Dusty Atmospheric Rivers: Characteristics and Origins

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(Manuscript received 29 January 2020, in final form 26 April 2020)

ABSTRACT: Atmospheric rivers (AR) are narrow bands of strong horizontal transport of water vapor in the midlatitudes that can cause extreme precipitation, which contributes to beneficial water supply and sometimes flooding. The precipitation productivity of an AR is affected by microphysical processes, including the influence of aerosols. Earlier case studies have shown that some ARs over the North Pacific Ocean contain dust from Africa and Asia that can strongly influence precipitation by acting as ice nuclei. This paper explores how commonly dust and ARs occur together, or in close proximity. A “dust score” is introduced to characterize the dustiness of the environment associated with ARs by using satellite-based observations. This method is applied to days on which one or more ARs made landfall along the west coast of the United States between 2001 and 2018. The dust score is used to describe the seasonality and year-to-year variability of dusty-environment ARs. Dusty ARs occur primarily in the early spring (March–April), and dust is preferentially found within the warm sector of AR-associated extratropical cyclones and is also enhanced in the cold sector. Year-to-year variability in dust score is dependent more on year-to-year variability in dust than on the frequency of AR days. This year-to-year variability is also strongly related to correlations between the frequency of ARs and the dustiness of the northeastern Pacific, motivating additional investigation into potential dynamical association between dust and ARs.

KEYWORDS: Atmosphere; Extratropical cyclones; Aerosols; Satellite observations; Seasonal cycle

1. Introduction

Atmospheric rivers (ARs) are narrow corridors of water vapor, usually associated with an extratropical cyclone, that transport moisture in the lower troposphere and typically contain a low-level jet (Ralph et al. 2018; Zhu and Newell 1998; Ralph et al. 2004, 2005; Waliser and Guan 2017; Dettinger et al. 2011; Lamjiri et al. 2017). They are the primary mechanism for transport of moisture from the tropics to the midlatitudes (Zhu and Newell 1998) and are responsible for 20%-50% of annual precipitation in California (Dettinger et al. 2011). The CalWater field campaign, beginning with the CalWater Early-Start in 2009 in Northern California (Ault et al. 2011; Ralph et al. 2016), brought meteorologists and atmospheric chemists together to understand and better predict the meteorological and aerosol chemical controls on precipitation from California’s landfalling ARs. A major finding of the CalWater field campaigns was that dust transported from Asia and Africa can sometimes be found within the ARs making landfall in Northern California (Ault et al. 2011; Creamean et al. 2013, 2014, 2015, 2016).

In the troposphere, homogeneous freezing (i.e., freezing of pure liquid water) occurs at temperatures lower than −38°C and relative humidity with respect to ice above 140% (Hooge and Möhler 2012). Freezing at warmer temperatures requires heterogeneous nucleation through the presence of an aerosol acting as an ice nucleating particle (INP). The temperature at which an INP “activates” (i.e., catalyzes freezing) depends on its chemical composition, particle size, and the external conditions. Dust is known to be a relatively warm ice nucleating particle, forming ice at temperatures less than −15°C. Dust is sometimes described as the most important INP (Kanji et al. 2017) because it is efficient, it nucleates at a warmer temperature than most other particles (Hooge and Möhler 2012), and it is abundant due to its high emission rate (Engelstaedter et al. 2006).

Microphysical observations from CalWater have indicated that trans-Pacific Ocean dust causes cloud glaciation in mixed-phase clouds and potentially enhances precipitation by acting as INPs (Creamean et al. 2013; Ault et al. 2011; Martin et al. 2019; Creamean et al. 2016, 2015). Ault et al. (2011), in a comparison of two meteorologically similar AR events, one with and one without dust, found that dust INPs may have enhanced storm-total precipitation by up to 40%. Creamean et al. (2013) found long-range transported dust layers in clouds coincident with enhanced ice fraction at relatively warm temperatures and Creamean et al. (2015) found that dust and biocological particle residues were commonly associated with deep convective clouds with large quantities of precipitation that had been initiated in the ice phase. Given that long-range transported dust from Asia and Africa accounts for a significant portion of dust in the western United States with a seasonal maximum in the spring (Creamean et al. 2014; VanCuren 2002; Yu et al. 2012), dust may regularly be an important modulator of AR precipitation.

Although these in situ observational studies have found results consistent with trans-Pacific dust acting as precipitation enhancing INP, there are, in general, very few measurements...
of dust during ARs. The limited availability of dust measurements has hindered progress in understanding the role of dust in these events. In this work, we build upon the findings of the CalWater field studies by using a new 18-yr record of dust aerosol optical depth ($\tau_d$) from Voss and Evan (2019, hereinafter VE19) to create a climatology of ARs in dusty environments through the development of a so-called dust score. We use this dust score climatology to investigate the seasonal and interannual variability of dusty-environment ARs, the drivers of this variability, and the position of dust relative to AR-associated extratropical cyclones.

The remainder of this paper is organized as follows: In the data section (section 2), we describe the various datasets used throughout the analysis. In the methods section (section 3), we describe the calculation of the dust score. In the results section (section 4) we describe a case study of an AR in a dusty Pacific environment, followed by an analysis of the location of dust relative to extratropical cyclones and we describe the seasonality and year-to-year variability in the frequency of ARs in dusty environments. We finish the results section with a decomposition of sources of year-to-year variability in the dust score. We conclude with a description of the limitations of the dust score and a summary of our results (section 5).

2. Data

Here we use daily satellite-based estimates of dust over the Pacific Ocean to calculate a dust score for each AR day between 2001 and 2018. We define an “AR day” as any day on which an AR was landfalling along the U.S. West Coast. We also use daily estimates of dust to understand, through the use of a case study and an extratropical cyclone-centric composite, how dust reaches the vicinity of an AR. Daily dust aerosol optical depth ($\tau_d$) for the years 2001 to 2018 from VE19 was used for this purpose. The VE19 record of $\tau_d$ is an observational satellite remote sensing estimate of column-integrated dust at 1° x 1° spatial resolution. Each estimate of $\tau_d$ is reported along with a 1σ (std dev) uncertainty value that takes into account the uncertainty in each of the data used in its calculation (VE19). Only $\tau_d$ over ocean was used. The estimate of $\tau_d$ over ocean is based off of isolation of the dust contribution to the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Level 3 (L3) dark target aerosol optical depth (AOD) at 550 nm. In the calculation of the estimate of $\tau_d$, it is assumed that the total AOD is the sum of the contributions from dust, pollution, biomass burning, and marine aerosol. The contribution of marine aerosol to the total AOD is parameterized based on surface wind speed from reanalysis. The contribution from pollution and biomass burning aerosol is estimated based on the ratio of fine- to coarse-mode AOD. Estimates of $\tau_d$ are only available for clear-sky pixels and are also absent where sun glint occurs. The estimate of $\tau_d$ represents dust at approximately 1030 local time, because this is the approximate overpass time of the Terra satellite. Occasionally pixels of very high ($>0.5$) $\tau_d$ were present within the AR feature, preferentially in the summer months (June–August). Inspection of MODIS Terra visible imagery on those dates at the location of the pixels with very high $\tau_d$ yielded indications that this was a result of smoke and thin cloud cover that was not screened out in the MODIS cloud clearing algorithm. To remove the impacts of these nondust artifacts, we replaced any $\tau_d \geq 0.5$ with a missing value prior to calculation of the dust score.

The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), 1800 UTC surface wind vectors and 500-hPa geopotential height were used in section 4a at 0.500° x 0.625° resolution. Daily mean MERRA-2 dust extinction optical depth at the same resolution was used in section 3. These variables were obtained from EarthData GEO DISC (http://disc.gsfc.nasa.gov).

The Parameter–Elevation Relationships on Independent Slopes Model (PRISM) daily total precipitation (obtained at http://www.prism.oregonstate.edu), at 4-km spatial resolution, was used in section 4a (PRISM Climate Group 2004). PRISM calculates a climate- elevation regression for each 30-arcsec model grid cell and interpolates station data weighted by the similarity of the station to the grid cell (i.e., location, elevation, coastal proximity, topography, vertical atmospheric layer, and orographic effectiveness of terrain). Daily total precipitation is modeled using a climatologically aided interpolation in which the long-term average of precipitation serves as a predictor, because it is the best first guess of the spatial pattern of precipitation.

National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory HYSPLIT model (Draxler and Rolph 2011) airmass forward trajectories (obtained at https://www.ready.noaa.gov/HYSPLIT.php) were used in section 4a. The HYSPLIT model calculation combines a Lagrangian approach for advection and diffusion calculations with an Eulerian approach, with a fixed three-dimensional grid, for pollutant air concentrations. The particle model is used here, which advects particles in the model domain by the mean wind field and spreads them using a turbulent component. National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis wind fields were used as input (Kalnay et al. 1996). These are airmass trajectories, and, as such, they do not include processes such as wet or dry removal and convective transport that may affect dust transport.

Climate Forecast System Reanalysis (CFSR) precipitable water, 250-hPa U- and V-winds, and sea level pressure (SLP) (Saha et al. 2010) are used in section 4a for an analysis of the synoptic conditions associated with a case study of a dusty-environment AR.

The CALIPSO Lidar Level 2 (L2) Vertical Feature Mask (VFM), version 3.02, was used in section 4a. The VFM describes the distribution of aerosol layers, vertically and horizontally, observed by the CALIPSO lidar, which is an active sensor that uses the 532- and 1064-nm channels. Feature classification flags indicate aerosol layers, as identified by the altitude- and latitude-dependent feature integrated color ratio, the layer-integrated volume depolarization ratio, and the feature mean attenuated backscatter coefficient. The algorithm used for cloud–aerosol discrimination is known to have some difficulty correctly classifying moderately dense dust and smoke layers at high latitudes and/or high altitudes. We limit our analysis to latitudes between 10° and 50°N and altitudes below 8 km to avoid these issues. Clouds within optically dense
aerosol layers may be identified as a single cloud layer. The feature subtype is selected from six aerosol type options (dust, polluted dust, clean marine, polluted continental, clean continental, smoke) based on the layer volume depolarization ratio. Desert dust is identified by volume depolarization ratio greater than 0.2.

To calculate a dust score for each AR day, we required a daily record of landfalling ARs between 2001 and 2018. For this, we used the Rutz catalog for AR tracking (obtained at http://www.insec.utah.edu/~rutz/ar_catalogs/) from MERRA-2 and identified days on which an AR was present in 0.625° × 0.5° grid boxes along the west coast of the U.S. (Rutz et al. 2014). To be considered an AR in the Rutz catalog, a feature must have a length that is greater than 2000 km and MERRA-2 vertically integrated water vapor flux (IVT) that is greater than 250 kg m⁻¹ s⁻¹ throughout. IVT is formally defined as

\[ \text{IVT} = \frac{1}{g} \int \rho_{\text{air}} \rho \mathbf{V} p \text{d}p, \tag{1} \]

where \( g \) is the gravitational acceleration, \( q \) is the specific humidity, \( \mathbf{V} \) is the total vector wind, \( p \) is pressure, and \( \rho_{\text{air}} \) is the surface pressure. The integration is done using data at the surface, 50-hPa intervals from the surface to 500, and 100-hPa intervals from 500 to 100 hPa. The AR length criterion is calculated as the greatest distance between two points within a continuous area with no IVT values below the 250 kg m⁻¹ s⁻¹ threshold. The method used to develop the Rutz catalog often identifies large regions of the tropics as being within ARs. However, this does not impact the domain used in our analysis as it is in the midlatitudes. This catalog was interpolated to a 1° × 1° grid and used in the calculation of the dust score.

In section 4b, EC center location, AR probability, and sea level pressure from Zhang et al. (2019) are used to investigate the position of dust relative to AR-associated ECs. EC center locations were tracked using an objective cyclone tracking scheme (Hodges 1994, 1995) based on 6-hourly SLP in the CFSR (Saha et al. 2010). The AR-associated ECs used in this analysis are only those that occurred within the cool seasons (November–March) from 2001 to 2010 with lifetimes greater than 24 h and moving distance greater than 1000 km within the domain 25°–55° N, 140°–115° W. MODIS Terra L3 cloud fraction from cloud mask (obtained at https://ladsweb.modaps.eosdis.nasa.gov) was used to test for cloud contamination.

3. Methods

An AR dust score is calculated for every AR day, defined as any day on which an AR made landfall along the U.S. West Coast, between 2001 and 2018 [Eq. (3)]. The AR dust score is calculated from the average of \( t_d \) within the boundaries of an AR feature as identified in the Rutz catalog only for over-ocean grid cells that fell within a domain that contained the entire West Coast and extended toward the central Pacific to a distance that reflects the approximate length scale (1800 km) of a wintertime North Pacific extratropical cyclone (Rudeva and Gulev 2007) 145°–116° W, 32°–49° N (Fig. 1). The probability of the presence of an AR at any 1° × 1° grid cell on a given day can be defined as \( P_{\text{AR}} \), which in this case is always 0 or 1. This can be divided by the total number of grid cells that have a probability of 1 to yield the probability of an AR at a given grid cell normalized by the size of the AR, which we will define as \( A \):

\[ A = \frac{P_{\text{AR}}}{\sum_{n=1}^{N} P_{\text{AR}}}, \tag{2} \]

where \( n \) is a 1° × 1° grid cell in the binary map of AR and \( N \) is the total number of nonmissing value pixels on a given day. Then, the dust score \( S \) can be expressed as

\[ S = \sum_{n=1}^{N} (t_d A). \tag{3} \]
Atmospheric rivers along the West Coast typically have moisture transport from the southwest to the northeast with an upper-level and lower-level jet (Ralph et al. 2017). These southwesterly winds make it unlikely that dust from North American sources will flow westward toward the vicinity of ARs over the Pacific on the day of an AR. It is possible that dust from North American sources may still be advected into the vicinity of an AR over the Pacific, for example, if offshore winds moved it out into the Pacific in the days preceding an AR event. In this case, this dust would impact the dust score. As a conservative measure, dust ($\tau_{d}$) over land or within one degree longitude of land is excluded from the average of $\tau_{d}$ used to calculate the dust score.

For AR days between 2001 and 2018, the median dust score was 0.015, the 75th- and 25th-percentile dust scores were 0.034 and 0.004, respectively, and the maximum and minimum dust scores were 0.304 and 0, respectively (Fig. 2). The mean dust score was 0.026 $\pm$ 0.024, where 0.024 is the 1σ uncertainty from the $\tau_{d}$ estimates used in its calculation.

There are several limitations to the AR dust score presented here. We calculate a new dust score for each AR day rather than a single score for each AR event. This may lead to longer-duration AR events having greater influence on our climatological analysis of the seasonality and interannual variability of ARs in dusty environments. We chose to group by AR day rather than AR event because we needed a record that spanned the temporal length of the $\tau_{d}$ record (2001–18), and we did not have a record of AR event objects for the entirety of that period. Our method of calculation of dust score uses a binary map that does not discriminate between AR events. Any grid cell with a $\tau_{d}$ estimate that is also the location of an AR feature in the Rutz catalog will be used in the dust score calculation. It is possible that multiple AR objects could be present within the domain on a given day. According to our method, these would be combined in the dust score for that day. Additionally, $\tau_{d}$ estimates are only available in clear-sky pixels. Dust that is present within, above, or below clouds will not be counted in the dust score. Therefore, any dust that is activated as CCN or IN will not be counted in the dust score. It is plausible that an AR day could have substantial dust within, above, or below cloud and still have a low dust score.

To evaluate the effect of missing data, due to cloud cover and sun glint, on the dust score a simple test was performed. Dust scores were calculated for every AR in the same manner as has been described above, except using MERRA-2 dust extinction optical depth interpolated to the same grid as $\tau_{d}$ ($1^\circ \times 1^\circ$). MERRA-2 dust extinction optical depth, while not independent from $\tau_{d}$, because MODIS AOD is assimilated into the reanalysis, does not have missing data due to clouds or sun glint. Dust scores were calculated from MERRA-2 dust extinction optical depth in two ways: 1) using all available pixels within the AR, and 2) subsampled such that data are missing in the same locations/days that are missing for $\tau_{d}$. This is similar to what has been done previously to evaluate clear sky biases over ocean for MODIS AOD (Zhang and Reid 2009). These two scores were then compared using a Student’s $t$ test. The average dust score from MERRA-2 calculated from all available pixels was found to be 0.019 $\pm$ 0.017 and the average dust score when sampled the same as $\tau_{d}$ was found to be 0.019 $\pm$ 0.018. These differences are not significant (significance level $p = 0.98$), suggesting that the dust score is, on average, not sensitive to missing data due to cloud cover and sun glint.

4. Results

a. Case study

To understand how dust can be transported from continental sources across the Pacific to potentially impact an AR, we present a case study of an AR that made landfall along the U.S. West Coast with dust in its vicinity on 29 March 2010. This case was chosen as an example because it had very good coverage of $\tau_{d}$ over the Pacific ocean on the date of the AR landfall, and a high score (0.064). On 29 March this AR had reached the West Coast between 36° and 49°N, with the highest IVT near 42°N, 121°W. Ten days prior to this event, major dust lofting events occurred over both the Gobi Desert (near 42°N, 95°E; red arrow in Fig. 3a) and the Taklamakan Desert (near 38°N, 80°E; blue arrow in Fig. 3a) in Asia. Lofted dust can clearly be seen in the MODIS Terra visible imagery on 19 March 2010 (Fig. 3a) and is evidenced by high $\tau_{d}$ over this region on the same date (Fig. 3b). Kurosaki and Mikami (2007) found the threshold wind speed at the normal land surface for dust emission over the Taklamakan Desert to be 6.7 $\pm$ 1.5 m s$^{-1}$. Over the Gobi Desert, this threshold for dust emission is greater, 13.8 $\pm$ 2.0 m s$^{-1}$. MERRA-2, hourly surface wind speeds over both deserts show peaks in velocity on 19 March 2010, with velocities exceeding 9 m s$^{-1}$ over the Taklamakan (Fig. 3c) and 18 m s$^{-1}$ over the Gobi (Fig. 3d), suggesting conditions favorable for dust emission. The approximate overpass time of MODIS Terra is indicated with a red line. A secondary peak in wind speed is present over both deserts on 21 March, leading to...
another dust event. These high wind speeds, westerly over the Taklamakan Desert and northeasterly over the Gobi Desert, are also shown in the blue 10-m wind vectors in Fig. 3b, consistent with the conditions found to be favorable for dust lofting over Asian deserts as described in Sun et al. (2001).

On 18 March 2010, 1 day prior to this dust event, there are few pixels over Asia with $t_d$ greater than 0.5 (Fig. 4a). The plume of high dust concentrations, as evidenced by the $t_d$ values greater than 0.7, is initially present near 42°N, 95°E on 19 March 2010 (Fig. 4b). After initial lofting, the plume was transported eastward passing eastern Beijing (40°N, 116°E) on 20 March 2010 (Fig. 4c). By 21 March 2010, the plume reached the Asian coast and the Pacific Ocean near 27°N, 122°E (Fig. 4d). On 22 March 2019, the plume appears elongated from 122° to 160°E (Fig. 4e). While a region of missing data, due to the effects of sun glint, prevents visualization, the continuity of the plume on this date was confirmed through use of visible imagery. The CALIPSO VFM classification indicated the presence of dust between 2 and 7 km from 25° to 35°N along a transect near 150°E (Fig. 5). An analysis of the mean state of dust over the North Pacific in cloudy and all-sky conditions, horizontally and vertically as retrieved by CALIPSO, can be found in Kim et al. (2019). In Fig. 4, 500-hPa geopotential height contours (blue) are aligned with this westward transport of dust. On 24 March 2019 (Fig. 4g), the plume had reached 180°E, extending across much of the Pacific Ocean, while partially obscured by cloud cover and sun glint. From 25 March to 28 March, dispersion of the plume and cloud cover prevent discrimination of the movement of the plume (Figs. 4h–k) but there are still broad regions of enhanced $t_d$.

At 1800 UTC 29 March 2010, as shown in the Climate Forecast System, version 2, reanalysis, an upper-level trough...
that approached from the southwest was present near 50°N, 145°W (Fig. 6). The downstream side of a cyclonically curved upper-level (250 hPa) jet was located over Oregon and Washington with a >50 m s⁻¹ jet streak exit region. An occluded front extended from the low pressure center and the southern half of the cold front was parallel to the jet exit region. Vectors of IVT (black arrows) show transport of water vapor south of the upper-level jet and along the northern edge of the region of high (>15 kg m⁻²) precipitable water. Daily total precipitation at 4 km from PRISM, as shown in the filled blue contours over land in Fig. 7, indicate that more than 2 in. (5 cm) of precipitation fell in most coastal areas of Oregon and Washington on this date, with a maximum at 44.9°N, 123.6°W in Polk County, Oregon, where more than 4.45 in. (11.30 cm) of precipitation fell. Moisture, evidenced by precipitable water greater than 15 kg m⁻², west of 140°W and south of 40°N was transported toward the northeast as an elongated plume with MERRA-2 IVT greater than 250 kg m⁻¹ s⁻¹ and greater than 2000 km in length, meeting the criteria to be classified as an AR from Rutz et al. (2014) (Fig. 7).

An elongated region of enhanced ρ_d was found coincident with an AR, visible within the horizontal boundaries of AR and along its edges. The enhanced ρ_d appears west of the region of highest IVT. While we cannot infer the altitude of the dust from ρ_d, CALIPSO VFM classification at 1122 UTC 29 March 2010 (Fig. 8) corroborates the presence of dust near 30°–40°N and 145°–140°W and shows that dust was present within the lowest two kilometers of the troposphere. Dust is also present during this observation between 4 and 6 kilometers.

To further understand the transport path of trans-Pacific dust for this event, HYSPLIT (Draxler and Rolph 2011) air-mass forward trajectories were conducted from the source regions of Asia, the Taklamakan and Gobi Deserts (Fig. 9). NCEP–NCAR reanalysis wind fields were used as input (Kalnay et al. 1996). Forward trajectories were initiated at matrix of grid points over the Taklamakan for 12-day

FIG. 4. The ρ_d and MERRA-2 500-hPa geopotential height and wind vectors from 18 to 29 Mar 2010. Dust is initially lofted on 19 Mar and is transported across the Pacific Ocean, arriving coincident with an atmospheric river on 29 Mar 2010. The black arrows follow the movement of the dust plume, and black brackets indicate its extension. The AR is indicated in (l).
trajectories. Sixty-five trajectories were released on 1800 UTC 19 March from 1°-spaced grid points from the region 36°–40°N, 37°–78°E at an altitude of 2 km. These are airmass trajectories and, as such, they do not include processes such as wet or dry removal and convective transport, which may affect dust transport. All of these trajectories traveled west, and 67% reached the longitude 128°W, along or near the North American west coast, within the 12 days. A matrix of 32 forward trajectories was released from the Gobi Desert between 39°–42°N, 100°–107°E at 1° spacing at the same altitude.
and time as from the Taklamakan. About 37% of these trajectories traveled west and reached 128°W within 12 days. Those trajectories that extend across the Pacific remain primarily confined between 30°–45°N between 135°E and 150°W. However, west of 150°W trajectories from both deserts diverge into two branches. The northern branch reached the North American coast over western Canada and the southernmost part of Alaska (approximately 50°N). The southern branch reached the North American coast between Oregon, near 40°N, and northern Baja California, Mexico, near 27°N.

FIG. 7. The 1800 UTC IVT (line contours), \( \tau_d \) over land (filled orange contours), and PRISM daily precipitation (filled blue contours) when the AR made landfall on 29 Mar 2010. IVT contours are shown in 50 kg m\(^{-1}\) s\(^{-1}\) increments between 250 and 600 kg m\(^{-1}\) s\(^{-1}\).

FIG. 8. Transect from 30°–50°N near 145°W of CALIPSO VFM dust classification at 1122 UTC 29 Mar 2010 overlaid on \( \tau_d \) centered upon the North Pacific Ocean on that date. The CALIOP orbital track is shown with a blue line. Contours of IVT greater than 250 kg m\(^{-1}\) s\(^{-1}\) are shown in black.
This transport pathway for Taklamakan and Gobi Desert dust reaching North America is consistent with previous studies, including Yu et al. (2019), in which the patterns of long-range transport of Asian dust were studied using the Multiangle Imaging Spectroradiometer (MISR) instrument combined with observation-initiated trajectory modeling. Yu et al. (2019) found that while the potential for trans-Pacific transport to North America peaks in the springtime for both deserts, Taklamakan dust exhibits higher potential for long-range transport and reaches a larger range of latitudes along the west coast of the U.S. than Gobi Desert dust. This is due to higher injection heights over the source region and mid-to low-level ascending air in the spring and summer. Taklamakan dust exhibits greater influence over North America for latitudes south of 50°N while Gobi dust exhibits greater influence for latitudes north of 50°N. However, both deserts exhibit influence over North America at 40°N, the approximate latitude of landfall of the AR on 29 March 2010. It is notable that in Yu et al. (2019) only 5% of trajectories released during springtime from the Taklamakan and Gobi Deserts passed over North America. As previously mentioned, in our analysis 67% and 37% of trajectories from the Taklamakan and Gobi Deserts, respectively, released on 19 March 2010 reached 128°W, indicating particularly favorable meteorology for long-range transport in our case study. It is also plausible that dust originating from other sources farther west, such as North Africa or the Middle East, mixed with Asian dust and traveled westward reaching the North American coast (Hu et al. 2019).

For this case of an AR in a dusty environment that made landfall on 29 March 2010 we have shown that dust can be lofted from Asian deserts and transported over the western Pacific to impact the environment surrounding an AR, even in the lowest 2 km near to where the low-level jet resides. While cloud cover and sun glint prevented discrimination of dust in parts of the eastern Pacific, dust, as evidenced by high \( \tau_d \) was clearly present within the boundaries of the AR feature. The AR dust score for this event was 0.064, which is within the top 10% of AR dust scores for AR days between 2001 and 2018.

### b. Composite analysis

We have shown through a case study that trans-Pacific dust can reach the eastern North Pacific and appear in the vicinity of an AR. However, is dust within such a system spatially randomly distributed or is dust preferentially concentrated in a specific location relative to the AR? Answering this question may help us to understand the mechanism through which dust may come into contact with an AR. While cloud cover prevents us from robustly investigating the position of dust within, above, or below an AR we are able to investigate the position of dust relative to the center of AR-associated ECs.

Zhang et al. (2019) found that 82% of atmospheric rivers are associated with an extratropical cyclone (EC), although it should be noted that the distance between the AR and the EC center varies greatly. Examples of the position of an AR relative to an extratropical cyclone are shown in Figs. 1 and 6. These examples are not representative of all cases. We created an EC-centric composite of \( \tau_d \) using EC center locations for the cool seasons (November–March) from 2000/01 to 2009/10 for ECs identified in Zhang et al. (2019) to be associated with an AR (Fig. 10a). For each AR-associated EC in the record we composited \( \tau_d \) within 15° latitude and longitude of the low-pressure center. The conclusions of this section remain the same when the distance from EC center used in the average ranges from 5° to 15°. We then selected only the ECs with average \( \tau_d \) in the top 10th percentile to composite. We also show in Fig. 10b the number of pixels \( N \) used at each grid cell for the composite shown in Fig. 10a (i.e., the number of non-missing values). Missing data in \( \tau_d \) may occur due to cloud cover or sun glint. Data may also be limited in cases in which the EC center is near to the northern edge of the domain of the \( \tau_d \) dataset (55°N) or near to land. In both panels, contours of sea level pressure (dashed black lines) and AR probability (solid black lines) are shown. We found that \( \tau_d \) was generally highest in the warm sector of the EC, east of the EC center. Dust was also enhanced in the southwestern quadrant of the EC, which is roughly the location of the EC cold sector (Fig. 10a). The cold sector of the extratropical cyclone is the area within the circulation where cold air, advected from higher latitudes, can be found (AMS 2020). It typically lies behind the cold front. The regions of highest mean \( \tau_d \) appear northeast of and within the region of the highest AR probability and east and south of the low pressure center. The region of highest mean \( \tau_d \) has few pixels used in the composite because of cloud cover and because this section of the cyclone is most likely to be over land, where \( \tau_d \) is excluded from the composite. It is possible that cloud contamination in the AOD retrievals used in the calculation of \( \tau_d \) could be more prevalent in this region than in other parts of the EC and could therefore appear as an enhancement of mean \( \tau_d \). To test whether this was the case, we created the same composite but replaced any \( \tau_d \)
with a missing value wherever MODIS *Terra* daily cloud fraction was greater than 60% (Fig. 2 in the online supplemental material). While this substantially decreased our sample size and decreased $t_d$ in the composite overall, the spatial pattern remained qualitatively the same. The same result was found when other cloud fraction thresholds were used, but when thresholds of 50% or less were used there were not enough $t_d$ estimates remaining for a thorough analysis. Naud et al. (2016) found that all of the atmospheric rivers sampled and analyzed during the CalWater Field campaign in which dust residues were dominant had meteorological conditions corresponding to the passage of a cold front. Likewise, VanCuren (2002) observed short Asian dust events along the U.S. West Coast at sea level in Interagency Monitoring of Protected Visual Environments (IMPROVE) measurements, but only during strong frontal passages. These previous observations could have indicated either an enhancement of dust in the post-cold-frontal region of the extratropical cyclone or more efficient removal, through activation or deposition, of dust in post-cold-frontal conditions.

c. Seasonality and interannual variability

We now aim to answer this question: When do these dusty-environment ARs occur seasonally and how often do they occur annually? Previous published studies have found that sources of trans-Pacific dust include deserts in Asia, North Africa, and the Middle East (Hu et al. 2019) and transport of dust across the Pacific occurs primarily in the springtime, when westerlies are strong but precipitation is weaker than in winter (Creamean et al. 2014; Hu et al. 2019). Dust emission over the deserts of Asia has a seasonality with a maximum in the springtime (MAM), as evidenced by high $t_d$ over the region (35°–45°N, 78°–110°E) in March, April, and May (Fig. 11a), and modeling efforts have suggested that trans-Pacific transport from other dust sources also peaks in the spring (Hu et al. 2019). However, the season for ARs reaching the West Coast is primarily from October to March, as shown through the mean number of AR days per month (Fig. 11b). In each month between October and March, there are greater than 9 AR days on average. To understand how the seasonality of dust and ARs impact the seasonality of ARs in dusty environments, we have grouped AR events by the percentile group of their dust score.

Ault et al. (2011) and Creamean et al. (2013) found that post–cold front precipitation was more enriched in dust and biological residues, the particles that remain after water is evaporated from precipitation samples, than in prefrontal or peak AR conditions. Both Ault et al. (2011) and Creamean et al. (2013) found that post–cold front precipitation was more enriched in dust and biological residues, the particles that remain after water is evaporated from precipitation samples, than in prefrontal or peak AR conditions. Both Ault et al. (2011) and Creamean et al. (2013) found that post–cold front precipitation was more enriched in dust and biological residues, the particles that remain after water is evaporated from precipitation samples, than in prefrontal or peak AR conditions. Both Ault et al. (2011) and Creamean et al. (2013) found that post–cold front precipitation was more enriched in dust and biological residues, the particles that remain after water is evaporated from precipitation samples, than in prefrontal or peak AR conditions. Both
By this method, AR days that have a dust score that is greater or equal to the 50th-percentile dust score fall into the 50th-percentile group. AR days that have a dust score that is greater than or equal to the 75th-percentile dust score group but are also counted within the 50th-percentile group, and so forth. We then count the number of AR days that are within each group for each month and divide by the number of years of data (2001–18) to show the average number of AR days per month within each percentile group (Fig. 12). Most ARs occur between October and March (black line) (Rutz et al. 2014). However, as the percentile group of AR dust score increases, the number of AR days in the months of October through February decreases much more than the number of AR days in March and April. AR days within the 95th-percentile dust score (orange line) almost exclusively occur between February and May. For each dust score, the percentage of pixels with $\tau_d$ estimates relative to the total possible pixels in the two-dimensional AR was calculated (i.e., the “data availability”). It was found that the seasonality did not change qualitatively when dust scores with data availability below specific thresholds (10%, 20%) were excluded from the analysis. This highlights that the seasonal cycle of ARs in dusty environments includes a maximum in the early springtime, at the confluence of the AR season and the trans-Pacific dust season.

To understand how variable the dust score is from year to year, we calculated the water-year mean dust score (Fig. 13a). A water year begins 1 October and ends on 1 September and is designated according to the calendar year in which it ends. The maximum in water-year mean dust score, 0.033, occurs in 2018 and the minimum, 0.018, occurs in 2004. The average dust score for the water years 2002 to 2018 was 0.026. The standard deviation of the water-year mean dust score, 0.004, is 16% of the mean. The water years 2007, 2012, and 2017 also stand out, with an annual mean dust score of 0.033, 0.031, and 0.028, respectively. There is no statistically significant trend in the water-year mean dust score.

Having found that there is interannual variability in the water-year annual mean dust score, we now aim to understand the source of this variability. Is it due to changes in dust, changes in the number of ARs hitting the west coast of the United States, or correlated changes in both of these factors? We address this question by performing a Reynolds decomposition on the time series of the annual AR dust score. The time series of dust score can be expressed as

$$ S = \tau_d A, $$

where $\tau_d$ and $A$ are a function of space and time and therefore $S$ is also a function of space and time. We can then use a Reynolds decomposition to define the mean and time-varying components of $\tau_d$ and $A$. For example, the mean $A$ is given by

$$ \overline{A} = \lim_{T\to\infty} \left( \frac{1}{T} \int_0^T A \, dt \right), $$

such that the time-varying component is defined as

$$ A' = A - \overline{A} $$

FIG. 12. Average number of days each month with ARs making landfall along the contiguous U.S. West Coast for the period from 2001 to 2018 grouped by dust score percentile; e.g., AR days with dust score greater than the 90th-percentile dust score for the 2001–18 period fall into the 90th-percentile dust score group. ARs with dust scores greater than the 75th-percentile dust score occur mostly during the spring, when the dust season in Asia is at its peak.

FIG. 13. Time series (2002–18) of water-year mean terms in Eq. (9). Equation (9) describes the Reynolds decomposition dust score time series which was performed to understand the contribution of changes in dust and AR occurrence to the variability of the dust score.
and then
\[ A = \bar{A} + A'. \] (7)

If we similarly decompose \( t_A \), then \( S \) is
\[ S = (\tau_d + \tau_d')(\bar{A} + A') \] (8)
or
\[ S = \tau_d\bar{A} + \tau_d'A + \tau_tA' + \tau_tA'. \] (9)

The four terms on the right-hand side in Eq. (9) are, from left to right:
1) the long-term mean of \( S \), which includes the seasonal cycle,
2) the contribution to \( S \) from changes only in \( \tau_d \),
3) the contribution to \( S \) from changes only in \( A \), and
4) the contribution to \( S \) from correlated changes in \( \tau_d \) and \( A \).

From Eq. (9), the total variance in the dust score \( S \) can be approximated as the sum of the variances from each term plus the covariance between the terms. The contribution of each of these terms to the total variance in the dust score can be used to understand the sources of interannual variability in the dust score. It must be noted that these terms are not completely independent; the correlation between each of the terms is nonzero, resulting in nonlinearity. Each of the covariance terms amount to less than 10% of the variance in dust score. We will exclude these small terms from the rest of our analysis in order to focus on the physically meaningful terms that explain more of the variance.

The sum of the variance of the first four terms in Eq. (9) accounts for 69% of the variance in the dust score. In Eq. (9), if \( \tau_d \) never had missing values then the annual mean \( \tau_d\bar{A} \) would be constant from year to year. However, given that \( \tau_d \) is missing at some locations in space and time, when any right-hand side term is missing \( S \) is missing as well. If one were to calculate the annual mean of each of the right-hand side terms separately and add them, the only way that one would get the same annual mean \( S \) would be to sample each right-hand side term in space and time only where there are values for the term. This means that the annual mean \( \tau_d\bar{A} \) will vary from year because the location and number of missing values for all the other terms are different from year to year. Therefore, in Eq. (9), \( \tau_d\bar{A} \), which represents the contribution of correlated seasonal variations of dust and ARs, is at a maximum in 2016 and is at a minimum in 2002 (Fig. 13b). The term \( \tau_d\bar{A} \) contributes 13% of the variance of those terms (Table 1). In Eq. (9), \( \tau_dA' \), which represents the contribution of independent changes in the location in space and time of ARs making landfall along the west coast of the United States, is at a maximum in 2007 and is at a minimum in 2016 (Fig. 13c). In Eq. (9), \( \tau_tA' \), which represents the contribution to the dust score from independent changes in dust, is at a maximum in 2007 and is at a minimum in 2015 (Fig. 13d). This aligns with the maximum in the dust score. Independent changes in dust contributed 40% to the variance of the dust score (Table 1). The term \( \tau_tA' \) contributes only 5% to the variance in the dust score (Table 1). The higher contribution of \( \tau_tA' \) than \( \tau_dA' \) to the variance of the dust score highlights that variability in background dust may be more important for the dust score than variation in ARs. Correlated perturbations in dust and AR feature position contributed 42% of the variance in dust score and are at a maximum in 2018 and a minimum in 2014 (Table 1; Fig. 13e). These correlated perturbations indicate that there may be a dynamical relationship between dust and ARs.

Missing data in \( \tau_d \) due to cloud cover or sun glint, may impact the variance budget described in Eq. (9). To test whether missing data would impact our conclusions, we performed two additional tests by filling the gaps in \( \tau_d \) with the long-term (2001–18) daily mean of \( \tau_d \) and, secondarily, filling the gaps with zeros. Filling gaps with the long term mean \( \tau_d \) resulted in an increase of the contribution of the \( \tau_d\bar{A} \) to the variance, but did not otherwise change our conclusions. Filling the gaps in \( \tau_d \) also did not change our conclusions, as the relative magnitudes of the contribution of each term to the variance was the same as when gaps were unfilled.

In the calculation of the dust score for each AR day, we used the average AR within the boundaries of the AR. However, there are often large areas of missing \( \tau_d \) within the AR due to cloud cover. For this reason, we decided to test whether our results would change if we were to extend the boundaries of the averaging region used to calculate the dust score beyond the AR itself. We calculated the dust score and performed the Reynolds decomposition, but extended the boundaries of the AR in one degree latitude and longitude increments. The results were nearly identical to when the dust score is calculated with only dust within the AR boundaries. The maximum and minimum dust score remained identical and the mean decreased by 0.003. Each term in Eq. (9) accounted for the same fraction of the variance of the dust score.

5. Conclusions and discussion

The AR dust score climatology presented here represents a new tool to investigate the characteristics and frequency of ARs in dusty environments. The mean dust score for the water years 2002 to 2018 was found to be 0.026 ± 0.004r (Fig. 13a). We have shown that there is a distinct seasonal cycle for ARs in dusty environments, with the highest dust score events occurring in March, due to the confluence of the AR season and the trans-Pacific dust season (Fig. 12). This may be useful information when planning field campaigns investigating aerosol impacts on ARs. We have also shown that dust is present

<table>
<thead>
<tr>
<th>Term</th>
<th>Contribution (%)</th>
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<tbody>
<tr>
<td>( \tau_d\bar{A} )</td>
<td>13%</td>
</tr>
<tr>
<td>( \tau_dA' )</td>
<td>40%</td>
</tr>
<tr>
<td>( \tau_tA' )</td>
<td>5%</td>
</tr>
<tr>
<td>( \tau_tA' )</td>
<td>42%</td>
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</tbody>
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Table 1. Variance of each term in Eq. (9) as a percentage of the sum of the variance of these terms. The term \( \tau_d\bar{A} \) represents the contribution of the climatological mean and seasonal cycles of dust and ARs to the variance in dust score; \( \tau_dA' \) represents the contribution from independent changes in dust, and \( \tau_tA' \) represents the contribution from independent changes in the location of ARs in space and time; \( \tau_tA' \) represents the contribution from correlated changes in dust and the location of ARs in space and time.
primarily in the warm sector of AR-associated extratropical cyclones (Fig. 10) and is also enhanced in the cold sector (Fig. 10).

We have decomposed the contribution of the seasonal and time-varying components of $\tau_d$ and AR location in space and time to the total variance in dust score [Eq. (9); Fig. 13]. We discovered that the correlated seasonal changes in $\tau_d$ and AR feature contribute 13% to the variance in dust score. While the contribution from independent changes in AR feature variability is small (5%), the contribution from independent changes in $\tau_d$ is much larger (40%). The contribution to the variance from correlated changes in $\tau_d$ with AR feature are also large (42%), which may indicate a dynamical relationship between dust and ARs. This motivates additional investigation into the meteorological conditions that lead to dusty ARs and the dynamics of these events. We will investigate this further in forthcoming work. The dust score presented here does not directly provide information about provenance. As a result, the question “To what extent do each of the major source regions (e.g., Africa, East Asia, Middle East) contribute to dust in the vicinity of ARs?” remains unanswered but could be addressed through additional in situ observations and/or modeling studies.

As discussed in section 3, there are several limitations to the AR dust score presented here. As a result of calculating a new dust score for each AR day, longer duration AR events may have greater influence on our climatological analysis of the seasonality and interannual variability of ARs in dusty environments. It is also possible that multiple AR objects could be present within the domain on a given day and would be combined in the dust score for that day. In addition, $\tau_d$ estimates are only available in clear-sky pixels. Dust that is present within, above, or below clouds will not be counted in the dust score. Therefore, any dust that is activated as cloud condensation nuclei or ice nuclei will not be counted in the dust score. It is plausible that an AR day could have substantial dust within, above, or below cloud and still have a low dust score.

Acknowledgments. This work was funded by the California Department of Water Resources contract 4600010378, Task Order OSCOP215 and the Army Corps of Engineers USACE (CESU) W912HZ-15-0019. We are grateful for the datasets and data archiving centers that supported this work and appreciate those who made our study possible, including the MERRA-2 team at the GMAO and staff at GSFC. We also thank the PRISM team and Oregon State University, along with the MODIS team. We thank Dr. Zhenhai Zhang for his data contributions and guidance.

Data availability statement. The AR dust score dataset described in this paper will be made publicly available at Pangea Open Access.

REFERENCES


