Characteristics of Atmospheric Rivers over Texas and their Contributions to Extreme Precipitation

Final Contract Report prepared for Texas Water Development Board (Contract No.: 2101792540)

Ashraf Rateb and Bridget R. Scanlon

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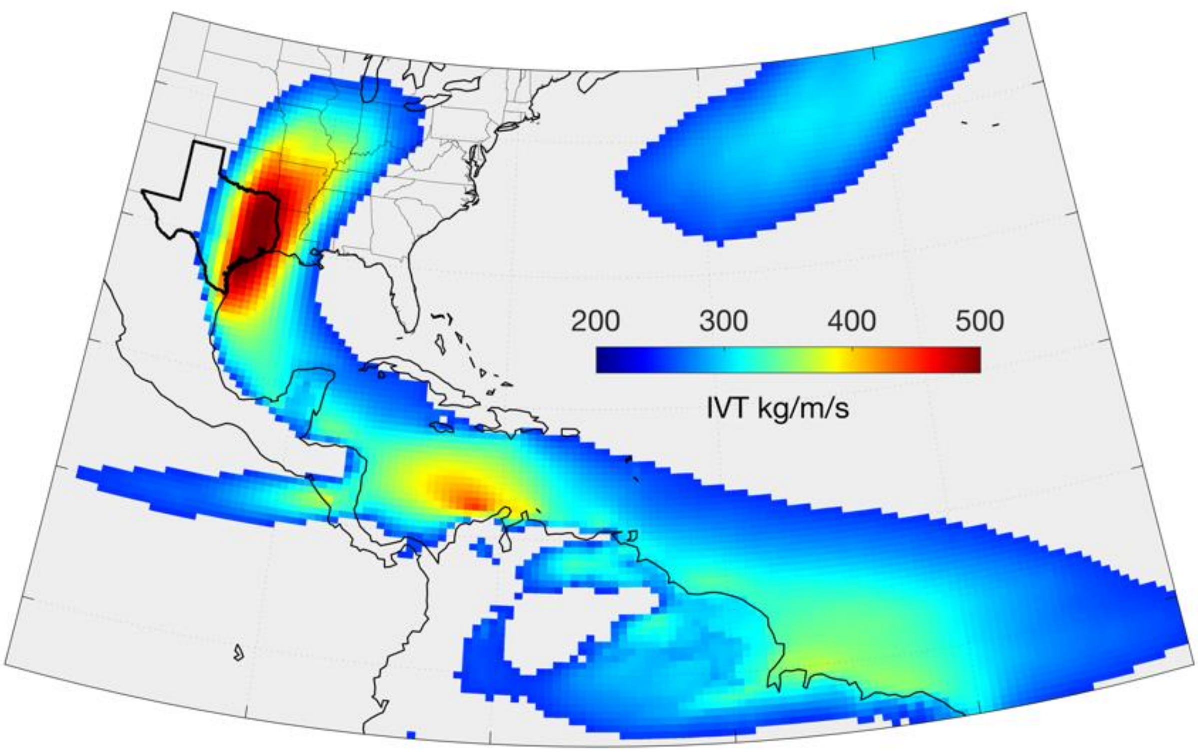

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by:
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List of Acronyms

Abbreviation	Meaning
AMO	Atlantic Multi-decadal Oscillation
AR	Atmospheric river
ARTMIP	Atmospheric River Tracking Method Intercomparison Project
CI	Credible interval
CMIP5	Coupled Model Intercomparison Project 5
DJF	December-January-February
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño-Southern Oscillation
ERA-interim	ECMWF Re-analysis
GoM	Gulf of Mexico
GP	Gaussian Processes
hPa	Hectopascal
ICZ	Intertropical Convergence Zone
IVT	Integrated water vapor transport
JJA	Jun-July-August
MAM	March-April-May
mb	Milibar
MCMC	Markov chain Monte Carlo
NAO	North Atlantic Oscillation
NHC	National hurricane center
NOAA	National Oceanic and Atmospheric Administration
ONI	Oceanic Nino Index
PDO	Pacific Decadal Oscillations
PRISM	Parameter-elevation Regressions on Independent Slopes Model
RBF	Radial basis functions
SON	September-October-November
SST	Sea surface temperature
TDI	Trend direction index
US	United States

Executive Summary

Atmospheric rivers (ARs) are defined as narrow atmospheric corridors that transport moisture from the tropics toward the poles. Like rivers in the sky, ARs play a major role in the global climate system and modulate global and regional water cycles. ARs are extensively studied along western and northwestern United States (US) coasts, where their roles in floods and as drought busters are well established. In the southern US, particularly in Texas, understanding of the contribution of ARs to flooding is limited and represents a substantial knowledge gap for managing flood risks and water resources. The objective of this research was to assess the frequency, magnitude, duration, and source of ARs over Texas and their relative contributions to total and maxima annual and seasonal precipitation over the state.

We evaluated the characteristics of ARs in Texas and surrounding regions using 40 years of atmospheric reanalysis and local precipitation data (1980–2019). We applied an AR detection algorithm based on the intensity of integrated water vapor transport (IVT) anomalies and shape (length and length/width ratio) characteristics to develop a database of ARs over Texas.

Results show that a total of 807 AR events were defined over the 40-year period (1980–2019), resulting in an average of ~20 ARs per year. AR landfalls are much more frequent in eastern Texas than in western Texas. The magnitude of an AR is based on the IVT intensity, with most ARs falling in the range of 250–1000 kg/m/s of precipitable water, with durations up to 72 hours. ARs in Texas are sourced primarily from the Atlantic Ocean, strengthening in the Caribbean, moving over the Yucatán Peninsula, and then funneling into western Mexico to make landfall over the coasts of Texas and Louisiana before moving inland to the US Midwest. ARs contributed 25–31% to total precipitation over the period 1981–2019, ranging from ≤10% in the western part of the state to 25–31% in the eastern part of the state. ARs may account for 42–54% of annual maximum precipitation in eastern Texas and ≤25% in western Texas. ARs' possible contribution to seasonal maximum precipitation are higher in winter and lower in summer. There is no relationship between ARs and hurricanes, as only 2% of ARs occur during the lifetime of hurricanes, based on the Hurricanes National Database from 1980–2019.

Relating the impact of interannual (e.g., El Niño Southern Oscillation [ENSO], North Atlantic Oscillation [NAO]), and decadal (Atlantic Multi-decadal Oscillation [AMO], Pacific Decadal Oscillation [PDO]) climate variability shows that ARs are more frequent during the warm phase of NAO, which is expected given that the dominant source of AR moisture is the Atlantic Ocean. During the warm phase of NAO, ARs exhibit the highest intensity of precipitable water, particularly in the eastern part of Texas and extending into neighboring states. This can lead to extreme precipitation events and potential flooding in affected regions. No significant temporal trends were found in the frequency of AR landfalls over Texas.

This study identified gaps in our analysis that should be considered in future research, including quantifying impacts of ARs in floods and the role of ARs in terminating droughts, as seen in the western US. The causes of ARs should be investigated, such as their relationship to atmospheric circulation and the low-level jet. Variations in extreme events should also be evaluated using large ensembles to better sample these extremes historically and into the future. Leveraging information content from different atmospheric, oceanic, and land variables can help to develop a short to medium lead time forecast (1–7 days) of AR events. Coupling these forecasting skills with reservoir operations and water management efforts is important for flood forecasting and harvesting precipitable water from ARs for beneficial use based on forecast-informed reservoir operations. This research has broader implications related to flood preparedness and mitigation,

reservoir operations, and overall management of water resources, particularly in populated areas of the state.

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1. Introduction

Texas is much more prone to climate extremes than other states in the United States (US) (Kunkel and others, 2022). Many climate extremes have had large impacts on water resources management and the state economy (Smith and others, 2010). Researchers have accumulated knowledge within the past few decades on the increased intensity of these extremes and the severity of their impacts: flooding, (Kunkel and others, 2022); temperature extremes and frequent droughts (Nielsen-Gammon and others, 2020); intense hurricanes (Risser and Wehner, 2017); and sea level rise (Liu and others, 2020). The impacts of these extremes (i.e., hurricanes) can affect millions of people and lead to property damage of billions of dollars (Amadeo, 2018). Anticipating and managing these extremes is essential and depends on developing an understanding of their physical mechanisms and quantifying their impacts. While much of the research on hydroclimate extremes in Texas focuses on tropical cyclones, including hurricanes, very little information is available on rainfall-inducing moisture transport from the Atlantic and Pacific Oceans, termed *"atmospheric rivers"* (ARs).

ARs are defined by the American Metrological Society as "*A long, narrow, and transient corridor of strong horizontal water vapor transport that is typically associated with a low-level jet stream ahead of the cold front of an extratropical cyclone*" (Ralph and others, 2018). Like rivers in the lower troposphere, ARs account for ~90% of the water vapor transport from the tropics and subtropics toward the poles even though they occupy only ~10% of the longitude (Zhu and Newell, 1998). ARs produce heavy rain or snow when they meet steep terrain and are lifted by a warm air current. On average, they carry more than double the amount of water vapor found in the Amazon River, greatly affecting local weather and climate. The amount of water vapor carried by ARs on average globally is more than double that of the Amazon River flow (215,000 m^3/s) (Ralph and others, 2018). ARs have a substantial impact on modulating global and regional water and energy cycles. For example, ARs contribute 30–50% of total precipitation in California and along the northwest coast (Dettinger, 2011; Guan and others, 2013) and are responsible for terminating 33–72% of persistent droughts in the US (Dettinger, 2013).

Over the southern and eastern coasts of the US the sources and contributions of ARs to local precipitation are known only for a limited number of events. In an earlier study, Dirmeyer and Brubaker (1999) found that the source of the AR that caused the Mississippi River floods in July 1993 was from the western Gulf of Mexico (GoM), Yucatán Peninsula, and Caribbean Sea, with some contributions from the eastern subtropical Pacific Ocean before July. This fetch of moisture transport was coined as the "*Maya Express*," analogous to the Pacific northward and northeastward moisture transport termed the "*Pineapple Express*" that makes landfall along the western coast of the US (Dirmeyer and Kinter III, 2009). The 2008 flood events are similar to the 1993 events (Coleman and Budikova, 2010). Heavy rainfall in 2008 in the eastern US was attributed to above-average moisture transport from the Caribbean (Dirmeyer and Kinter III, 2009, 2010). Similarly, the floods in May–June 2010 in Nashville, Tennessee; eastern Texas; western Arkansas; south-central Kansas; and central Oklahoma have been linked to ARs (Higgins and others, 2011). In the Midwest, the contribution of ARs to flooding was investigated by Lavers and Villarini (2013), who found that 42% of the basins studied had ~50% of their floods linked to ARs. A recent study by Slinskey and others (2020) shows that ARs in the south and the Midwest have varied seasonally with limited areal extent (<200,000 km^2) contributing 20–25% to spring and summer precipitation.

There is limited knowledge on the characteristics of ARs in the southern US, including magnitude, frequency, and duration and their role in modulating total and extreme precipitation in this region. The relationship between AR events and hurricanes is also unknown. In addition, the role of climate variability (El Niño–Southern Oscillation [ENSO], North Atlantic Oscillation [NAO], Pacific Decadal Oscillations [PDO], and Atlantic Multi-decadal Oscillation [AMO]) in amplifying or dampening the frequency of ARs and modulating the associated precipitation patterns has not been established.

Recognizing the origin of AR events and quantifying their contributions to local precipitation in Texas is crucial for developing long lead time forecasts, which are essential for effective emergency management to mitigate flood impacts and optimize water management. By understanding the role of ARs in the region's precipitation patterns, reservoir operators can make better-informed decisions regarding water storage and release, thereby minimizing the negative consequences of extreme weather events on local communities and infrastructure.

1.1. Scope of this Work

The objective of this study was to answer the following questions:

a) How frequent are AR landfalls over the southern US, particularly over Texas, within the past four decades (1980–2019)?

b) What are the characteristics (e.g., intensity, duration, seasonality) of ARs over Texas?

c) What is the contribution of ARs to local total and extreme annual and seasonal precipitation in Texas?

d) How does interannual to multi-decadal climate variability in surrounding oceans (i.e., Atlantic and Pacific) affect AR distribution and modulate related precipitation?

e) Has the dynamics of AR occurrence varied over time between 1980 and 2019?

2. Data and Methods

2.1. Data

2.1.1. Atmospheric reanalysis

This study uses atmospheric reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim) between 1980 and 2019. ERA-Interim was initiated in 2006 by ECMWF to bridge the gap between legacy data: ERA-40 (1957–2002) and future reanalysis data (Berrisford and others, 2009). The ERA-Interim reanalysis employs the Integrated Forecast System (IFS) cycle Cy31r2 to generate consistent, high-quality atmospheric data. The IFS developed by the ECMWF in 2006, a state-of-the-art numerical weather prediction system, assimilates observational data and simulates atmospheric variables over time to produce reliable, accurate representations of historical and current weather patterns. In the ERA-Interim setup, there are approximations for 60 distinct vertical levels, with the uppermost level situated at 0.01 hPa. Data are available between 1979 and 2019 at regular grids (1.5°×1.5°) of 4× daily (6-hour), and can be acc accessed through ERA-Interim | ECMWF.

2.1.2. Precipitation

Daily total precipitation based on the Parameter-elevation Regressions on Independent Slopes Model (PRISM) was used in this study. The PRISM product was developed by the PRISM climate group at Oregon State University using the PRISM interpolation method (Daly and others, 2000). Current versions of the daily total precipitation uses higher resolution weather radar observations (Daly and others, 2021). Data are available at a spatial grid of 4×4 km for the continuous US between 1980 to present.
Data can be accessed through the PRISM Climate Group, Oregon State University (https://prism.oregonstate.edu/).

2.1.3. Climate teleconnection indices

To investigate the interrelationship between AR landfall over Texas, related precipitation patterns and intensity and changes in the surroundings oceans at interannual, decadal, and multi-decadal scales, we evaluated climate teleconnection indices of the Atlantic and Pacific oceans. Four indices were evaluated for the period 1980 to 2019.

- **Oceanic Niño Index (ONI)**

The Oceanic Niño Index (ONI) serves as an important metric in understanding the strength and occurrence of ENSO events, which have a significant impact on global climate patterns (Trenberth and Hoar, 1997). ONI is derived from sea surface temperature (SST) anomalies in the central and eastern equatorial Pacific and is calculated as the three-month running mean of these anomalies in the Niño 3.4 region (5°N–5°S, 120°W–170°W) (Barnston, 1997). An El Niño (La Niña) event is generally identified when ONI values are above +0.5°C (-0.5°C) for a minimum of five consecutive overlapping three-month periods, indicating warmer (cooler) than average SSTs in the region. El Niño events are associated with wetter and cooler conditions in Texas, particularly during winter and early spring months. Conversely, La Niña events are more frequent and intense, while El Niño events are less frequent and weaker. La Niña events often lead to warmer and drier conditions in Texas (Parazoo and others, 2015).

- **North Atlantic Oscillation (NAO)**

NAO is a prominent climate pattern that plays a significant role in influencing weather and climate variability across the North Atlantic region, including Europe, North America, and North Africa (Hurrell and others, 2003). NAO is characterized by the fluctuations in atmospheric pressure difference between the Icelandic Low and the Azores High, which lead to variations in the strength and direction of westerly winds and storm tracks across the North Atlantic (Hurrell and others, 2001). The NAO index is calculated as the normalized pressure difference between these two pressure centers (Jones and others, 1997). A positive (negative) phase of NAO is associated with a strengthened (weakened) Icelandic Low and Azores High, leading to enhanced (diminished) westerly winds and storminess across the North Atlantic. Positive NAO phases are generally associated with mild, wet winters in the southeastern US, including Texas. NAO impact can be modulated by other climate factors such as ENSO) and the Pacific Decadal Oscillation (PDO) (Hurrell and others, 2003).

- **Pacific Decadal Oscillations (PDO)**

The PDO is a long-term oceanic and atmospheric climate pattern that occurs primarily in the North Pacific Ocean. It consists of two phases, a positive (warm) phase and a negative (cool) phase, each lasting for an approximately 20–30-year period. PDO is characterized by persistent SST anomalies and related atmospheric circulation changes, which can significantly impact regional climate, ocean ecosystems (Mantua and Hare, 2002). PDO has been linked to the modulation ENSO) impacts, as well as to the variability of the Aleutian Low and the North Pacific High pressure systems (Newman and others, 2016). During the positive phase of the PDO, SST are warmer than average in the eastern North Pacific and cooler in the central North Pacific. This phase is associated with increased precipitation in the Pacific Northwest and decreased precipitation in the southwestern US (Gershunov and others, 2017). Conversely, the negative phase of the PDO features cooler SST in the eastern North Pacific and warmer temperatures in the central North Pacific, leading to drier conditions in the Pacific Northwest and wetter conditions in the southwestern US. PDO can influence the climate and weather patterns in Texas, indirectly, compared to regions closer to the Pacific coast, through ENSO modulations. When ENSO and PDO positive phase sync, El Niño events tend to be more frequent and intense while La Niña events are less frequent and weaker. Conversely, during the negative (cool) phase of the PDO, La Niña events are more frequent and intense, while El Niño events are less frequent and weaker (Moon and others, 2015).

- **Atlantic Multi-decadal Oscillations (AMO)**

The AMO is a natural climate variation influencing SSTs in the North Atlantic Ocean (Schlesinger and Ramankutty, 1994). The AMO has a timescale of 60 to 80 years, with each warm or cool phase lasting approximately 30 to 40 years. During the AMO's warm phase, above-average SSTs are observed across much of the North Atlantic, while below-average SSTs are prevalent during the cool phase. These temperature variations impact climate and weather patterns, including Atlantic hurricane activity, droughts, floods, and the position of the Intertropical Convergence Zone.

The AMO interacts with other climate phenomena like ENSO and PDO, affecting regional climate variability. For instance, the AMO modulates the influence of ENSO on North American precipitation patterns (Kushnir and others, 2010). In Texas, the AMO affects the frequency and intensity of droughts, particularly when interacting with ENSO and PDO. The warm phase of the AMO is associated with increased Atlantic hurricane activity and enhanced moisture transport, leading to more precipitation. In contrast, the cool phase is linked to drier conditions (Enfield and others, 2001; McCabe and others, 2004).

Data for these indices can be obtained from Climate Indices: Monthly Atmospheric and Ocean Time Series: NOAA Physical Sciences Laboratory (https://psl.noaa.gov/data/climateindices/list/).

2.1.4. Hurricane database

The database of tropical cyclones, including hurricanes, that made landfall over Texas between 1980 and 2019 was obtained from the National Hurricane Center (NHC) archive. Data include 56 events represented by extratropical, tropical depressions, tropical storms, and categories of 1 to 5 storms for the period 1980–2019. The metadata include pressure and wind speed and track paths.

Data can be accessed through the Historical Hurricane Tracks from noaa.gov.

2.2. Methods

2.2.1. Atmospheric river detection

ARs can be detected based on the value and shape of the IVT (Lavers and others, 2012). IVT represents the amount of precipitable water if all the moisture vapor content was condensed. IVT is calculated from the integration of the vertical moisture transport and advection of moisture based on the horizontal wind vectors for the vertical pressure levels from the 300 to 1000 hPa (Hectopascal: A unit of pressure equal to a millibar (1 hPa = 1 mb)) as:

$$IVT = \sqrt{\left(\frac{1}{g}\int_{300}^{1000} qu\, dp\right)^2 + \left(\frac{1}{g}\int_{300}^{1000} qv\, dp\right)^2} \qquad (1)$$

where g is gravitational accelerations in *m/s*, q is specific humidity in *kg/kg*, u, v are wind fields in zonal and meridional directions (*m/s*), respectively, and dp is the differential pressure of adjacent levels.

We used an AR detection algorithm developed by Guan and Waliser (2015) to extract the IVT object (contiguous region) that would represent an AR at 3- and 6-hour time steps using reanalysis data. The following set of necessary requirements should be met to define an IVT object as an AR:

- IVT intensity ≥85th percentiles of objects with a fixed lower limit of ~100 kg/m/s at each grid cell
- IVT geometry ratio, where the length (>2000 km) is > 2× the width.
- IVT direction where the mean IVT is oriented within ±45° of the pole.
- Landfall over the coastline, where the remaining length > 1000 km is over the ocean.

For a detailed description of the detection algorithm, the reader is referred to (Guan and Waliser, 2015, 2019).

2.2.2. Atmospheric river catalog

We evaluated a global catalog of ARs developed by recent improvements in the approach from Guan and Waliser (2015) and incorporated more features of ARs, including speed and lifetime. We used the coordinates for the Texas coastline and masked the global results of AR landfall locations. Then, we used a backward trajectory in looking at the IVT anomalies that were associated with these masked events and evaluated the associated local precipitation.

2.2.3. Contribution of atmospheric rivers to precipitation in Texas

The contribution of ARs to total precipitation and to extreme annual and seasonal precipitation between 1981 and 2019 was calculated as follows:

- For the fraction of total precipitation that can be attributed to ARs, we derived the total precipitation rate at each grid cell during the AR days and divided it by the total precipitation that the grid point experienced during the entire 39-year period. AR days include the day of the AR event plus precipitation during the following day to account for the difference between the universal time of the ERA-Interim and the PRISM data dates. For the fraction of extreme precipitation during a year or a climate season that can be attributed to ARs, we use the block maxima approach to derive maximum precipitation during a year or climate season. We divided the observations at yearly or seasonal timescales into nonoverlapping (blocks) or durations (a year) and thus minimize the dependency between the events and cover longer periods. We derived 39 events for the annual extremes (1981–2019) and during the climate seasons at each grid cell, then cross-referenced the extremes days during a year or a climate season with the AR days. If the AR days matched the days of the extremes, we considered that the AR influences these extremes. Then, the number of matched days is divided by the total number of extremes annually or during a climate season for each grid cell and the results represent the possible percent contributions of ARs to annual and seasonal extremes. We generated the results for the annual and for the climate seasons as Fall: September–November; Winter: December–February; Spring: March–May; and Summer: June–August.

- To investigate the impact of natural climate variability in the Atlantic and Pacific oceans from interannual to multi-decadal timescales, NAO, ENSO, AMO, and PDO indices were compared with ARs. The monthly data were smoothed using a moving average of 6-month, 12-month, 24-month, and 36-month periods to suppress intra-annual and annual variability in the indices. We used the 24-month smoothed version of the indices and cross-referenced their positive and negative phases with the AR days chronology. To derive the signature of the climate teleconnections in modulating the AR-related rainfall, for each state of the climate indices, we generated a composite map of the corresponding AR-induced precipitation during each phase of the climate.

2.2.4. Trends in occurrences of atmospheric rivers

To understand the long-term trend of AR occurrences, we studied the trend in the total number of AR landfalls each year from 1980 through 2019 using Gaussian Process Regression (GPR) (Rasmussen and Williams, 2006). The yearly occurrences of ARs are represented by a latent function ($\boldsymbol{f}$) which assumes that the function can be smoothed to model the trend. GPR relaxes the assumption of parametric methods over ($\boldsymbol{f}$) (e.g., linearity) by assuming $\boldsymbol{f}$ is a random process, generated from a multivariate Gaussian distribution. The random function (f) can be inferred using the Bayesian theorem, and its posterior also follows a Gaussian distribution, which makes uncertainty in the trend as part of the inference. GPR is robust to overfitting. The posterior over ($\boldsymbol{f}$) follows Bayes theorem as follows:

$$p(\mathbf{f}|X, y) \propto \mathrm{p}(\mathrm{y}|\mathbf{f})\mathrm{p}(\mathbf{f}|\mathrm{X}) \tag{2}$$

where y is the likelihood based on observations (i.e., number of ARs) and the $p(\mathbf{f}|X)$ is the priors which follow the Gaussian distribution as:

$$p(\mathbf{f}|X) \sim \mathcal{N}\ (\mathbf{f}|\boldsymbol{\mu}(X), \mathbf{K}((X, X)) \tag{3}$$

where the $\mathbf{f}$ vector is for all function values over the time index; $\boldsymbol{\mu}(X)$ is vector for all mean functions, and $\mathbf{K}(X, X)$ is a covariance matrix between the inputs.

We use the Radial Basis functions (RBF) to fit the yearly number of ARs. RBF is defined as:

$$K_{RBF}(x, \grave{x}) = \sigma^2 exp\left(-\frac{(x-\grave{x})^2}{2\lambda^2}\right) \tag{4}$$

where σ is the variance noise; λ is the length scale of the function (horizontal change of the function), the longer λ is, the smoother the function.

Besides the GPR trend, we evaluated the AR trends using a probabilistic index called Trend Direction Index (TDI). TDI quantifies the probability of a random process (f) changing monotonicity at an observed time (x) conditioned on the observed data. TDI is the probability of the slope sign changing and conveys a plausible answer to the question: what is the probability of AR frequency trend progressing (i.e., increasing in upward direction) or de-progressing (i.e., increasing in downward direction) at any given time?

$TDI(t, \delta|\Theta)$ is trending in the up direction where $\mu_{df}(t + \delta|\Theta) \neq 0$ indicates the posteriors mean of the df is not constant and progressing in up or in down directions as:

$$TDI(t, \delta|\Theta) = \begin{cases} Unknown, \mu_{df}(t + \delta|\Theta) = 0 \\ Trending_{up} \ , \ \mu_{df}(t + \delta|\Theta) \neq 0 \end{cases} \quad (5)$$

$$TDI(t, \delta|\Theta)_{down} = 1 - TDI(t, \delta|\Theta)_{up} \quad (6)$$

where t is time, δ is the instantaneous slope, Θ is hyperparameter of the kernel functions (herein the RBF kernel), and Y is the vector of the input data.

In practice, the yearly number of ARs is fitted using the Stan probabilistic programming (Gelman and others, 2015) in the r framework (Team, 2021). Four independent Markov Chains were used to sample 50×10^3 of the posterior distributions of the kernel hyper parameters and the quantities of interest, (e.g., slope, derivates of the slopes, and TDI) using Hamilton Monte Carlo (MCMC) sampling methods. The model convergence was diagnosed using the MCMC diagnostic test (i.e., R-hat test) (Vehtari and others, 2021).

3. Results

3.1. Characteristics of Atmospheric Rivers over Texas

3.1.1. Origin of atmospheric rivers

We derived a database of 807 AR landfalls over Texas using ERA-Interim between 1981 and 2019. In these events the Texas coastline coordinates overlap with IVT landfall locations. This number of AR events suggests a frequency of ~20 AR events per year. ARs are much more frequent in eastern Texas than in western Texas. Moisture sources originate from the Atlantic Ocean near the coastlines of French Guiana, strengthening in the Caribbean, traveling over the Yucatán Peninsula, then funneling into the western GoM to landfall on the Texas and Louisiana coastline and move inland to the Midwest. Our composite map of all 807 ARs indicates that the northern equatorial Pacific contributed to a small extent (Figure 1). Absence of steep, high topography in Texas and Louisiana allows the remaining moisture from the AR to be transported to the Midwest. The warm air masses from the dry could drive the shifting the AR trajectories to the Midwest, impacting the orientation of moisture bands. However, the Balcones Escarpment, which comprises elevated topography extending from Del Rio to the Red River with altitudes ranging from 100 to 300 m (Caran and Baker, 1986), may play a role in deriving the portions of the AR landfall over East and Central Texas. Some studies found the Balcones could alter the location of maximum accumulation of precipitation, resulting in a slight shift to the north and west (Nielsen and others, 2016). The overall impact of AR landfalls is significantly influenced by the atmospheric conditions (Nielsen and others, 2016).

3.1.2. Climatology of atmospheric rivers

We derived the chronology of AR landfalls, termed AR days, which represent the AR landfall days and the next day to account for uncertainty in the universal time of the reanalysis data and the US Central time. The total number of AR days over the 39-year time period (1981–2019) is 1712 days, between March 4th , 1981, through August 19th, 2019, with 59% of the AR days between December through May (Figure 4). The intensity of AR landfall related precipitation ranges from 100 to 500 mm/month. During the fall and early summer, the AR-related peak rainfall is over the eastern part of Texas and extends into Louisiana. The maximum rainfall occurs during the fall in October over Texas coastlines and then migrates to Louisiana, Arkansas, and Mississippi (Figure 2).

3.1.3. Frequency of atmospheric rivers

The frequency of ARs is defined by how often the same grid point along the Texas Gulf coast experiences AR landfall (AR days). Therefore, AR frequency is not the number of AR occurrences, but the total number of AR days divided by the number of years. Most frequent AR days are localized in eastern Texas. On average, areas between Harris and Hardin counties experience 10 to 13 AR days per year, which could potentially influence flooding in the Neches and San Jacinto River Basins. Meanwhile less frequent AR days (2–4 days on average) occur between Waller and Austin counties as well as Matagorda County, potentially affecting flooding in the Brazos River Basin. Over the southwestern San Antonio River (i.e., Bee County), AR days occur ~7 times per year. While the rest of the southern Texas coastline (South Kleberg County) experiences fewer AR days (1–2 days/yr) (Figure 3).

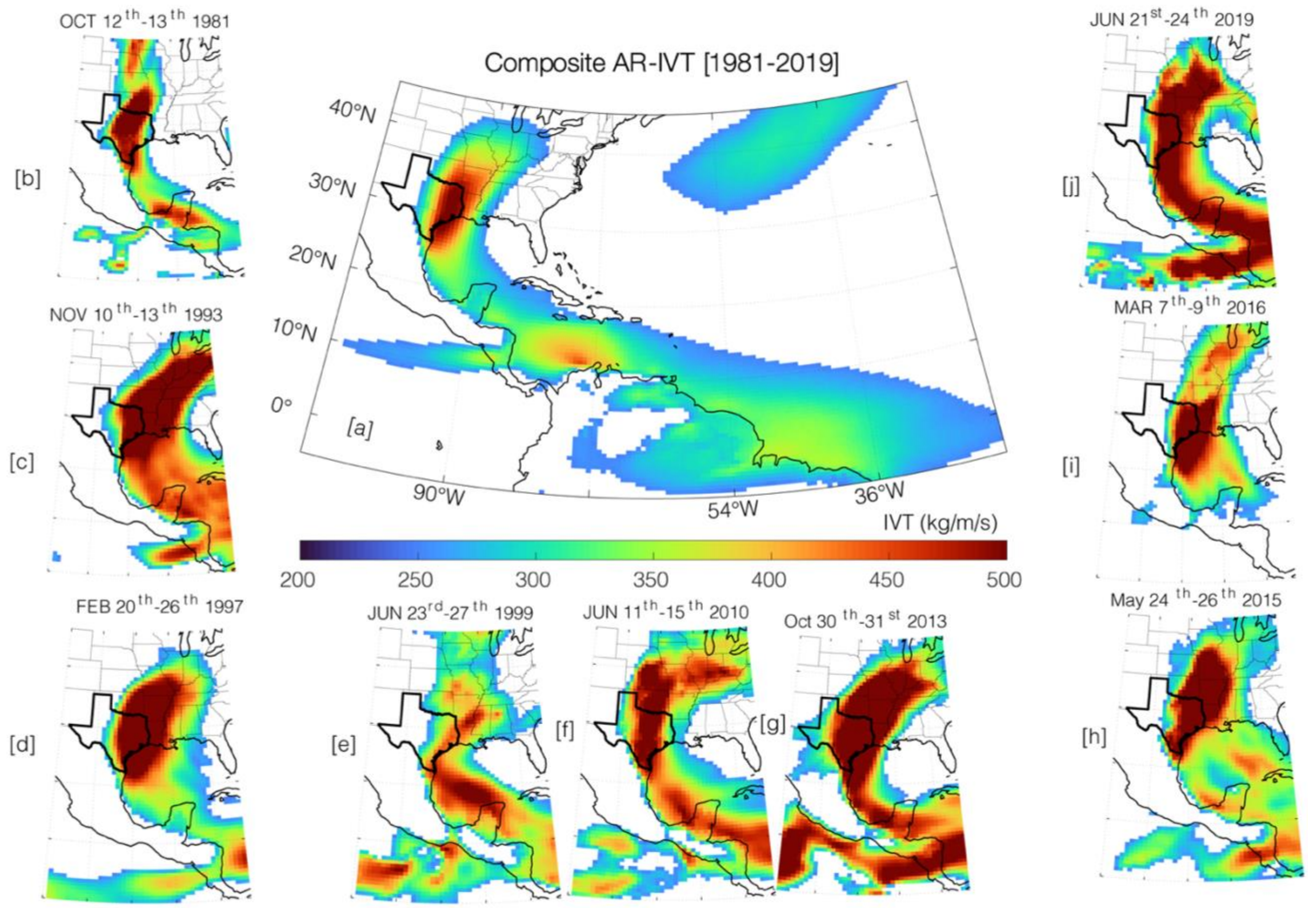

Figure 1. A composite map of integrated water vapor transport (IVT) during 807 AR events between 1981 through 2019, based on ERA-Interim data. Panels b–h depict some of the notable ARs that caused flooding, such as the 2015 event that triggered the Wimberley flooding.

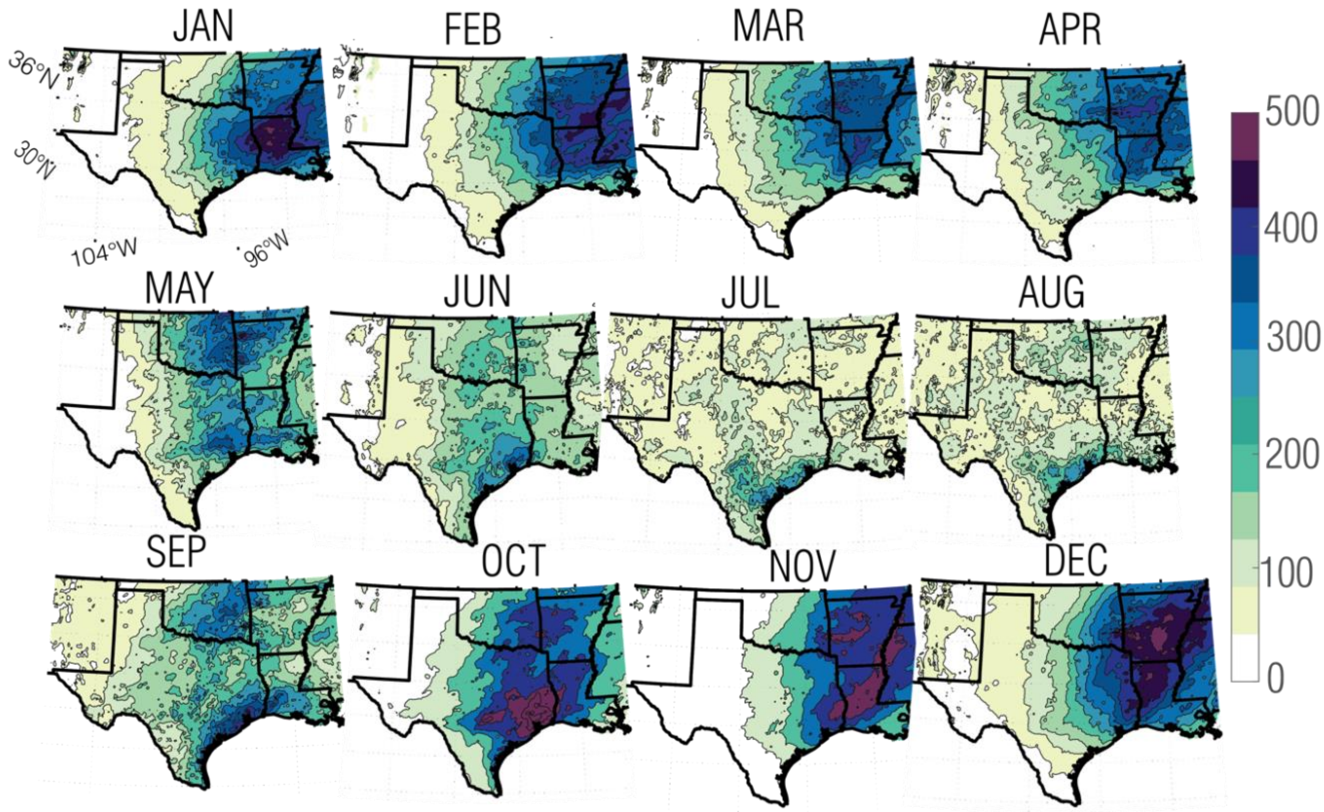

Figure 2. Precipitation climatology during 1712 AR days between March 4th, 1981, through August 19th, 2019, based on the PRISM data.

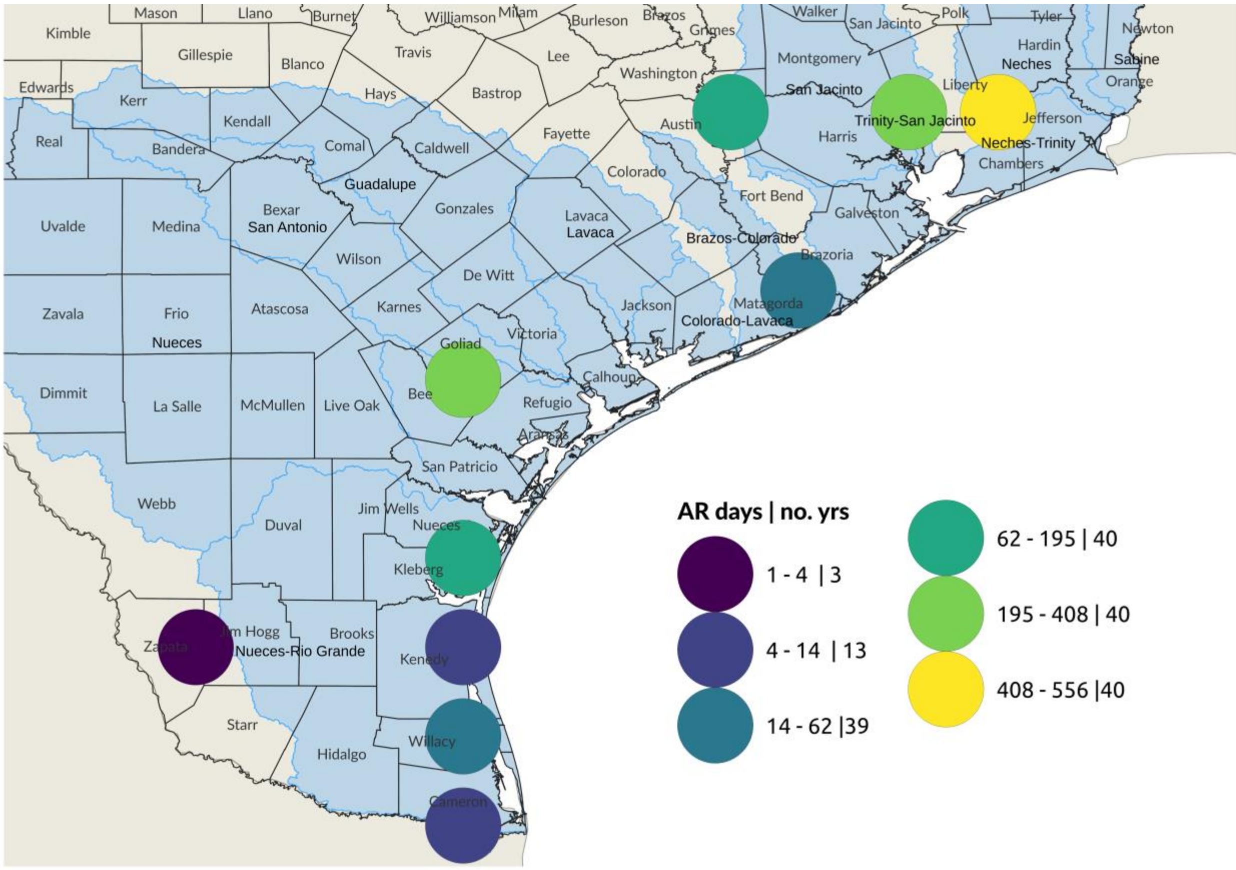

Figure 3. Frequency of AR days at AR landfall locations and the corresponding number of years. Blue polygons represent the major rivers in Texas.

3.2. Categories of Atmospheric Rivers and their Impacts

We classified ARs into five categories using **their lifetime and the IVT intensity** when they make landfall based on a classification scheme developed by **Ralph and others (2019)**. This classification describes the ARs in terms of their beneficial or hazardous impacts. The five categories are outlined:

1) Weak ARs (i.e., AR-1), which are primarily beneficial and include ARs that last up to 24–48 hours with IVT intensity between 250 and 750 kg/m/s, or last for only 24 hours with IVT 500–750 kg/m/s. Over Texas, this category makes up 31% of the total occurrences of ARs during 1980–2019 and hit mostly during the summer. In the past 40 years, about ~250 category 1 AR events made landfall over Texas (Figures 4,5).
2) Moderate ARs (i.e., AR-2), which are primarily beneficial ARs, occur for periods of >24 hours, with IVT intensities of 250–750 kg/m/s. AR-2 events can be hazardous if they occur over a time shorter than 24 hours and carry more moisture (750–1000 kg/m/s). Most ARs over Texas belong to this category. It represents ~65% of the total AR occurrences during all the seasons with few during summer (Figure 4). An example of these events is the AR that triggered the Wimberly flood on May 17th–24th and 26th, 2015, where continuous rain resulted in soil saturation and led to flooding in southern Blanco County by Memorial Day (May 29th). May 2015 was the wettest month on record across Texas (NOAA, 2015). Similarly, the AR-2 event on June 11th–14th 2010 resulted in intense rain in eastern Texas, south-central Kansas, and Oklahoma.
3) Strong ARs (i.e., AR-3) have balanced beneficial and hazardous impacts. These events may last three days, and their impact is modulated by the intensity of the IVT. Events that last >24 hours with IVT intensities of 500–1000 kg/m/s are mostly beneficial, while higher IVTs (1000–1750) with shorter lift times (<24 hours) can be hazardous. The occurrence of these events over Texas is rare and represents <1% of the reported ARs. Examples of this category include events that impacted Texas on July 7th, 2010, and April 29–30, 2016.
4) Extreme ARs (i.e., AR-4) are frequently hazardous, but also can be beneficial. An AR-4 carries moisture >750 kg/m/s and lasts at least 24 hours. Events with IVT intensities of 750–1000 kg/m/s and lifetimes of 48–72 hours can be beneficial (Figures 4,5).l. The percentage of AR-4s over Texas is 2% with a higher likelihood during the winter. Examples of these events include November 14, 1993; May 30–31, 2004; December 26–27, 2015; and March 9, 2016.
5) Exceptional ARs (i.e., AR-5) are primarily hazardous events. AR-5 carries moisture exceeding 1000 kg/m/s and last between 24 and 72 hours. Only 24 events (~1%) were recorded over the past 40 years and are less likely to happen during the summer. Examples of these hazardous events are on July 21, 2001, and October 29–30, 2009.

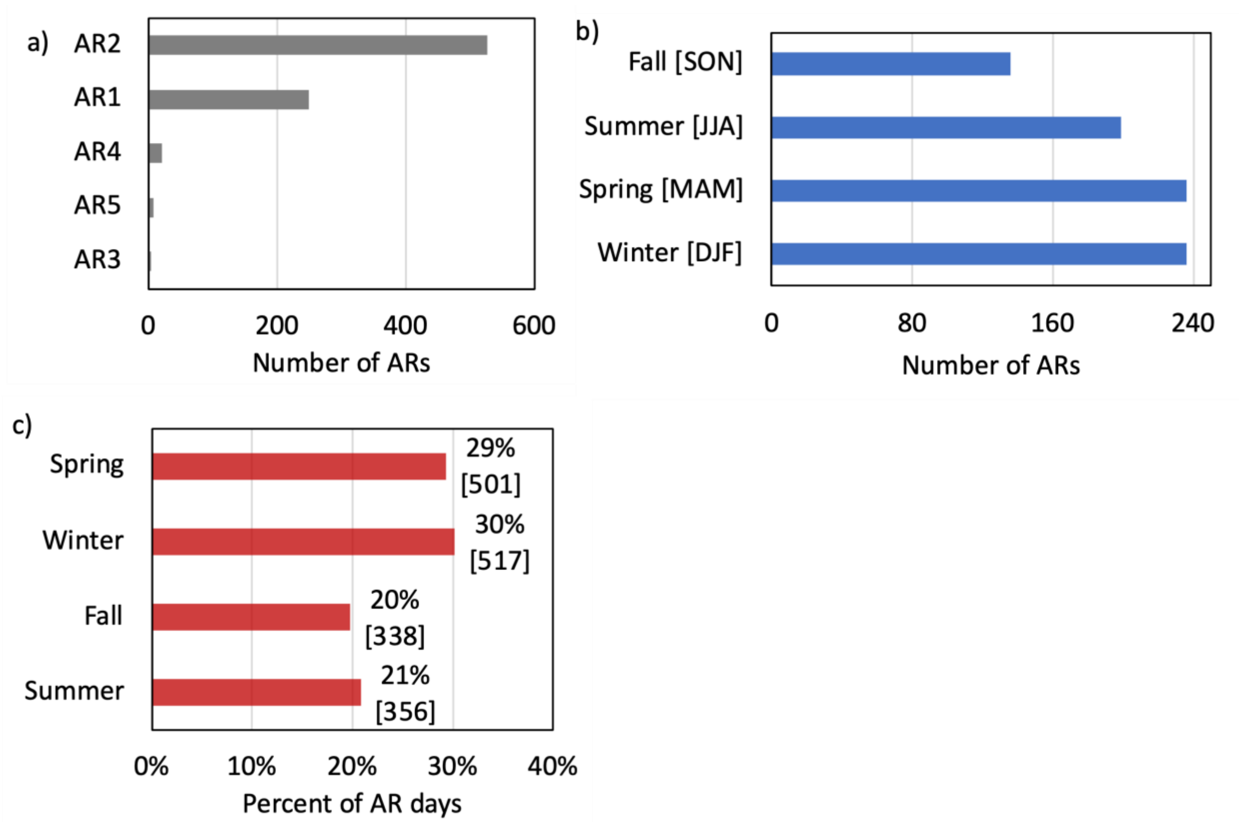

Figure 4. [a] Classification of ARs that impact Texas and their number between 1980 and 2020 based on classification developed by Ralph and others (2019).[b] Number of ARs through the seasons.[c] number of AR days and their percentage per season.

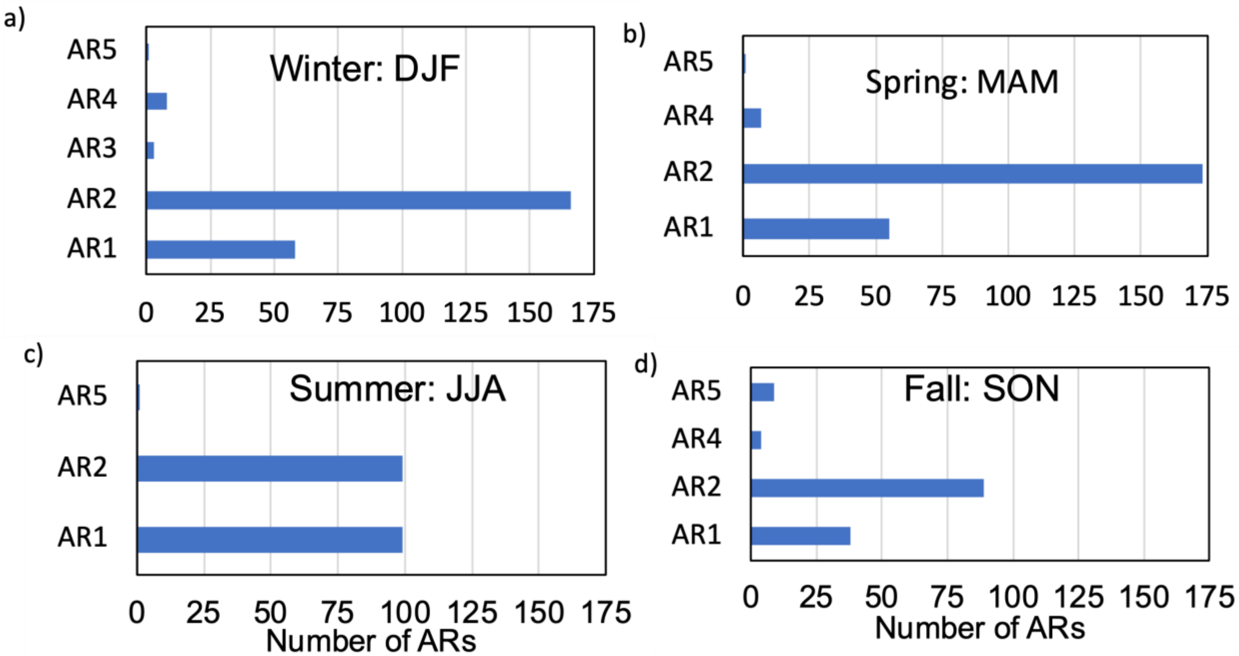

Figure 5. Classification of AR landfalls over Texas based on climate seasons using ERA-Interim results for the period between 1980 and 2019.

3.3. Contribution of Atmospheric Rivers to Precipitation in Texas

For total precipitation in Texas, ARs contribute 25–31% over most of the eastern and central portions of Texas and neighboring states of Arkansas and northern Louisiana. This percentage increases slightly to ~ 33% in the foothills of the Balcones Escarpment in eastern central Texas. In the western and most of the southern parts of Texas, ARs contribute less than 10% to total precipitation (Figure 6).

For maxima precipitation during a year or climate season, ARs contribute to 42–54% of the maxima annual precipitation in the eastern part of the state and over most of Louisiana and Arkansas and Eastern Oklahoma. The percentages increase to 58% in some localized regions in Texas, Louisiana and Arkansas (Figure 7). For the western part of Texas, ARs contribute to less than 25% of maximum annual and seasonal extremes precipitation events, except in winter where in northern Texas ARs contribute to 43%. Winter is the season where seasonal extremes are most influenced by ARs contribute to 43–58% of extreme events. Such higher contributions extend throughout most of Louisiana, Arkansas, and eastern Oklahoma. It is followed by spring, with AR percentage contributions of 38–46% over smaller areas in southeastern Texas. ARs contribute to <20% of summer maxima (Figure 8).

3.4. Relationship between Atmospheric Rivers and Hurricanes

ARs and hurricanes are generally not linked as only 15 out of 500 AR events (3%) occurred during the lifetime of hurricanes (1–2 weeks; 1980–2019). However, we found that a few and shorter AR events (lifetime <24 hours) could follow or precede tropical storms. It is possible for ARs to be triggered by moisture associated with tropical storms in surrounding oceans. For example, an exceptional AR occurred during the lifetime of the Herman tropical cyclones. The tropical cyclones developed on September 3rd over central America, and ended on September 10th, 2010, and impacted Mexico, Texas, Oklahoma, and Kansas. During its lifetime, moisture in the Caribbean was strengthened with moisture movement from the Pacific across Mexico, which developed an exceptional AR-like object in the GoM between September 6 and 7 with IVT of ~3700 kg/m/s. The AR object extended into the Midwest, Great Lakes, and eastern Canada.

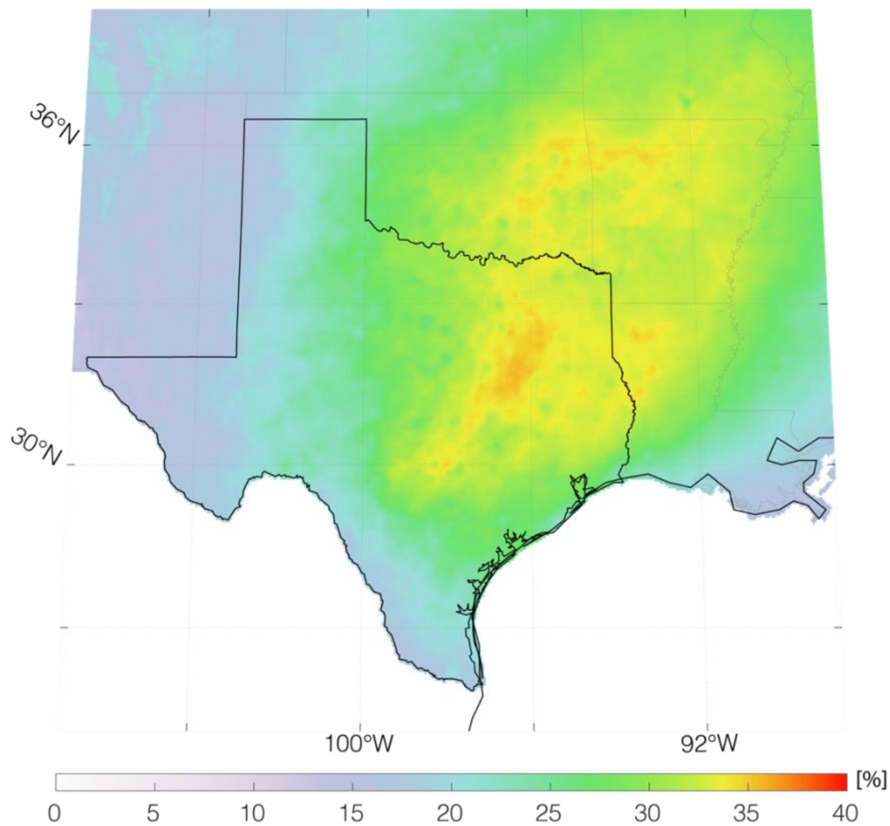

Figure 6. Fraction of possible contribution of AR-induced precipitation to the total, based on 1712 AR days between March 4th, 1981, through August 19th, 2019.

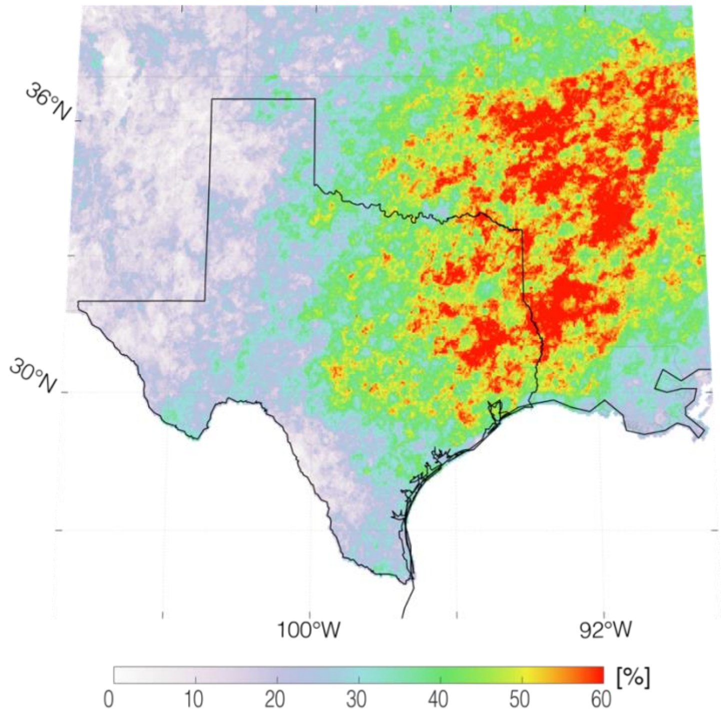

Figure 7. Fraction of possible contribution of AR-induced precipitation to the annual maxima based on 1712 AR days between March 4th, 1981, through August 19th, 2019.

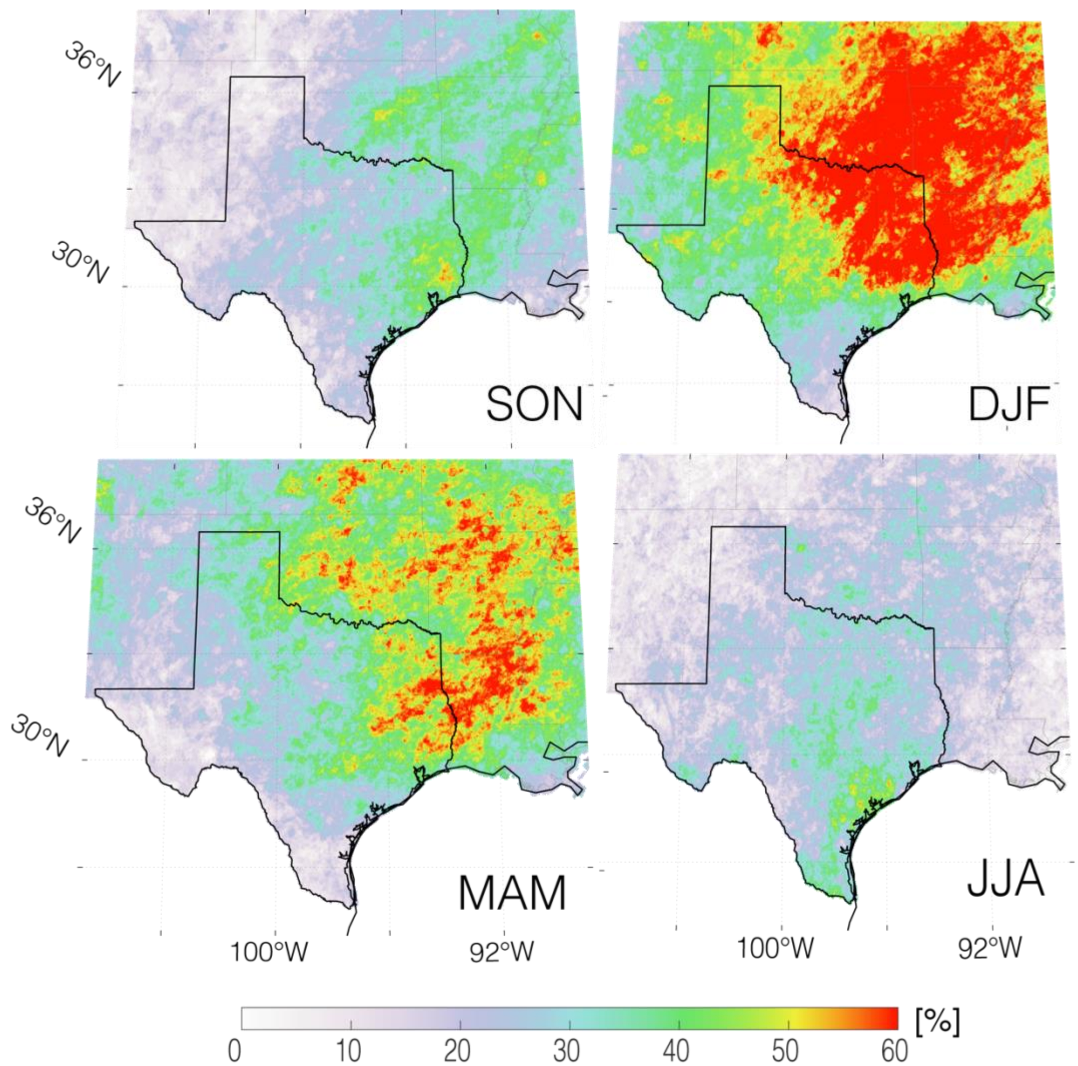

Figure 8. Fraction of possible contribution of AR-induced precipitation to the seasonal maxima based on 1712 AR days between March 4th, 1981, through August 19th, 2019.

3.5. Impact of Climate Variability on Atmospheric Rivers and Precipitation Patterns

The occurrence of ARs varies with the conditions of the Pacific and Atlantic Oceans on interannual to multi-decadal scales. El Niño conditions are associated with 28% of AR days, similar to La Niña which are associated with 25% of AR days. The disparity in the number of AR days during the warm and cold phases of NAO is significant, with a higher occurrence during the warm phase compared to the cold phase. About 17% of AR days correlate with the positive phase of NAO, while only 8% of AR days occur during the negative phase. At decadal to multi-decadal time scales, the positive phases of PDO and AMO correlated with 47% and 59% of AR days, respectively.

For modulating AR-related precipitation during these warm and cold phases, warm conditions in the Atlantic Ocean corresponded to more intense precipitation (300–500 mm/mo) localized in the eastern part of Texas and Louisiana during fall and winter (Figure 9). During the negative phase, precipitation intensity during these seasons decreased to <350 mm/mo. For La Niña, the AR-related precipitation anomaly is concentrated over Louisiana and Arkansas during winter whereas Texas gains < 200 mm/mo under these conditions. Less intense AR-precipitation anomalies occur during the negative phase of NAO (during summer) when rainfall is less than 280 mm and localized in the Texas Coastal Plain (Figure 9).

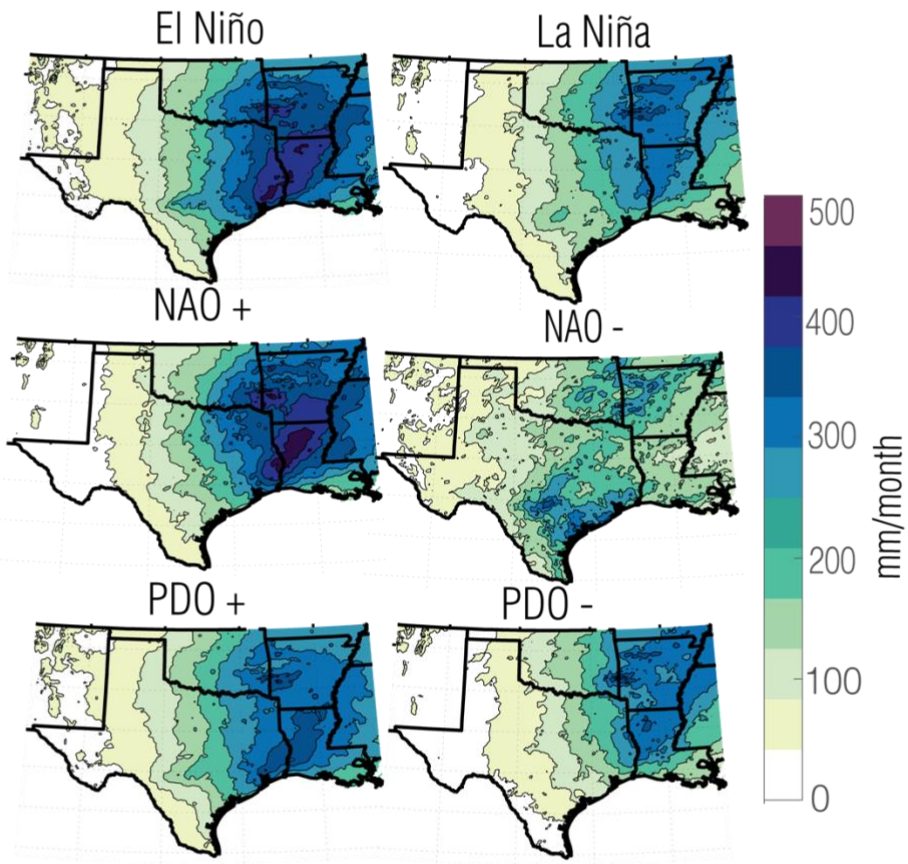

Figure 9. AR-induced precipitation during various phases of interannual and decadal climate variability, based on 1712 AR days from March 4th, 1981, to August 19th, 2019.

3.6. Trends of Atmospheric River Occurrences over Texas

The trend in AR landfall over Texas was investigated according to the method outlined in Section [3.2.4] (Figure 10). Assuming a linear relationship of increasing/decreasing ARs over the past 40 years (1980–2019), we found an average of ~20 events annually, and an insignificant decrease in ARs (0.08/yr). This negative trend (decrease in AR occurrences) has a mean probability of 62% $\pm$37% at 95 CI (confidence interval). Thus, the mean probability of the increase is 38 $\pm$ 43% at 95 CI. The uncertainty in the trend reflects the absence of a consistent trigger for AR occurrences (Figure 10).

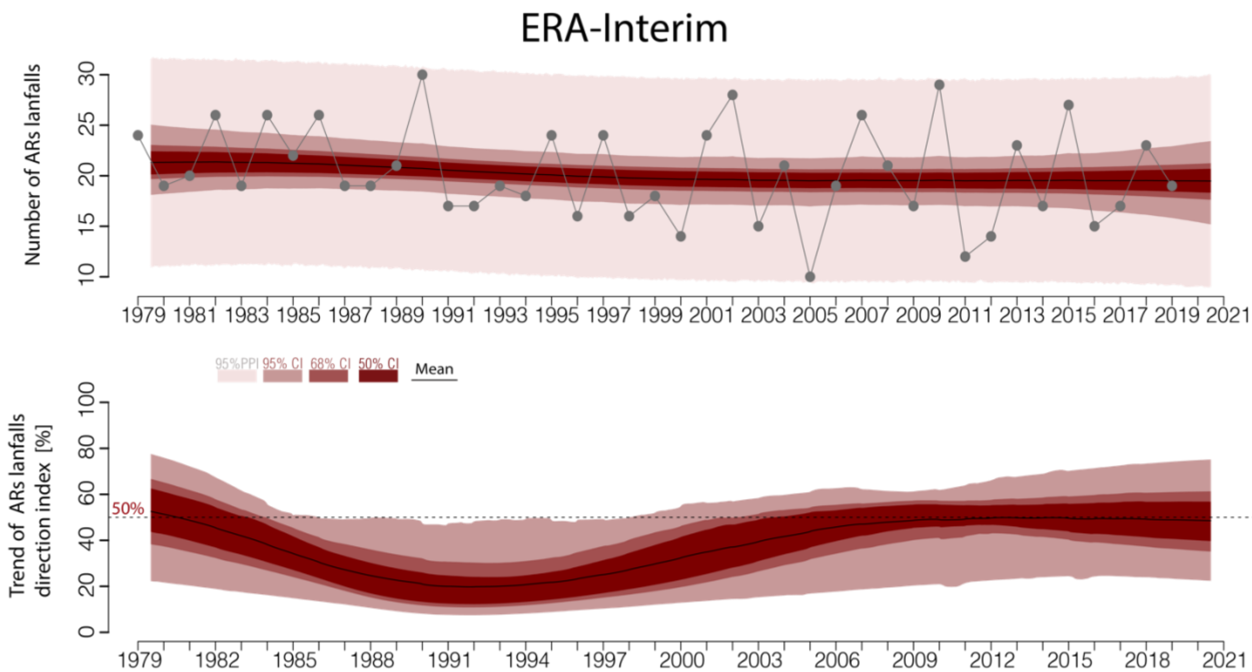

Figure 10. Upper panel shows the frequencies of the AR yearly landfall over Texas and the GPR fitted model and its uncertainty using 95; 68 50 credible intervals. Lower panel shows probabilistic change in the trend of the AR landfalls over Texas.

4. Discussion

In the discussion of our findings, we observed that the tropical Atlantic sources of moisture for ARs impacting the South Central (SC) US are consistent with previous studies that investigated historical AR events, such as the 1993 and 2008 floods in the US Midwest (Dirmeyer and Kinter III, 2009, 2010). Although the eastern tropical Pacific appears to play a minor role in providing water vapor to SC-US compared to the tropical Atlantic, its contribution, along with the Caribbean, has been documented in events like the flash flooding in Nashville, Tennessee, on May 1–2, 2010 (Moore and others, 2012). Our composite maps (Figure 1) reveal a coherent structure of 807 AR anomalies originating from the tropical Atlantic, with noticeable intensification in the Caribbean region and moisture contributions from the eastern tropical Pacific. These insights improve our understanding of the complex interplay between moisture from the Pacific and Atlantic Oceans and their influence on ARs and their effects on precipitation patterns in Texas and surrounding states.

The climatology of AR occurrences in winter and spring is consistent with results from previous studies that evaluated long-term hydro-climatology of AR events in central and southeastern US (Lavers and Villarini, 2013; Debbage and others, 2017; Nayak and Villarini, 2017).

The prevalence of AR landfall during winter and spring also reflects patterns observed for ARs along the West Coast in California (Rutz and others, 2014; Guan and Waliser, 2015, 2019). This increased frequency and precipitation during winter and spring can be attributed to the seasonal shift in weather patterns, which directs ARs from equatorial regions toward mid-latitudes (Dacre and others, 2015) understanding of seasonal variability and its connection to weather patterns is crucial for developing comprehensive flood mitigation and water management strategies in Texas and other states.

The contribution of ARs to total precipitation and to annual and seasonal extreme precipitation provides increased understanding of climate drivers of floods and water resources in Texas. Comparing these results with reported estimates for AR-attributable annual maximum precipitation, we find that the result of 42%–54% in the eastern part of Texas and 58% in some localized regions is consistent with previous studies. For example, in the southeastern US Mahoney and others (2016) found ~41% of annual precipitation extremes can be attributed to AR events while in the Central US. Lavers and Villarini (2013) estimated ~50% of annual maxima are derived from ARs. Considering different regions of the US, the contribution of ARs to total precipitation and seasonal flooding is lower in Texas than reported in other parts of US. In Texas, ARs contribute 25%–31% of total annual precipitation while in the southeastern US the contribution of ARs is slightly higher (30–35%: (Nayak and Villarini, 2017; Miller and others, 2019) and increases to 30%–50% in the western US (Dettinger, 2011; Guan and others, 2013). Similarly, AR contributions to seasonal flooding in winter and spring ranges from 43–58%, which is less than their impact on flooding in the eastern US (70%: (Nayak and Villarini, 2017; Slinskey and others, 2020). Along the West Coast, AR seasonal extremes terminate 33%–40 of persistent droughts in California and 64%–70% of droughts in the in the Pacific Northwest (Dettinger, 2013). In Alaska, ARs contribute ~13% to total annual precipitation which increases to ~33% along the coastal regions (Sharma and Déry, 2020). One key factor of the varied contributions of ARs to precipitation among different areas in the US is the presence/absence of steep topography that allows more of the moisture transported by the AR to fall over their interiors, slopes, and bases. The orographic effect is related to the Appalachian Mountains in the eastern US and to the Sierra Nevada Mountains in California and to the Olympic, Cascades, and

Rocky Mountains in the northwestern US. In the Eastern US, south of the Appalachian Mountains, half of the daily extremes can be attributed to AR events. AR contributions vary among the river basins, considering their proximity to the Blue Ridge Escarpments and the surrounding terrains (Miller and others, 2019). In California., the storm from December 29–31 2005 over and around the coastal terrains replenished a quarter of the depleted water in the Central Valley (Smith and others, 2010). Coastal mountains result in ARs contributing >90% to extreme precipitation in British Columbia and southeastern Alaska (Sharma and Déry, 2020). The lack of steep terrain features in Texas might explain the modest contributions of ARs to total annual precipitation. Topography in the southern US works like a funnel transporting moisture to the Midwest US (Mahoney and others, 2016; Rabinowitz and others, 2019). However, given that the most frequent ARs that impact Texas are category AR-2, that can be beneficial and hazardous at same time, and the high contributions of ARs to the winter and spring extremes, occurrences of ARs and related precipitation have strong implications for flood preparedness and water resources management.

Considering the frequency of AR occurrences during El Niño, it was reported that the convection in the eastern Pacific Ocean derives anomalous circulations in the western subtropical Atlantic, which enhances tropical and subtropical moisture transport (Rasmusson and Mo, 1993; Knippertz and Wernli, 2010). During the positive phase of NAO where the difference in standardized lower pressures of 500 hPa between sub-polar low near Greenland and the subtropical central Atlantic Ocean high, the strength of the jet stream increases in intensity and shifts the positioning of the meridional and zonal moisture heat transport patterns toward the north and northwest directions in Central America, the Caribbean, the GoM, and the southern and southeastern US (Hurrell, 1995). The decadal and multi-decadal conditions during the warm phases can enhance the aforementioned conditions.

In the Eastern US, the frequency and intensity of AR-related extreme precipitation have been increasing (Teale and Robinson, 2020), while in Alaska, no change in AR-related amounts of precipitation during 1979–2012 occurred. (Sharma and Déry, 2020). Su and Smith (2021) show a significant trend in AR-precipitable water along all coastal regions of the US (GoM, North Atlantic, Pacific Ocean coastlines in California and the Northwest) with a trend of 0.12 mm/yr at 95% confidence level.

Climate models based on Coupled Model Intercomparison Project (CMIP) phases 5 and 6 show more frequent ARs globally under future climate, but associated with higher uncertainty derived by AR tracking methods (O'Brien and others, 2022). It is worth noting that different tracking methods (Shields and others, 2018; Lora and others, 2020) and different reanalysis data provide different outputs.

5. Conclusions

Using atmospheric reanalysis data and an AR detection algorithm to study the characteristics of ARs over Texas and their contributions to precipitation between 1980 and 2019 reveal the following:

- A total of 807 AR events made landfall over Texas over a 40-year period (1980–2019) resulting in ~ 20 ARs/yr.
- ARs contribute 25–31% of total precipitation in eastern Texas, relative to ≤10% in western Texas.
- ARs account for 42–54% of annual extreme precipitation events in eastern Texas, relative to ≤25% in western Texas.
- ARs greatly impact winter precipitation extremes but have less effect on summer extremes.
- The IVT anomalies associated with most of the ARs have intensities ranging from 250 to 1000 kg/m/s with duration up to 72 hours.
- There is no relationship between ARs and hurricanes as only 2% of ARs occur during the lifetime of hurricanes during the past 40 years.
- The positive phase of the NAO plays a crucial role in the frequency of AR days in Texas and surrounding states, compared to the influences of ENSO, AMO, and PDO. This is primarily due to the Atlantic origin of AR moisture. Distinct precipitation intensity patterns related to ARs are observed during the different phases of NAO, ENSO, AMO, and PDO.
- The trend associated with ARs occurrences over the past 40 years is insignificant.

6. Recommendations and Path Forward

The result of this work can be used to develop recommendations for further study and guide a path forward. One of the recommendations would be to quantify the contribution of these ARs to specific flood events. Future work should also consider linking the AR days with specific storms that affected reservoirs operations, or the storms that alleviated droughts in Texas. We presented the example of the 2015 Wimberley flooding that was triggered by AR events. One prospect of this work is to investigate the likelihood of AR events under climate warming using different simulations of the climate models, and quantify their magnitude, intensity and change in their distributions. Such analyses will be helpful in forecasting and managing future flooding and improving management of water resources.

Forecasts for AR within short to medium lead times, ranging from a few days to several weeks, primarily focus on predicting AR events and their associated impacts. These forecasts draw upon a variety of data sources, utilizing numerical models such as the Global Forecast System and the ECMWF model to monitor and track AR formation and movement. To further enhance the predictive accuracy of AR forecasts, statistical and machine learning techniques can be employed, incorporating large-scale climate drivers and teleconnections, into the analysis.

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8. Appendix I: Responses to TWDB Comments on Draft Final Report

This appendix includes those comments followed by the UT BEG response in *blue italics*.

Overall Comments:

A well written report. All study objectives appear to have been met. This project has advanced the understanding of atmospheric rivers (ARs) and their impact on Texas. To ensure future research makes full use of the work described in the report, please provide electronic files associated with this project. In particular, data describing the 807 AR events identified over Texas in the 1980–2020 time period (e.g., date/time of initiation, date/time of conclusion, location of AR, classification of event, etc.) would be extremely useful to future efforts.

Required changes:

1. Please ensure that the final report includes the figures that were missing in the draft final report.
   The figures have been embedded in the final report.
2. Please add a list of acronyms.
   A list of acronyms has been provided in the final report.
3. Please double check the report for typos such as those in the following (non-exhaustive) list:
   The final version will undergo professional revision by an academic writer.
   a. Page 2, 2nd paragraph, 1st sentence: "using 40-year of atmospheric" should be "using 40 years of atmospheric".
      Corrected
   b. Page 2, 3rd paragraph, 4th sentence: "landfall in the coastlines" should be "landfall on the coastlines".
      Corrected
   c. Page 2, 4th paragraph, 1st sentence: "El Nino" should be "El Niño".
      Corrected
   d. Page 5, Figure 1 caption: "map integrated water" should be "map of integrated water".
      Corrected
   e. Page 6, 2nd paragraph, 4th sentence: "the Amazon river flow (215,000 m^3/sec) [*Ralph* et al., 2018] ARs have" should be "the Amazon River flow (215,000 m^3/sec) [*Ralph* et al., 2018]. ARs have".
      Corrected
   f. Page 6, 3rd paragraph, 2nd sentence: "Mississippi river floods" should be "Mississippi River floods".
      Corrected
   g. Page 7, 1st paragraph, last sentence: "midwest" should be "Midwest".
      Corrected
   h. Page 8, 3rd paragraph, last sentence: "Oregon State Univ" should be "Oregon State University".
      Corrected
   i. Page 10, 1st paragraph, last sentence: "the reader referred" should be "the reader is referred".
      Corrected

j. Page 16, 3rd paragraph, 2nd sentence: "Texas gains less the 200 mm/mo" should be "Texas gains less than 200 mm/mo".
Corrected
k. Page 20, 1st paragraph, 1st sentence: "between the 1980 and 2020" should be "between 1980 and 2020".
Corrected

4. Please check the final report for proper and consistent definition and use of acronyms and variables.
   a. Please refer to "year" and "years" consistently. These words are sometimes spelled out and sometimes abbreviated as "yr" or "yrs" in the report.
   Year and years spelled out throughout the text and yr used for units, e.g., mm/yr.
   b. "United States" is sometimes abbreviated "US" and sometimes "US" or "US" throughout the report.
   US is adopted through the whole report.
   c. On page 6, the acronym for "Gulf of Mexico" is introduced as "GoM" but not used in the rest of the document.
   GoM used in many parts in the final report.
   d. Throughout the document, both "ERA-interim" and "ERA-Interim" are used as the acronym for European Centre for Medium-Range Weather Forecasts Re-Analysis.
   ERA-Interim is adopted through the final report.
   e. In Section 3.1.2, the acronym for "digital elevation model" is introduced as "DEM" but not used in the rest of the document.
   DEM is removed
   f. No definition is provided for the acronym "PRISM" used throughout the document.
   PRISM defined as Parameter-elevation Regressions on Independent Slopes Model
   g. The acronym "GP" is not defined and is only used once in the document (Section 3.2.4).
   Spelled out and acronym deleted.
   h. The variable "Y" is defined after Equations 5 and 6 in Section 3.2.4 but does not appear in either equation.
   y is the likelihood based on observations (number of ARs)
5. Please double check calculations in the report including the following:
   a. Throughout the document, analysis is described for a "40-year time period" stretching from 1980 to 2020. If the data sets include complete years of data for each year, this would correspond to data sets 41 years in length. Please confirm whether complete or only partial years of data were available for the 1980 to 2020 time period.
   The analysis for the Atmospheric river (catalog; no of ARs) is from 1980 through 2019 (40 years). However, the results for the impact of ARs on precipitation is for 1981 through 2019, given the unavailability of PRISM data for 1980. These periods are clarified in the final report.

b. In Section 4.1.2, the observation that 58% of AR days occur between December and June. If ARs were equally likely to occur in each month, the expected occurrence from December through June would be 7/12=58%. If there is a period during the year when ARs occur at a rate significantly more or less than 67 events per month over the 40-year time period (807 total events/12 months), that should be noted. A figure or table showing the distribution of AR events throughout the year may also be helpful to convey this information.
Thank you for the suggestion. We have updated Figure 3 to include the number of AR days and their respective percentages throughout the season. Accordingly, from December to May, the number of AR days accounts for approximately 60%, and from June to November, it represents 40%.

c. In Section 4.2, page 15, in regard to AR-5 events, the authors note that "Only 24 events (~1%) were recorded over the last 40 yr". Please double check the calculation as 24 AR-5 events out of 807 total AR events would be ~3%.
It was a miscalculation for the number and percentage of AR categories. This section has been revised in the final report. The AR-5 percentage is only 0.87% (7 events only).

d. Section 4.4, page 15, the authors note that "only 15 out of 500 AR events (3%) occurred during the lifetime of hurricanes." Please ensure that the correct number of AR events used in this calculation as the total number of AR events is listed as 807 events throughout the rest of the report. Also note, if this percentage needs to be corrected, it also needs to be corrected in the 5th bullet on page 20.
As mentioned in response to c, the section has been revised in the final report and the number and their percentages are corrected.

6. Please address following:
   a. In the Executive Summary (page 2), please clarify whether "total precipitation" is "total annual precipitation". Also, please define the time period of the accumulation.
   It is the total precipitation, not the total annual. The period 1981-2019 is added.
   b. In the Executive Summary (page 2), please include the definition (or value range) of "extreme precipitation". Given that "extreme precipitation" could refer to low and high extremes, please include the threshold value for "high extremes" here.
   Extreme precipitation is defined in the methodology as block maxima (annual or seasonal). We clarified it throughout the document in the final version.
   c. In the Executive Summary (page 2), please provide some context to why the analysis on AR frequency during various phases of teleconnections, particularly the NAO and PDO, was undertaken.
   We added the following "For the impact of the interannual (e.g., El Niño Southern Oscillation (ENSO, El Niño), North Atlantic Oscillation), and decadal climate variability,"
7. Please change the last sentence of Section 1, paragraph 1, on page 8 to remove the reference to "moisture transport related to non-tropical cyclones". Add in "rainfall-inducing" before "moisture transport".
   Corrected
8. Please omit the sentence that includes "uses the cycle of the integrated forecast system" in Section 3.1.1 on page 8.

Omitted

9. Please correct the first sentence of Section 3.1.2 on page 8 to attribute the PRISM climate group to Oregon State University (not the University of Oregon).
   Corrected
10. In Section 3.1.3, page 9, please include the key citations for each index. Also include a brief description of the key periodicities associated with each index.
   This section has been thoroughly updated in the final report, incorporating additional information and appropriate citations.
11. In Section 3.2.3, page 11, please revise the seasons that fall is SON, winter is DJF, spring is MAM, and summer is JJA.
   Revisited and corrected.
12. In Section 3.2.3, page 11, please clarify the statement: "assigned anomalies to warm and cold phases".
   Clarified as "We used the 24-month smoothed version of the indices and cross-referenced their positive and negative phases with the AR days chronology."
13. In Section 3.2.3, page 11, please clarify whether contemporaneous values of the climate index were used or whether tests were conducted at different time lags. It sounds like it may have been a contemporaneous assessment. Please include mention of the time lag (or contemporaneous, if the case may be) in the narrative description of the results from the teleconnection assessment.
   Although we do not incorporate time lags, we account for the varying sampling of climate teleconnections and atmospheric river (AR) days. By cross-referencing AR days with the corresponding climate index values, we create a composite of AR-induced precipitation for each phase. This has been further clarified in the revised text.
14. In Section 3.2.4., page 11, please change "dynamics" to "trends" or "characteristics".
   Changed
15. In Section 3.2.4, page 11, please clarify the statement: "is modeled by assuming the function can be smoothed".
   Clarified as "…that the function can be smoothed to model the trend."
16. In Section 3.2.4, page 12, please explain the terms "progressing" and "de-progressing".
   Explained as "AR frequency trend progressing (i.e., increasing in upward direction) or de-progressing (i.e., increasing in downward direction)"
17. In Section 4.1.1, the primary source of ARs in Texas is identified as the Atlantic Ocean. This source accounts for 472 of 807 AR events (~60% of AR events). Please provide any additional insight obtained during this analysis related to other sources of AR events (roughly 40% of AR events).
   The figure of 472 AR events represents a subset based on the NCEP NCAR data, serving as an example for the composite of AR integrated vapor transport (IVT). In our most recent update, we have limited our analysis to the ERA-Interim data, and accordingly, updated Figure 1. The revised figure now displays the total IVT anomalies during the 807 events, highlighting the anomaly's extension to the Atlantic tropics and intensification in the Caribbean due to moisture influx from the Pacific. Additional details have been incorporated in the revised version of the document.
18. In Section 4.1.1, page 13, please include a citation that refers to the influence of the Balcones Escarpment on driving AR landfall. Else, reword the section to convey the fact

that this could potentially be a reason for the preferential location of ARs over Eastern Texas.

Rephrased as "Balcones Escarpment, which comprises of elevated topography, extending from Del Rio to the Red River with altitudes ranging from 100–300 m (Caran and Baker, 1986). may play a role in deriving the portions of the AR landfall over East and central Texas, Some studies found the Balcones could alter a the location of maximum accumulation of precipitation, resulting in a slight shift to the north and west (Nielsen and others, 2016)"

19. In Section 4.1.2, page 13, please omit "patterns of" before AR landfall related precipitation.
    Omitted and replaced by "intensity."
20. In Section 4.1.3, page 14, please provide a citation to back the statement that ARs impacted flooding the Neches and San Jacinto Rivers.
    Reworded as "AR could influence potential flooding in these basins".
21. In Section 4.1.3, page 4, please change "western Texas coastlines" to "southern Texas coastline".
    Changed
22. Please clarify the exact AR classification scheme utilized by this project. Section 4.2 reports that the authors classified ARs into five categories "based" on the scheme developed by Ralph et al. (2019). From the description provided, it is unclear how ARs were classified, particularly the **criteria used to distinguish between categories**.
    For example, it is unclear from the text if AR-2 events occur for periods longer or shorter than 24 hours.
    Also, unclear if an event that lasted for 36 hours with IVT intensity of 600 kg/m/s would be classified as an AR-1 or AR-2 event. Please ensure that Figure 4 (not provided with the draft final report) clarifies the scheme used for this project.
    The classification of the ARs is done according to the Ralph et al. 2019 using IVT intensity over the during the landfall and the lifetime of the ARs for their impact. Usually ARs with low intensity (>750 kg/m/s) are usually beneficial especially if they last more than 24 hrs. ARs with higher intensity, and shorter lifetime are hazardous
    AR-2 can occur from the periods [0–72 hr], and their impact differs with the intensity of the IVT. ARs-2 with IVT >750 are beneficial and also hazardous ARs wit IVT < 750 are primarily beneficial.
    IF an event lasted with 36 hours with IVT ~ 600 kg/m/s, it should be classified as the AR3.
    *Under bullet of AR-3 We mentioned "*Events that last >24 hours with IVT intensities of 500–1000 kg/m/s are mostly beneficial, while higher IVTs (1000-1750) with shorter lift times (<24 hr) can be hazardous*"*
23. In Section 4.2, point 2), page 14, please provide a citation for the statement that "May 2015 was the wettest month on record across Texas."
    Citation has been provided [NOAA., 2015]
24. In Section 4.3, paragraph 2, please include the definition of "extreme precipitation" here.
    The term "extreme precipitation" has been clarified as "the maximum precipitation occurring during a year or climate season." Section 3.2.3 elaborates on the Block Maxima method, which is used to define extreme precipitation events within a specific climate season or year.

25. In Section 4.3, paragraph 2, last sentence, clarify whether "summer extremes" is a reference to the percent total of summer rainfall exceeding a particular threshold.
    The term has been clarified as "summer maxima," referring to the maximum values during the summer season.
26. On page 20, 4th bullet, please clarify if the range of IVT anomalies from 250 to 1000 kg/m/s is associated with most of the ARs that coincide with seasonal precipitation maxima or most of the 807 total ARs identified during the study. If the latter, this point should be given in a separate bullet.
    This particular result has been isolated and presented as a separate bullet point. Thank you for the suggestion.

Recommended changes:

1. As described in section 3.2.3 of the report, the metric developed to describe the contribution of AR events to extreme precipitation events represents the frequency that annual or seasonal extremes of precipitation coincided with AR events. **When this metric is mentioned throughout the report, the reader could easily confuse this metric as being related to the amount of precipitation that is attributed to ARs during extreme precipitation events.** To avoid confusion, please consider modifying wording related to this metric throughout the report. Examples that should be considered include:
   The amount of the precipitation that are related to ARs: defined using AR days as Days of landfall+1 to account for the difference between the universal time of the ERA-Interim and the experienced high rainfall at local scale. The interpretation of these extremes is influenced by an AR event, and accordingly the fraction of contributions ARs to the annual and extremes is correct.
   a. In the Executive Summary (page 2), please consider modifying the statement "ARs contribute 42-54% of annual extreme precipitation in eastern Texas and ≤25% in western Texas" to something similar to "AR events coincide with 42-54% of annual extreme precipitation events in eastern Texas and ≤25% in western Texas."
      Changed to ARs may account for.
   b. In the Executive Summary (page 2), please consider modify the statement "AR contributions to precipitation extremes are highest in winter and lowest in summer" to something similar to "ARs coincide with more precipitation extremes in winter and fewer in summer".
      Changed to "AR possible contribution."
   c. In the Figure 5 caption on page 5, please consider modifying "Fraction of the annual and seasonal extreme precipitation that can be attributed to AR event" to something similar to "Fraction of the annual and seasonal extreme precipitation events that can be attributed to AR events".
      *Corrected as "*Fraction of possible contribution of AR-induced precipitation*"; now figures 7.8.*
   d. In Section 3.2.3 (page 10, second bullet point), please consider modifying the phrase "the results represent the percentage contributions of ARs to annual and seasonal extremes" to something similar to "the results represent the percent of time that annual and seasonal extremes coincide with ARs".

Changed to "for each grid cell and the results represent the possible percent contributions of ARs"

e. In Section 4.3, page 15, please consider modifying the sentence "For extreme precipitation, on an annual scale, ARs contribute 42-54% in the eastern part of the state …." to something similar to "**ARs contribute to 42-54% of annual maximum precipitation events in the eastern part of the state** …."
Changed as recommended.

f. In Section 4.3, page 15, please consider modifying the phrase "For the western part of Texas, the contributions are less than 25% during a year and over all climate seasons" to something similar to "For the western part of Texas, ARs contribute to less than 25% of annual and seasonal maximum precipitation events".
Changed as suggested "For the western part of Texas, ARs contribute to less than 25% of maximum annual and seasonal extremes… "

g. In Section 4.3, page 15, please consider modifying the phrase "except in winter where in northern Texas ARs contribute 43% to extreme precipitation" to something similar to "except in winter when ARs contribute to 43% of extreme precipitation events in northern Texas".
Changed as suggested to "For the western part of Texas, ARs contribute to less than 25% of maximum annual and seasonal extremes precipitation events , except in winter where in northern Texas ARs contribute to 43% ."

h. In Section 4.3, page 15, please consider modifying the sentence "Winter is the season where seasonal extremes are most influenced by ARs, with contributions ranging from 43-58%" to something similar to "Winter is the season where seasonal extremes are most influenced by ARs with 43-58% of extreme events coinciding with ARs."
Changed to "Winter is the season where seasonal extremes are most influenced by ARs contribute to 43-58% of extreme events."

i. In Section 4.3, page 15, please consider modifying the sentence "ARs contribute <20% to summer extremes" to something similar to "ARs contribute to <20% of summer extremes."
Changed as suggested.

j. Section 6, page 20, 3rd bullet: please consider modifying "ARs account for 42-54% of annual extreme precipitation in eastern Texas" to something similar to "ARs account for 42-54% of annual extreme precipitation events in eastern Texas".
Changed as suggested.

k. Section 6, page 20, 4th bullet: please consider modifying "AR contributions to precipitation extremes are highest in winter and lowest in summer" to something like "The frequency that seasonal precipitation extremes coincide with ARs is highest in winter and lowest in summer".
Paraphrased as "ARs greatly impact winter precipitation extremes but have less effect on summer extremes."

2. Section 1, paragraph 2, page 6, please consider rewording "a warm conveyor belt" to terminology that a lay audience can understand.

Simplified as "ARs produce heavy rain or snow when they meet steep terrain and are lifted by a warm air current."

3. Section 3.1.2, page 8, Please consider omitting the statement: "…with the spatial similarity of the physiographic features resulting in climate data at each grid cell of the digital elevation model (DEM)."
   The sentence has been omitted.
4. In Section 4.1.3, please consider referring to flooding in "river basins" rather than "rivers" as there is no "Brazos-Colorado" River.
   Corrected as "river basins."
5. In Section 4.5, page 16, the authors note that "the positive phases of PDO and AMO correlated with 47% and 59% of AR days, respectively." For completeness and to provide context, please consider providing the percentage of AR days that occurred during neutral and negative phases of PDO and AMO as well.
   The concept of a neutral phase for PDO and AMO is not well-defined, as these oscillations are characterized primarily by their positive and negative phases. Considering that both PDO and AMO exhibit multidecadal-scale fluctuations with a ~40-year window (refer to Section 3.1.3), we did not specifically categorize a neutral phase for either oscillation in our analysis.
6. Please consider mentioning the development of short to medium lead time forecast capabilities related to AR events in Section 7 of the report (as was done in the Executive Summary).
   This text has been added to section 7 "Forecasts for AR within short to medium lead times, ranging from a few days to several weeks, primarily focus on predicting AR events and their associated impacts. These forecasts draw upon a variety of data sources, utilizing numerical models such as the Global Forecast System and the ECMWF model to monitor and track AR formation and movement. To further enhance the predictive accuracy of AR forecasts, statistical and machine learning techniques can be employed, incorporating large-scale climate drivers and teleconnections, into the analysis."