominant seasonal pattern. We categorize regions based on their year-to-year seasonality characteristics, including consistent patterns (e.g., India, Central Asia), patterns with occasional outliers (e.g., British Columbia coast, Gulf of Alaska), and regions lacking a clear dominant season of peak AR frequency (e.g., South Atlantic, parts of Australia). Hence, not all regions exhibit a consistent seasonal cycle of AR activity. Additionally, different algorithms may detect a consistent seasonal pattern for the same region but disagree on the exact dominant season. This is exemplified by the conflicting results obtained for China. Integrated Vapor Transport (IVT) often corroborates consistent or inconsistent patterns across regions. In conclusion, this study suggests that variations in the consistency of seasonal patterns are related not only to the detection technique but also to atmospheric circulation, synoptic and low-frequency anomalies. Understanding the variations in the consistency of seasonal pattern in areas like Britain remains challenging due to algorithmic and physical differences. These findings emphasize the need for a multi-faceted approach to AR research, considering not just detection methodologies but also regional characteristics and atmospheric processes. Understanding the specific reasons for inconsistent seasonal patterns is an important next step for future research to improve forecasts and preparedness.

Plain Language Summary

While atmospheric rivers (ARs) are known for causing extreme weather, understanding their seasonal patterns can add to our understanding and help with preparedness and forecasts. However, the seasonal pattern is more complex than previously thought. This study reveals that AR seasonality varies not only by location, year, and even the method used to identify them. Some regions have a consistent peak season with occasional outliers in some cases (e.g., India, Central Asia, British Columbia coast, Gulf of Alaska) while others experience significant year-to-year variations making it hard to identify a dominant season (e.g., South Atlantic, parts of Australia). Interestingly, while different detection methods often agree on a seasonal trend for areas with consistent patterns, they may disagree on the exact peak season (e.g., China). Furthermore, atmospheric moisture patterns, often measured by quantities like Integrated Water Vapor Transport, frequently reflect the inconsistencies observed in AR occurrences, such as the lack of a clear dominant season. This suggests that inconsistent seasonal patterns are not only due to limitations in detection techniques but also influenced by atmospheric moisture transport patterns. Further research is necessary to pinpoint the specific atmospheric processes that contribute to these inconsistencies, ultimately leading to more accurate AR forecasts.

1 Introduction

Atmospheric Rivers (ARs) are narrow bands of concentrated moisture often found along weather fronts. These dynamic features exhibit a unique and diverse lifecycle, lasting from hours to days and significantly impacting global weather patterns (Zhou et al. (2018)). Initially identified through calculations of water vapor flux involving wind velocity and specific humidity, these narrow filamentary structures possess distinct morphological features (Newell et al. (1992)). ARs are recognized as key contributors to global meridional moisture flux, with each hemisphere typically hosting four or five of these struc-
tures simultaneously (Newell & Zhu (1994)). The primary moisture source arises from either the transport of tropical moisture towards extratropical regions or local convergence along trailing cold fronts, as confirmed by comprehensive trajectory analyses (Bao et al. (2006); Cordeira et al. (2013)). This close association with weather fronts, and by extension, extratropical cyclones, plays a crucial role in the formation and persistence of ARs (Sodemann & Stohl (2013); Dacre et al. (2015); Guo et al. (2020)).

Given this background, ARs are believed to peak during the winter half of the year due to their strong association with extratropical cyclones (Gimeno et al. (2014)). Several studies support this claim (A. D. Lavers & Villarini (2015); Nayak & Villarini (2017); Neiman et al. (2008)), with some exclusively focusing on winter-time ARs (Payne & Magnusdottir (2014); Warner et al. (2015); Kim & Alexander (2015)). This aligns with the definition of ARs, where they are typically associated with the low-level jet (LLJ) stream along the cold front of an extratropical cyclone. Additionally, the frequency of warm conveyor belts (WCBs) also peaks in winter due to stronger baroclinic instability and large-scale forcing for ascent during the cold season. However, the relationship between ARs and extratropical cyclones is not absolute. ARs and WCBs are distinct phenomena with asynchronous seasonality. Studies have shown that ARs can be more frequent in summer due to enhanced vertically integrated humidity values in the warm season (F. M. Ralph et al. (2020)).

Although a significant percentage of ARs might be associated with extratropical cyclones, neither their location nor intensity can be solely determined by this relationship (Zhang et al. (2019)). Other studies indicate that the season during which ARs peak depends on the region (Mundhenk et al. (2016); Zhou, O’Brien, et al. (2021)). The seasonal pattern associated with ARs appears to be more complex than previously thought, as evidenced by recent research might require further investigation.

This research focuses on understanding the seasonal patterns of AR occurrence, a critical factor influencing AR precipitation, which in turn drives floods and droughts. While ARs are a vital source of moisture, their duration and intensity during these seasonal occurrences can unleash devastating floods (D. A. Lavers & Villarini (2013); Mahoney et al. (2016); Griffith et al. (2020)). For example, studies in California and Australia highlight the vital role ARs play in replenishing soil moisture (M. D. Dettinger (2013); Reid et al. (2022); Guan et al. (2010); Ye et al. (2020)). Predicting their occurrence would improve water resource management in these regions. Conversely, ARs have been directly linked to devastating floods in various locations, causing significant infrastructure damage and disruptions (Stohl et al. (2008); D. A. Lavers et al. (2011); M. Dettinger (2011); F. Ralph et al. (2006)). While localized studies have shed light on regional factors influencing AR behavior, such as orographic lifting (F. M. Ralph et al. (2006); Neiman et al. (2002); B. L. Smith et al. (2010)), one must recognize that large-scale dynamics also influence AR strength and intensity (Zavadoff & Kirtman (2020); Hu & Dominguez (2019)), potentially contributing to variations in the associated seasonal cycle.

ARs are well-established contributors to global precipitation patterns, but a critical question remains: how consistent are their seasonal patterns across different regions? This study hypothesizes significant regional and temporal variability in AR seasonality depending on the region, including the timing of peak activity. We suspect that in some regions, year-to-year variations in peak AR occurrence might be so substantial that they obscure any underlying trends to identify a dominant season. This would suggest a weakly consistent or potentially inconsistent seasonal signal for ARs in those specific locations. By examining regional variability in the peak season of AR occurrence and assessing the impact of detection algorithms and atmospheric variables, this research aims to improve our understanding of both ARs and large-scale atmospheric dynamics, ultimately paving the way for improved climate models and prediction capabilities.
2 Data and Methodology

2.1 Data

This study utilizes data from the year 1981 to 2016, from the Atmospheric River Tracking Method Intercomparison Project (ARTMIP), a global collaborative effort that produced a catalogue of datasets from different AR detection algorithms. We focus on ARTMIP Tier 1 experiments, which utilize a common reanalysis dataset: MERRA-2 (Modern Era Retrospective analysis for Research and Applications, version 2) (Shields et al. (2018)). While some ARTMIP algorithms rely on Integrated Vapor Transport (IVT) calculated from specific humidity, zonal, and meridional wind variables at 3-hour intervals (e.g., Guan & Waliser (2015)), others utilize Integrated Water Vapor (IWV).

Prior research has highlighted how AR analysis conclusions can be influenced by the chosen detection algorithm, particularly the use of absolute versus relative thresholds on IVT or IWV (Zhou, O’Brien, et al. (2021); O’Brien et al. (2020); Lora et al. (2020); Shields et al. (2018)). Considering this sensitivity, we selected five commonly used algorithms for our study:

- **TECA-BARD v1.0.1:** This relative threshold-based approach employs a Bayesian framework and filters out Inter-Tropical Convergence Zone regions using a spatial filter on the IVT field up to 25° latitude (O’Brien et al. (2020)).
- **Reid et al.:** This condition-based algorithm employs an absolute threshold directly applied to the IVT field. It shares similarities with other algorithms in the ARTMIP catalogue, utilizing comparable thresholds and geometric constraints (Reid et al. (2020)).
- **Mundhenk:** Notably, this relative threshold algorithm differs by applying its threshold to the anomalous IVT field and specifically excludes tropical cyclones from lower latitudes during AR identification (Mundhenk et al. (2016)).
- **Guan and Waliser:** While also using a relative threshold on IVT, this algorithm incorporates an additional constraint based on the IVT direction, ensuring substantial poleward transport aligned with the feature’s elongation. This often results in no ARs being identified close to the equator (Guan & Waliser (2015); Guan et al. (2018)).
- **ClimateNet:** This Deep Learning-based algorithm reflects AR detection based on expert-labeled data and therefore does not rely on specific thresholds (Prabhat et al. (2021)).

Given the dependence of several algorithms on IVT, we also analyze the seasonal pattern of IVT derived from MERRA-2. To further capture atmospheric dynamics, we utilize another variable: Moist Wave Activity (WA) (S. Smith et al. (2021)) calculated using MERRA-2. It serves as a metric for significant moisture intrusions from lower latitudes to higher latitudes, encompassing features like the warm conveyor belt in addition to ARs. Calculated through a local wave activity transformation on the column water budget equation, WA determines the amplitude of moist intrusions, providing insights into how far moisture is displaced/transported and the quantity of displaced moisture, utilizing a semiempirical scaling approach (S. Smith et al. (2021); Lu et al. (2018)). The inclusion of both IVT and WA provides a robust analysis framework to provide valuable insights into atmospheric moisture transport relevant to this study’s investigation.

2.2 Methodology

This study calculates the AR frequency for each season: December-January-February (DJF), March-April-May (MAM), June-July-August (JJA), and September-October-November (SON) across five ARTMIP detection algorithms, IVT and WA. AR frequency reflects the average number of days with an AR event during each season for each grid point.
This allows us to identify the season with the highest AR activity for each grid point and algorithm which is representative of the season with peak AR activity. Our objective is to explore how much the season of maximum AR activity varies geographically across different algorithms over the time period of our study.

We initially considered using standard deviation to analyze the spread of peak AR activity across seasons. However, standard deviation has limitations when applied to cyclical data like seasons. When seasons were placed on a linear standard deviation scale, chronologically close seasons appeared to be further apart than one standard deviation unit. This highlights the issue of unequal spacing between seasons on a linear scale. Beyond quantifying the spread of seasonal patterns, we were also interested in identifying the dominant season for peak AR frequency.

To achieve this, we introduce a novel "consistency scale" that represents seasons on a circular plane, naturally incorporating their cyclical nature. As illustrated in Figure 1(a), this scale assigns unique coordinates to each of the four seasons within a 2-D plane. For each year and grid point, the season with the highest AR frequency is assigned its corresponding coordinates. The average of these coordinates across all years is calculated, resulting in a point within the circle with a radius of 1. The magnitude of this point in the polar coordinate system magnitude (distance from the origin) represents the consistency scale value, where 0 indicates the most variable dominant season and 1 represents perfect consistency (i.e., the same season dominates every year).

Figure 1. Panel (a) is an Illustration of the Consistency Scale in a 2-D Plane and Panel (b) shows how the regions that this study will focus upon

For the sake of discussion, the Consistency Scale values are categorized into five distinct classes: Highly Consistent (1-0.8), Consistent (0.8-0.6), Moderately Consistent (0.6-0.4), Inconsistent (0.4-0.2), and Highly Inconsistent (0.2-0). These categories reveal the stability of a region’s dominant season for AR activity. Imagine a region consistently dominated by winter (DJF) across years: Highly Consistent implies minimal "wavering" from this dominance. Consistent regions might have occasional "outliers" of AR activity in other seasons, while Moderately Consistent experiences significant wavering with frequent shifts between dominant seasons. Inconsistent regions lack a clear dominant season with AR events spread relatively evenly across seasons. Highly Inconsistent signifies extreme wavering, with no season holding consistent dominance and AR events occurring sporadically without clear seasonal patterns. Essentially, higher consistency values indicate stronger, less wavering dominant seasons, while lower values suggest increasing instability and difficulty identifying a dominant season.
This consistency scale also allows for the straightforward identification of the dominant AR season in regions classified as Highly Consistent or Consistent. We achieve this by dividing the 2-D circle into four sectors, each representing a specific season. Figure 1(a) shows DJF (315°-45°), MAM (45°-135°), JJA (135°-225°) and SON (225°-315°). The average vector across all years is calculated, and the sector it falls within on the divided circle determines the dominant season. This information is obtained by finding the angle the average vector makes with the horizontal axis. This method can be applied to various detection algorithms, including IVT and WA, offering valuable insights into identifying the peak season of AR activity.

In addition, to aid in the discussion of results, we have identified regions of strong AR activity and classified them into seven distinct regions in Figure 1(b). Region 1 encompasses parts of the North Pacific Ocean, the coast of British Columbia, California, and Alaska. For brevity, we will refer to Region 1 as NPO going forward. Region 2 spans the North Atlantic Ocean, particularly the British and European coastline, and will be referred to as NAO. Central Asia is represented by Region 3 (CA), India by Region 4 (IN), South America by Region 5 (SA), the South Atlantic Ocean by Region 6 (SAO), and the Indian Ocean (including parts) by Region 7 (IndO).

3 Results

3.1 Temporal Variation in the Maximum Season of AR Activity Across Different Detection Algorithms

Figure 2. Spatial distribution of the peak AR season (by year) using the TECA-BARD v1.0.1 and Mundhenk algorithms. Panels (a-c) show the TECA-BARD v1.0.1 output for three different years, highlighting the year-to-year variations. Panels (d-f) illustrate the Mundhenk algorithm’s results, also showing variations by year and discrepancies compared to TECA-BARD v1.0.1 in some areas.

Figure 2 depicts AR activity for three arbitrarily chosen years (1985, 2005, and 2015) as a sample within our larger dataset. It serves as a representative example of the substantial spatial and temporal variations in peak season of AR activity observed throughout our study period. We can see variations not only across different locations (spatial) but also in the peak season of AR activity from one year to the next (temporal) for the same location. The white spaces within the figure indicate years where the respective AR detection algorithms did not identify any AR events. It’s important to note that these
are single-year snapshots, and peak AR activity can occur even when there’s only one AR event compared to none in a given year.

The observed spatial and temporal variations in peak AR activity (Figure 2) are further influenced by the choice of detection algorithm. Detection algorithms vary in their definitions and the filters they apply. For example, the TECA-BARD v1.0.1 algorithm consistently filters out specific regions due to its design focus, as described in (Warner et al. (2013), (Zhou, O’Brien, et al. (2021)). In contrast, the Mundhenk algorithm does not apply these filters. These contrasting approaches can lead to different results, even in areas where both algorithms detect AR activity. A clear illustration of this is seen in British Columbia during 1985. The TECA-BARD v1.0.1 algorithm identifies SON as the peak AR season, while the Mundhenk algorithm suggests DJF. This example highlights how the choice of detection algorithm is also one of the factors that can influence the identification of the peak AR season.

Figure 3. Plots show the number of California coordinates with a given season as the season of peak AR activity for each respective year. Each panel represents a different detection algorithm used.
To further illustrate the year-to-year variation in peak AR season across detection algorithms, we consider California (32°N to 42°N and 114.5°W to 124.5°W) as an example region. Figure 3 plots the number of coordinates sharing the same peak AR season for each year in our study. Most coordinates show SON or DJF as the peak season in some years, while others peak over MAM or JJA. For instance, among the 360 coordinates representing California, in 1989, the Guan and Waliser algorithm (3a), TECA-BARD v1.0.1 (3d), and IVT (3f) identify over 300 coordinates with MAM as the peak season. Mundhenk (3b), Reid et al. (3c), and ClimateNet (3e) also show a peak around MAM, but with fewer coordinates (around 200). In 1990, only the Guan and Waliser algorithm identifies JJA as the peak season for most coordinates. This plot highlights the inter-annual variations in peak AR season, which can also differ between algorithms. The next section will quantify the extent of this temporal variation for each grid point to facilitate comparisons across detection algorithms.

3.2 Analysis of AR Consistency Patterns Across Different Detection Algorithms

We applied the previously described consistency scale to analyse the variation in peak season of AR activity for different grid points and algorithms. As shown in Figure 4, consistency values vary across regions and detection algorithms. Interestingly, some regions exhibit similar patterns across algorithms. For regions where the consistency scale reveals inconsistencies in the algorithm, we will further analyze these patterns in conjunction with IVT to determine whether the variations stem from the algorithm or reflect underlying dynamical conditions.

Table 1. Summary of Defined Regions with Abbreviations

<table>
<thead>
<tr>
<th>Region Name</th>
<th>Description</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>North Pacific Ocean, British Columbia Coast, California, Alaska</td>
<td>NPO</td>
</tr>
<tr>
<td>2</td>
<td>North Atlantic Ocean, British and European Coastline</td>
<td>NAO</td>
</tr>
<tr>
<td>3</td>
<td>Central Asia</td>
<td>CA</td>
</tr>
<tr>
<td>4</td>
<td>India</td>
<td>IN</td>
</tr>
<tr>
<td>5</td>
<td>South America</td>
<td>SA</td>
</tr>
<tr>
<td>6</td>
<td>South Atlantic Ocean</td>
<td>SAO</td>
</tr>
<tr>
<td>7</td>
<td>Indian Ocean (including parts)</td>
<td>IndO</td>
</tr>
</tbody>
</table>

NPO exhibits diverse consistency patterns across different detection algorithms. Reid et al. (4c), TECA-BARD v1.0.1 (4d), ClimateNet (4e), and IVT (4f) reveal predominantly consistent and highly consistent values, with occasional pockets of moderate consistency or inconsistency. In contrast, Guan and Waliser (4a) and Mundhenk (4b) primarily show inconsistent regions, with isolated pockets of consistency. This sort of variation could be due to detection technique used. For example, the design of the Guan and Waliser algorithm (4a) limits its detectable frequencies to a maximum of 15%, resulting in less geographical and seasonal variability. Moreover, in algorithms like Guan and Waliser, where AR shapes are determined by the 85th percentile, IVT often extends further inland, resulting in a higher frequency of detection (F. M. Ralph et al. (2020)). This could be one reason why it appears inconsistent, especially over the land portion of this region. The IVT anomaly-based method shown in (4b Mundhenk algorithm) is conceptually similar to the Guan and Waliser algorithm, relying on threshold percentiles to identify ARs. Given the region’s status as an AR hotspot, it is clear that the extent to which the seasonal cycle is consistent depends on the chosen algorithm, especially over California. However, off the coast of Washington and British Columbia, as well as the Gulf of Alaska, there is some agreement among the algorithms and IVT, suggesting that these
areas might be mostly consistent with occasional outliers in the peak season of AR activity. The difference in AR seasonality across the Pacific coast could be due to the presence of two distinct types of ARs: windy ARs in the north around British Columbia and wet ARs farther south (Zhou et al. (2022)).

**NAO**, representing Region 2, paints a contrasting picture of seasonal AR activity. While all detection methods identify some areas in Region 2 with inconsistent seasonal patterns for AR activity, the size of these areas varies depending on the specific method used. This observation aligns with the fact that the region consists of inconsistent areas in IVT shown in (4f). The inconsistency seen in IVT suggests that atmospheric conditions might be responsible for the absence of a clear dominant seasonal pattern. While no algorithm perfectly replicates the IVT pattern, Reid et al. (4c), TECA-BARD v1.0.1 (4d), and ClimateNet (4e) algorithms seem to capture closer approximations in certain areas compared to Guan and Waliser (4a) or Mundhenk (4b) algorithms. This therefore suggests potential algorithm-specific strengths or limitations in identifying AR events in NAO’s complex seasonal dynamics. Three algorithms and IVT point towards a lack of consistent seasonal pattern with two algorithms TECA-BARD v1.0.1 and ClimateNet having significant pockets of a consistent seasonal pattern off the British and European coast. Due to this, defining the areas that have the least annual variability over this region remains challenging.

**CA** presents a comparatively uniform picture of AR activity across different algorithms. Notably, IVT (4f) exhibits a highly consistent pattern throughout the region. Reid et al. (4c) Algorithm, likely due to its reliance on IVT, showcases similar consistency across most areas. Notably, ClimateNet (4e) also identifies ARs with strong seasonal patterns in some regions and none over the others. Similarly TECA-BARD v1.0.1 (4d) does not identify ARs over the region. In contrast, the Mundhenk algorithm (4b), weakly mirrors IVT’s consistent pattern, suggesting its effectiveness in capturing broader regional trends. However, specific sub-regions within subplot (b) also exhibit pockets of inconsistency, highlighting the challenges of accurately representing fine-grained spatial variations. Finally, the Guan and Waliser (4a) algorithm paints a distinct picture, predominantly identifying moderately consistent and inconsistent regions. However, it’s crucial to note that even within subplot (a) of this algorithm, pockets of strong consistency emerge in certain sub-regions. This suggests that ARs might have a strong seasonal pattern in this region due to similarities in consistency scale values among some algorithms and IVT.

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**Figure 4.** Consistency scale applied to the different detection algorithms and IVT. Region descriptions are shown in Table 1.
IN, reveals a largely consistent picture of AR activity across most algorithms, with a notable exception in ClimateNet (4e). This discrepancy could be due to the fact that ClimateNet also identifies tropical cyclones, and lower latitudes, such as India, might be filtered out in the algorithm’s processing. While Reid et al. (4c) and TECA-BARD v1.0.1 (4d) algorithms echo the IVT data pattern with striking consistency, suggesting a robust seasonal signature, subplot Mundhenk (4b) presents a similar landscape primarily marked by consistent regions. Interestingly, Guan and Waliser (4a) exhibits a wider range of consistency levels, hinting at potential limitations in capturing the overall regional trend. Despite these slight variations observed in some algorithms, the agreement between most methods and IVT data points towards a prevalent seasonal pattern in this region.

SA presents a compelling outlier in the analysis. Subplot (e) depicts ClimateNet’s results, where the region appears predominantly highly consistent. This characteristic is absent in any other algorithm or the IVT data. This discrepancy likely arises because ClimateNet relies on IWV as input. Since IWV is higher during warm seasons due to increased availability of water vapor, more ARs are detected by ClimateNet. However, for the other algorithms that rely on IVT, this is not the case. Greater wind speeds are required to support enhanced IVT, which is less common during these warm months. This explains why other algorithms, potentially using IVT or a combination of IWV and wind speed, identify the region as primarily inconsistent or highly inconsistent, mirroring the spread of consistency levels observed in the IVT data (subplot (f)). Notably, Reid et al. (4c) algorithm and IVT (5f) exhibit pockets of consistency within the region. This consensus from most methods, despite the outlier, strongly suggests that this region lacks a consistent seasonal pattern of AR activity.

SAO presents a case of widespread inconsistency in AR activity. All algorithms, including Guan and Waliser (4a), Mundhenk (4b), and Reid et al. (4c), primarily identify inconsistent areas in SAO. Even those methods exhibiting some pockets of consistency, like TECA-BARD v1.0.1 (4d), ClimateNet (4e), and IVT data (4f), reveal mostly inconsistent or moderately consistent patterns. This overwhelming trend strongly suggests that SAO has a lot of interannual variability in its seasonal pattern.

IndO reveals a varied pattern of consistency across algorithms and IVT. Both algorithms shown in subplot Guan and Waliser (4a) and Mundhenk (4b) consists of predominantly inconsistent regions. ClimateNet (4e) algorithm leans towards inconsistency as well, but with less dominance compared to subplots (a) and (b). Notably, Reid et al. (4c) algorithm deviates from this pattern, showcasing a lower prevalence of inconsistency and even featuring pockets of consistent regions. Meanwhile, TECA-BARD v1.0.1 (4d) algorithm and IVT (4f) share similarities in their depiction of inconsistent regions, both highlighting a peculiar "strip" phenomenon within the region. This characteristic features low values on the scale flanked by higher values on either side. However, given these varied findings, definitively defining areas where a consistent seasonal pattern might exist is challenging.

3.3 Seasonality Associated with ARs for Consistent and Highly Consistent Regions for Different Detection Algorithms

In Figure 5, across the northern half of NPO, most algorithms agree on the dominant season. In parts of the Gulf of Alaska, JJA emerges as the dominant season with consistency values ranging from 0.6 to 0.8. This observation aligns well with the IVT data. Similarly, all algorithms and the IVT data point to DJF as the dominant season off the coast of British Columbia and the remaining areas of the Gulf of Alaska. Interestingly, further offshore off the Californian coast, DJF regains dominance. All algorithms and the IVT data show areas with high consistency scale values in this oceanic region. However, along the Californian coast itself, there’s less agreement among methods. Algorithms Mundhenk (5b), Reid et al. (5c), and ClimateNet (5e) support DJF as the dominant sea-
Figure 5. Spatial distribution of the season in which AR frequency peaks for consistent (0.6-0.8) and highly consistent regions (0.8-1) for the different detection algorithms and IVT. The color scale in the center uses two concentric color wheels: the outer one represents highly consistent regions with a consistency scale values of 1-0.8, and the inner one represents consistent regions with a consistency scale values of 0.8-0.6. These color scales are applied to all algorithms shown alongside in the figure.
son, reflected by consistent values on the consistency scale. In contrast, algorithms Guan and Waliser (5a), TECA-BARD v1.0.1 (5d), and the IVT data itself exhibit lower consistency scale values, making it difficult to pinpoint a clear dominant season in this coastal area.

Across NAO, most algorithms struggle to identify a clear dominant seasonal pattern for ARs throughout the region. However, two notable exceptions emerge. TECA-BARD v1.0.1 (5d) identifies a significant portion off the coast of the British Isles and Europe with a prevalent autumn season. In contrast, the ClimateNet algorithm (subplot (e)) suggests the same dominant autumn season off the coast of Britain but identifies DJF as the dominant season further south, along the coast of Spain and Portugal. This lack of unanimous agreement across the consistency scale range leads to an inconclusive picture. It is unclear which parts of the NAO experience a consistent seasonal pattern for AR activity and which season might be dominant. Further investigation is needed to reconcile these discrepancies and understand the factors driving seasonal variations across this region.

Across CA, IVT has a strong dominance of JJA across it. There is close agreement to this by Reid et al. algorithm shown in subplot (c) with differences in the scale it is depicted on. This is also supported by subplots Mundhenk (5b) and ClimateNet (5e) algorithms that partly mirror this pattern on the consistency scale. Similarly across IN, subplots Mundhenk (5b) Algorithm, Reid et al. (5c) Algorithm, TECA-BARD v1.0.1 (5d) Algorithm and IVT (5f) have a strong agreement that the dominant season is JJA with algorithm in subplot Guan and Waliser (5a) algorithm partially aligning with the seasonal pattern.

SA and SPO exhibit predominantly inconsistent patterns across all algorithms, suggesting an absence of a well-defined seasonal pattern for AR activity. However, as discussed in Section 3.2, ClimateNet (subplot (e)) might be susceptible to seasonal biases due to its reliance on IWV. Since IWV naturally increases during warm seasons, ClimateNet might be misinterpreting this increase for consistent AR occurrences, potentially explaining the observed dominance of JJA in its results.

In contrast, the situation in IndO is more complex. While some algorithms detect seasonal patterns in specific areas, there’s a lack of consensus on the dominant season across different methods or with IVT data. For example, TECA-BARD v1.0.1 suggests MAM as the dominant season in the Indian Ocean, while IVT data points to DJF for the same region.

Beyond the previously discussed regions, the Great Lakes and Korean/Japanese regions stand out with a clear seasonal pattern. All algorithms except ClimateNet and IVT data agree on JJA as the dominant season in both regions, although they show slight variations in signal strength. However, other regions, like China, exhibit discrepancies. In China, Reid et al. (5c) and ClimateNet (5e) identify MAM as the dominant season, contrasting with JJA identified by the majority of algorithms and IVT data (5f). Notably, IVT also detects a small pocket with MAM dominance within the larger JJA-dominated region of China.

The Southern Hemisphere displays greater complexity in its seasonal AR activity compared to the North. Australia, despite significant AR activity, only shows consistent dominant seasons in northern regions. Further south, the oceanic region reveals a more unified picture with MAM emerging as the dominant season across multiple detection methods and IVT data. Similarly, Madagascar stands out with a distinct DJF season, showing strong agreement among algorithms except for ClimateNet, which consistently diverges in its seasonal patterns in this hemisphere. The Mundhenk algorithm (5b) also seems to identify the least amount of seasonal pattern as compared to the other algorithms across both Hemispheres.
While most of the regions analyzed exhibit year-round AR activity, only certain areas within these regions display a consistent seasonal cycle. This analysis highlights the diverse seasonal patterns of AR activity across different regions. Notably, agreements and intriguing discrepancies emerge when comparing the results from various algorithms and the IVT data. These findings underscore the complexity of AR seasonality, which varies geographically and may not be fully captured by all detection methods. This study aims to contribute to our understanding of whether seasonally adjusted selection criteria are necessary for year-round AR identification.

4 Discussion

The study by Mundhenk et al. (2016) supports the idea that AR seasonality varies geographically, rather than consistently peaking in winter. Our application of multiple detection algorithms reinforces this observation. Several regions, such as Korea/Japan and the British Columbia coast, exhibit a consistent peak season across multiple algorithms, aligning with the findings of Mundhenk et al. (2016). Similarly, studies suggest peak AR frequency in August for Alaska, September/October for Western Canada, and November for Washington and Oregon. Our analysis agrees with these observations, with these regions classified as “consistent” in our study, indicating a dominant season with occasional outlier (F. M. Ralph et al. (2020), Rutz et al. (2014)).

Large areas of California and South America exhibit less consistent seasonal patterns for AR activity, making it difficult to pinpoint a dominant peak season. Interestingly, the ocean region off the California coast shows a consistent pattern, with winter (DJF) as the peak season, which aligns with past studies. While some pockets within these regions might have consistent patterns, algorithms sometimes reveal inconsistencies that match the moisture transport patterns (IVT), suggesting links to atmospheric processes.

To delve deeper into seasonal pattern inconsistencies, we examined Moist Wave Activity (WA) alongside Integrated Vapor Transport (IVT) over 16 years from 2000-2016. Although IVT, a commonly used parameter for ARs, became our focus, WA can also offer valuable insights. IVT represents the total seasonal moisture transport, emphasizing the average amount of moisture moved, primarily by ARs. WA, on the other hand, focuses on the seasonally averaged displacement of moisture, considering both quantity and distance traveled.

Figure 5b shows the WA consistency scale, revealing a generally consistent pattern with some regional inconsistencies, often concentrated near oceans. While WA suggests consistent seasonal transport mechanisms, potentially indicating more regular AR/WCB activity, interpreting it has nuances. High consistency values of WA doesn’t directly guarantee consistent timing for individual events, and consistency could stem from overall AR/WCB activity without implying consistent seasonality for each event. The consistency of WA might be linked to consistent IWV, strongly influenced by large-scale atmospheric flow. However, inconsistencies could also arise from low-frequency anomalies, potentially contributing to IVT inconsistencies as well.

IVT, encompassing various transport forms, includes the time-mean circulation along with synoptic and low-frequency eddies. The time-mean circulation drives most zonal transport in oceanic regions. Synoptic and low-frequency anomalies, however, are responsible for much of the mean moisture transport from ocean to land, particularly evident near oceans (NPO, NAO - including southwestern US and Europe). Low-frequency variability plays a crucial role in driving mean poleward transport towards the Arctic, especially during summer. Synoptic variability heavily influences moisture transport in the midlatitudes Newman et al. (2012). The impact of these eddies is reflected in the low
consistency values observed over SA, SAO, and IndO regions. Therefore, inconsistencies beyond AR activity can likely be attributed to these dynamical aspects.

Figure 6. Comparing consistency scales applied to 16 years of integrated vapor transport (IVT) and moist wave activity (MWA): Exploring links between moisture transport and inconsistencies in AR seasonal patterns.

Changes in the atmospheric circulation could also be linked to climate variability over the region, influencing the seasonal cycle (Mundhenk et al. (2016)). Numerous studies connect ARs with various global climate modes, focusing on phenomena such as ENSO (Payne & Magnusdottir (2014); Kim et al. (2019)), MJO (Reid et al. (2022); Guan et al. (2012); Zhou, Kim, & Waliser (2021)), and QBO (Mundhenk et al. (2018)), among others. Although insights into consistencies may emerge at sub-seasonal to seasonal scales, uncertainty persists regarding the relationship between these phenomena and ARs. For instance, a regional study in the northwest United States found no evidence of ENSO-SST-related forcing on AR predictability (Goldenson et al. (2018)). Another study concluded that the relationship between ENSO and AR count would depend on the parameters used (O’Brien et al. (2020)). Further research specific to regions is necessary to determine the extent to which each of these phenomena contribute to the yearly variation in the peak AR season. Additionally, the use of the suggested ENSO Longitude Index might be a more appropriate method to capture ENSO diversity compared to traditional metrics (Patricola et al. (2020)).

While atmospheric circulation does impact the seasonal pattern, detection techniques also play a role in contributing towards deciding whether or not a region has a consistent seasonal pattern. For example, algorithms Guan and Waliser (Figure ??a) and Mundhenk (Figure 4b) over NPO might have different sensitivities to weaker ARs (Lora et al. (2020)), resulting in varied seasonal patterns. Spatial correlation offers a concise way to compare these inconsistencies across algorithms and with other factors like IVT and WA. Examining Figure 6, we see TECA-BARD v1.0.1 exhibiting the strongest correlation with IVT, while ClimateNet shows the weakest. Reid et al. and Guan and Waliser algorithms have similar values, followed by Mundhenk. Guan and Waliser captures dominant seasons at higher latitudes like IVT, potentially explaining its slightly higher correlation, putting it on par with the Reid et al. algorithm. Finally, the correlation between WA and long-term IVT (IVT16) is around 0.5, which might be influenced by WA’s nature as a flow-based diagnostic.

Studying seasonal patterns and variations in algorithms is challenging, potentially attributed to the use of AR frequency as a metric. Previous studies, including this one, have noticed significant yearly variations in AR frequency (Ma & Chen (2022); Nayak & Villarini (2017); Mcguirk et al. (1987)), implying that adopting a different, more stable metric could unveil more distinct seasonal patterns associated with ARs. Many fu-
Figure 7. Spatial correlation matrix between different detection algorithms, integrated vapor transport (IVT), IVT (16 years), and moist wave activity (MWA) (16 years).

5 Conclusion

ARs significantly impact human lives, making accurate prediction crucial. While studying seasonal patterns is vital for anticipating potential catastrophic AR events, our research underscores that a consistent seasonal pattern for ARs exists only in specific regions. Our research builds on the known variability of AR seasonality by location, confirming consistent patterns in some regions like coastal British Columbia and the Gulf of Alaska, aligning with previous findings (Mundhenk et al. (2016)). However, our study reveals deviations from the dominant season of peak AR activity within certain regions. This is evident even in regions such as British Columbia, Gulf of Alaska and U.S West Coast, that exhibit occasional years with different peak activity, highlighting temporal variability. However, the degree of this variability differs across regions, resulting in some areas with no obvious dominant season of AR activity.

The proposed consistency scale in this study facilitates a comprehensive comparison and quantification of variations in seasonal patterns, emphasizing that ARs exhibit a strong seasonal cycle over specific areas such as over India and Central Asia. Furthermore, it underscores that the seasonal pattern in these regions varies based on the chosen detection algorithm. Specially over California, the presence or absence of a consistent seasonal pattern depends on which AR detector is being used. Sometimes, despite detecting a dominant seasonal pattern, there is a lack of consensus among different algorithms on what that dominant season is.

Beyond limitations inherent to detection algorithms, dynamical features also contribute to discrepancies between them. This is evident when comparing their seasonal patterns to IVT, particularly over the South Atlantic Ocean and parts of Australia. While
this study offers valuable insights, our understanding of large-scale dynamics and circu-
lation remains limited, restricting the scope of our conclusions.

The consistency scale introduced here has additional limitations related to its def-
inition. It does not distinguish between interannual and interdecadal variability. For ex-
ample, a region might experience alternating dominant seasons year-to-year, or one dom-
inant season for a decade followed by another. Both scenarios would have the same con-
sistency scale value. Nevertheless, the scale effectively helps us determine whether a re-
gion exhibits a consistent peak season of AR activity throughout the study period.

The definition of peak season in this study is based on an average value and is de-
pendent on how the seasonal bins are designed. However, the identified peak seasons are
consistent with those found in existing literature. We have explored various reasons why
some regions lack a clear dominant season for peak AR activity. The variables used to
connect these variations to atmospheric conditions are IVT and WA. Since IVT encom-
passes multiple forms of transport and WA is a flow-based diagnostic representing the
activity’s equivalent latitude, pinpointing the variations to low-frequency anomalies with
high accuracy remains challenging. Further investigations on seasonal to sub-seasonal
timescales are necessary to delve deeper into the reasons for these spatial and tempo-
rnal variations.

Furthermore, regions like Britain exhibit inconclusive results across different algo-
rithms. This highlights the need for further research to definitively establish the pres-
ence or absence of a seasonal cycle for AR activity in these areas.

Understanding AR behavior in a specific region requires identifying its seasonal cy-
cle, which offers valuable insights into overall AR activity and dominant seasons. While
consensus among multiple algorithms effectively reveals the dominant season in many
regions, this approach presents challenges in areas like Britain. In such cases, the lack
of agreement between algorithms and IVT data hinders the clear identification of a sea-
sonal cycle. One potential explanation for the low consistency scale values could be in-
consistencies in IVT and IWV driven by low-frequency anomalies. Further investigation
into AR activity in these regions is crucial to deepen our understanding of their seasonal
patterns.

Our study offers significant advancements in our understanding of AR behavior and
its seasonal variations. This has direct implications for local meteorologists, equipping
them with deeper insights into regional AR activity and enabling better prediction and
mitigation strategies. Additionally, the study provides a valuable tool - the consistency
scale empowers researchers to evaluate seasonal changes in various atmospheric variables
and assess the impact of climate change on ARs by analyzing dramatic shifts in seasonal
activity. Importantly, the study emphasizes the crucial role of carefully choosing detec-
tion algorithms for accurate assessments of AR seasonality.

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