

# Large-Scale Environments of Successive Atmospheric River Events Leading to Compound Precipitation Extremes in California

MEREDITH A. FISH,<sup>a,b</sup> JAMES M. DONE,<sup>c</sup> DANIEL L. SWAIN,<sup>d,c,e</sup> ANNA M. WILSON,<sup>f</sup> ALLISON C. MICHAELIS,<sup>g</sup>  
PETER B. GIBSON,<sup>f,h</sup> AND F. MARTIN RALPH<sup>f</sup>

<sup>a</sup> Department of Earth and Planetary Sciences, Rutgers, The State University of New Jersey, Piscataway, New Jersey

<sup>b</sup> Rutgers Institute of Earth, Ocean, and Atmospheric Sciences, Rutgers, The State University of New Jersey, New Brunswick, New Jersey

<sup>c</sup> Capacity Center for Climate and Weather Extremes, National Center for Atmospheric Research, Boulder, Colorado

<sup>d</sup> Institute of the Environment and Sustainability, University of California, Los Angeles, Los Angeles, California

<sup>e</sup> The Nature Conservancy of California, San Francisco, California

<sup>f</sup> Center for Western Weather and Water Extremes, Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California

<sup>g</sup> Department of Geographic and Atmospheric Sciences, Northern Illinois University, DeKalb, Illinois

<sup>h</sup> National Institute of Water and Atmospheric Research, Wellington, New Zealand

(Manuscript received 14 March 2021, in final form 11 November 2021)

**ABSTRACT:** Successive atmospheric river (AR) events—known as AR families—can result in prolonged and elevated hydrological impacts relative to single ARs due to the lack of recovery time between periods of precipitation. Despite the out-sized societal impacts that often stem from AR families, the large-scale environments and mechanisms associated with these compound events remain poorly understood. In this work, a new reanalysis-based 39-yr catalog of 248 AR family events affecting California between 1981 and 2019 is introduced. Nearly all (94%) of the interannual variability in AR frequency is driven by AR family versus single events. Using *k*-means clustering on the 500-hPa geopotential height field, six distinct clusters of large-scale patterns associated with AR families are identified. Two clusters are of particular interest due to their strong relationship with phases of El Niño–Southern Oscillation (ENSO). One of these clusters is characterized by a strong ridge in the Bering Sea and Rossby wave propagation, most frequently occurs during La Niña and neutral ENSO years, and is associated with the highest cluster-average precipitation across California. The other cluster, characterized by a zonal elongation of lower geopotential heights across the Pacific basin and an extended North Pacific jet, most frequently occurs during El Niño years and is associated with lower cluster-average precipitation across California but with a longer duration. In contrast, single AR events do not show obvious clustering of spatial patterns. This difference suggests that the potential predictability of AR families may be enhanced relative to single AR events, especially on subseasonal to seasonal time scales.

**KEYWORDS:** Atmospheric river; ENSO; Extreme Events; Precipitation; Anomalies

## 1. Introduction

Compound weather events—variously defined as multivariate extremes, combinations of two or more extreme events occurring simultaneously or successively, or the combination of nonextreme events that lead to an extreme impact (Seneviratne et al. 2012; Zscheischler et al. 2020)—often bring greatly elevated societal impacts relative to single extreme weather events. Early studies on compound events focused on a broad range of physical event types, including the co-occurrence of storm surge and precipitation (Wahl et al. 2015; van den Hurk et al. 2015), precipitation and wind extremes (Martius et al. 2016), and heat and precipitation extremes (AghaKouchak et al. 2014; Kirono et al. 2017; Zscheischler and Seneviratne 2017; Sedlmeier et al. 2018). These studies collectively highlight the importance

of a formal framework for characterizing compound events, especially in the context of risk assessments (Palmer and Räisänen 2002; Leonard et al. 2014; Zscheischler et al. 2018). Fewer studies have directly addressed the causes and impacts of “same type” successive compound events, yet numerous case studies of meteorological temporal clustering exist (e.g., Martius et al. 2013; Grams et al. 2014; Barton et al. 2016). In 2017, Northern California experienced a record wet water year, which featured a large number of successive extreme precipitation events. These storm sequences yielded very large cumulative rainfall accumulation for many locations in Northern California (White et al. 2019; Moore et al. 2020) and did not allow time for watershed recovery between storms, thus contributing to the crisis at Oroville Dam in February 2017, during which excessive runoff damaged both the main and emergency spillways and prompted the evacuation of 188 000 people (Huang et al. 2018; White et al. 2019; Henn et al. 2020).

Cyclone families, defined as a temporally clustered series of extratropical cyclones and first identified by Bjerknes and Solberg (1922), arise via the development of multiple successive cyclones along the polar front and have long been studied in the meteorological community. Identification and analysis

Supplemental information related to this paper is available at the Journals Online website: <https://doi.org/10.1175/JCLI-D-21-0168.s1>.

Corresponding author: Meredith A. Fish, [meredithfish1@gmail.com](mailto:meredithfish1@gmail.com)

DOI: 10.1175/JCLI-D-21-0168.1

© 2022 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the AMS Copyright Policy ([www.ametsoc.org/PUBSReuseLicenses](http://www.ametsoc.org/PUBSReuseLicenses)).

of cyclone families affecting western Europe has shown that while these events occur under a variety of synoptic regimes, they occur more frequently during specific periods than would be expected through random chance (Mailier et al. 2006; Pinto et al. 2014). This suggests that certain atmospheric conditions and dynamical mechanisms must favor clustered cyclone development (Mailier et al. 2006; Pinto et al. 2014). For example, cyclone families impacting the United Kingdom often occur during persistent, zonal, and extended North Atlantic jet conditions with the presence of Rossby wave breaking on either side constraining the jet's latitudinal movement (Pinto et al. 2014; Priestley et al. 2017, 2020). Secondary cyclones—also known as cyclone families—often form following periods of enhanced Rossby wave breaking, which leads to an increase in upper-level jet speed and a decrease in low-level stability, creating an environment suitable for cyclone development in the same vicinity as the primary cyclone (Priestley et al. 2020). Additionally, deformation and shear (e.g., Chaboureaud and Thorpe 1999), latent heating (e.g., Reed et al. 1993; Schemm and Sprenger 2015), and low-level forcing (e.g., Dacre and Gray 2006) associated with primary cyclones are critical to the development of secondary cyclones across the Atlantic Ocean basin. However, much less attention has been given to cyclone clustering in the North Pacific, and the physical processes that lead to cyclone families in the region remain largely unexplored (Mailier et al. 2006; Blender et al. 2015; Dacre and Pinto 2020).

Recently, this meteorological “event family” framework has been applied to atmospheric rivers (ARs) affecting Northern California (Fish et al. 2019). ARs are long, narrow, and transient corridors of horizontal water vapor transport that form along a low-level jet (often, but not always, ahead of a cold front) and are typically, but not exclusively, associated with extratropical cyclones (Zhu and Newell 1998; Ralph et al. 2004, 2005; Guan and Waliser 2017; Ralph et al. 2017). Indeed, in the North Pacific, 45% of extratropical cyclones are associated with ARs, yet 82% of ARs are associated with cyclones (Zhang et al. 2019). The relationship between these two phenomena can be synergistic: cyclones tend to enhance the magnitude of water vapor transport in ARs, and the moisture and subsequent precipitation provided by ARs can strengthen cyclones through latent heating (Zhang et al. 2019). While a direct study linking cyclone clustering and AR clustering has not been completed, the greater-than-random co-occurrence between ARs and cyclones allows us to infer the relevance of cyclone families to this study.

Using in situ observations of AR conditions from the Bodega Bay Atmospheric River Observatory in Northern California, Fish et al. (2019) concluded that, similar to cyclone families, ARs that occur within 120 h of another AR exhibit large-scale characteristics distinct from those associated with single AR events. In that study, the use of a single point observational dataset constrained the identification and analysis to a 13-yr dataset from 2005 to 2017, restricting the ability of a long-term trend analysis or investigation of the relation to important teleconnections in the region, such as El Niño–Southern Oscillation (ENSO) or the Madden–Julian oscillation (MJO). Both ENSO and MJO teleconnections

have been shown to influence Pacific AR activity and U.S. West Coast precipitation through modifications to midlatitude Rossby wave patterns over the Pacific basin (e.g., Horel and Wallace 1981; Alexander et al. 2002; Waliser et al. 2003; Guan et al. 2012; Gibson et al. 2020). The dynamical mechanism for the warm phase ENSO-associated precipitation teleconnection is the poleward propagation of a Rossby wave train into the midlatitudes, initially triggered by enhanced deep convective activity over the longitude-shifted region of warm tropical SST (Horel and Wallace 1981; Trenberth et al. 1998; Alexander et al. 2002 and references therein; McPhaden et al. 2006). This warm-phase teleconnection supports a seasonally strengthened Gulf of Alaska/western U.S. trough, which in turn can lead to increased extratropical cyclone and AR activity, while the likelihood of a ridge over the western United States increases during the cold phase (e.g., Gibson et al. 2020). Multiple studies have demonstrated that AR frequency changes throughout the North Pacific basin during ENSO. During the warm phase, the subtropical jet enhancement and cyclonic Rossby wave breaking displaces the AR landfalls south. Conversely, during the cold phase, the subtropical jet retraction and anticyclonic Rossby wave breaking displaces the AR landfalls north (Bao et al. 2006; Ryoo et al. 2013; Mundhenk et al. 2016).

In addition to ENSO, MJO, which is characterized by the eastward propagation of tropical convection on 30–60-day time scales, strongly influences North American precipitation patterns via the development of a quasi-stationary Rossby wave in the midlatitudes (Waliser et al. 2003; Moon et al. 2011; Zhou et al. 2012; Guan et al. 2012; Zhang 2013; Arcodia et al. 2020). Mundhenk et al. (2016) found increased AR frequency throughout the central and eastern Pacific during MJO phases 7 and 8, while Guan et al. (2012) identified significant relationships between high-impact AR events and active (amplitude  $\geq 1$ ) MJO phase 6. Increased California precipitation and landfalling ARs have previously been linked to phases 6–8 of the MJO (Guan et al. 2012; Bui 2020), with possible future expansion into phase 5 due to climate change (Zhou et al. 2020). The MJO–AR relationship is further modified by the quasi-biennial oscillation, an interannual oscillation in the tropical stratosphere (Mundhenk et al. 2018). Additional teleconnections, such as the Pacific–North American pattern (Guan and Waliser 2015; Brands et al. 2017) and the Pacific decadal oscillation (Liu et al. 2016), have been shown to increase AR activity throughout Alaska and British Columbia and along the U.S. West Coast, respectively.

In the present study, we use reanalysis data to create a novel 39-yr dataset of AR families affecting California, and subsequently evaluate the large-scale conditions linked to these successive events and their relationship to precipitation along the U.S. West Coast. We seek 1) to understand the characteristics of AR families and their causative processes, 2) to examine relationships between AR families and modes of climate variability, and 3) to quantify the precipitation accumulation associated with AR families. In the sections that follow, we describe the interannual variability of AR families using the new AR family catalog, discuss the persistence of each identified cluster, and investigate the physical

mechanisms of two clusters that exemplify two dynamical regimes. To address subseasonal predictability, a brief analysis linking ENSO and the MJO to AR families is presented. Both ENSO and the MJO act to modulate midlatitude variability, including that related to AR landfalls, through geographically remote teleconnections to the tropics. While ENSO is an interannual mode of variability and the MJO varies on subseasonal time scales, both the MJO and ENSO have the potential to increase the predictability of extratropical North Pacific flow regimes on subseasonal time scales.

## 2. Methods

### a. Atmospheric reanalysis data

Following Fish et al. (2019), the Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) dataset (Gelaro et al. 2017) is used to create a daily climatology of several relevant atmospheric variables at 3-h resolution. We use MERRA-2 primarily due to its high spatial resolution,  $0.625^\circ \times 0.5^\circ$  (longitude–latitude), and its incorporation of numerous observations assimilated from a wide range of sources, including satellite-derived atmospheric motion and surface wind vectors that are critically important for the accurate detection of ARs.

The daily climatology computed in Fish et al. (2019) is expanded spatially to an area spanning all longitudes over the latitudes  $20^\circ\text{S}$ – $90^\circ\text{N}$ . A smoothed daily climatology over the 30-year period, 1987–2016, is created using a 21-day running mean technique (Hart and Grumm 2001). This climatology is calculated for the following relevant atmospheric variables: 500- and 850-hPa geopotential heights, 850-hPa air temperature, 250-hPa wind speed, sea level pressure, and integrated water vapor (IWV). Integrated water vapor transport (IVT), an often-important identifier of AR activity, is included only for two clusters discussed in more depth, as the multiday events resulted in widespread smoothing well below the commonly applied IVT threshold of  $250 \text{ kg m}^{-1} \text{ s}^{-1}$ , therefore making interpretations less clear than for other selected variables. IVT is calculated from the water vapor mixing ratio and wind components at each atmospheric level then summed across the 1000–300-hPa layer (Neiman et al. 2008).

These reanalysis data are sampled to calculate anomalies over the duration of the MERRA-2 dataset (1980–2019). Anomalies associated with successive AR events are subsetted according to the AR detection algorithm defined in section 2b and the AR family algorithm defined in section 2c. We also use MERRA-2 to evaluate case study mean composites and to calculate wave activity flux (WAF), an approximate measure of wave-activity pseudomomentum developed by Takaya and Nakamura (2001). WAF has been used in related studies (e.g., Gibson et al. 2020) to diagnose the horizontal Rossby wave activity in relation to large-scale ridge development and decay, which is relevant to several of the identified clusters. To target slowly propagating wave signals, a 10-day low-pass filter was applied in the WAF calculation (Takaya and Nakamura 2001). While this method focuses on low-frequency WAF, future work should expand to explore the impacts of mesoscale

processes on AR families, which have already shown to be important in California events (e.g., Michaelis et al. 2021). MERRA-2 was additionally used to calculate velocity potential at 250 hPa to describe upper-level divergence (Hendon 1986) and to serve as a proxy for tropical convection. As a proxy for storm track activity (Chang and Fu 2003), 24-h variance of daily-mean sea level pressure was calculated according to Eq. (2) from Chang et al. (2013):

$$\text{SLP}_{\text{variance}} = \overline{[\text{SLP}(t + 24 \text{ h}) - \text{SLP}(t)]^2},$$

where the overbar indicated an event average, in this case over all the events which fall in the same cluster.

To objectively identify large-scale variability within the catalog of successive AR events, we perform *k*-means clustering on anomalous 500-hPa geopotential heights in the North Pacific. The *k*-means method is an iterative clustering procedure that minimizes the sum of variance within each cluster and maximizes the variance between the clusters (Diday and Simon 1976). This method was chosen for its success in previous studies aimed at identifying large-scale circulation patterns (Fereday et al. 2008; Moron et al. 2008; Jiang 2011; Roller et al. 2016), with similar cluster accuracy to self-organizing maps (Gibson et al. 2017) and low computation time compared to other methods.

Prior to clustering, data are weighted according to the following:

$$W = \sqrt{\cos\left(\phi \frac{\pi}{180}\right)},$$

where *W* is the weight and  $\phi$  is latitude. The weight is applied to the anomalous 500-hPa geopotential heights over North Pacific latitudes ( $20^\circ$ – $85^\circ\text{N}$ ). Accuracy (within each cluster) and uniqueness (between the clusters) calculations are evaluated across a range of *k* values to determine the optimal *k* (Lee and Feldstein 2013; Gibson et al. 2016). Given the relatively flat uniqueness and accuracy curves and the qualitative discernibility of large-scale atmospheric patterns, *k* = 6 is subjectively chosen as the most conservative and physically interpretable value, while prioritizing accuracy and aiming for equal sample size distribution across clusters (see Fig. S1 in the online supplemental material). Clustering is conducted using data within a box in the North Pacific extending from  $120^\circ\text{W}$  to  $270^\circ\text{E}$  and from  $20^\circ$  to  $85^\circ\text{N}$ ; results were largely insensitive to changes of  $10^\circ$ – $30^\circ$  longitude and  $10^\circ$ – $20^\circ$  latitude (not shown).

### b. AR detection algorithm

We identify AR objects using the global AR detection algorithm, namely “tARget” version 2.0 (Guan et al. 2018), applied to the 6-h MERRA-2 reanalysis data, described above in section 2a. The AR detection algorithm uses integrated water vapor transport (IVT), direction, and geometry, described in detail in Guan and Waliser (2015) and refined in Guan et al. (2018). The key requirements are as follows: 1) the maximum 85th percentile or  $100 \text{ kg m}^{-1} \text{ s}^{-1}$  of IVT intensity, whichever is greater, at each grid cell; 2) mean IVT

within 45° of an AR object and with large poleward component; and 3) object length greater than 2000 km with a length-to-width ratio greater than 2. We chose this AR catalog due to the length of the dataset (1980–2019) and use of the high-resolution MERRA-2 reanalysis.

We evaluate AR objects that made landfall anywhere along the California coast during a particular water year (WY; defined as 1 October–30 September periods spanning two calendar years, beginning in October 1981 and ending in May 2019). The WY is referred to by the second calendar year (e.g., 1 October 1981–30 September 1982 is WY 1982). The AR landfall is defined as the coastal grid point that first detects AR conditions. There can only be one landfall per AR event.

### c. AR families algorithm

Fish et al. (2019) used observational data to define AR families as successive AR events that made landfall at Bodega Bay, California, and found a 120-h aggregation period to be suitable for Northern California AR events. Therefore, we classify AR objects (i.e., AR conditions identified in reanalysis data) as an AR family if two or more AR objects occur within the 120-h aggregation period. The AR objects were not geographically constrained, but ~76% of all families were composed of landfalling events within 5° latitude of one another. Once an AR object initiates a new AR family or follows a previously occurring AR object by less than 120 h (i.e., was included in an AR family), that AR object can no longer initiate a new AR family. Additionally, AR objects are counted at first landfall and their propagation is tracked.

We further filter AR family events to retain only AR families with at least one 12-h AR object, which removes instantaneous and short-duration (6 h, 1 time step) AR objects. AR objects less than two grid points wide are also removed, since these objects are too narrow for the IVT computation (Guan et al. 2018). Therefore, AR families consisting of only narrow AR objects are removed. These additional requirements left ~900 AR objects, with almost 600 considered a part of an AR family, creating 248 AR families; the remaining 300 are single AR objects (Fig. S2). Single AR objects are formally defined as AR objects occurring without another AR object within 120 h before or after the event.

Clustering is performed at single time-step resolution from the first to last 3-h window of the AR family event (i.e., each time step within the AR family has an associated cluster). The majority of AR family events exhibit the same cluster throughout the event duration. For those events exhibiting more than one cluster, the mode cluster is used to partition the AR family event.

### d. Precipitation data

To investigate the impacts of AR families and whether large-scale atmospheric variability is related to precipitation outcomes, PRISM daily precipitation observations from 1981 to 2019 is used. PRISM uses point data and a digital elevation model to generate gridded estimates of precipitation and other climate variables (Daly et al. 1994, 2001, 2002). The

PRISM daily precipitation dataset is chosen for its strength in representing precipitation in mountainous regions such as the western United States and its high spatial resolution of 4 km.

### e. ENSO data

The ENSO longitude index (ELI) is a physically based metric dependent on the average Pacific longitude where equatorial SST exceeds the threshold for deep convection, set by the tropical mean SST and varying annually (Williams and Patricola 2018). We use the ELI to characterize ENSO variability and its relation to AR families over 1981–2019. While the traditional Niño-3.4 index based on SST anomaly was also evaluated (not shown), the ELI was ultimately chosen due to its stronger relationship between tropical Pacific deep convection and geographically remote teleconnections, particularly those relevant to western U.S. precipitation (Patricola et al. 2020).

The ELI dataset used here is provided by Patricola et al. (2020) and calculated using the monthly  $2.0^\circ \times 2.0^\circ$  Extended Reconstructed SST v5 (Huang et al. 2017). ENSO events are defined as the December–February (DJF) average of the ELI (Patricola et al. 2019). El Niño events exhibit an ELI greater or equal to  $162^\circ\text{E}$ , La Niña events exhibit an ELI less than  $158^\circ\text{E}$ , and neutral events have an ELI less than  $162^\circ\text{E}$  but greater than or equal to  $158^\circ\text{E}$ . Nine years were classified as El Niño (1983, 1987, 1992, 1993, 1995, 1998, 2003, 2010, 2016) and another nine as neutral (1988, 1990, 1991, 1997, 2002, 2005, 2007, 2015, 2019) and the remaining 21 years were classified as La Niña. Relationships between ELI and AR families are then based on the corresponding occurrences of AR families over DJF for each WY.

### f. Madden–Julian oscillation data

The MJO is the oscillation of convection in the near-equatorial west Pacific that influences global weather on weekly to monthly time scales (e.g., Madden and Julian 1971; Hendon and Salby 1994; Matthews 2000; Waliser et al. 2003; Zhang 2005, 2013). We use real-time multivariate MJO (RMM) data between 1980 and 2019 as in Wheeler and Hendon (2004). The MJO is tracked using RMM1 and RMM2, which are mathematical methods that combine cloud percentage and winds at two atmospheric levels, upper and lower, and describe the strength and location of the MJO.

### g. Sea surface temperature data

The NOAA Daily Optimum Interpolation Sea Surface Temperature Anomaly dataset was used to evaluate SST anomalies between 1981 and 2019 (Reynolds et al. 2007; Banzon et al. 2016; Huang et al. 2020). This dataset is daily at  $0.25^\circ$  resolution and includes observations from various sources such as satellites, ships, and buoys.

### h. Outgoing longwave radiation data

The NOAA interpolated outgoing longwave radiation (OLR) dataset was used to analyze OLR anomalies from WYs 1981 to 2019 (Liebmann and Smith 2006) as a proxy for tropical convection. The data are interpolated in time and

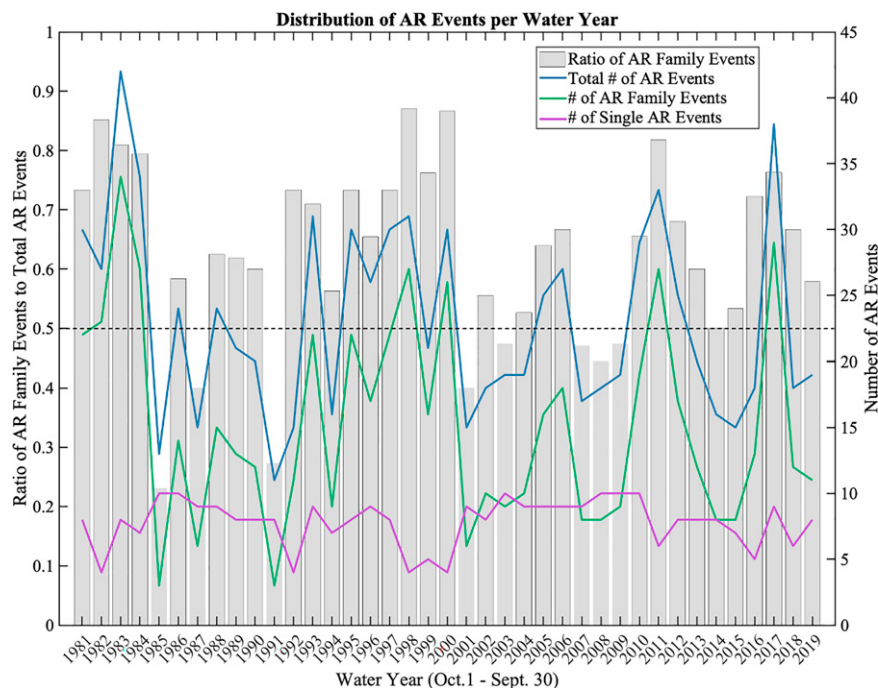


FIG. 1. The distribution of AR events per water year by total AR events (blue), number of AR events within AR families (green), and number of single AR events (purple). The gray bars show the ratio of AR events within AR families to total AR events per water year. The bars outlined (not outlined) in black have a higher (lower) than 0.5 ratio.

space and averaged to daily values with a resolution of  $2.5^\circ$  latitude  $\times$   $2.5^\circ$  longitude.

### 3. Results

#### a. Interannual variability of AR families

The 39-yr time series, from WY 1981 to 2019, allows for the evaluation of interannual variability of 1) the total number of AR events, 2) the number of events in AR families, 3) the resulting single AR events, and 4) the ratio of events in AR families to the total number of AR events (Fig. 1). The total number of AR events ranges from a minimum of 11 in WY 1991 to a maximum of 42 in WY 1983. Events within AR families range from four AR events in WY 1985 to 34 AR events in WY 1983. Single AR events have a much smaller range with 4–10 single AR events occurring per WY.

The interannual variability in ARs occurring as part of a family event is high and is responsible for a large fraction of variability in AR frequency overall (94%). Contrarily, single ARs contribute only 4.6% of the variability in overall AR frequency. The close correspondence between family associated ARs and overall AR variability is especially striking during both very active WYs (e.g., 1983 and 2017) and very inactive WYs (e.g., 1985, 1987, and 1991). As both WY 1983 and WY 2017 were exceptionally wet seasons in California, with widespread hydrologic impacts, these cases suggest that the frequency of AR families could potentially be an important modulator of seasonal precipitation accumulation, although a

formal assessment would require further research. The ratio of AR family events to total AR events highlights the codependence well, with ratios greater than 0.5 occurring during active WYs and less than 0.5 during inactive WYs. Out of the 39-yr time series, only eight WYs had a ratio of AR family events to total AR events less than 0.5 (1985, 1987, 1991, 2001, 2003, 2007, 2008, 2009). In 31 of 39 years (79%), more than half of ARs occurred as part of an AR family, rather than as a single event.

#### b. Large-scale 500-hPa height patterns associated with successive ARs

The  $k$ -means cluster analysis of AR family events ( $k = 6$ ) on the anomalous 500-hPa geopotential height ( $z_{500}$ ) field reveals primary modes of large-scale variability during these events (Fig. 2). We find that there are two dominant types of large-scale patterns associated with AR families: high-amplitude meridional flow and strongly zonal flow. Clusters 1, 3, 5, and 6 all exhibit anomalously high geopotential heights upstream (west) of an anomalously low geopotential height region associated with AR activity, although magnitudes and precise locations vary (Figs. 2a,c,e,f). Clusters 2 and 4 exhibit a much more zonal pattern that distinctly lacks any upstream positive geopotential height anomalies (Figs. 2b,d).

Interestingly, when the same method is applied to single AR events, the accuracy across a range of clusters (from  $k = 2$  to  $k = 20$ ) was low (median pattern correlation less than 0.2) compared to AR family events (not shown). This result, which is robust to spatial shifts in the domain, suggests that

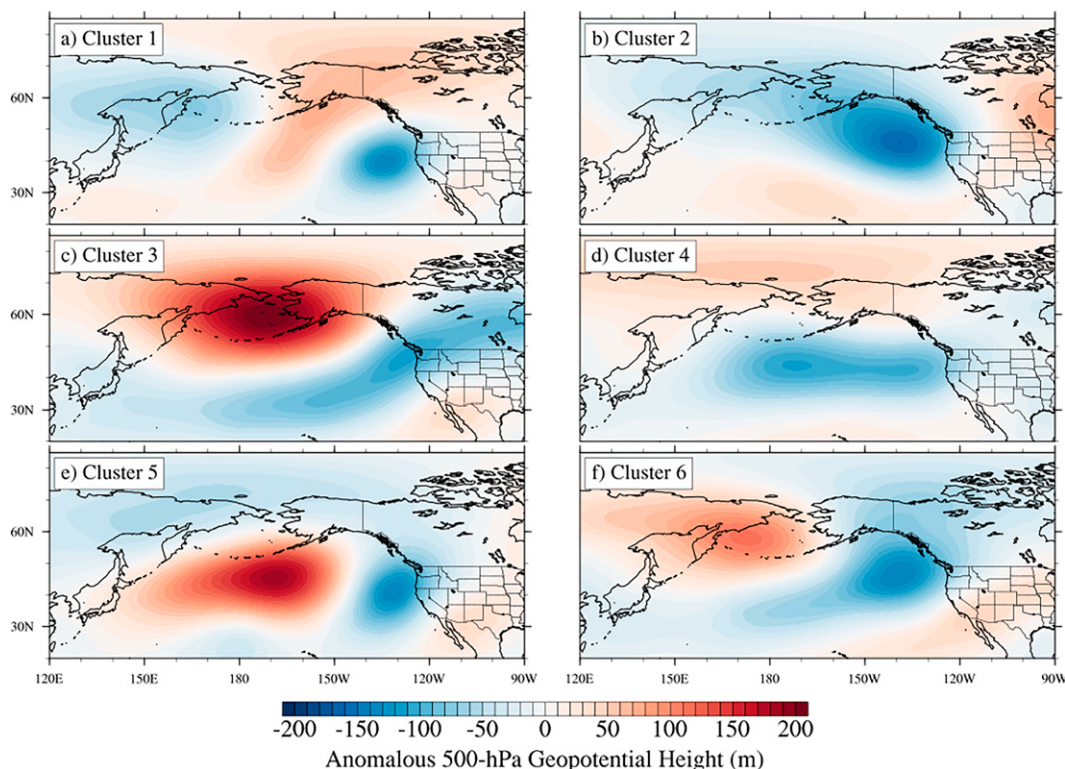


FIG. 2. The  $k$ -means clustering ( $k = 6$ ) on anomalous 500-hPa geopotential heights (shaded; m) for all time steps within AR families. Cluster 1:  $n = 1524$ , cluster 2:  $n = 2058$ , cluster 3:  $n = 911$ , cluster 4:  $n = 1681$ , cluster 5:  $n = 1160$ , cluster 6:  $n = 990$ .

atmospheric variability associated with single AR events is much higher than for AR families. In other words, while there is clear evidence of preferred large-scale patterns conducive to AR family events, the range of patterns capable of producing a single landfalling AR in the study region is much more diverse. This also hints that AR families may potentially be physically linked to certain underlying modes of variability, whereas single events may be less so.

Clusters 1, 3, 5, and 6 all exhibit upstream positive  $z500$  anomalies, classifying them as meridional patterns (Figs. 2a,c,e,f). Cluster 1 is similar to the anomalous pattern shown for WY 2017 AR families in Fish et al. (2019), with moderate positive geopotential height anomalies (i.e., ridging) in the central Pacific and two regions of negative geopotential height anomalies and associated minima just west of the Bering Sea and off the coast of Northern California, respectively (Fig. 2a). In cluster 3, a widespread region of anomalously high geopotential heights is centered over the Bering Sea, extending southward into the North Pacific, northward into the Arctic, eastward to Canada, and westward into eastern Russia (Fig. 2c). This large region of positive anomalous geopotential height is suggestive of a large-scale blocking pattern that would influence the propagation of cyclonic storms across the North Pacific as described by Shutts (1983) and Carrera et al. (2004). Blocking induces an equatorward displacement and/or enhancement of the storm

track downstream of the high-latitude ridge, yielding negative geopotential height anomalies across much of the subtropical and midlatitude Pacific ( $20^{\circ}$ – $45^{\circ}$ N). The region of negative anomalous  $z500$  is located east of Hawaii toward the Pacific Northwest, with a minimum located offshore of Washington state and British Columbia (Fig. 2c). Cluster 3 is similar to composite patterns shown by Moore et al. (2020) for extreme precipitation events affecting Northern California. Cluster 5 exhibits a region of positive anomalous  $z500$  south of the Aleutian Islands around  $30^{\circ}$ N (Fig. 2e). Negative geopotential height anomalies concentrate along the U.S. West Coast, extending in a more meridional alignment compared to other clusters (Fig. 2e). Cluster 6 has equal spatial extent of negative and positive regions of geopotential height anomalies (Fig. 2f). Similar to cluster 3, cluster 6 has an elongated region of negative  $z500$  anomalies extending from the minimum, centered at  $50^{\circ}$ N,  $145^{\circ}$ W, southeast into the subtropical region of the east central Pacific (Fig. 2f). The region of positive  $z500$  anomalies is located in the western Bering Sea, off the coast of Russia, extending into the northern Eurasian continent (Fig. 2f).

Clusters 2 and 4 are less meridional and lack upstream ridging and are thus classified as zonal patterns. Instead, cluster 2 has a broad region of negative geopotential heights extending from the eastern edge of the Gulf of Alaska to eastern Russia through the Bering Sea (Fig. 2b). This cluster has the lowest

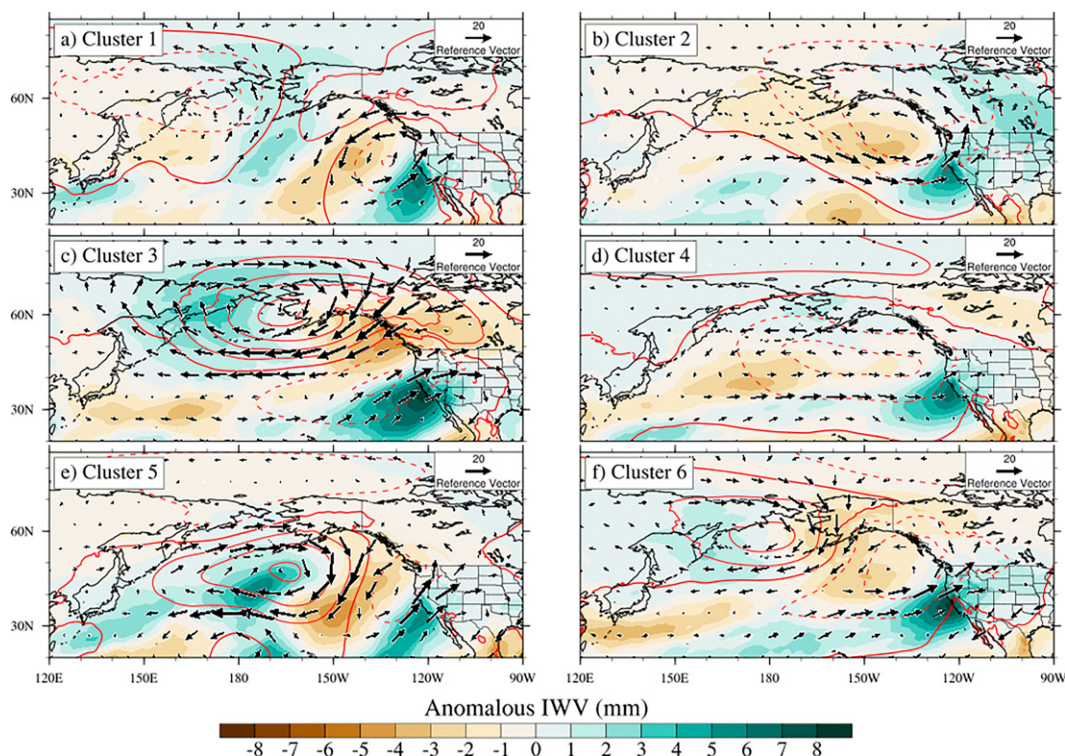


FIG. 3. Anomalous IWP (colored contours; mm), anomalous SLP (red line contours; hPa), and anomalous 250-hPa wind vectors (vectors;  $\text{m s}^{-1}$ ) of the  $k$ -means identified clusters for AR families.

average negative  $z500$  anomaly of all clusters. While this cluster exhibits no upstream positive anomaly, anomalously high geopotential heights are still present throughout the domain, downstream over central eastern Canada and northeast of Hawaii (Fig. 2b). Cluster 4 is characterized by a zonally elongated region of negative geopotential heights, with a minimum in the central Pacific extending toward the U.S. West Coast (Fig. 2d). This pattern is similar to that of AR families with  $\geq 3$  AR events (Fish et al. 2019). Indeed, cluster 4 has the most (16) AR families with  $\geq 3$  AR events (see Table ST 1 in the online supplemental material).

### c. Thermodynamic and kinematic composite patterns associated with successive AR events

Cluster 3 has the largest magnitude and spatial extent of anomalous IWP with positive values extending from Hawaii to the California coast and penetrating inland as far as Arizona and Utah (Fig. 3c). Along the California coast, the climatological average IWP ranges from 12 to 16 mm; however, cluster 3 AR families are associated with IWP 8 mm above average, corresponding to a 50%–66% increase (Fig. 3c). Cluster 3 exhibits above average anticyclonic flow in the same region as the anomalous positive SLP and positive  $z500$  anomaly (Fig. 2c). Cluster 6 AR families also exhibit a large magnitude of anomalous IWP similar to cluster 3 (also +8 mm) (Fig. 3f). However, for cluster 6 events, the region of anomalous IWP is more narrowly concentrated around coastal California, with a sharper gradient relaxing to climatological

values on all sides, likely related to the general atmospheric state and geopotential height pattern (Fig. 3f). In clusters 3 and 6, negative geopotential height anomalies extend into the subtropics, which are particularly favorable for poleward transport of moist air from low latitudes (Fig. 2). Anomalous 250-hPa wind vectors are above climatological conditions and directed onshore toward the northeast for cluster 6 AR families, indicating an enhanced upper-level jet off the U.S. West Coast enabling strengthened moisture transport (Fig. 3f). An anomalous positive and negative SLP dipole is located over the western Pacific, consistent with their midtropospheric counterparts (Fig. 3f). This pattern signifies increased extratropical cyclone activity in the central to eastern Pacific coinciding with enhanced moisture transport into California. Cluster 2 AR families have the smallest spatial extent and lowest magnitude of anomalous IWP, but the largest spatial extent of anomalously negative SLP collocated with positive 250-hPa wind vectors directed onshore (Fig. 3b). Similar to their associated negative geopotential height anomalies, clusters 1 and 5 show more meridionally elongated positive IWP anomaly regions and anomalous 250-hPa wind vectors (Figs. 3a,e). Both clusters 1 and 5 have small regions of negatively anomalous SLP, constrained close to the U.S. West Coast (Figs. 3a,e). Cluster 4's IWP anomaly, zonal anomalous 250-hPa wind vectors, and zonally elongated negative SLP anomaly closely resemble previous results for ARs affecting California (Ralph et al. 2004; Dettinger et al. 2011; Lamjiri et al. 2017), including those of long durations (Ralph et al. 2013; Payne and

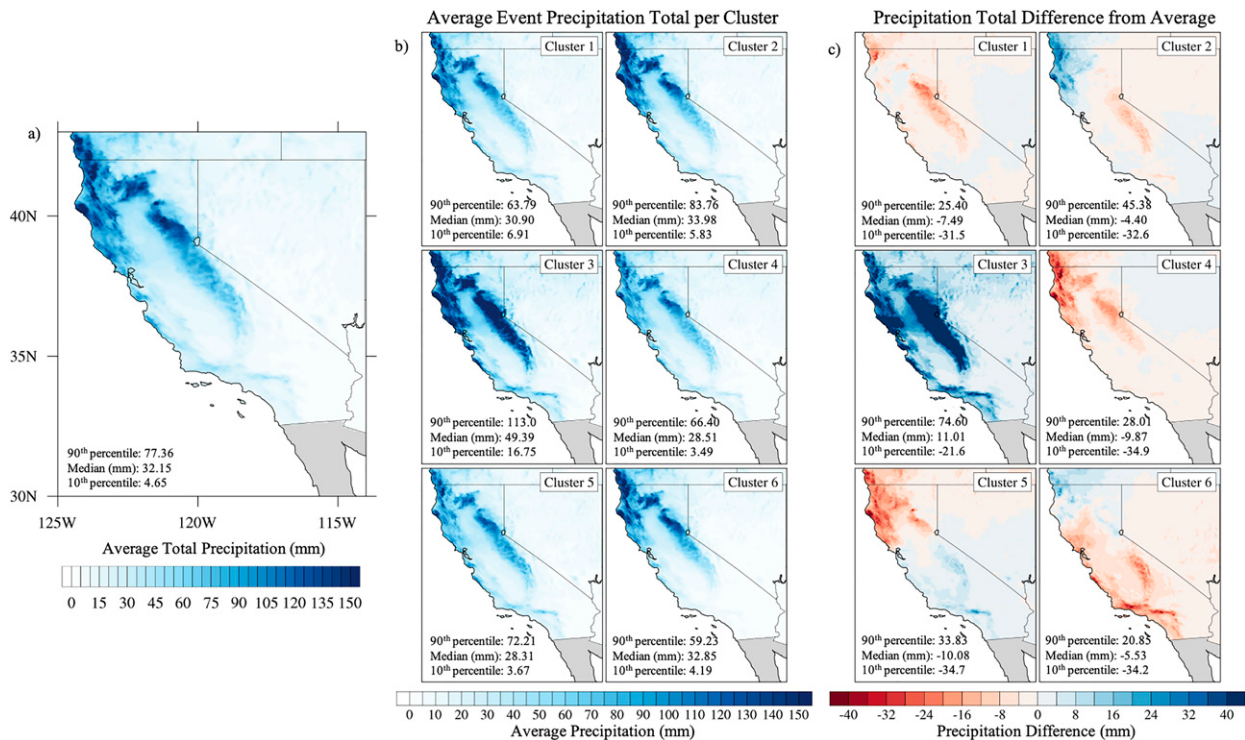


FIG. 4. Average precipitation total (mm) for (a) all AR family events and (b) AR family events defined by mode cluster, and (c) the difference between each cluster average [in (b)] and the all AR family event average [in (a)]. For each cluster the 90th percentile, median, and 10th percentile are shown.

Magnusdottir 2016; Lamjiri et al. 2017; Fish et al. 2019; Moore et al. 2020) (Fig. 3d).

#### d. Precipitation impacts

AR family events are typically characterized by multiday (2–5 day) durations (Fish et al. 2019). Indeed, extreme precipitation events in Northern California are often multiday events (White et al. 2019; Moore et al. 2020; 2021). For the events in this catalog, the average total precipitation accumulation across all AR family events varies substantially across California, with the highest values collocated with areas of enhanced orography (Fig. 4a). Most AR family events affect the northern Sierra Nevada mountains and the coastal mountains of Northern and Central California (Fig. 4a). The Transverse Ranges in Southern California can also receive heavy AR-related precipitation, but these are more often single events associated with a single, slow-moving closed low pressure system (Oakley et al. 2018) (Fig. 4a). The AR family events in this catalog were sorted to evaluate how the different large-scale environments affected the average precipitation total per cluster (Fig. 4b). While each cluster shows high precipitation totals across both the Coast Ranges and inland Sierra Nevada Mountains, clusters 2 and 6 show a preference for increased precipitation in coastal Northern California. Cluster 3 affects the entirety of the Sierra Nevada mountains, Northern California, and coastal central California. Cluster 5

AR family events not only affect Northern California and the Sierra Nevada mountains, but also the Transverse Ranges in Southern California.

We evaluate precipitation differences between clusters by comparing the anomaly of each cluster's average cumulative precipitation to the average precipitation accumulation across all AR families (Fig. 4c). We find that cluster 3 generally brings much wetter conditions throughout California relative to the AR family mean, while cluster 4 brings below average precipitation, especially to Northern California, which coincides with each cluster's IWV anomaly (Figs. 3c,d). Cluster 6 AR families precipitate less in Central and Southern California compared to cluster 5 events, which produce average precipitation totals in the same area. Comparing the precipitation spatial patterns to the cluster composites, the lower geopotential heights of clusters 6 and 2 are located farther north in the Gulf of Alaska (Figs. 2f,b), drawing precipitation away from Southern California, compared to cluster 5 (Fig. 2e).

#### e. Persistence of the clusters

Given the differing large-scale features of the clusters, we assess the temporal evolution of the similarity (pattern correlation) between the composite z500 pattern for each cluster (Fig. 2) and conditions for up to 60 days prior to each event's start day to determine how long the patterns precede the AR family event. The resultant time series (Fig. 5) can be used to

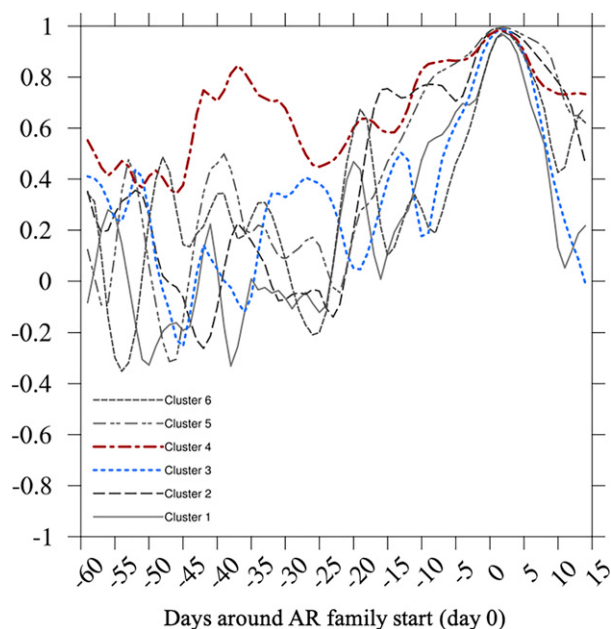


FIG. 5. Temporal evolution of each AR cluster's anomalous 500-hPa height pattern correlation with its own respective composite pattern (Fig. 2) from 60 days prior to event onset to 15 days past event start. The resultant pattern correlation time series are smoothed using a 3-day running mean.

discern the level of persistence that a particular pattern exhibits in the lead-up to the AR family event as well as allows us to identify if any seasonal or subseasonal mechanisms are playing a role. We find that two clusters (4 and 5) consistently maintain a high ( $>0.6$ ) pattern correlation (and thus high persistence) for at least 5–10 days prior to events, while the pattern correlation of three other clusters (1, 3, and 6) is low in comparison. Clusters 2 and 4 consistently exhibit a high pattern correlation 10 or more days prior to AR family start. Cluster 4 pattern correlations reach a secondary maximum (pattern correlation 0.6–0.8) between 25 and 45 days prior to AR family start, suggestive of a possible subseasonal signal that has similar large-scale characteristics to cluster 4. Following the event onset (day 0), all clusters exhibit pattern persistence for the first  $\sim 5$  days. After the typical AR family ends, clusters 1 and 3 decline in pattern correlation the quickest, while clusters 2 and 5 maintain the highest pattern correlation for the longest period, suggesting the continuation of the pattern beyond the end of the AR family and for long-lasting blocking patterns over the midlatitude North Pacific (Fig. 5).

#### f. Evolution and mechanisms of two clusters

Of the non-persistent (1, 3, 6) and persistent (2, 4, 5) clusters, we subsequently focus on clusters 3 and 4, respectively, to further explore the development, evolution, and decay of these events. To understand the temporal evolution leading to each cluster's large-scale environment, we examined conditions  $\pm 10$  days from the AR family start date. These two clusters were chosen due to their differing precipitation impacts across California (Fig. 4c) and large-scale characteristics as

cluster 3 exhibits the strongest (in terms of magnitude) ridging and cluster 4 exhibits solely zonal geopotential height anomalies across the Pacific (Figs. 2c,d). These differences led us to hypothesize that the mechanisms supporting these two clusters are different, and so too are their relation to mean tropical forcing on subseasonal time scales.

#### 1) NON-PERSISTENT: CLUSTER 3

Cluster 3 is characterized by a positive z500 anomaly in the Bering Sea (Fig. 2) on day 0, but this pattern is absent 10 days prior (Fig. 6). Between days  $-10$  and  $-4$  (Figs. 6a–g), a positive z500 anomaly slowly builds near the Aleutian Islands, then steadily grows until day 0 (Fig. 6k) and persists until day  $+5$  (Fig. 6p), after which it decays and retreats westward (Figs. 6q–u). High SLP variance occurs near the Aleutian Islands between days  $-10$  and  $-7$  (Figs. 6a–d), with a region of higher variability off the coast of Japan starting at day  $-5$  (Fig. 6f). Enhanced SLP variance, an indicator of storm track activity (Chang and Fu 2003), may relate to enhanced latent heat release through large-scale condensation in the warm sector of extratropical cyclones (Chang et al. 2002). It has previously been shown that latent heat release and upper-level divergent outflow associated with extratropical cyclones contributes to downstream ridge building through the redistribution of kinetic energy via the ageostrophic geopotential flux and/or downstream advection of low potential vorticity (Orlanski and Sheldon 1995; Keller et al. 2019 and references therein). We extrapolate those results to suggest that the enhanced cyclone activity (higher SLP variance) in the present case may be causally linked to the amplified downstream ridge, and that the continued storm track activity subsequently acts to maintain the ridge. The increased variance persists throughout the central Pacific from days 0 to  $+4$  (Figs. 6k–o), then declines while the ridge starts to decay (Figs. 6p–r). While not explored here, dry adiabatic dynamical processes (such as warm air and negative potential vorticity advection linked to baroclinic waves and extratropical cyclones) can also play an important role in ridge amplification (e.g., Nakamura et al. 1997 and references therein).

In conjunction with the height changes at 500-hPa and sea level, anomalously positive IWV first appears at day  $-6$  east of Hawaii (Fig. 6e). As the evolution progresses, the spatial footprint of the IWV expands and moves eastward, likely becoming entrained in extratropical cyclones and/or ARs, until the moisture reaches the U.S. West Coast at day 0 (Fig. 6k). There also appears to be a modest maximum of SLP variance near the West Coast in successive AR cases, suggesting that cyclone centers occur with increased frequency near the coast during such events (with possible implications for impacts beyond precipitation, including strong winds and coastal inundation). The large region of enhanced water vapor content persists onshore until day  $+7$  (Fig. 6r). Together, these three variables show that 1) the ridging associated with cluster 3 precedes the development of the AR family by several days (Figs. 6g–k), 2) the moisture is of subtropical origin, and is present before the ridge builds (Figs. 6e–k), and 3) increased SLP variability and associated

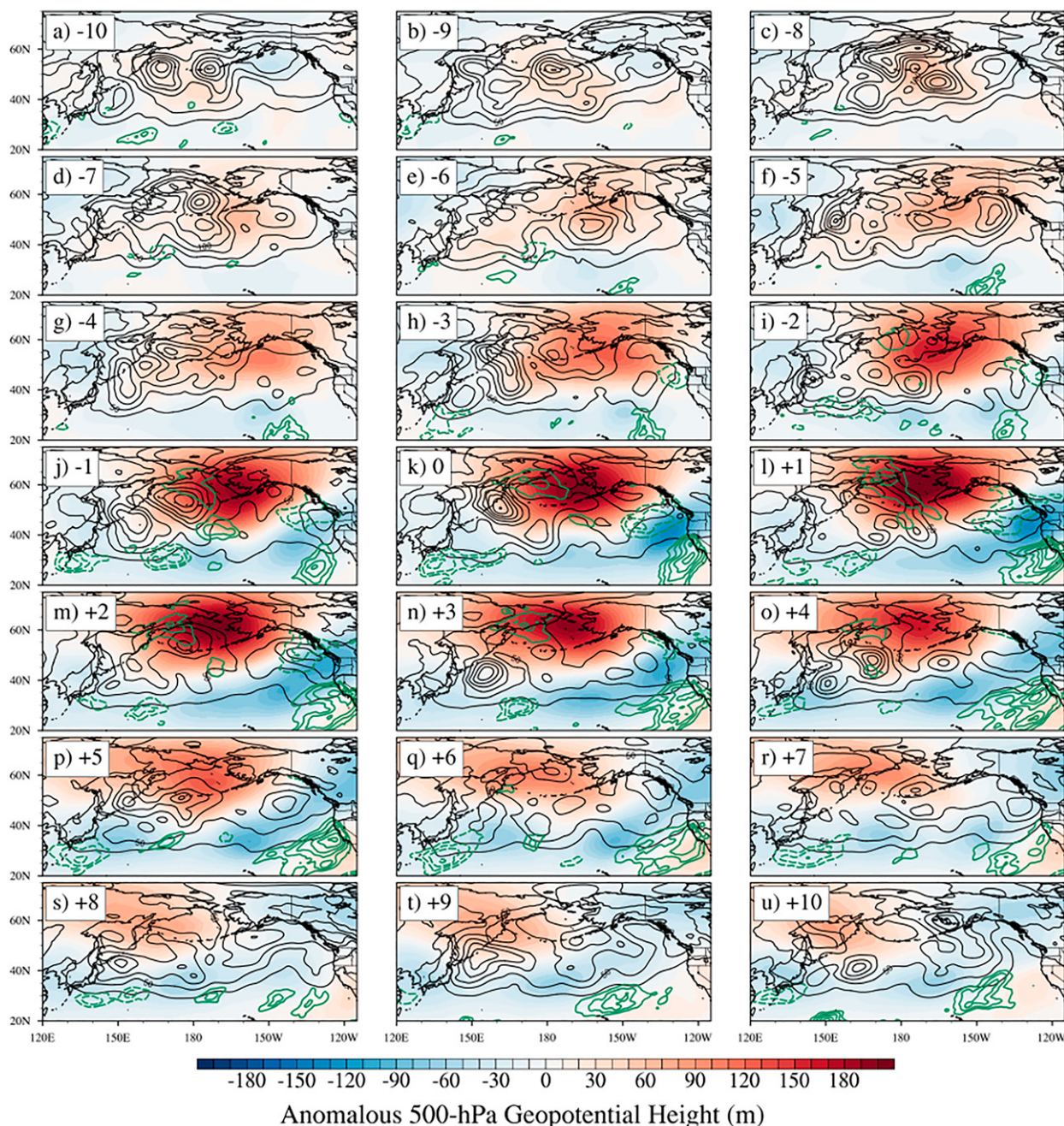


FIG. 6. The average daily composite of anomalous 500-hPa geopotential heights (colored contours; m), sea level pressure variance (black contours), and anomalous IWV greater or less than 3 mm (green contours) from the -10 to +10 days around the start of each AR family (day 0) within cluster 3.

storm activity off the coast of Japan is a plausible physical ridge-building mechanism (Figs. 6a–k).

Analysis of horizontal 250-hPa WAF yields further insights into the development of the high-latitude ridge and presence of Rossby wave activity (Fig. 7). WAF vectors show the instantaneous direction of Rossby wave packets, with the temporal evolution allowing us to understand the directional change over time. In the days leading up to cluster 3-type events, WAF

vectors depict an eastward-directed Rossby wave pathway originating from the central Pacific from days -4 (Fig. 7d) to 0 (Fig. 7h). By day -1, the propagation extends toward the southeast between Hawaii and the U.S. West Coast (Fig. 7g). Around the same time, a Rossby wave source in the Gulf of Alaska develops, as indicated by WAF vector divergence, and the WAF vectors increase in magnitude (Figs. 7f–j). By day +2, a wave sink develops northeast of Hawaii, indicated by the

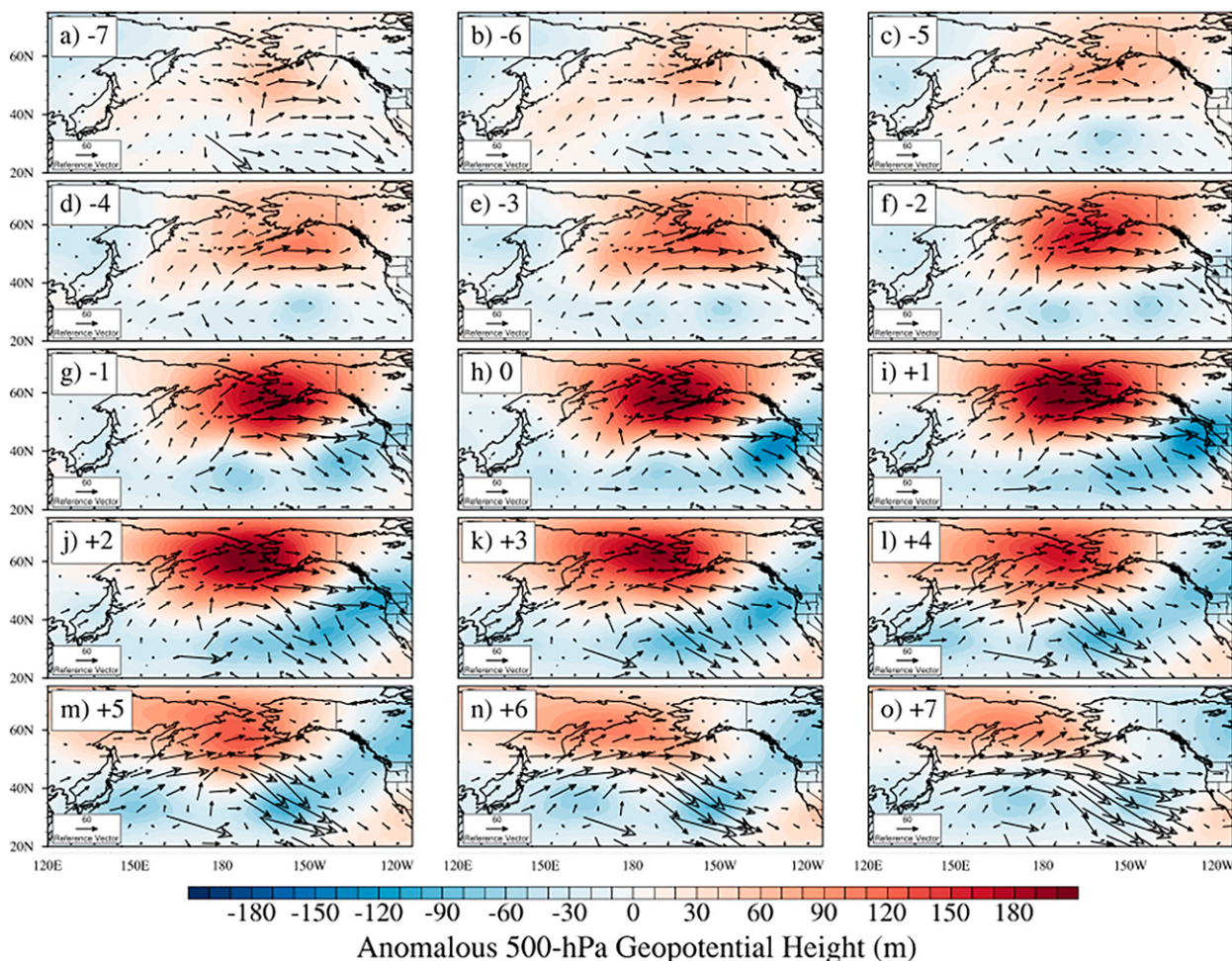


FIG. 7. Wave activity flux (WAF; vectors;  $\text{m}^2 \text{s}^{-2}$ ) and anomalous 500-hPa geopotential heights (colored contours; m) of WAF during the daily composite from the  $-7$  to  $+7$  days around the start of each AR family in cluster 3.

convergence of WAF vectors, and the WAF vectors start to retreat westward, continuing to increase in magnitude as the high-latitude ridge moves westward and begins to decay (Fig. 7j). While overturning potential vorticity contours are typically indicative of Rossby wave breaking (e.g., Masato et al. 2011 and references therein) a divergence–convergence dipole (not shown) is evident downstream of the ridge, which is also consistent with Rossby wave breaking (e.g., Wolf and Wirth 2017). This composite evolution of WAF for cluster 3 AR family events is consistent with the extreme precipitation case study presented in Moore et al. (2020).

We suggest that the cluster 3 large-scale z500 pattern development may owe its existence to the upstream local maxima in SLP variance and associated storm track activity, which is known to favor downstream ridge development. Additionally, and consistent with previous work, the WAF and subsequent Rossby wave activity suggests that the transfer of energy downstream from the high-latitude ridge acts to reinforce the persistent downstream trough, thus supporting successive extratropical cyclone development, increased AR activity,

and resultant precipitation along the U.S. West Coast (Ryoo et al. 2013; Payne and Magnúsdóttir 2014; Mundhenk et al. 2016; Hu et al. 2017; Benedict et al. 2019; Moore et al. 2020, 2021).

While Rossby wave propagation in the extratropics appears to be an important factor for AR families in cluster 3, we also consider the potential role of tropical drivers. Analysis of anomalous velocity potential (VP), which describes planetary-scale characteristics of upper-level divergence (Hendon 1986), is specifically relevant for understanding connections to the MJO (Ventrice et al. 2013). VP evolution throughout cluster 3 AR family events shows two distinct signs (Fig. 8): 1) increased upper-level divergence (negative VP anomalies) from day 0 to  $+7$  between Hawaii and the U.S. West Coast, reflecting an environment favorable for extratropical cyclone activity (Figs. 8k–r), and 2) increased upper-level convergence (positive VP anomalies) in the Gulf of Alaska from days  $-5$  to  $+2$  in a region east of the high-latitude ridge, locally enforcing the upper level ridge (Figs. 8f–m). The convergence–divergence dipole from day 0 to  $+2$  reflects expected regions of

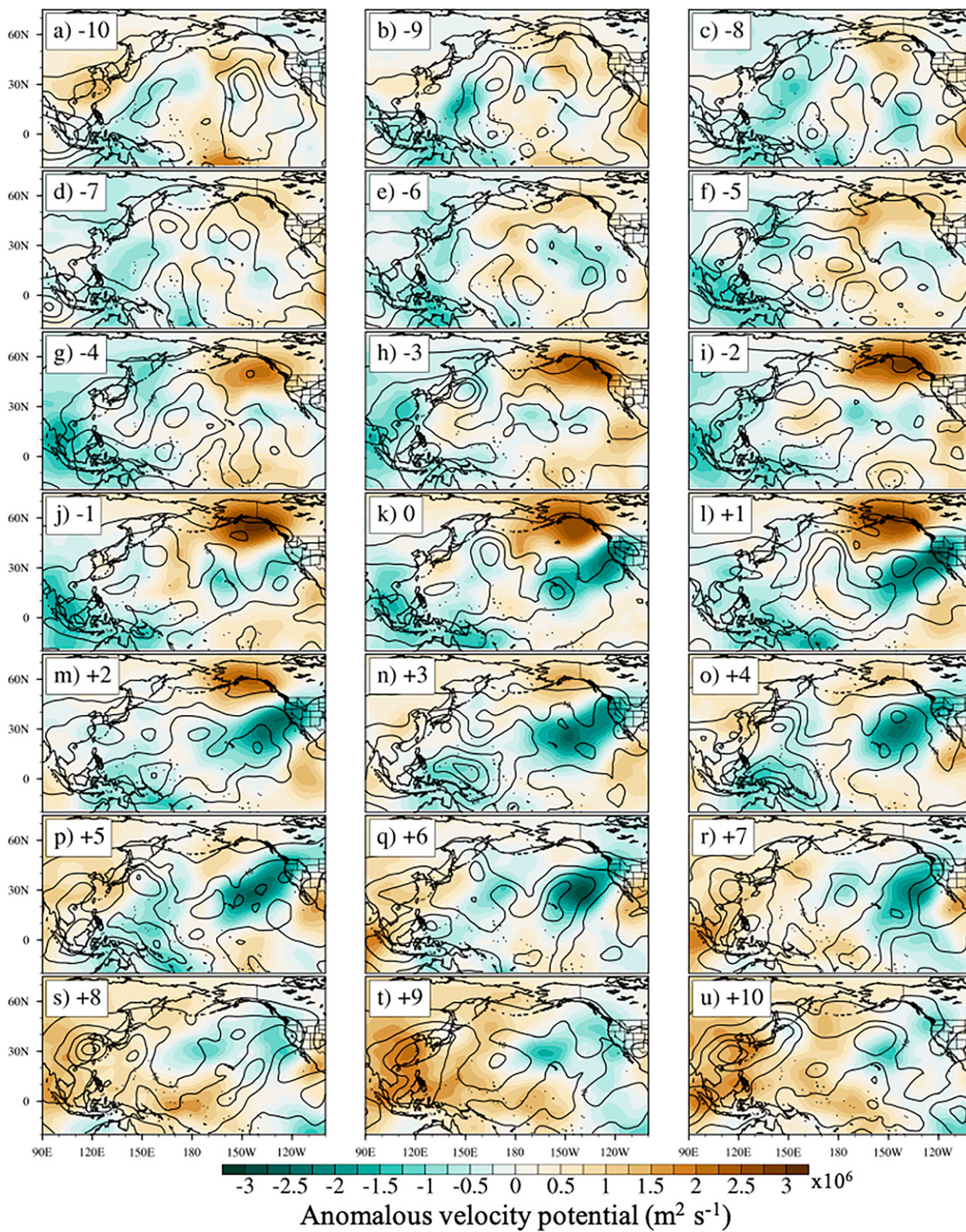


FIG. 8. Anomalous velocity potential (colored contour,  $\times 10^6 \text{ m}^2 \text{ s}^{-1}$ ) and velocity potential variance (line contour,  $\times 10^6$ ) during the daily composite from the -10 to +10 days around the start of each AR family in cluster 3.

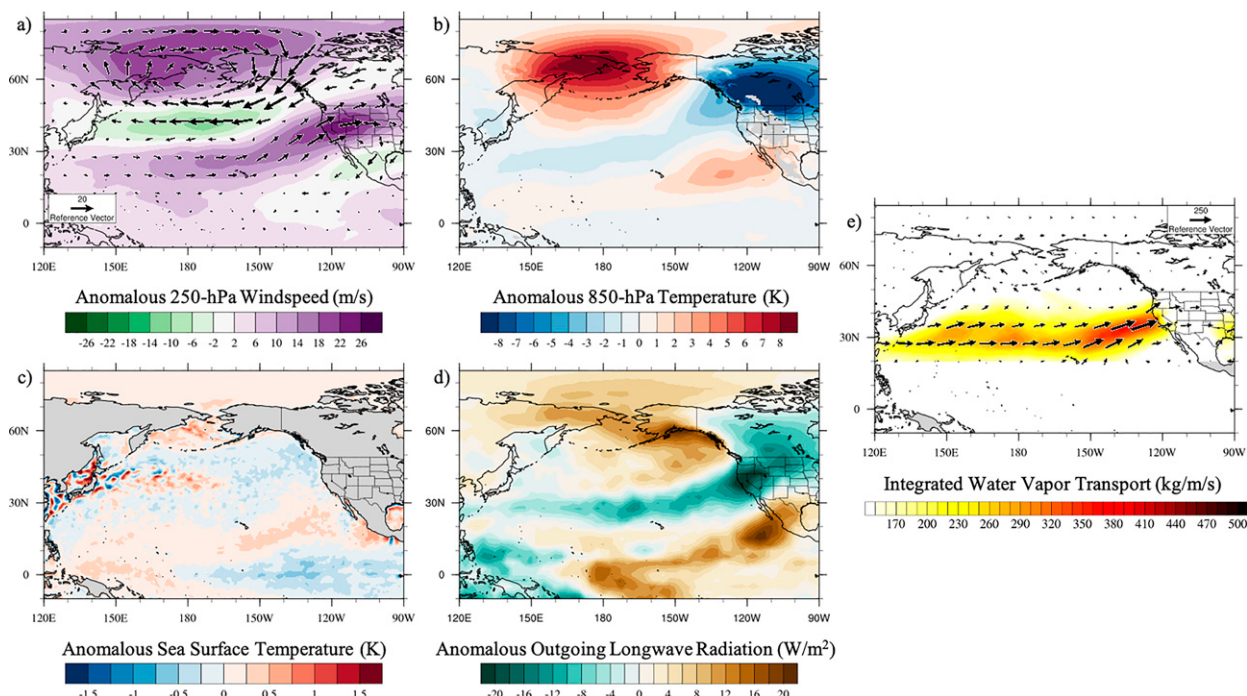


FIG. 9. Cluster 3 AR family composite over the entire event duration of (a) anomalous 250-hPa wind speed magnitude (colored contours;  $\text{m s}^{-1}$ ) and vectors (black arrows), (b) anomalous 850-hPa air temperature (colors; K), (c) anomalous SST (colors; K), and (d) anomalous OLR (colors;  $\text{W m}^{-2}$ ).

descent and ascent (Figs. 8k–m) consistent with a strengthened geopotential height gradient (Fig. 2c) and jet feature (Fig. 9a) helping to direct successive cyclones and ARs toward the U.S. West Coast. The increased AR activity is evident in the composite of integrated water vapor transport; the transport is particularly strong east of Hawaii (Fig. 9e). Additionally, from days  $-10$  to  $+6$ , above average VP exists over the Maritime Continent (Figs. 8a–q). The combination of warm SST anomalies (Fig. 9c) and below average OLR anomalies in the same region (Fig. 9d) suggests enhanced convection over the Maritime Continent and patterns similar to phase 5 of the MJO (Ventrice et al. 2013). This pattern could induce an extratropical Rossby wave response, potentially leading to the development of the high-latitude ridge. Further, the anomalous jet pattern (Fig. 9a) and high-latitude ridging (Fig. 2c) is most similar to the equatorward shift of the North Pacific jet discussed by Winters et al. (2019a,b) and also consistent with cold downstream temperature anomalies (Fig. 9b), expected due to the large surface anticyclone (Winters et al. 2019a,b).

In sum, cluster 3 AR families are characterized by a large-scale, high-latitude ridge that develops approximately four days prior to event initiation while a stationary Rossby wave propagates across the central and eastern Pacific (Figs. 2, 6, and 7). We hypothesize that enhanced tropical convection (i.e., negative OLR and VP anomalies fueled by warm SSTs over the Maritime Continent) aids in the Rossby wave train setup. Simultaneously, latent heat release associated with increased SLP variance (i.e., extratropical cyclone activity) off the coast of Japan reinforces downstream ridge development over the Bering Sea (Figs. 6, 8,

and 9c). The subsequent transfer of energy downstream from this high-latitude ridge supports the persistent downstream trough, further indicated by the concurrent negative VP anomalies, creating an environment supportive of successive extratropical cyclones and AR activity off the U.S. West Coast.

## 2) PERSISTENT: CLUSTER 4

In contrast to the high-amplitude meridional flow of cluster 3, we analyze the development and evolution of cluster 4 AR families, which are characterized by an elongated region of negative  $z500$  anomalies and lack of upstream ridging (Fig. 2d). Cluster 4 events also exhibit the greatest temporal persistence, maintaining a high  $z500$  pattern correlation both 10 days prior to AR family start and 10 days after (Figs. 5 and 10). This persistence is suggestive of a sub-seasonal-scale process conducive to successive cyclones and ARs. In addition to consistent negative  $z500$  anomalies across the Pacific Ocean, SLP variance suggests a weaker more zonally elongated pattern of cyclonic activity (i.e., extratropical storm track) spread across the western and central Pacific (Figs. 10d–o), rather than being confined to the far western Pacific as in cluster 3. This pattern is concurrent with the zonally elongated North Pacific jet. Enhanced IWV, which appears one day prior to AR family start (Fig. 10j), is of lower peak magnitude than cluster 3 and persists offshore of California through day  $+5$  (Fig. 10p). These results support the earlier result that cluster 4 events have less water vapor content than cluster 3 events (Fig. 3d) and are fed by the zonal propagation of cyclones and ARs across the Pacific, as shown by the integrated water vapor transport of the cluster 4 events

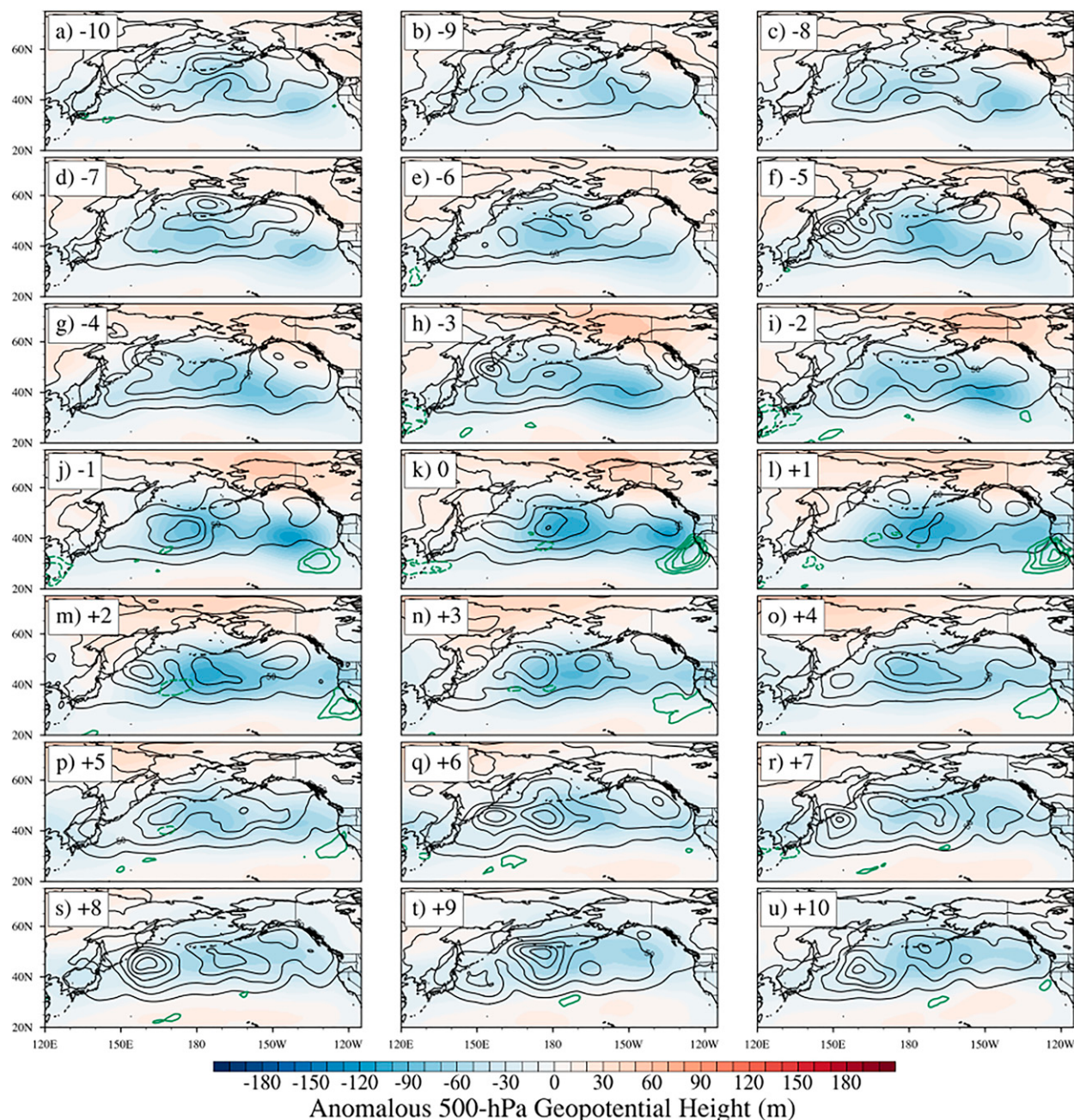


FIG. 10. As in Fig. 6, but for cluster 4.

(Fig. 12e) with a large-scale pattern that is maintained beyond the extent of the AR family itself.

Anomalous negative VP suggests widespread anomalous upper-level divergence across the eastern Pacific for 10 days prior to the AR family initiation (Figs. 11a–m), while upper-level convergence (positive VP anomalies) persists across the western Pacific for the full period of  $-10$  to  $+10$  days (Fig. 11). This pattern suggests that the eastern Pacific is an active region of low-level convergence indicative of cyclonic and/or convective activity (Fig. 11). In addition to their

midtropospheric patterns, cluster 4 AR families are associated with zonally elongated 250-hPa wind maxima (“jet extension”) (Fig. 12a) (Winters et al. 2019a,b) and cooler 850-hPa temperature across the U.S. West Coast (Fig. 12b). This pattern is further supported by the eastward Rossby wave pathway, as seen in the WAF (Fig. S3). The lack of clear sources and/or sinks for Rossby wave development for cluster 4 events suggests that cluster-4 AR families were not sustained by stationary Rossby waves. Analysis of anomalous OLR shows an opposite pattern in the tropical Pacific

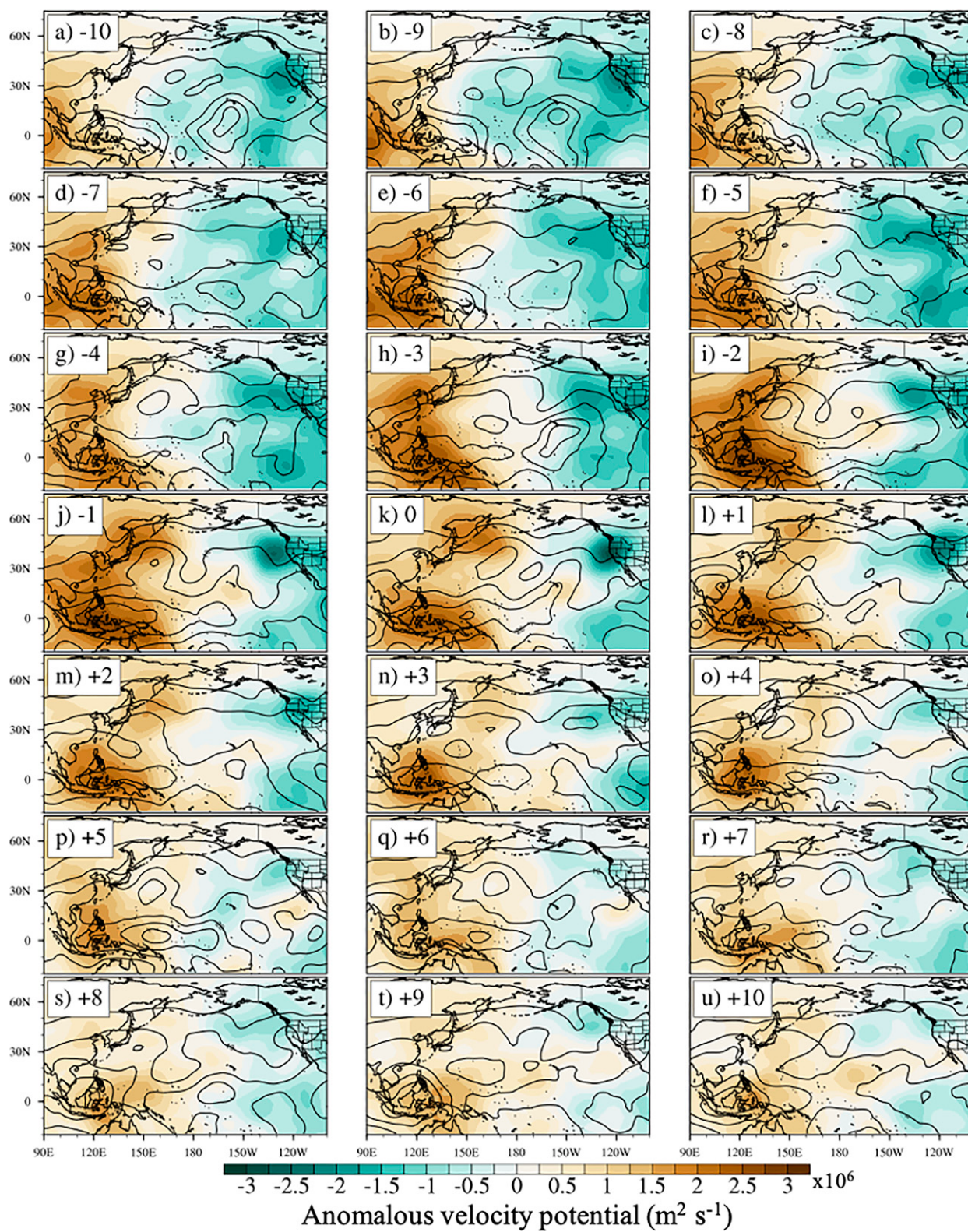


FIG. 11. As in Fig. 8, but for cluster 4.

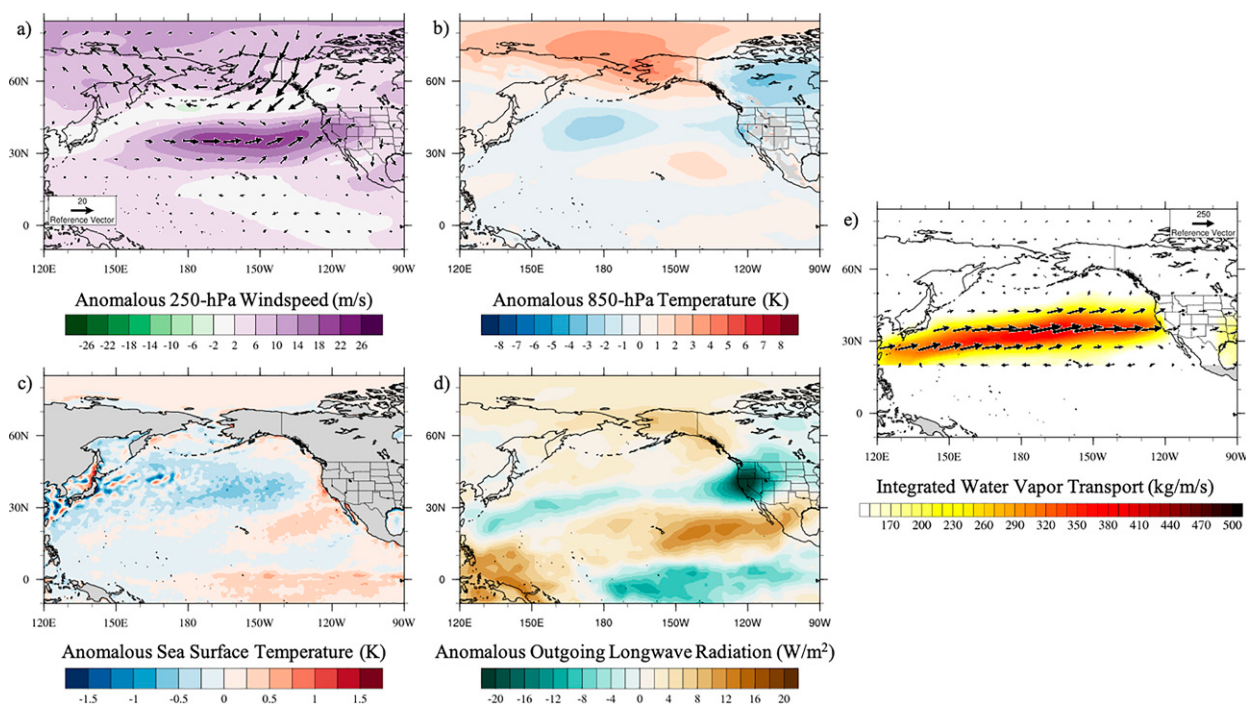


FIG. 12. As in Fig. 9, but for cluster 4.

compared to cluster 3 events, as cluster 4 displays increased OLR anomaly over the Maritime Continent and the central Pacific shows decreased OLR (Fig. 12d). Additionally, cluster 4 exhibits increased SST anomalies over the central and eastern tropical Pacific, a pattern resembling a warm ENSO/SST anomaly field (Fig. 12c). The combined SST and OLR anomalies indicate enhanced convection over the eastern tropical Pacific. We hypothesize that the divergent outflow associated with this convection enhances tropopause potential vorticity gradients thus favoring a strong zonal North Pacific jet directed into the U.S. West Coast.

#### g. Cluster relationships to teleconnections

Given the distinctly different tropical Pacific conditions between clusters 3 and 4 and differences in presumptive causal physical processes, we seek to more formally quantify the relationships of these clusters to climate phenomena

including ENSO and the MJO. Using the ELI metric, we find that the DJF AR family time steps within each cluster are sorted by ENSO phases (La Niña, neutral, or El Niño) depending on the overall WY characterization (Table 1/S4). Out of 3625 total DJF AR family time steps, 2004 occurred in La Niña years, 578 in neutral years, and 1043 in El Niño years (although we note that there are 21 La Niña years and only 9 neutral and 9 El Niño years in this dataset). Cluster 2 is the most frequently occurring cluster across all phases of ENSO, and cluster 6 occurs least frequently. Cluster 3 occurrence is strongly associated with La Niña conditions, with 412 out of 611 (~67%) of total cluster 3 time steps occurring during the ENSO cool phase (Table 1, Fig. 13). Interestingly, cluster 3 is largely absent during El Niño years (51 out of 611 total time steps, or 8%). Cluster 5, with a central Pacific ridge (Fig. 2e), has the highest fraction (72%) of occurrence during La Niña conditions (Fig. 13). Cluster 4 most frequently occurs in El Niño

TABLE 1. December–February (DJF) AR family time steps partitioned according to DJF average ELI into La Niña, neutral, or El Niño years and according to corresponding cluster. Total time steps per phase are provided in the bottom row. Total time steps per cluster are provided in the rightmost column. Overall total number of time steps are at bottom right. A graphical representation of the table data is provided in Fig. S4. The relative risk of each cluster occurring during each ENSO phase is given in brackets.

| Cluster No. | La Niña (21 years) | Neutral (9 years) | El Niño (9 years) | Total |
|-------------|--------------------|-------------------|-------------------|-------|
| 1           | 291 [0.73]         | 154 [1.73]        | 116 [0.53]        | 561   |
| 2           | 583 [0.64]         | 171 [0.69]        | 333 [0.77]        | 1087  |
| 3           | 412 [1.47]         | 148 [1.43]        | 51 [0.18]         | 611   |
| 4           | 253 [0.46]         | 33 [0.25]         | 316 [2.43]        | 602   |
| 5           | 331 [1.93]         | 16 [0.16]         | 112 [0.69]        | 459   |
| 6           | 147 [0.57]         | 57 [1.09]         | 123 [1.39]        | 327   |
| Total       | 2004               | 578               | 1043              | 3625  |

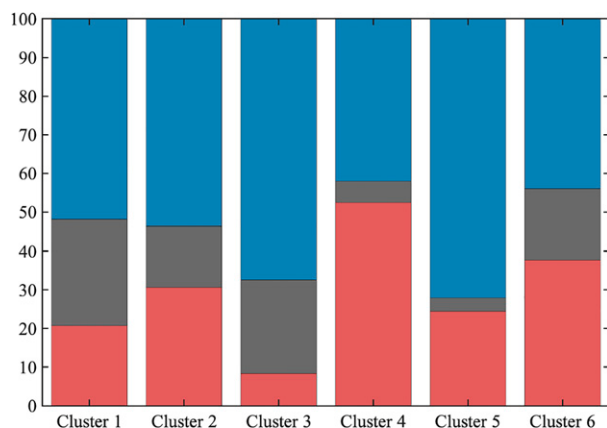


FIG. 13. The fraction of DJF time step occurrence per cluster compared to the total DJF time steps within each ENSO phase [La Niña (blue), neutral (gray), El Niño (red)]. Exact values of fractions are found in Table 1.

years [316 out of 602 (52%) of total cluster time steps], the most of any cluster, with infrequent occurrences in neutral years (Fig. 13).

To quantify these relationships further we calculate relative risk ratios for each cluster, defined as the ratio of the probability of occurrence in a given ENSO phase to the probability of occurrence in the other two ENSO phases (Table 1). We find that cluster 4 has  $\sim 2.4$  times the risk during El Niño. However, during neutral years, cluster 4 has 0.25 times the risk, meaning that it is 75% less likely to occur. Cluster 3 has  $\sim 1.5$  times the risk during La Niña. Additionally, cluster 3 is 82% less likely to occur during El Niño years. Cluster 5 has  $\sim 1.9$  times the risk during La Niña and is 84% less likely during neutral years. These relative risk ratios may be useful in a water and flood management context to provide more nuanced information regarding the

likelihood of high-impact AR family events given a particular set of ENSO conditions.

Using the RMM values to characterize high-amplitude ( $\geq 1$ ) MJO events, we find that cluster 3 events most often occur in MJO phase 5 and cluster 4 events most often occur in MJO phase 7 (Fig. 14a, Table 2), which correspond to phases previously linked to enhanced California precipitation. In contrast, clusters 1, 2, and 5 most often occur in MJO phases 2, 3, and 2, respectively, which are often associated with below average precipitation impacts across the U.S. West Coast (Fig. 13b, Table 2). Previous work has shown that remote tropical forcings such as the MJO and ENSO provide seasonal and subseasonal predictability for U.S. West Coast weather (e.g., Waliser et al. 2003; Patricola et al. 2020). Our finding that specific phases are associated with increased AR activity through serial clustering not only enhances our process-based physical understanding of such events, but also offers new paths toward enhanced predictability and early warning of high-impact events.

#### 4. Discussion and conclusions

This study introduces a new catalog of AR families that affected California during 1981–2019. Using this 39-yr dataset we conducted analysis of the background climatology and interannual variability of these successive events. In 79% of years, half (or more) of all AR events occur as part of AR families (i.e., as successive AR events). Further, there is a strong positive relationship between the total number of AR families per year and the overall number of AR events, and a great majority of the interannual variability in AR frequency driven by AR family frequency (94%) versus single AR events. Clustering the anomalous 500-hPa geopotential heights associated with AR families indicates that there are distinct large-scale patterns associated with different types of landfalling AR family events. In contrast, single AR events do not show obvious clustering of spatial

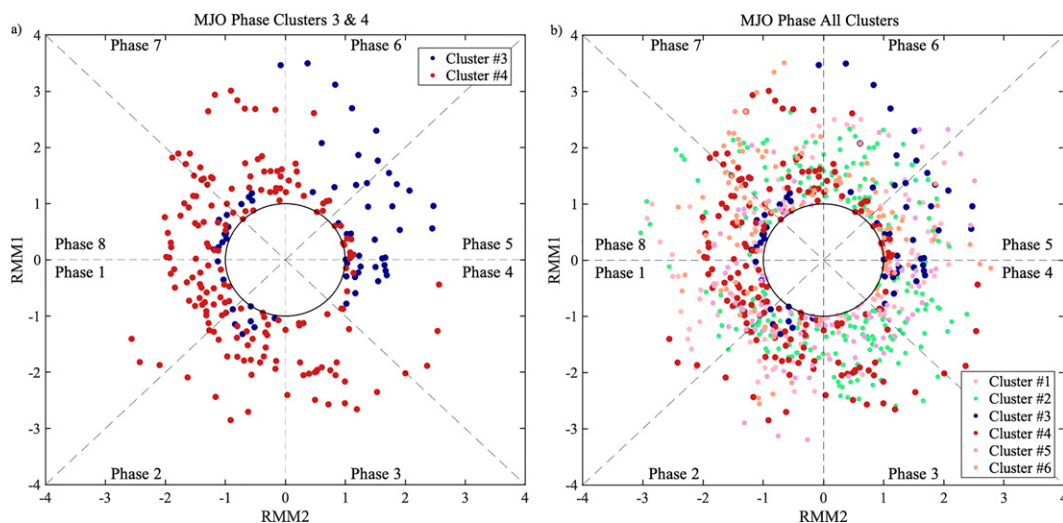


FIG. 14. MJO phase diagram for high amplitude events ( $RMM \leq 1$ ) of (a) clusters 3 (blue dots) and 4 (red dots) and (b) all clusters (refer to legend for differentiation).

TABLE 2. The average number of AR family days (top number) and the average amplitude (bottom number) per MJO phase (columns) and cluster (rows) of all high-amplitude ( $>1$ ) events. Total number of phase and cluster days on the bottom row and rightmost column, respectively. Values in brackets in the rightmost column are the total number of days per cluster, irrespective of amplitude.

| Cluster No. | Phase 1    | Phase 2    | Phase 3    | Phase 4    | Phase 5    | Phase 6    | Phase 7    | Phase 8    | Total        |
|-------------|------------|------------|------------|------------|------------|------------|------------|------------|--------------|
| 1           | 25<br>1.90 | 31<br>1.66 | 18<br>1.22 | 12<br>1.47 | 17<br>1.70 | 15<br>1.90 | 12<br>1.55 | 17<br>1.78 | 147<br>[246] |
| 2           | 14<br>1.75 | 29<br>1.57 | 51<br>1.80 | 30<br>1.70 | 14<br>1.68 | 40<br>1.67 | 26<br>1.85 | 16<br>2.23 | 220<br>[288] |
| 3           | 2<br>1.11  | 7<br>1.25  | 0<br>—     | 12<br>1.38 | 17<br>1.73 | 11<br>2.33 | 5<br>1.69  | 9<br>1.54  | 63<br>[143]  |
| 4           | 32<br>1.63 | 28<br>1.76 | 24<br>2.06 | 8<br>1.80  | 10<br>1.08 | 12<br>1.41 | 38<br>1.88 | 26<br>1.63 | 178<br>[273] |
| 5           | 17<br>1.55 | 20<br>1.79 | 15<br>1.53 | 15<br>1.51 | 5<br>2.37  | 3<br>2.79  | 11<br>1.38 | 6<br>1.61  | 92<br>[173]  |
| 6           | 9<br>1.72  | 8<br>1.95  | 0<br>—     | 9<br>1.48  | 18<br>1.49 | 11<br>1.51 | 26<br>2.21 | 20<br>1.77 | 101<br>[146] |
| Total       | 99         | 123        | 108        | 86         | 81         | 92         | 118        | 94         |              |

patterns. This difference suggests that the potential predictability of AR families may be enhanced relative to single AR events, especially on subseasonal to seasonal time scales.

The resultant clusters for AR families feature either meridional (clusters 1, 3, 5, and 6) or zonal patterns (clusters 2 and 4). The variability in location and magnitude of persistent ridging defines each meridional cluster, and the orientation and center location of low geopotential height regions define each zonal cluster. Additionally, the water vapor, sea level pressure, and jet stream variability vary greatly across different types of AR families. Cluster 3, in particular, is associated with the greatest amount and largest spatial extent of water vapor. Meridional clusters are associated with anomalous easterly jet-level flow particularly on the east side of associated  $z500$  ridges, while zonal clusters occur during jet extension periods. Clusters 2 and 4 exhibit the longest pattern persistence, while patterns associated with clusters 1, 3, and 6 develop within 5 days of AR family start. The North Pacific blocking ridge characteristic of cluster 3 events appears to be associated with increased upstream sea level pressure variance, and later reinforces the downstream trough off the U.S. West Coast. The large region of anomalous moisture prior to AR family onset provides an ample moisture source for the development of successive AR activity in California once a favorable large-scale circulation pattern arises. Meanwhile, the broad region of low geopotential heights, extended Pacific jet, and relative lack of Rossby wave sources allow the cluster 4 pattern to persist well beyond the AR family time scale. Adding to the robustness of our results, Moore et al. (2021) clustered multiday precipitation events in California and identified four similar clusters that dominated the large-scale variability of these events. The similarity between the results from Moore et al. (2021) and the results presented here suggests that multiday precipitation impacts are likely driven by AR families and/or successive cyclones. While a detailed analysis of the physical drivers of these multiday events at all relevant scales, including global teleconnections, is out of the scope of this work, investigating the physical driver of cluster frequency and the sequential links between clusters could be worthwhile avenues to pursue in future research.

We find that individual AR family clusters tend to be associated with specific ENSO and/or MJO phases. Cluster 3 events (meridional) most often occur in La Niña or neutral years, while cluster 4 events (zonal) most often occur in El Niño years. Cluster 4 has  $\sim 2.4$  times the risk during El Niño years, while cluster 3 has 1.5 times the risk during La Niña. Cluster 5 also has a strong correspondence with La Niña, exhibiting  $\sim 1.9$  times the risk. Cluster 3 events most often occur during MJO phase 5 of the MJO, while cluster 4 occurs most frequently during MJO phase 7, both of which are phases that have previously been linked to increased precipitation in California. On average, cluster 3 AR families result in the greatest accumulated precipitation per event, and cluster 4 events result in the least accumulated precipitation per event. These substantial differences in precipitation accumulation across clusters suggest linkages between AR family surface impacts and the associated large-scale patterns. In particular, AR family events associated with high-amplitude upstream blocking and enhanced moisture content, as in cluster 3, clearly favor enhanced precipitation across much of California. Conversely, AR family events associated with low-amplitude, largely zonal patterns, as in cluster 4, tend to produce less intense precipitation in California. Collectively, this suggests that the type of large-scale pattern present over the North Pacific may be a useful predictive factor regarding the precipitation impacts of successive AR events in California.

This study enhances understanding of the large-scale variability relevant to successive AR events affecting California, which has previously gone largely unexplored. Given that many of these events produce extreme precipitation, these findings have implications for meteorological and hydrologic hazard situational awareness. The presence of persistent upstream ridging across the far North Pacific, shown here to be associated with certain types of AR families, has previously been shown to be associated with extreme precipitation events in Northern California (Moore et al. 2020, 2021) and increased frequency for ARs affecting the Pacific Northwest

(Benedict et al. 2019). This cross-study agreement suggests that it may be possible to use such patterns as predictors for increased AR activity and associated extreme precipitation in a statistical and/or dynamical modeling context. Critically, our findings suggest that the predictability of ARs occurring as part of a family may be higher than that of single AR events, which is potentially of considerable relevance in a water and flood management context given the outsized hydrologic impacts of such events.

**Acknowledgments.** MAF, AMW, ACM, PBG, and FMR were supported by Grant W912HZ-15-2-0019 from the U.S. Army Corps of Engineers and Grant 4600013361 from California Department of Water Resources. DLS was supported by a joint collaboration between the Institute of the Environment and Sustainability at the University of California, Los Angeles; the Center for Climate and Weather Extremes at the National Center for Atmospheric Research; and the Nature Conservancy of California. This research was additionally supported by NSF awards 1854940 (to JMD) and 1854761 (to DLS). The MERRA-2 reanalysis dataset is available through the National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office at MDISC, which is managed by the NASA Goddard Earth Sciences Data and Information Services Center. The RMM data are hosted by the Australian Government Bureau of Meteorology ([bom.gov.au/climate/mjo/](http://bom.gov.au/climate/mjo/)) and provided by the NOAA/OAR/ESRL PSD in Boulder, CO, USA. We would also like to acknowledge high-performance computing support from Cheyenne provided by NCAR's Computational and Information Systems Laboratory, sponsored by the National Science Foundation. AR data were provided by Bin Guan, accessible via a public repository at <https://ucla.box.com/ARcatalog>. Development of the AR detection algorithm and databases was supported by NASA. The authors thank Andreas Prein for the preprocessed PRISM data and Patricola et al. (2020) for the publicly available ELI data.

## REFERENCES

- AghaKouchak, A., L. Cheng, O. Mazdinyasni, and A. Farahmand, 2014: Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophys. Res. Lett.*, **41**, 8847–8852, <https://doi.org/10.1002/2014GL062308>.
- Alexander, M. A., M. Newman, J. R. Lanzante, N.-C. Lau, and J. D. Scott, 2002: The atmospheric bridge: The influence of ENSO teleconnections on air–sea interaction over the global oceans. *J. Climate*, **15**, 2205–2231, [https://doi.org/10.1175/1520-0442\(2002\)015<2205:TABTIO>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<2205:TABTIO>2.0.CO;2).
- Arcodia, M. C., B. P. Kirtman, and L. E. P. Siqueira, 2020: How MJO teleconnections and ENSO interference impact U.S. precipitation. *J. Climate*, **33**, 4621–4640, <https://doi.org/10.1175/JCLI-D-19-0448.1>.
- Banzon, V., T. M. Smith, T. M. Chin, C. Liu, and W. Hankins, 2016: A long-term record of blended satellite and in situ sea-surface temperature for climate monitoring, modeling and environmental studies. *Earth Syst. Sci. Data*, **8**, 165–176, <https://doi.org/10.5194/essd-8-165-2016>.
- Bao, J. W., S. A. Michelson, P. J. Neiman, F. M. Ralph, and J. M. Wilczak, 2006: Interpretation of enhanced integrated water vapor bands associated with extratropical cyclones: Their formation and connection to tropical moisture. *Mon. Wea. Rev.*, **134**, 1063–1080, <https://doi.org/10.1175/MWR3123.1>.
- Barton, Y., P. Giannakaki, H. von Waldow, C. Chevalier, S. Pfahl, and O. Martius, 2016: Clustering of regional-scale extreme precipitation events in southern Switzerland. *Mon. Wea. Rev.*, **144**, 347–369, <https://doi.org/10.1175/MWR-D-15-0205.1>.
- Benedict, J. J., A. C. Clement, and B. Medeiros, 2019: Atmospheric blocking and other large-scale precursor patterns of landfalling atmospheric rivers in the North Pacific: A CESM2 study. *J. Geophys. Res. Atmos.*, **124**, 11 330–11 353, <https://doi.org/10.1029/2019JD030790>.
- Bjerknes, J., and H. Solberg, 1922: Life cycle of cyclones and the polar front theory of atmospheric circulation. *Geophys. Publ.*, **3**, 3–18.
- Blender, R., C. C. Raible, and F. Lunkeit, 2015: Non-exponential return time distributions for vorticity extremes explained by fractional Poisson processes. *Quart. J. Roy. Meteor. Soc.*, **141**, 249–257, <https://doi.org/10.1002/qj.2354>.
- Brands, S., J. M. Gutiérrez, and D. San-Martin, 2017: Twentieth-century atmospheric river activity along the west coasts of Europe and North America: Algorithm formulation, reanalysis uncertainty and links to atmospheric circulation patterns. *Climate Dyn.*, **48**, 2771–2795, <https://doi.org/10.1007/s00382-016-3095-6>.
- Bui, H. X., 2020: Increased impacts on US West Coast. *Nat. Climate Change*, **10**, 603–604, <https://doi.org/10.1038/s41558-020-0828-7>.
- Carrera, M. L., R. W. Higgins, and V. E. Kousky, 2004: Downstream weather impacts associated with atmospheric blocking over the northeast Pacific. *J. Climate*, **17**, 4823–4839, <https://doi.org/10.1175/JCLI-3237.1>.
- Chaboureaud, J. P., and A. J. Thorpe, 1999: Frontogenesis and the development of secondary wave cyclones in FASTEX. *Quart. J. Roy. Meteor. Soc.*, **125**, 925–940, <https://doi.org/10.1002/qj.49712555509>.
- Chang, E. K. M., and Y. Fu, 2003: Using mean flow change as a proxy to infer interdecadal storm track variability. *J. Climate*, **16**, 2178–2196, <https://doi.org/10.1175/2773.1>.
- , S. Lee, and K. L. Swanson, 2002: Storm track dynamics. *J. Climate*, **15**, 2163–2183, [https://doi.org/10.1175/1520-0442\(2002\)015<2163:STD>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<2163:STD>2.0.CO;2).
- , Y. Guo, X. Xia, and M. Zheng, 2013: Storm-track activity in IPCC AR4/CMIP3 model simulations. *J. Climate*, **26**, 246–260, <https://doi.org/10.1175/JCLI-D-11-00707.1>.
- Dacre, H. F., and S. L. Gray, 2006: Life-cycle simulations of shallow frontal waves and the impact of deformation strain. *Quart. J. Roy. Meteor. Soc.*, **132**, 2171–2190, <https://doi.org/10.1256/qj.05.238>.
- , and J. G. Pinto, 2020: Serial clustering of extratropical cyclones: A review of where, when and why it occurs. *npj Climate Atmos. Sci.*, **3**, 48, <https://doi.org/10.1038/s41612-020-00152-9>.
- Daly, C., R. P. Neilson, and D. L. Phillips, 1994: A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *J. Appl. Meteor.*, **33**, 140–158, [https://doi.org/10.1175/1520-0450\(1994\)033<0140:ASTMFM>2.0.CO;2](https://doi.org/10.1175/1520-0450(1994)033<0140:ASTMFM>2.0.CO;2).
- , G. H. Taylor, W. P. Gibson, T. W. Parzybok, G. L. Johnson, and P. Pasteris, 2001: High-quality spatial climate data sets for the United States and beyond. *Trans. ASAE*, **43**, 1957–1962, <https://doi.org/10.13031/2013.3101>.
- , W. P. Gibson, G. H. Taylor, G. L. Johnson, and P. Pasteris, 2002: A knowledge-based approach to statistical mapping of climate. *Climate Res.*, **22**, 99–113, <https://doi.org/10.3354/cr022099>.

- Dettinger, M. D., F. M. Ralph, T. Das, P. J. Neiman, and D. R. Cayan, 2011: Atmospheric rivers, floods and the water resources of California. *Water*, **3**, 445–478, <https://doi.org/10.3390/w3020445>.
- Diday, E., and J. C. Simon, 1976: *Digital Pattern Recognition*. Springer, 208 pp.
- Fereday, D. R., J. R. Knight, A. A. Scaife, C. K. Folland, and A. Philipp, 2008: Cluster analysis of North Atlantic–European circulation types and links with tropical Pacific sea surface temperatures. *J. Climate*, **21**, 3687–3703, <https://doi.org/10.1175/2007JCLI1875.1>.
- Fish, M. A., A. M. Wilson, and F. M. Ralph, 2019: Atmospheric river families: Definition and associated synoptic conditions. *J. Hydrometeorol.*, **20**, 2091–2108, <https://doi.org/10.1175/JHM-D-18-0217.1>.
- Gelaro, R., and Coauthors, 2017: The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). *J. Climate*, **30**, 5419–5454, <https://doi.org/10.1175/JCLI-D-16-0758.1>.
- Gibson, P. B., P. Uotila, S. E. Perkins-Kirkpatrick, L. V. Alexander, and A. J. Pitman, 2016: Evaluating synoptic systems in the CMIP5 climate models over the Australian region. *Climate Dyn.*, **47**, 2235–2251, <https://doi.org/10.1007/s00382-015-2961-y>.
- , S. E. Perkins-Kirkpatrick, P. Uotila, A. S. Pepler, and L. V. Alexander, 2017: On the use of self-organizing maps for studying climate extremes. *J. Geophys. Res. Atmos.*, **122**, 3891–3903, <https://doi.org/10.1002/2016JD026256>.
- , D. E. Waliser, B. Guan, M. J. DeFlorio, F. M. Ralph, and D. L. Swain, 2020: Ridging associated with drought across the western and southwestern United States: Characteristics, trends, and predictability sources. *J. Climate*, **33**, 2485–2508, <https://doi.org/10.1175/JCLI-D-19-0439.1>.
- Grams, C. M., H. Binder, S. Pfahl, N. Piaget, and H. Wernli, 2014: Atmospheric processes triggering the central European floods in June 2013. *Nat. Hazards Earth Syst. Sci.*, **14**, 1691–1702, <https://doi.org/10.5194/nhess-14-1691-2014>.
- Guan, B., and D. E. Waliser, 2015: Detection of atmospheric rivers: Evaluation and application of an algorithm for global studies. *Geophys. Res. Lett.*, **120**, 12 514–12 535, <https://doi.org/10.1002/2015JD024257>.
- , and —, 2017: Atmospheric rivers in 20 year weather and climate simulations: A multimodel, global evaluation. *J. Geophys. Res. Atmos.*, **122**, 5556–5581, <https://doi.org/10.1002/2016JD026174>.
- , —, N. P. Molotch, E. J. Fetzer, and P. J. Neiman, 2012: Does the Madden–Julian oscillation influence wintertime atmospheric rivers and snowpack in the Sierra Nevada? *Mon. Wea. Rev.*, **140**, 325–342, <https://doi.org/10.1175/MWR-D-11-00087.1>.
- , —, and F. M. Ralph, 2018: An intercomparison between reanalysis and dropsonde observations of the total water vapor transport in individual atmospheric rivers. *J. Hydrometeorol.*, **19**, 321–337, <https://doi.org/10.1175/JHM-D-17-0114.1>.
- Hart, R., and R. Grumm, 2001: Using normalized climatological anomalies to rank synoptic-scale events objectively. *Mon. Wea. Rev.*, **129**, 2426–2442, [https://doi.org/10.1175/1520-0493\(2001\)129<2426:UNCATR>2.0.CO;2](https://doi.org/10.1175/1520-0493(2001)129<2426:UNCATR>2.0.CO;2).
- Hendon, H. H., 1986: The time-mean flow and variability in a nonlinear model of the atmosphere with tropical diabatic forcing. *J. Atmos. Sci.*, **43**, 72–89, [https://doi.org/10.1175/1520-0469\(1986\)043<0072:TTFMFAV>2.0.CO;2](https://doi.org/10.1175/1520-0469(1986)043<0072:TTFMFAV>2.0.CO;2).
- , and M. L. Salby, 1994: The life cycle of the Madden–Julian oscillation. *J. Atmos. Sci.*, **51**, 2225–2237, [https://doi.org/10.1175/1520-0469\(1994\)051<2225:TLCOTM>2.0.CO;2](https://doi.org/10.1175/1520-0469(1994)051<2225:TLCOTM>2.0.CO;2).
- Henn, B., K. N. Musselman, L. Lestak, F. M. Ralph, and N. P. Molotch, 2020: Extreme runoff generation from atmospheric river driven snow melt during the 2017 Oroville dam spillway incident. *Geophys. Res. Lett.*, **47**, e2020GL088189, <https://doi.org/10.1029/2020GL088189>.
- Horel, J. D., and J. M. Wallace, 1981: Planetary-scale atmospheric phenomena associated with the Southern Oscillation. *Mon. Wea. Rev.*, **109**, 813–829, [https://doi.org/10.1175/1520-0493\(1981\)109<0813:PSAPAW>2.0.CO;2](https://doi.org/10.1175/1520-0493(1981)109<0813:PSAPAW>2.0.CO;2).
- Hu, H., F. Dominguez, Z. Wang, D. A. Lavers, G. Zhang, and F. M. Ralph, 2017: Linking atmospheric river hydrological impacts on the U.S. West Coast to Rossby wave breaking. *J. Climate*, **30**, 3381–3399, <https://doi.org/10.1175/JCLI-D-16-0386.1>.
- Huang, B., and Coauthors, 2017: Extended Reconstructed Sea Surface Temperature, version 5 (ERSSTv5): Upgrades, validations, and intercomparisons. *J. Climate*, **30**, 8179–8205, <https://doi.org/10.1175/JCLI-D-16-0836.1>.
- , C. Liu, V. Banzon, E. Freeman, G. Graham, B. Hankins, T. Smith, and H.-M. Zhang, 2020: Improvements of the Daily Optimum Interpolation Sea Surface Temperature (DOISST) version 2.1. *J. Climate*, **34**, 2923–2939, <https://doi.org/10.1175/JCLI-D-20-0166.1>.
- Huang, X., A. D. Hall, and N. Berg, 2018: Anthropogenic warming impacts on today's Sierra Nevada snowpack and flood risk. *Geophys. Res. Lett.*, **45**, 6215–6222, <https://doi.org/10.1029/2018GL077432>.
- Jiang, N., 2011: A new objective procedure for classifying New Zealand synoptic weather types during 1958–2008. *Int. J. Climatol.*, **31**, 863–879, <https://doi.org/10.1002/joc.2126>.
- Keller, J. H., and Coauthors, 2019: The extratropical transition of tropical cyclones. Part II: Interaction with the midlatitude flow, downstream impacts, and implications for predictability. *Mon. Wea. Rev.*, **147**, 1077–1106, <https://doi.org/10.1175/MWR-D-17-0329.1>.
- Kirono, D. G. C., K. J. Hennessy, and M. R. Grose, 2017: Increasing risk of months with low rainfall and high temperature in southeast Australia for the past 150 years. *Climate Risk Manage.*, **16**, 10–21, <https://doi.org/10.1016/j.crm.2017.04.001>.
- Lamjiri, M. A., M. D. Dettinger, F. M. Ralph, and B. Guan, 2017: Hourly storm characteristics along the U.S. West Coast: Role of atmospheric rivers in extreme precipitation. *Geophys. Res. Lett.*, **44**, 7020–7028, <https://doi.org/10.1002/2017GL074193>.
- Lee, S., and S. B. Feldstein, 2013: Detecting ozone- and greenhouse gas-driven wind trends with observational data. *Science*, **339**, 563–567, <https://doi.org/10.1126/science.1225154>.
- Leonard, M., and Coauthors, 2014: A compound event framework for understanding extreme impacts. *Wiley Interdiscip. Rev.: Climate Change*, **5**, 113–128, <https://doi.org/10.1002/wcc.252>.
- Liebmann, B., and C. A. Smith, 2006: Description of a complete (interpolated) outgoing longwave radiation dataset. *Bull. Amer. Meteor. Soc.*, **77**, 1275–1277, <https://doi.org/10.1175/1520-0477-77.6.1274>.
- Liu, X., X. Ren, and X.-Q. Yang, 2016: Decadal changes in multi-scale water vapor transport and atmospheric river associated with the Pacific decadal oscillation and the North Pacific Gyre Oscillation. *J. Hydrometeorol.*, **17**, 273–285, <https://doi.org/10.1175/JHM-D-14-0195.1>.
- Madden, R. A., and P. R. Julian, 1971: Detection of a 40–50 day oscillation in the zonal wind in the tropical Pacific.

- J. Atmos. Sci.*, **28**, 702–708, [https://doi.org/10.1175/1520-0469\(1971\)028<0702:DOADOI>2.0.CO;2](https://doi.org/10.1175/1520-0469(1971)028<0702:DOADOI>2.0.CO;2).
- Mailier, P. J., D. B. Stephenson, C. A. T. Ferro, and K. I. Hodges, 2006: Serial clustering of extratropical cyclones. *Mon. Wea. Rev.*, **134**, 2224–2240, <https://doi.org/10.1175/MWR3160.1>.
- Martius, O., and Coauthors, 2013: The role of upper-level dynamics and surface processes for the Pakistan flood of July 2010. *Quart. J. Roy. Meteor. Soc.*, **139**, 1780–1797, <https://doi.org/10.1002/qj.2082>.
- , S. Pfahl, and C. Chevalier, 2016: A global quantification of compound precipitation and wind extremes. *Geophys. Res. Lett.*, **43**, 7709–7717, <https://doi.org/10.1002/2016GL070017>.
- Masato, G., B. K. Hoskins, and T. J. Woolings, 2011: Wave-breaking characteristics of midlatitude blocking. *Quart. J. Roy. Meteor. Soc.*, **138**, 1285–1296, <https://doi.org/10.1002/qj.990>.
- Matthews, A. J., 2000: Propagation mechanisms for the Madden–Julian Oscillation. *Quart. J. Roy. Meteor. Soc.*, **126**, 2637–2651, <https://doi.org/10.1002/qj.49712656902>.
- McPhaden, M. J., S. E. Zebiak, and M. H. Glantz, 2006: ENSO as an integrating concept in Earth science. *Science*, **314**, 1740–1745, <https://doi.org/10.1126/science.1132588>.
- Michaelis, A. C., A. C. Martin, M. A. Fish, C. W. Hecht, and F. M. Ralph, 2021: Modulation of atmospheric rivers by mesoscale frontal waves and latent heating: Comparison of two U.S. West Coast events. *Mon. Wea. Rev.*, **149**, 2755–2776, <https://doi.org/10.1175/MWR-D-20-0364.1>.
- Moon, J.-Y., B. Wang, and K.-J. Ha, 2011: ENSO regulation of MJO teleconnection. *Climate Dyn.*, **37**, 1133–1149, <https://doi.org/10.1007/s00382-010-0902-3>.
- Moore, B. J., A. B. White, D. J. Gottas, and P. J. Neiman, 2020: Extreme precipitation events in northern California during winter 2016–17: Multiscale analysis and climatological perspective. *Mon. Wea. Rev.*, **148**, 1049–1074, <https://doi.org/10.1175/MWR-D-19-0242.1>.
- , —, —, and —, 2021: Characteristics of long-duration heavy precipitation events along the West Coast of the United States. *Mon. Wea. Rev.*, **149**, 2255–2277, <https://doi.org/10.1175/MWR-D-20-0336.1>.
- Moron, V., A. W. Robertson, M. N. Ward, and O. Ndiaye, 2008: Weather types and rainfall over Senegal. Part I: Observational analysis. *J. Climate*, **21**, 266–287, <https://doi.org/10.1175/2007JCLI1601.1>.
- Mundhenk, B. D., E. A. Barnes, and E. D. Maloney, 2016: All-season climatology and variability of atmospheric river frequencies over the North Pacific. *J. Climate*, **29**, 4885–4903, <https://doi.org/10.1175/JCLI-D-15-0655.1>.
- , —, —, and C. F. Baggett, 2018: Skillful empirical sub-seasonal prediction of landfalling atmospheric river activity using the Madden–Julian oscillation and quasi-biennial oscillation. *npj Climate Atmos. Sci.*, **1**, 20177, <https://doi.org/10.1038/s41612-017-0008-2>.
- Nakamura, H., M. Nakamura, and J. L. Anderson, 1997: The role of high- and low-frequency dynamics in blocking formation. *Mon. Wea. Rev.*, **125**, 2074–2093, [https://doi.org/10.1175/1520-0493\(1997\)125<2074:TROHAL>2.0.CO;2](https://doi.org/10.1175/1520-0493(1997)125<2074:TROHAL>2.0.CO;2).
- Neiman, P. J., F. M. Ralph, G. A. Wick, J. D. Lundquist, and M. D. Dettinger, 2008: Meteorological characteristics and overland precipitation impacts of atmospheric rivers affecting the West Coast of North America based on eight years of SSM/I satellite observations. *J. Hydrometeorol.*, **9**, 22–47, <https://doi.org/10.1175/2007JHM855.1>.
- Oakley, N. S., J. T. Lancaster, B. J. Hatchett, J. Stock, F. M. Ralph, S. Roj, and S. Lukashov, 2018: A 22-year climatology of cool season hourly precipitation thresholds conducive to shallow landslides in California. *Earth Interact.*, **22** (14), 1–35, <https://doi.org/10.1175/EI-D-17-0029.1>.
- Orlanski, I., and J. P. Sheldon, 1995: Stages in the energetics of baroclinic systems. *Tellus*, **47A**, 605–628, <https://doi.org/10.3402/tellusa.v47i5.11553>.
- Palmer, T. N., and J. Räisänen, 2002: Quantifying the risk of extreme seasonal precipitation events in a changing climate. *Nature*, **415**, 512–514, <https://doi.org/10.1038/415512a>.
- Patricola, C. M., J. P. O'Brien, M. D. Risser, A. M. Rhoades, T. A. O'Brien, P. A. Ullrich, D. A. Stone, and W. D. Collins, 2020: Maximizing ENSO as a source of western US hydroclimate predictability. *Climate Dyn.*, **54**, 351–372, <https://doi.org/10.1007/s00382-019-05004-8>.
- Payne, A. E., and G. Magnúsdóttir, 2014: Dynamics of landfalling atmospheric river over the North Pacific in 30-yr of MERRA reanalysis. *J. Climate*, **27**, 7133–7150, <https://doi.org/10.1175/JCLI-D-14-00034.1>.
- , and —, 2016: Persistent landfalling atmospheric rivers over the west coast of North America. *J. Geophys. Res. Atmos.*, **121**, 13 287–13 300, <https://doi.org/10.1002/2016JD025549>.
- Pinto, J. G., I. Gómara, G. Masato, H. F. Dacre, T. Woolings, and R. Caballero, 2014: Large-scale dynamics associated with clustering of extratropical cyclones affecting western Europe. *J. Geophys. Res. Atmos.*, **119**, 13 704–13 719, <https://doi.org/10.1002/2014JD022305>.
- Priestley, M. D. K., J. G. Pinto, H. F. Dacre, and L. C. Shaffrey, 2017: Rossby wave breaking, the upper level jet, and serial clustering of extratropical cyclones in western Europe. *Geophys. Res. Lett.*, **44**, 514–521, <https://doi.org/10.1002/2016GL071277>.
- , H. F. Dacre, L. C. Shaffrey, S. Schemm, and J. G. Pinto, 2020: The role of secondary cyclones and cyclone families for the North Atlantic storm track and clustering over western Europe. *Quart. J. Roy. Meteor. Soc.*, **146**, 1184–1205, <https://doi.org/10.1002/qj.3733>.
- Ralph, F. M., P. J. Neiman, and G. A. Wick, 2004: Satellite and CALJET aircraft observations of atmospheric rivers over the eastern North Pacific Ocean during the winter of 1997/1998. *Mon. Wea. Rev.*, **132**, 1721–1745, [https://doi.org/10.1175/1520-0493\(2004\)132<1721:SACAOO>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<1721:SACAOO>2.0.CO;2).
- , —, and R. Rotunno, 2005: Dropsonde observations in low-level jets over the northeastern Pacific Ocean from CALJET-1998 and PACJET-2001: Mean vertical-profile and atmospheric-river characteristics. *Mon. Wea. Rev.*, **133**, 889–910, <https://doi.org/10.1175/MWR2896.1>.
- , T. Coleman, P. J. Neiman, R. J. Zamora, and M. D. Dettinger, 2013: Observed impacts of duration and seasonality of atmospheric-river landfalls on soil moisture and runoff in coastal Northern California. *J. Hydrometeorol.*, **14**, 443–459, <https://doi.org/10.1175/JHM-D-12-076.1>.
- , and Coauthors, 2017: Dropsonde observations of total integrated water vapor transport within North Pacific atmospheric rivers. *J. Hydrometeorol.*, **18**, 2577–2596, <https://doi.org/10.1175/JHM-D-17-0036.1>.
- Reed, R. J., G. A. Grell, and Y. Kuo, 1993: The ERICA IOP 5 storm. Part II: Sensitivity tests and further diagnosis based on model output. *Mon. Wea. Rev.*, **121**, 1595–1612, [https://doi.org/10.1175/1520-0493\(1993\)121<1595:TEISPI>2.0.CO;2](https://doi.org/10.1175/1520-0493(1993)121<1595:TEISPI>2.0.CO;2).
- Reynolds, R. W., T. M. Smith, C. Liu, D. B. Chelton, K. S. Casey, and M. G. Schlax, 2007: Daily high-resolution-blended analyses for sea surface temperature. *J. Climate*, **20**, 5473–5496, <https://doi.org/10.1175/2007JCLI1824.1>.

- Roller, C. D., J. H. Qian, L. Agel, M. Barlow, and V. Moron, 2016: Winter weather regimes in the northeast United States. *J. Climate*, **29**, 2963–2980, <https://doi.org/10.1175/JCLI-D-15-0274.1>.
- Ryoo, J. M., Y. Kaspi, D. W. Waugh, G. N. Kiladis, D. E. Waliser, E. J. Fetzer, and J. Kim, 2013: Impact of Rossby wave breaking on U.S. West Coast winter precipitation during ENSO events. *J. Climate*, **26**, 6360–6382, <https://doi.org/10.1175/JCLI-D-12-00297.1>.
- Schemm, S., and M. Sprenger, 2015: Frontal-wave cyclogenesis in the North Atlantic—A climatological characterisation. *Quart. J. Roy. Meteor. Soc.*, **141**, 2989–3005, <https://doi.org/10.1002/qj.2584>.
- Sedlmeier, K., H. Feldmann, and G. Schädler, 2018: Compound summer temperature and precipitation extremes over central Europe. *Theor. Appl. Climatol.*, **131**, 1493–1501, <https://doi.org/10.1007/s00704-017-2061-5>.
- Seneviratne, S. I., and Coauthors, 2012: Changes in climate extremes and their impacts on the natural physical environment. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, Cambridge University Press, 109–230.
- Shutts, G. J., 1983: The propagation of eddies in diffluent jet-streams: Eddy vorticity forcing of ‘blocking’ flow fields. *Quart. J. Roy. Meteor. Soc.*, **109**, 737–761, <https://doi.org/10.1002/qj.49710946204>.
- Takaya, K., and H. Nakamura, 2001: A formulation of a phase-independent wave-activity flux of stationary and migratory quasigeostrophic eddies on a zonally varying basic flow. *J. Atmos. Sci.*, **58**, 608–627, [https://doi.org/10.1175/1520-0469\(2001\)058<0608:AFOAPI>2.0.CO;2](https://doi.org/10.1175/1520-0469(2001)058<0608:AFOAPI>2.0.CO;2).
- Trenberth, K. E., G. W. Branstator, D. Karloy, A. Kumar, N. C. Lau, and C. Ropelewski, 1998: Progress during TOGA in understanding and modeling global teleconnections associated with tropical sea surface temperatures. *J. Geol. Res.*, **103**, 14 291–14 324, <https://doi.org/10.1029/97JC01444>.
- van den Hurk, B., E. van Meijgaard, P. de Valk, K. J. van Heerlingen, and J. Gooijer, 2015: Analysis of a compounding surge and precipitation event in the Netherlands. *Environ. Res. Lett.*, **10**, 035001, <https://doi.org/10.1088/1748-9326/10/3/035001>.
- Ventrice, M. J., M. C. Wheeler, H. H. Hendon, C. J. Schreck III, C. D. Thorncroft, and G. N. Kiladis, 2013: A modified multivariate Madden–Julian oscillation index using velocity potential. *Mon. Wea. Rev.*, **141**, 4197–4210, <https://doi.org/10.1175/MWR-D-12-00327.1>.
- Wahl, T., S. Jain, J. Bender, S. D. Meyers, and M. E. Luther, 2015: Increasing risk of compounding flooding from storm surge and rainfall for major US cities. *Nat. Climate Change*, **5**, 1093–1097, <https://doi.org/10.1038/nclimate2736>.
- Waliser, D. E., K. M. Lau, W. Stern, and C. Jones, 2003: Potential predictability of the Madden–Julian oscillation. *Bull. Amer. Meteor. Soc.*, **84**, 33–50, <https://doi.org/10.1175/BAMS-84-1-33>.
- Wheeler, M. C., and H. H. Hendon, 2004: An all-season real-time multivariate MJO index: Development of an index for monitoring and prediction. *Mon. Wea. Rev.*, **132**, 1917–1932, [https://doi.org/10.1175/1520-0493\(2004\)132<1917:AARMMI>2.0.CO;2](https://doi.org/10.1175/1520-0493(2004)132<1917:AARMMI>2.0.CO;2).
- White, A. B., B. J. Moore, D. J. Gottas, and P. J. Neiman, 2019: Winter storm conditions leading to excessive runoff above California’s Oroville dam during January and February 2017. *Bull. Amer. Meteor. Soc.*, **100**, 55–70, <https://doi.org/10.1175/BAMS-D-18-0091.1>.
- Williams, I. N., and C. M. Patricola, 2018: Diversity of ENSO events unified by convective threshold sea surface temperature: A nonlinear ENSO index. *Geophys. Res. Lett.*, **45**, 9236–9244, <https://doi.org/10.1029/2018GL079203>.
- Winters, A. C., D. Keyser, and L. F. Bosart, 2019a: The development of the North Pacific jet phase diagram as an objective tool to monitor the state and forecast skill of the upper-tropospheric flow pattern. *Wea. Forecasting*, **34**, 199–219, <https://doi.org/10.1175/WAF-D-18-0106.1>.
- , L. F. Bosart, and D. Keyser, 2019b: Antecedent North Pacific jet regimes conducive to the development of continental U.S. extreme temperature events during the cool season. *Wea. Forecasting*, **34**, 393–414, <https://doi.org/10.1175/WAF-D-18-0168.1>.
- Wolf, G., and V. Wirth, 2017: Diagnosing the horizontal propagation of Rossby wave packets along the midlatitude waveguide. *Mon. Wea. Rev.*, **145**, 3247–3264, <https://doi.org/10.1175/MWR-D-16-0355.1>.
- Zhang, C., 2005: Madden–Julian Oscillation. *Rev. Geophys.*, **43**, RG2003, <https://doi.org/10.1029/2004RG000158>.
- , 2013: Madden–Julian Oscillation: Bridging weather and climate. *Bull. Amer. Meteor. Soc.*, **94**, 1849–1870, <https://doi.org/10.1175/BAMS-D-12-00026.1>.
- Zhang, Z., F. M. Ralph, and M. Zheng, 2019: The relationship between extratropical cyclone strength and atmospheric river intensity and position. *Geophys. Res. Lett.*, **46**, 1814–1823, <https://doi.org/10.1029/2018GL079071>.
- Zhou, S., M. L’Heureux, S. Weaver, and A. Kumar, 2012: A composite study of the MJO influence on the surface air temperature and precipitation over the continental United States. *Climate Dyn.*, **38**, 1459–1471, <https://doi.org/10.1007/s00382-011-1001-9>.
- Zhou, W., D. Yang, S.-P. Xie, and J. Ma, 2020: Amplified Madden–Julian oscillation impacts in the Pacific–North America region. *Nat. Climate Change*, **10**, 654–660, <https://doi.org/10.1038/s41558-020-0814-0>.
- Zhu, Y., and R. E. Newell, 1998: A proposed algorithm for moisture fluxes from atmospheric rivers. *Mon. Wea. Rev.*, **126**, 725–735, [https://doi.org/10.1175/1520-0493\(1998\)126<0725:APAFMF>2.0.CO;2](https://doi.org/10.1175/1520-0493(1998)126<0725:APAFMF>2.0.CO;2).
- Zscheischler, J., and S. I. Seneviratne, 2017: Dependence of drivers affects risks associated with compound events. *Sci. Adv.*, **3**, e1700263, <https://doi.org/10.1126/sciadv.1700263>.
- , and Coauthors, 2018: Future climate risk from compound events. *Nat. Climate Change*, **8**, 469–477, <https://doi.org/10.1038/s41558-018-0156-3>.
- , and Coauthors, 2020: A typology of compound weather and climate events. *Nat. Rev. Earth Environ.*, **1**, 333–347, <https://doi.org/10.1038/s43017-020-0060-z>.