Santa Ana Winds: A Descriptive Climatology

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ABSTRACT

The criteria used to define Santa Ana winds (SAWs) are dependent upon both the impact of interest (e.g., catastrophic wildfires) and the location and/or time of day examined. We employ a comprehensive definition and methodology for constructing a climatological SAW time series from 1981 through 2016 for two Southern California regions, Los Angeles and San Diego. For both regions, we examine SAW climatology, distinguish SAW-associated synoptic-scale atmospheric patterns, and detect long-term, significant SAW trends. San Diego has 30% fewer SAW days compared to Los Angeles with 80% of SAW events starting in Los Angeles first. Further, 45% of San Diego SAW events are single-day events compared to 35% for Los Angeles. The longest duration event spanned 16 days for Los Angeles (27 November–12 December 1988) and 8 days for San Diego (9–16 January 2009). Although SAW-driven fires can be large and devastating, these types of fires occurred on only 6% and 5% of SAW days for the Los Angeles and San Diego regions, respectively. Finally, we find and investigate an extended period of elevated SAW day count occurring after 2005. This new climatology will allow us to produce month- and season-ahead forecasts of SAW days, which is useful for planning end-of-year staffing coverage by the local, state, and federal fire agencies.

1. Introduction

Santa Ana winds (SAWs) across southwest California and the northern Baja Peninsula of western North America are a type of downsloping, offshore wind (from the northeast quadrant) that has been observed to occur between September and May (Cao and Fovell 2016), with isolated occurrences in June. Air moving from the desert toward the coast accelerates through gaps in the local terrain via the Venturi effect, which results in SAWs along and in the lee of the Transverse and Peninsular Ranges (Burroughs 1987) (Fig. 1). The stronger and more widespread SAW events are usually associated with a combination of surface offshore pressure gradients, cold air advection at 850 hPa, and negative vorticity advection at 500 hPa (i.e., subsidence at the midtropospheric level) (Abatzoglou et al. 2013). In extreme cases, mountain

waves and associated hydraulic jumps can develop, resulting in damaging winds in the lee of higher terrain (Cao and Fovell 2016; Durran 1990). Sustained surface wind velocities on average have been observed to be $7\text{--}13\text{ m s}^{-1}$ ($15\text{--}30\text{ mi h}^{-1}$) (Small 1995) with gusts in excess of 25 m s^{-1} (56 mi h^{-1}) (Sommers 1978; Keeley et al. 2004; Cao and Fovell 2013). This claim is also substantiated by observational data from a small sampling of six Remote Automated Weather Stations (RAWS) and three Automated Surface Observing Stations (ASOS) during multiple SAW events.

Besides the wind, one of the other main characteristics associated with SAWs is the dry adiabatic warming that occurs in the lee of the Transverse and Peninsular Ranges (Fig. 1). Most early and late season (September/October and April/May) SAWs are accompanied by warm ambient surface temperatures $\geq 21^{\circ}\text{C}$ ($\geq 70^{\circ}\text{F}$) as observed by RAWS and ASOS. However, during the winter months, SAWs are often associated with lower temperatures due to the increasing southern extent of continental polar air intrusions into the Great Basin (i.e., Nevada and Utah), in addition to the shorter daylight hours and lower elevation

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FIG. 1. Map of Southern California with SAWTI zones (color shading) and major mountain ranges (dashed black lines) and passes (red arrows). The inset map shows the locations of station observations used to calculate mean sea level pressure differences.

sun angle. The adiabatic process also aids in drying out the atmosphere, often resulting in relative humidity values less than 15%, also observed by ASOS and RAWS.

The extreme dry and windy conditions during SAW events create favorable conditions for producing catastrophic wildfires, particularly in the fall and early winter when the native vegetation is most receptive to ignitions (Nauslar et al. 2018; Westerling et al. 2004). During such events, fires can quickly propagate across the wildland urban interface regions, threatening lives and property. Ignitions do tend to be more common during the summer months compared to when SAWs occur (Bartlein et al. 2008; Jin et al. 2014), but this does not necessarily equate to a greater area burned. According to a recent study, the number of hectares burned by fires associated with SAWs is greater than fires burning under non-SAW conditions (Kolden and Abatzoglou 2018). Some of the largest and most destructive fires related to SAWs in recent history occurred in October 2003 and 2007, and December 2017. Of particular note was the Thomas Fire, one of the largest in California's recorded history, which started on 4 December 2017 and consumed 114 078 hectares (ha; or 281 893 acres) across Ventura and Santa Barbara Counties. The fire resulted in two fatalities and destroyed 1063 structures (Nauslar et al. 2018). The Witch Fire of 21 October 2007, in San Diego County, burned 80 124 ha (197 990 acres) and caused two fatalities (Fovell and Cao 2017; Keeley et al. 2009) (http://cdfdata.fire.ca.gov/incidents/incidents_details_info?incident_id=225), and the Cedar Fire, also in San Diego County, started on

25 October 2003, burned 113 424 ha (280 278 acres), and caused 14 fatalities (Keeley et al. 2004) (http://cdfdata.fire.ca.gov/incidents/incidents_details_info?incident_id=57). Both were SAW related.

These fires have sparked a renewed interest in the study of SAWs, with one example being the recent development and implementation of the Santa Ana Wildfire Threat Index (SAWTI) (Rolinski et al. 2016). This index categorizes SAWs with respect to large fire potential¹ by combining weather and fuel parameters over a 3-km horizontal resolution domain across Southern California (see Fig. 1 for approximate domain extent). During the development phase of this index, a 30-yr historical dataset (now 35 years) containing fire weather parameters (including the SAWTI output) was created, which allowed for the development of a SAW climatology. Understanding this overall climatology is not only useful for conveying frequency, duration, and intensity, but also for observing changes that may be related to teleconnection indices. Other studies on the climatology of SAWs have been done in the past (Guzman Morales et al. 2016; Raphael 2003), but here we want to expose the SAW differences between two study areas of Southern California using a new, unique dataset as well as reveal the associated nuances with SAWs. Future applications of this climatological dataset could help relate historical events to fire history, specifically the fire outbreaks of October and November 1993, October 2003 and

¹ The potential for an ignition to reach or exceed 121 ha.

2007, November 2008, and December 2017. In addition, this climatology can be leveraged by meteorologists and researchers to understand the various SAW characteristics and associated atmospheric dynamics to improve operational forecasting techniques. Federal, state, and local fire agencies also stand to benefit by making better informed decisions regarding staffing level augmentation and the predeployment of fire resources across the region. And, finally, air quality managers can better understand how SAWs might affect particulate matter and ozone concentrations, which can result in public health concerns, across the highly populated areas of Los Angeles and San Diego.

The goal of this paper is to present a descriptive climatology of SAWs for two study areas that will be routinely updated and made available upon request. SAW varieties, data sources, methodologies, and the results will be discussed with an emphasis related to fire activity. This paper is organized as follows: [section 2](#) presents the Southern California geography and our SAW definition, [section 3](#) outlines our unique approach to select days when SAW conditions matched our criteria, [section 4](#) discusses our SAW climatology dataset, and finally [section 5](#) summarizes our main findings.

2. SAW domain and definition

Before proceeding further, it is important to discuss [Fig. 1](#) in greater detail since we will be referencing this geography repeatedly. Besides some of the major geographic features and wind corridors, the map shows four colored areas that are zones related to the SAWTI. These zones span Southern California from Santa Barbara County (zone 4) to San Diego County (zone 3). Our climatology will focus on zones 1 and 3, which we will refer to simply as “Los Angeles” and “San Diego”, respectively. Zone 4 has been excluded due to the fact that the majority of wind events (known as “sundowners”) are more locally driven and are confined to a small area along the Santa Barbara coastline ([Blier 1998](#); [Hatchett et al. 2018](#)). Zone 2, which lies between Los Angeles and San Diego, was also excluded because most of the causal effects and characteristics related to SAWs are redundant to the Los Angeles area. [But that is not to say that zone 2 is without its notable high wind corridors such as the area through and below the Cajon and Banning passes, and downstream over the Santa Ana Mountains (not labeled) where some of the strongest winds occur in this zone.] For the sake of brevity, we will focus our analysis on zones 1 and 3, which experience the widest variety of SAW events.

Developing a set of criteria for selecting SAWs can be complex due to the spatiotemporal variability in the magnitude and occurrence of such phenomenon. The

peer-reviewed literature demonstrates the many contrasting criteria used to define SAWs (e.g., [Raphael 2003](#); [Hughes and Hall 2010](#); [Jones et al. 2010](#); [Abatzoglou et al. 2013](#); [Guzman Morales et al. 2016](#)). For our study we embark on a holistic approach, defining a SAW as being a *synoptically driven offshore wind that typically results in adiabatic warming and subsequent drying in the lee of the Southern California Transverse and Peninsular Ranges* ([Fig. 1](#)). By the term “synoptically driven,” we are referring to the equatorward migration of Rossby waves into the Great Basin. This excludes other causal mechanisms for SAW-like conditions (which we will make reference to in [section 3](#)) and inherently eliminates the normal nocturnal land breezes. To construct a SAW time series dataset that adheres to our specific definition, we employ a blend of coarse and dynamically downscaled reanalysis data complemented by surface observations. Finally, we complete a rigorous, iterative data distillation process, resulting in a SAW dataset that adheres to our definition.

3. Creating the SAW time series

a. Step 1

To capture the near-surface weather characteristics that are related to our SAW definition, we used the weather component of the SAWTI called “Large Fire Potential” (LFP_w):

$$LFP_w = 0.001W_s^2D_d, \quad (1)$$

where W_s is the 10-m wind velocity (mi h^{-1}) and D_d is the 2-m dewpoint depression ($^{\circ}\text{F}$) ([Rolinski et al. 2016](#)). The term LFP_w in theory quantifies the potential for a large fire to occur based on dry and windy conditions. While temperature and humidity are not *directly* incorporated into LFP_w , the inclusion of dewpoint depression does help distinguish days impacted by the adiabatic warming and drying process inherent in our SAW definition. We leverage historical meteorological output used for creating the SAWTI generated from dynamically downscaling the North American Regional Reanalysis (NARR) using version 3.5 of the Weather Research and Forecasting model (WRF) ([Skamarock et al. 2008](#)). NARR was downscaled using a 27-km WRF horizontal resolution outer, 9-km intermediate, and 3-km innermost domain with 51 vertical levels. The specific blend of WRF parameterization schemes was found to validate best against observations during SAWs ([Rolinski et al. 2016](#)).

Our goal was to represent the worst period of each day, when both the spatial extent and duration of LFP_w impacted the fuels, supporting large fire occurrence. To

achieve this, LFP_w was calculated hourly at each WRF grid point within the SAWTI domain and was then averaged over five 8-h overlapping time periods. Finally, the daily maximum 8-h average LFP_w was spatially averaged over each zone (see Rolinski et al. 2016). To emphasize the winds, our SAW criteria used both the zone-averaged maximum 8-h $LFP_w \geq 6$ and $W_s \geq 4.5 \text{ m s}^{-1}$ (10 mi h^{-1}). From thorough investigation of historical data and operational experience, these criteria are the primary defining thresholds that distinguish SAW days from any other day. Thus, historical data that met the quantitative thresholds described above now exist as our preliminary time series (Fig. 2).

b. Step 2

Since LFP_w does not account for wind direction, observed mean sea level pressure MSLP gradients were necessary to further distill candidate SAW days. Therefore, we examined observed MSLP gradients between Los Angeles International Airport (LAX) and Tonopah Airport (TPH) for the Los Angeles area (Small 1995), and from San Diego International Airport (SAN) to Barstow-Daggett Airport (DAG) for the San Diego Area (Fig. 1). Observed MSLP differences were standardized at each hour of the day over the entire 35-yr dataset. This removed the diurnal cycle, which can be dominated by the nocturnal land-breeze occurrence. Our pressure gradient criteria required at least 12 or more consecutive hours per day of standardized offshore gradients. This distillation process removed not only the months of July and August but also other random days from consideration.

c. Step 3

In our SAW definition, we are specific about the synoptic-scale atmospheric patterns that force SAWs. Thus, for the next step in our data distillation process (Fig. 2), it was important to analyze the clustered, lower- and midtropospheric synoptic-scale patterns (or map types) associated with SAW days. Multiple quantitative tools can be used to reduce the dimensionality of an atmospheric dataset to a comprehensible level (two dimensions), including empirical orthogonal functions (EOFs) and self-organizing maps (SOMs) (Kohonen 1988). A self-organizing map is an array of nodes, or in this case the predominant synoptic weather patterns from a historical dataset where nodes of close proximity are more similar relative to those farther apart. More frequent weather patterns are concentrated among more SOM nodes, each node illustrating the subtle differences between these frequent weather types. Recently, SOMs have been applied to synoptic climatology and have been found to have advantages over EOFs

FIG. 2. Data distillation flowchart illustrating the sequence of steps used to create the final climatological SAW dataset.

(Cavazos 1999, 2000; Hewitson and Crane 2002; Cassano et al. 2006; Liu et al. 2006). Thus, we applied SOMs in this next step to verify that our time series only contained legitimate SAW days.

The SOMs ingested NARR data averaged over the hours coinciding with the maximum LFP_w 8-h period for each SAW day. NARR variables important for distinguishing SAW days were used to create the SOM array including 500-hPa height (Z500), MSLP, 850-hPa wind speed magnitude (WSPD850), and 850-hPa temperature advection (TADV850). MSLP and Z500 were chosen because they capture the surface and upper-air synoptic patterns, while WSPD850 and TADV850 do well in showing the low-level synoptic winds and potential downward momentum transfer. The spatial extent for WSPD850 and TADV850 was limited to areas immediately surrounding Southern California, while Z500 and MSLP covered much larger domains (see Fig. 3 for relative spatial extents for each variable). Therefore, only localized patterns from the more spatially varying WSPD850 and TADV850 influenced the SOM and their reduced spatial extent allowed the smoother, larger-scale variables (Z500 and MSLP) to contribute more to the SOM characteristics. Each NARR variable was standardized at each 3-hourly

FIG. 3. Composite mean (January 1981–June 2016) (top left) NARR Z500 (gpm), (top right) MSLP (hPa), (bottom left) 850-hPa wind speed (m s^{-1}), and (bottom right) 850-hPa temperature advection (K s^{-1}) for SOM node 5.

output using the 1981–2010 mean and standard deviation. The dimensions of the SOM array determine the level of synoptic weather pattern generalization that will be produced. We ran several SOM iterations using multiple array dimensions. Ultimately, we subjectively selected a SOM node dimension of 6×5 after careful evaluation finding that most SAW synoptic patterns were represented without containing relatively redundant nodes. The reader is encouraged to peruse the work of Cavazos et al. (2002) and Hewitson and Crane (2002), who describe the SOM procedures in more detail.

d. Step 4

Finally, we began an iterative process to distill and validate the SAW time series using SOMs (Fig. 2). After our initial SOM array was completed, we scrutinized SAW days associated with SOM nodes that appeared to represent non-SAW atmospheric patterns. To elaborate on this further, there are a number of scenarios that can

result in questionable SAW days. For example, in rare cases when surface cyclogenesis occurs over the Southern California Bight during the winter months, precipitation can develop in conjunction with offshore flow, which Small (1995) refers to as a “wet” Santa Ana (an example of this occurred on 8 December 1982). While some may consider this to be a legitimate SAW event, we discarded most of these days from our dataset due to the significant influx of moisture, which can offset the adiabatic warming and drying specified in our definition. Another interesting, but rare, offshore wind scenario can occur when decaying tropical cyclones migrate north into Southern California. A specific example of this occurred on 24 September 1997 when Hurricane Nora approached the area from the south to generate SAW-like conditions. Last and on a more localized level, strong outflow associated with mesoscale convective complexes/systems over eastern California near the Colorado River can sometimes generate brief easterly flow through the Banning Pass and across the desert side of the Peninsular Ranges

during the summer months. To remove these occurrences, we took a more subjective approach by using the National Centers for Environmental Prediction (NCEP) surface and 500-hPa daily weather maps (<http://www.wpc.ncep.noaa.gov/dailywxmap/explanation.html>) to inspect more closely the overall synoptic pattern responsible for offshore flow. While these non-SAW atmospheric patterns were relatively easy to detect using NCEP maps, another more challenging category subject to removal was a transition day (i.e., from onshore to offshore or vice versa). These days were often identified when the initial LFP_w criteria were barely met. For these, we analyzed the map sequence surrounding the event (i.e., the progression of surface and 500-hPa patterns supportive of SAWs) to determine if these days were in alignment with our SAW definition. (It is important to note that not *all* transition days were removed, but only a select few.)

If, upon further investigation, any days were removed from the time series, another SOM was built and inspected. This process was repeated until the SOM was free of any non-SAW atmospheric nodes. This evolution allowed us to develop a final SOM node array for Los Angeles that (to the best of our knowledge) is built from a time series free of questionable SAW days (Fig. 4). As a result of this subjective distillation process, we removed 33 days for Los Angeles. This same distilling procedure (steps 1 through 4) was repeated for the San Diego area (Fig. 5), resulting in 47 days removed through step 4.

4. Results

a. SAW day count

Our climatological SAW dataset consists of 1859 (1237) SAW days between 1981 and 2016 for Los Angeles (San Diego), which is approximately 14% (10%) of the total day count. San Diego has about 30% fewer SAW days than Los Angeles, which illustrates that there are distinct differences between the two areas. Specifically, on average, there are 52 (36) SAW days per year ranging from as few as 22 (12) to as many as 81 (59) for Los Angeles (San Diego). Other important studies (Jones et al. 2010; Guzman Morales et al. 2016) consistently report the annual distribution of monthly SAW events. Although not invalid, in contrast we are showing SAW *day count* statistics to prevent masking underlying information when aggregating to the event level. For example, according to our established criteria for Los Angeles, December 2017 had 2 SAW events, which by any standards would be considered below normal, yet the SAW day count was 16, which was well above normal. One of these events lasted 15 days [12 days according to Nauslar et al. (2018)], which contributed

to the widespread propagation of the Thomas Fire. Firefighting suppression efforts were challenged due to the extended duration of this event and because fewer firefighting resources were available this time of the year. Expressing SAWs as a single event in this case diminishes their significance and reduces their causal impact, thus minimizing the role SAW days can have on significant fire activity.

Comparing SAW day count to one of the more widely used fire datasets (Short 2017), which spans the period 1992–2015 and contains 6328 (9701) records for Los Angeles (San Diego), shows that fires of any size occurred on 561 (472) days having SAWs or 30% (38%) for Los Angeles (San Diego). Out of those days, large fires occurred 6% (5%) of the time for Los Angeles (San Diego). Therefore, while fires associated with SAWs can be infrequent, the result of such fires will often devastate communities. We also want to recognize, however, that many SAW days occur when fuels are wet and unsupportive of wildfire activity, which would elevate the percentages for true eligible days.

b. Seasonal cycle

Box-and-whisker plots (Figs. 6 and 7) show the monthly frequency of SAW days with mean day counts peaking in January, followed by slightly lower mean day counts in November and December, which is mostly consistent with other studies (Raphael 2003; Jones et al. 2010). Discrepancies from other climatologies can be attributed to differing data, methodologies, and defining criteria. Not surprisingly, minimal frequencies occur in June with no occurrences in July or August. December and January have the largest interannual variability, which can be due to periods of atmospheric blocking resulting in subsequent exchanges between zonal and meridional flow over the eastern Pacific and western United States (Carrera et al. 2004). There are two outliers on these plots that are worth highlighting. For Los Angeles, June 1981 had four consecutive SAW days from 13 to 16 June, with the 15 June having the worst SAW conditions of any June in the dataset. The other notable outlier occurred in May 2014 across the San Diego area, which resulted in a significant fire outbreak over western San Diego County.

c. Duration

Even though we are mainly focusing on SAW *days* in this paper, we also recognize the significance of SAW *events* consisting of one or multiple consecutive SAW days. For example, 45% of SAW days in San Diego consist of single-day events compared to only 35% in the Los Angeles area. Another noteworthy observation is that most events that last more than 4 or 5 days are essentially comprised of multiple shorter duration SAW

FIG. 4. (top) Composite mean NARR Z500 (gpm) derived from self-organizing maps for hours when our SAW criteria were met for Los Angeles (zone 1) between January 1981 and June 2016. (bottom) SOM node frequency (%) mapped to each SOM node labeled and colored with darker red shades corresponding to more frequent nodes. Black up (down) arrows indicate an upward (downward) statistically significant (p value < 0.05) trend in the annual SOM node frequency over the 1981–2016 period.

FIG. 5. (top) Composite mean NARR Z500 (gpm) derived from SOMs for hours when our SAW criteria was met for San Diego (zone 3) between January 1981 and June 2016. (bottom) SOM node frequency (%) mapped to each SOM node labeled and colored with darker red shades corresponding to more frequent nodes.

events. Typically in these cases, a 500-hPa trough migrating through the Great Basin and into the Rocky Mountains is followed by another trough a day or two later having a similar trajectory. This in turn helps

reinforce the offshore flow that was established in the wake of the initial trough. This can be seen in Figs. 8 and 9 by noting the sequence of SOM nodes that occurred during the course of the event. The longest Los Angeles

FIG. 6. Zone1 SAW monthly day count frequencies with year of notable outlier labeled.

SAW event lasted 16 days, spanning from 27 November to 12 December 1988. Although not in our dataset, December 2017 (see [section 4a](#)) was the longest event since then. The longest event for the San Diego area lasted 8 days from 9 to 16 January 2009.

d. Ranking

We integrated hourly LFP_w for each day across the time series using Simpson's method. Daily integrated

LFP_w allows us to quantitatively distinguish SAW days when offshore flow is both long in duration and large in magnitude, elevating the potential for large wildfires. [Tables 1](#) and [2](#) rank SAW days in descending order based on the integrated LFP_w for Los Angeles and San Diego, respectively. Not surprisingly, there were 5 overlapping days between both areas; 22 October 2007 had the highest integrated LFP_w for both areas. Specifically, this day's integrated LFP_w for San Diego

FIG. 7. Zone 3 SAW monthly day count frequencies with year of notable outlier labeled.

FIG. 8. Time series of Los Angeles area daily maximum LFP_w and associated SOM node number (black boxes) for a long-duration SAW event spanning from 27 Nov to 12 Dec 1988.

is >1.6 times the second highest integrated LFP_w SAW day. According to [Cao and Fovell \(2016\)](#), this event was likely the strongest across the San Diego area since 1957. Additionally, this October event helped to spawn one of the worst fire outbreaks in California history. Fires of any size occurred on 70% (90%) of the top 10 days for Los Angeles (San Diego) with 20% (40%) of these days coinciding with fires 121 ha (300 acres) or greater for the Los Angeles and San Diego areas, respectively.²

Regarding associated map types, if we expand the number of records for Los Angeles to include another 10 days, SOM nodes 18 and 30 become more frequent ([Figs. 10 and 11](#)). Large fires occurred on most of the node 18 dates. As it turns out, this node is related to scenarios involving lower-stratospheric intrusions and strong subsidence associated with exit regions of anticyclonically curved jet streaks ([Langford et al. 2015; Huang et al. 2009](#)). This was the case during the Springs Fire (2 May 2013) when unusually strong late-season SAWs helped to push this fire to the coast (traveling almost 16 km from its origin). In the San Diego area, SOM nodes 24 and 27 frequent the top 10 integrated LFP_w days, with node 27 occurring on all three days of the October 2007 SAW event coinciding with the Witch Fire.

e. Timing

We examined zone-averaged wind speeds to determine the peak wind timing during SAWs. Since we are evaluating spatially averaged winds, this timing is a function of the wind speed spatial extent and magnitude, which are impacted by the following: horizontal thermal and pressure gradient fluctuations ([Hughes and Hall](#)

2010), mountain lee wave amplitudes and the location of the hydraulic jump downwind ([Brinkmann 1974; Durran 1990](#)), the extent to which the SAWs are opposed (enhanced) by the sea breeze (land breeze) ([Fosberg et al. 1966](#)), and, last, the vertical momentum transfer to the surface and aloft across the region of interest [as suggested by [Durran \(1990\)](#)]. We emphasize that this is not an exhaustive list and that these mechanisms are related to and interact with each other.

Arrival times of SAW events vary throughout the year, with most events beginning during the predawn hours and peaking by mid to late morning ([Fosberg et al. 1966; Raphael 2003; Jones et al. 2010; Guzman Morales et al. 2016](#)), similar to downslope winds at other locations ([Brinkmann 1974; Whiteman and Whiteman 1974](#)). Peak wind velocity can occur when cooling is maximized across the Great Basin coinciding with a land breeze in the lee of the Transverse and Peninsular Ranges. Further, as the land surface is warmed by the sun, local vertical momentum transfer (a result of vertical shear) transitions to nonlocal, influenced by both shear and buoyant forces, bringing stronger winds aloft to the surface ([Crawford and Hudson 1973; Mahrt 1981](#)). We have found that SAWs peak in velocity around 1100 LST from November to February, and around 0900 LST in April, May, and September. We hypothesize this early and late SAW season shift to earlier peak diurnal winds to be the result of a higher sun angle earlier in the day, which would initiate stronger, vertical mixing sooner. This would weaken and lift the ridge-top inversion earlier, slowing lee-side winds, and create enhanced momentum transport earlier in the day over the lee slopes, mixing stronger winds aloft down to the surface and also altering the downslope progression of the hydraulic jump ([Richard et al. 1989](#)). Finally, this increased vertical mixing could slow winds aloft throughout the rest of the day as surface roughness is felt higher in the atmosphere.

² The period 7–8 January 1982 falls outside our fire dataset, but it is unlikely that any fire activity occurred due to a week's worth of precipitation ending the day before this event.

FIG. 9. Time series of San Diego area daily maximum LFP_w and associated SOM node number (black boxes) for a long-duration SAW event spanning from 27 Nov to 3 Dec 1989.

Operational experience suggests a lag in SAW event start times between Los Angeles and San Diego, with most events starting in San Diego after they begin in Los Angeles. The temporal resolution of this new dataset provides an opportunity to quantify this lag. For all Los Angeles events, we calculated the hour lag between the event start time in Los Angeles and San Diego, searching for the San Diego event start time during the previous, same, or following day. To determine SAW days, we only evaluate criteria for hours beginning at midnight and ending at 2359 LST. Therefore, it is possible that the 21% of Los Angeles events that met our criteria starting at midnight could have started hours before midnight on the previous day. To avoid underestimating the lag, we did not include these events. Confirming our intuition, 80% of events (both single and multiday SAW events) begin in Los Angeles first. This lag can be explained by the time it takes surface high pressure over the eastern Pacific to migrate eastward into the Great Basin, while altering the orientation of the isobaric field across Southern California. Interestingly, our analysis reveals a bimodal lag hour distribution with most lag times between 0 and 22 h and a primary peak at approximately 2 h (Fig. 12). We hypothesize that the secondary peak at around 20 h could be a signature of the necessary diurnal phase alignment of both synoptic and local forcing important for SAWs. For example, if the synoptic forcing is out of phase with local influences (e.g., land-sea breeze), the event start time will be delayed until both are in phase (typically in the predawn hours). The remaining 20% of events either have no lag or precede Los Angeles, splitting at 10% each.

f. SAW types

The most frequent Z500 pattern for SAW days consists of a ridge, varying in amplitude over the eastern Pacific and/or western United States (Los Angeles

nodes 12, 15, 16, and 24 and San Diego nodes 8, 23, 29, and 15, listed in order of descending frequency) (see Figs. 4 and 5). These nodes are associated with SAWs that are generally warm and dry with varying degrees of wind velocities. In contrast, high-amplitude positive-tilt troughs are the least frequent pattern for Los Angeles (nodes 1, 7, 2, and 13) and relate to cooler and windier SAW events. San Diego is different, with its least frequent node (27) having an expansive ridge over the eastern Pacific extending into California occurring primarily in the fall. This node is associated with fires of any size almost 95% of the time with large fires occurring on ~40% of those days. Fires occur ~20% (~30%) of time with the most (least) frequent nodes previously discussed. With the exception of node 16, the other least frequent nodes for San Diego (1 and 7) consist of deep troughs similar to Los Angeles. In the middle of the SAW season (November through March) most SOM nodes can occur except for node 6 (25) for Los Angeles (San Diego). Fall and spring nodes include 5, 6, 11, and 12 for Los Angeles and 13, 19, 25, and 26 for San Diego, which are all typically associated with warmer SAWs.

TABLE 1. Zone 1 top 10 SAW days ranked by integrated LFP_w ($^{\circ}\text{F mi}^2 \text{ h}^{-1}$). Boldface dates denote overlapping days between Los Angeles and San Diego.

Date	$\int LFP_w$	SOM node
22 Oct 2007	1023	18
21 Oct 2007	1013	12
2 Nov 2011	884	14
4 Oct 2013	835	05
15 Dec 1996	817	30
30 Apr 2014	816	05
9 Feb 2002	806	30
22 Oct 2008	786	18
8 Jan 1982	770	24
7 Jan 1982	769	21

TABLE 2. Zone 3 top 10 SAW days ranked by integrated LFP_w (°F mi² h⁻¹). Boldface dates denote overlapping days between Los Angeles and San Diego.

Date	$\int$ LFP _w	SOM node
22 Oct 2007	2177	27
15 Dec 1996	1309	30
10 Feb 2002	1289	24
9 Feb 2002	1068	24
21 Oct 2007	1047	27
18 Dec 2000	1005	28
3 Dec 2006	1005	24
23 Oct 2007	998	27
30 Apr 2014	964	20
1 Jan 2008	859	17

SAW types can also be distinguished based on their spatial extent, which is influenced by a number of factors, one of which is the marine layer along the coast. To illustrate this we chose two events, of which one was associated with a moderate to strong marine layer

(30 November 2008) and the other (22 October 2007) was not. [Figure 13](#) shows the presence of marine air during the 2008 event, denoted by the low dewpoint depression values along the coast and into the foothills with a weak eddy circulation over the Southern California Bight. [Figure 14](#) for the same event shows a gravity wave breaking over the higher terrain with only minor perturbations within the isentropes downstream toward the coast. In contrast, the event in 2007 has a major gravity wave breaking over the higher terrain with a secondary wave downstream ([Fig. 15](#)). Offshore flow can be seen at the coast with high dewpoint depression values west of the Transverse Range indicating the absence of a marine layer with ample low-level mixing ([Fig. 16](#)). We do not fully understand all the mechanisms responsible for SAW spatial extent differences, but we do know that during stronger events, the marine layer is dislodged and critical fire weather leading to catastrophic wildfires can occur at the coast. This was the case with the 1993 Laguna Hills Fire

FIG. 10. Composite mean (January 1981–June 2016) (top left) NARR Z500 (gpm), (top right) MSLP (hPa), (bottom left) 850-hPa wind speed (m s⁻¹), and (bottom right) 850-hPa temperature advection (K s⁻¹) for SOM node 18.

FIG. 11. Composite mean (January 1981–June 2016) (top left) NARR Z500 (gpm), (top right) MSLP (hPa), (bottom left) 850-hPa wind speed (m s^{-1}), and (bottom right) 850-hPa temperature advection (K s^{-1}) for SOM node 30.

(Small 1995), the May 2014 fires (Fovell and Cao 2017), and the 2018 Woolsey Fire. During weaker events, the marine layer and associated capping temperature inversion often preclude offshore winds from surfacing at the coast. A more thorough and targeted study is warranted to document the causal mechanisms responsible for the spatial extent of SAWs across Southern California.

g. Tendencies

Finally, we examine the Los Angeles area standardized monthly and yearly SAW day count time series (Fig. 17, top row). Monthly and yearly SAW day counts are standardized using the mean and standard deviation from the period 1990 to 2010. Yearly SAW day counts were tabulated for each season which begins in September and ends in June of each year. As depicted by the gray shaded region in all rows of Fig. 17, an elevated yearly SAW day count persists for all years after 2005. Using changepoint analysis (Killick and Eckley 2014) on the yearly SAW day count time series, we found two

distinct time periods: one with a yearly day count mean of 46 days spanning from 1981 through the 2005 season and another period of relatively elevated yearly SAW day counts with a mean of 71 days beginning in the 2006 SAW season. Notably, this elevated SAW period coincides with predominantly cool phases of both the Pacific decadal oscillation (PDO) and the Niño-3.4 index (Fig. 17, second and third rows), and mostly warm Atlantic multidecadal oscillation (AMO; Schlesinger and Ramankutty 1994; Kerr 2000) phases (Fig. 17, fourth row). Using a 0.05 level of significance, we report statistically significant relationships (both linear and nonlinear) between the SAW day count and PDO and AMO, which is consistent with Li et al. (2016), but we use 1-yr and 3-month moving averages. The Niño-3.4 was investigated following Raphael (2003) who found that most warm El Niño–Southern Oscillation (ENSO) events were associated with fewer SAW days. We found a statistically significant relationship between the SAW day count and Niño-3.4 using 3-month moving

FIG. 12. Histogram of San Diego SAW event start time lag hours relative to Los Angeles with fitted bimodal Gaussian curve (red). Positive (negative) lag hours indicate events that start in Los Angeles (San Diego) before San Diego (Los Angeles).

averages only. Of these three indices, PDO had the strongest relationship with SAW day count. Although Li et al. (2016) found AMO to have the strongest relationship, PDO more closely matched their SAW time series between 1983 and 1999, which is during the first half of our time series.

The year 2000 has been reported to demarcate a transition to a period when SAW monthly day counts are more closely related to AMO fluctuations compared to PDO (Li et al. 2016). In our Fig. 17, the year 2000 clearly coincides with dramatic changes in PDO and,

arguably, Niño-3.4 behavior. Further, 2000 is shortly after the AMO flip from a mainly cool to an extended warm period. Beginning in 2000, a SAW season day count gradual upward trend persists well into the elevated period reported earlier [also denoted by Li et al. (2016)]. Toward the end of our dataset, after 2014, an end to the elevated period is suggested with more predominantly below normal SAW monthly day counts. Intriguingly, 2014 demarcates a dramatic flip from cool to warm phases for the PDO and Niño-3.4 indices while the AMO amplitude becomes much more variable. We are now leveraging our new SAW climatology, producing 1- and 3-month forecasts of anticipated above/below normal numbers of SAW days. These forecasts are currently utilized by California fire agencies to determine end-of-year staffing levels. Further development of these forecasts is planned, and a future publication is possible that will document the forecast methodology and skill.

To dissect the monthly contributions to the annual elevated SAW day count period, mean changepoint analysis was performed on the SAW day count for each month (using a significance level of 0.05). With the exception of November and December (the middle months of the SAW season), all months entered a predominantly above normal SAW day count later in the entire period. Specifically, years 2001–07 demarcated shifts to a period of mean elevated SAW day counts for October, January, March, April, and May. In contrast, November and December had two time series regimes demarcated by years 1984 and 1986, respectively,

FIG. 13. The 2-m AGL dewpoint depression ($^{\circ}\text{F}$) and 10-m AGL wind barbs (kt; $1 \text{ kt} \approx 0.51 \text{ m s}^{-1}$) across Southern California valid 0800 LST 30 Nov 2008. Red line indicates location of cross section.

FIG. 14. Vertical cross section showing potential temperature contours (K; black lines) and wind vector projection onto cross-barrier vector (color shading) near the Cajon Pass. See Fig. 13 for location of cross section. Valid 0800 LST 30 Nov 2008.

much earlier in the time series with the later and longer period experiencing mean elevated SAW day counts. September, February, and June had no statistically significant time series shifts across the entire period.

A shift in time series variance across this multi-decadal period is also important to detect, having ramifications for, among other things, predictability. For most SAW months, we found no statistically significant contrasting variance regimes except for September and June. Change point analysis based on variance detected shifts to larger variance regimes after 2007 and 2008 for June and September, respectively. This is intriguing given that September and June are the months that begin and end the SAW season, respectively, and, as a result, typically have the fewest SAW days. Thus, recent increases in variance for these months could be indicative of a growing SAW season with future September and June months having more day counts. Whether or not this is a start of a long-term trend or permanent shift is yet to be seen and would be inconsistent with other findings that indicate a future decrease in SAWs (Hughes et al. 2011; Li et al. 2016; Guzman Morales 2018).

Given the varying synoptic-scale SAW atmospheric patterns (or SOM nodes), it is interesting to detect any long-term trends for each SOM node. For each SOM node, we performed both a simple linear regression (testing the linear regression hypothesis) and a Mann–Kendall trend

test to detect any statistically significant (p value < 0.05) long-term trends in the annual frequency. Here we only report nodes with statistically significant trends confirmed using both tests (Figs. 4 and 5, black arrows). The top two most frequent SOM nodes for Los Angeles (12 and 15) have upward trends, which indicate a growing dominance of these node types in the latter part of this period. In fact, all nodes with significant upward trends for both zones have a ridge, varying in amplitude, straddling the eastern Pacific and western United States. In contrast, the only nodes with a downward trend are colder, cutoff low or trough patterns (nodes 7 and 3 for Los Angeles and San Diego, respectively). For all Los Angeles nodes with an upward trend, mean annual count change point analysis indicated a somewhat abrupt shift to an elevated frequency period occurring around or after 2000. Interestingly, this coincides with dramatic shifts in all oceanic indices as reported above.

5. Conclusions

Santa Ana winds (SAWs) can be challenging to define and diagnose due to their spatial and temporal complexity. While many others have studied the climatology and characteristics of such phenomena, our paper offers a unique perspective by examining SAWs in two areas (Los Angeles and San Diego) within Southern California. In doing so, we were able to extract new and

FIG. 15. Vertical cross section showing potential temperature contours (K; black lines) and wind vector projection onto cross-barrier vector (color shading) near the Cajon Pass. See Fig. 16 for location of cross section. Valid 0800 LST 22 Oct 2007.

interesting results (see section 4), which we hope will benefit our readers.

The development of our SAW climatology involved a series of four steps that began with leveraging the Santa Ana Wildfire Threat Index (SAWTI) (Rolinski et al. 2016) to develop an initial 35-yr dataset from LFP_w . This dataset was then complemented using observed MSLP

gradients between the deserts and the coast and SOMs to eliminate residual non-SAW days. We are confident that our distillation process has left us with an accurate (though not perfect) representative climatology of SAWs.

Our climatology shows that there are distinct differences in SAW characteristics between Los Angeles and

FIG. 16. The 2-m AGL dewpoint depression ($^{\circ}\text{F}$) and 10 m AGL wind barbs (kt) across Southern California valid 0800 LST 22 Oct 2007. Red line indicates location of cross section.

FIG. 17. (top) Zone 1 SAW monthly (black bars) and SAW season (red line) standardized day count. The SAW season spans from September to the following June of each year. Seasonal data are plotted at January (the midpoint of the season). Gray shading highlights period of increased SAW activity. (second row) The 3-month moving average standardized PDO with positive (negative) regions shaded red (blue) and 3-month moving average SAW day count (gray line). (third row) The 3-month moving average Niño-3.4 anomalies with positive (negative) regions shaded red (blue) and 3-month moving average SAW day count (gray line). (bottom) The 3-month moving average AMO with positive (negative) regions shaded red (blue) and 3-month moving average SAW day count (gray line; right-hand y axis).

San Diego. Specifically, there are 30% fewer SAW days in San Diego as compared to Los Angeles with more single-day events in San Diego, meaning that SAWs generally last longer across the northern portions of the SAW domain. In addition, the arrival of SAWs in the San Diego area tends to lag the Los Angeles area 80% of the time. Despite these differences, both areas have peak occurrences in January and minima in June.

The highest ranked SAW day in our dataset was 22 October 2007, coinciding with some of the worst fire activity in the state's history. However, even when extreme conditions exist, significant fire activity is infrequent with less than half of the top 10 days associated with large fires. Going a step further, we discovered that large fires occurred less than 10% of the time on SAW days within our 35-yr dataset.

SAW types were briefly evaluated through the use of SOMs. Our 6×5 SOM array would theoretically give us 30 types of events, each of which could be studied in

more detail. Instead we chose to highlight a few of the SOM Z500 nodes that were more frequent than others. In addition, we illustrated the difference in SAW spatial coverage by comparing two events, one associated with a marine layer and the other without. Having the understanding and ability to forecast this aspect of SAWs becomes critical when coastal wildfires are occurring.

Using changepoint analysis, our Los Angeles time series showed several notable shifts in the number of SAW standardized day counts since 1981, with the most significant shift occurring after 2006 when SAW day counts were consistently elevated. This elevated period coincided with the predominantly cool PDO and Niño-3.4 phases and a more variable but decreasing AMO amplitude. Despite differences in our approach and time period examined, we report relationships that are mostly consistent with other studies. It is apparent from this and previous studies that the relationship between SAWs

and the oceanic indices sampled varies depending on the period of interest and magnitude of the index. While these relationships need to be explored further, we are already using them to produce 1- and 3-month ahead forecasts of anomalous SAW activity with some skill. Our changepoint analysis also showed a shift to larger variances in shoulder season months, generally after 2008, which is a trend that will have to be monitored closely. We also showed which SOM nodes were trending up or down, with nodes reflecting significant ridging across California to be increasing in recent years. While large fire occurrence related to SAWs can be infrequent, fires that do occur are often devastating. Our goal moving forward is to maintain our dataset so that it can be used for future research and application to further explore the nuances of this weather phenomenon.

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