

Forecast Skill of Synoptic Conditions Associated with Santa Ana Winds in Southern California

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ABSTRACT

Santa Ana winds (SAW) are synoptically driven mesoscale winds observed in Southern California usually during late fall and winter. Because of the complex topography of the region, SAW episodes can sometimes be extremely intense and pose significant environmental hazards, especially during wildfire incidents. A simple set of criteria was used to identify synoptic-scale conditions associated with SAW events in the NCEP–Department of Energy (DOE) reanalysis. SAW events start in late summer and early fall, peak in December–January, and decrease by early spring. The typical duration of SAW conditions is 1–3 days, although extreme cases can last more than 5 days. SAW events exhibit large interannual variations and possible mechanisms responsible for trends and low-frequency variations need further study. A climate run of the NCEP Climate Forecast System (CFS) model showed good agreement and generally small differences with the observed climatological characteristics of SAW conditions.

Nonprobabilistic and probabilistic forecasts of synoptic-scale conditions associated with SAW were derived from NCEP CFS reforecasts. The CFS model exhibits small systematic biases in sea level pressure and surface winds in the range of a 1–4-week lead time. Several skill measures indicate that nonprobabilistic forecasts of SAW conditions are typically skillful to about a 6–7-day lead time and large interannual variations are observed. NCEP CFS reforecasts were also applied to derive probabilistic forecasts of synoptic conditions during SAW events and indicate skills to about a 6-day lead time.

1. Introduction

Southern California is characterized by complex topography that fundamentally influences the climate of the region. During fall and winter, a downslope flow known locally as the Santa Ana winds (SAW) occasionally affects Southern California (Lea 1969; McCutchan and Schroeder 1973; Small 1995; Raphael 2003; Hughes and Hall 2009). A surface high pressure system over the Great Basin and a low pressure system offshore of Southern California

induce a synoptic pressure gradient that drives surface winds into the Los Angeles Basin from the northeast quadrant (Whiteman 2000). The winds can squeeze through the Santa Clara River Valley and the Cajon and Banning Passes that open to the Los Angeles Basin, with wind speeds that can reach hurricane strength in some locations (Fig. 1). During SAW occurrences, it has been noted that offshore flow can sometimes appreciably extend to adjacent waters of the California Bight and parts of Baja California with strong surface wind jets, dust, and wildfire smoke plumes, substantially modifying thermodynamical, upwelling, and biophysical processes within the coastal waters (Lynn and Svejksky 1984; Castro et al. 2003; Hu and Liu 2003; Trasvina et al. 2003; Sosa-Avalos et al. 2005; Castro et al. 2006).

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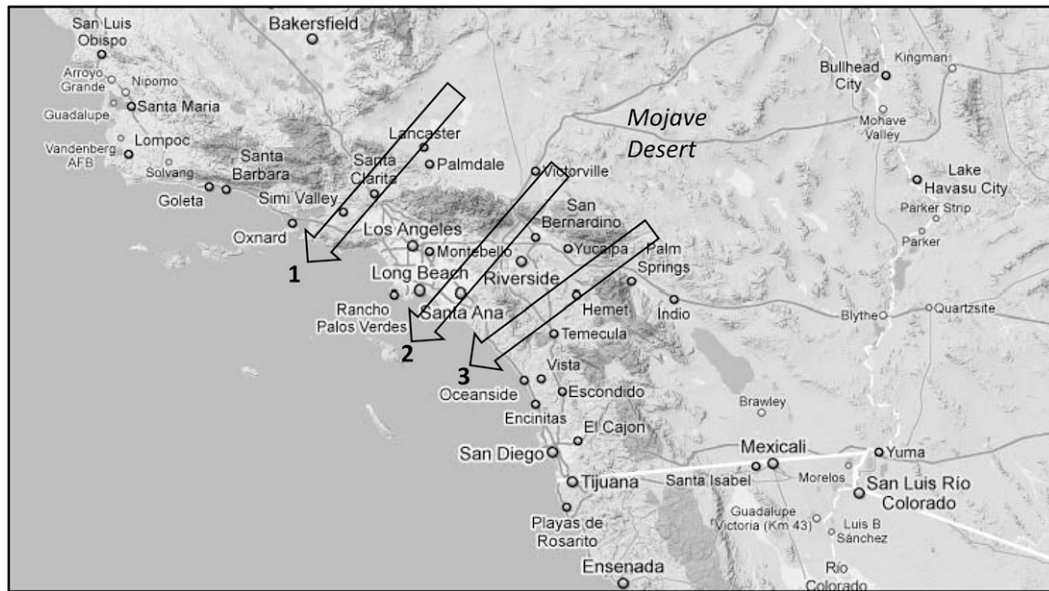


FIG. 1. Geographic features of Southern California. Shading indicates orography and arrows the main regions where Santa Ana winds are typically intense: 1) Santa Clara River Valley, 2) Cajon Pass between San Gabriel and the San Bernardino Mountains, and 3) Banning Pass between San Bernardino and the San Jacinto Mountains.

Previous studies based on weather station data and/or coarse synoptic weather charts have shown that SAW occurrences are more frequent in fall and winter months with peak activity in December and January. Usually, offshore winds tend to pick up in the morning hours during SAW events and may persist throughout the day unless interactions with sea-breeze circulations occur. Climatological studies of SAW include Raphael (2003), who used 33 yr of daily weather maps and a subjective method to identify SAW occurrences. Conil and Hall (2006) performed simulations with a mesoscale numerical model and employed an objective classification scheme to demonstrate that SAW is one of three distinct modes of weather regimes in Southern California.

One of the most notorious environmental hazards associated with SAW is wildfire (Schroeder and Buck 1970; Small 1995; Westerling et al. 2003). The intense downslope winds frequently become hot and dry descending to lower elevations, rapidly increasing the ignitability of fuels and the spread of fire so as to make predictions of wildfire behavior and fire fighting extremely difficult (Schroeder et al. 1964, 264–274; Ryan 1969; Minnich 1987; Keeley and Fotheringham 2001; Moritz 2003; Westerling et al. 2003; Keeley et al. 2004; Miller and Schlegel 2006). Transport of wildfire smoke and desert dust can also dramatically alter visibility and air quality with serious health, social, and economic consequences (Svejkovsky 1985; Reheis and Kihl 1995; Corbett 1996; Lu et al. 2003; Westerling et al. 2003; Phuleria et al. 2005; Wu et al. 2006).

This paper is part of an ongoing research effort to further understand the dynamics and predictability of SAW and its local environmental impacts such as wildfires and interactions with coastal waters of Southern California. Here we focus on the synoptic-scale conditions that lead to Santa Ana winds; namely, the development of the surface high pressure over the Great Basin, surface low pressure off the coast of Southern California, and northeasterly winds over the Los Angeles Basin. Three specific objectives focus on aspects of SAW at the synoptic scale. First, the climatological properties of the synoptic-scale conditions associated with SAW are assessed. This is accomplished using the National Centers for Environmental Prediction–Department of Energy (NCEP–DOE) reanalysis and a climate run of the NCEP Climate Forecast System (CFS) model. Second, the forecast skill of synoptic-scale conditions associated with SAW is investigated. Ideally, one would like to investigate this problem using a large sample of forecasts derived from an operational numerical weather prediction model with high spatial resolution. Although NCEP routinely uses several mesoscale forecast models [e.g., North American Mesoscale (NAM), 12 km; Rapid Update Cycle (RUC), 13 km and 20 km], publicly available forecasts from these models are limited to less than 3 yr of data (see online at <http://nomads.ncdc.noaa.gov>). In addition, occasional changes in data assimilation and physical parameterizations in the operational models make evaluation of forecast skill more complicated. For these reasons, the forecast skill of synoptic-scale conditions

associated with SAW is evaluated here using 28 yr of NCEP CFS reforecasts (CFSR). Third, this paper compares the skills of nonprobabilistic and probabilistic forecasts of synoptic conditions associated with SAW events. The paper is organized as follows. Section 2 describes the datasets used in this research. Section 3 discusses the statistical characteristics of SAW in the observations and climate run of the CFS model. The methodology to produce forecasts of SAW conditions and forecast evaluation are presented in section 4. Section 5 summarizes the main conclusions of this study.

2. Data

Synoptic conditions associated with SAW events and their climatological characteristics were studied with sea level pressure and surface zonal and meridional wind components (10 m above terrain) from the NCEP–DOE global reanalysis II (Kanamitsu et al. 2002). The NCEP–DOE reanalysis updated the NCEP–National Center for Atmospheric Research (NCAR) reanalysis (usually known as reanalysis I). The NCEP–DOE data are also available at the same spatial and vertical resolution and 6-hourly intervals as reanalysis I. Most importantly, the NCEP–DOE reanalysis fixed known human errors contained in the reanalysis (Kanamitsu et al. 2002). In this study, daily averages from 1979 to 2008 were used at 2.5° latitude–longitude resolution. Since the NCEP–DOE reanalysis has low resolution, climatological characteristics of SAW events were further described with the North American Regional Reanalysis (NARR; Mesinger et al. 2006). The NARR dataset derives from first-guess forecasts with the NCEP Eta regional numerical model and a comprehensive data assimilation system. The Eta model used 32-km horizontal grid spacing and 45 vertical layers to produce meteorological fields at 3-h intervals. Lateral boundary conditions for the Eta first-guess forecasts came from the NCEP–DOE reanalysis 2. The NARR domain covers all of North America, Greenland, Central America, and parts of northern South America. An important improvement of NARR relative to previous global reanalyses was the assimilation of precipitation from rain gauges over the United States, Canada, and Mexico and satellite-derived precipitation over the oceans. Daily averages of zonal and meridional components of the wind at 10 m (U , V), temperature at 2 m (T), relative humidity at 2 m (RH), and precipitation (P) for the period 1979–2008 were used.

Forecasts of synoptic conditions associated with SAW were developed in this study with NCEP CFSR. A comprehensive discussion of the CFS model version 1

and reforecasts is provided by Saha et al. (2006). The NCEP–DOE reanalysis and the NCEP Global Ocean Data Assimilation System (GODAS) were used to provide atmospheric and oceanic initial conditions for the reforecasts. NCEP uses CFSR runs to calibrate and evaluate the skill of seasonal forecasts. Each run consists of a full 9-month integration. The reforecasts cover the entire year and are available from 1981 to 2008.

Each ensemble run is based on 15 initial conditions (ICs) spanning each month. The first 5 ICs are on the 9th–13th; the second 5 ICs are on the 19th–23rd; and the last 5 ICs are on the second-to-last day of the month, the last day of the month, and the first, second, and third days of the next month. The dates of ICs were selected to coincide with the generation of real-time atmospheric and oceanic fields and to stay within computing requirements (see Saha et al. 2006 for details). This study focuses on daily fields of sea level pressure (SLP) and 10-m surface winds from 1981 to 2008 and at lead times of 1–28 days. The NCEP–DOE reanalysis was used to validate the CFS forecasts of synoptic conditions associated with SAW events.

The climatological characteristics of SAW events were additionally examined in a Coupled Model Intercomparison Project (CMIP) run of the CFS model. Daily averages of SLP, U , and V at 10 m were used for a total of 32 yr. Additional details are discussed in Wang et al. (2005).

3. Climatology of synoptic conditions during SAW events

In this section, we analyze the climatological characteristics of SAW conditions in the observations (i.e., NCEP–DOE reanalysis) and CMIP run of the CFS model. The definition adopted here for synoptic-scale conditions associated with SAW events is the simplest possible and includes the essential ingredients of high surface pressures over the Great Basin, low surface pressures off the coast of Southern California, and northeasterly winds over the Los Angeles Basin.

The identification of SAW days was done in the following way. For any given day, the spatial mean of SLP was subtracted from the daily SLP map to generate anomalies in the domain (30°–50°N, 130°–100°W). That day was considered a SAW event if all of the following three conditions were satisfied:

- 1) At least 30% of the Great Basin domain (35°–45°N, 120°–107.5°W) had positive SLP anomalies.
- 2) The domain off the coast of Southern California (30°–35°N, 120°–115°W) had negative SLP anomalies.

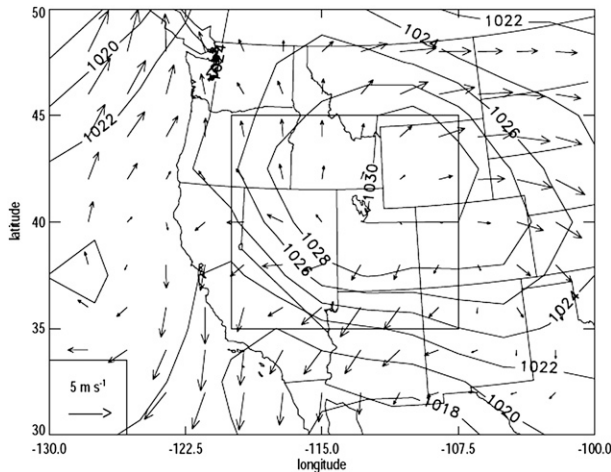


FIG. 2. Composites of sea level pressure (contours) and 10-m surface winds (vectors). Composites are for 936 days of Santa Ana wind conditions identified with NCEP–DOE reanalysis (1979–2008). The inset shows the scale for vectors. The contour interval is 2 hPa. The square region (thick lines) indicates the Great Basin domain.

- 3) Surface winds over the Los Angeles Basin (32.5°–35°N, 117.5°–115°W) were from the northeast quadrant (wind direction between 0° and 90°). This location corresponds to one grid point from the NCEP–DOE reanalysis located over the Los Angeles Basin.

The definition of SAW was applied to the NCEP–DOE reanalysis fields (1981–2008) and a 32-yr run of the CMIP CFS model. For both datasets, synoptic conditions associated with Santa Ana winds were identified when all three conditions above were met. Note that this study focuses on the synoptic-scale conditions associated with SAW events and, given the low spatial resolution of the reanalysis and CFS, the above conditions do not resolve mesoscale-to-local features related to SAW. Furthermore, in order to include synoptic conditions associated with weak and very intense SAW events, the definition above does not impose a priori cutoff thresholds on SLP gradients and surface winds. The criteria above ensure that the statistics analyzed here include a wide range of synoptic-scale conditions that define SAW events. It is important to note, however, that from the wildfire management perspective, one would like to include surface wind speeds and relative humidity in the definition of SAW events, given their substantial influence on wildfire behavior. Unfortunately, surface relative humidity from the CMIP CFS run and CFS reforecasts were not available to this study.

While criteria I–III could also have been applied to NARR, the resolution of the NARR data would have to be degraded (to 2.5° latitude–longitude) for the analysis

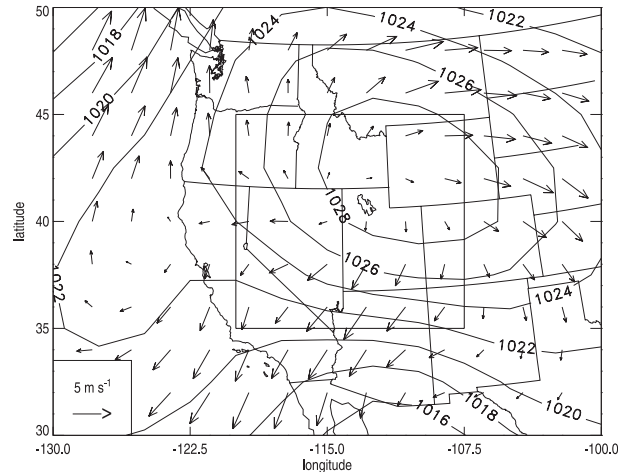


FIG. 3. As in Fig. 2, but for synoptic conditions associated with Santa Ana winds identified from CFS climate run. The total number of days is 1181.

to be consistent with the CFS CMIP run and CFSR forecasts. We recall also that CFS reforecasts were initialized with NCEP–DOE reanalysis. Last, while different criteria have been proposed for SAW events (Small 1995; Raphael 2003; Conil and Hall 2006; Hughes and Hall 2009), the definition above allows a simple methodology to analyze the climatological characteristics and forecast skill of basic SAW conditions.

Figure 2 shows the observed composite pattern of SAW events with high SLP over the Great Basin (exceeding 1030 hPa), low SLP off the coast of Southern California, and northeasterly winds over the Los Angeles Basin. The climatology of SAW conditions in the CFS (Fig. 3) compares relatively well with the observations, although some differences are apparent. The maximum SLP over the Great Basin is less than in the observations. In addition, the southwest–northeast gradient in SLP is stronger in the observations than in the CFS model. Other systematic biases in the CFS model are discussed in the next section.

Figure 4 (top) shows the monthly mean number of independent SAW events in the observations and CFS climate run. An independent event is defined as one or more consecutive days of SAW conditions and separated from other occurrences by at least 1 day. The observed mean number of SAW events is consistent with previous studies and shows an increase in October, maximum in December–January, and decrease by April–May. The distribution of SAW events in the CFS model follows the same pattern, although it tends to underestimate the frequency of events. In addition, the observations show that SAW events (Fig. 4, bottom) typically last between 1 and 3 days (about 76% of the distribution) and, on rare

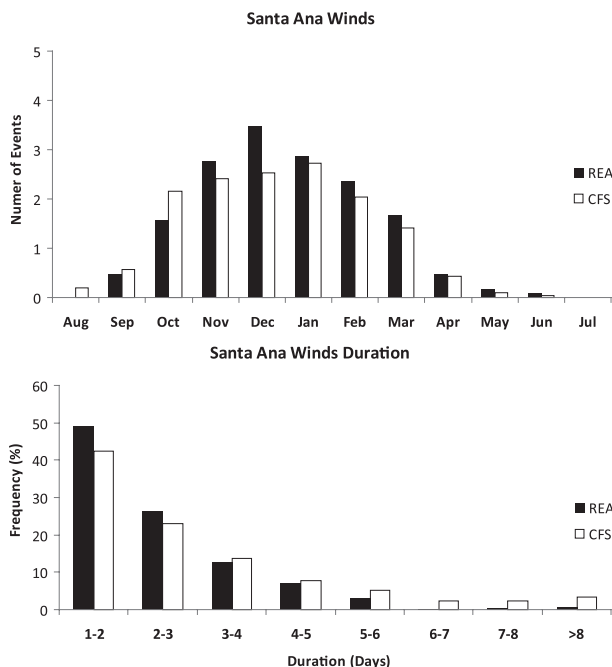


FIG. 4. (top) Mean number of Santa Ana wind events per month. (bottom) Frequency distribution of duration of events. The dark bars refer to NCEP–DOE reanalysis and the clear bars refer to the CFS climate run.

occasions, they last more than 5 consecutive days. The durations of SAW events in the CFS model agree well with the observations, with differences less than 7%.

The SLP difference between the Great Basin and Southern California during SAW events was investigated in the following way. For each event, the difference between SLP at each grid point in the Great Basin domain and the grid point in the Los Angeles Basin was computed. Figure 5 shows the frequency distributions of the maximum SLP difference between the Great Basin and Southern California for both NCEP–DOE reanalysis and CFS CMIP run. Both distributions have positive skewness and the CFS model overestimates maximum SLP differences between 5 and 15 hPa and underestimates maximum SLP differences larger than 15 hPa.

The observed interannual distribution in the occurrence of SAW events (Fig. 6) shows large variations ranging from a minimum of 8 events in 1995–96 to a maximum of 26 events in 1987–88 and 25 events in 2007–08. An important question is whether low-frequency modes of large-scale variability in the climate system can considerably modulate seasonal occurrences of SAW. One possible candidate is the El Niño–Southern Oscillation (ENSO), which is the most significant mode of interannual variability. Based on data from 1968 to 2000, Raphael (2003) suggested that most warm ENSO cases

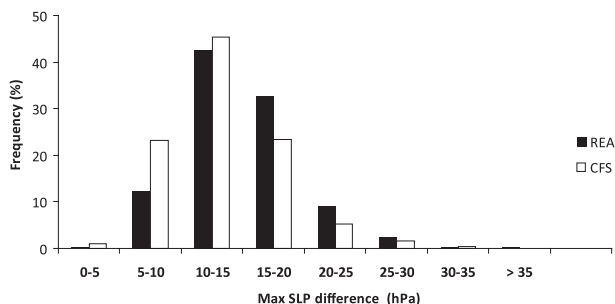


FIG. 5. Frequency distribution of maximum sea level pressure difference between the Great Basin (35°–45°N, 120°–107.5°W) and Southern California (30°–35°N, 120°–115°W) domains. The dark bars refer to the NCEP–DOE reanalysis and the clear bars refer to CFS climate run.

tend to be associated with below-average frequency of Santa Ana events. In that study, time series of Southern Oscillation index (SOI) were not well correlated with seasonal frequency of Santa Anas during September–April. However, Raphael (2003) argues that significant positive correlations are found in February and March, which indicates that possible modulations of ENSO on SAW events are more likely to be found late in the season. Differences in methodology, datasets, and the small sample size (28 yr) used in our study make the comparison difficult to infer statistically significant relationships between SAW and ENSO.

Since the low horizontal resolution of the reanalysis does not resolve mesoscale features associated with SAW in Southern California, composites based on NARR data were also computed for the SAW days identified previously. The events used in the composites were identified with NCEP–DOE reanalysis. To characterize wildfire potential associated with SAW, we calculated the Fosberg Fire Weather index (FWI; Fosberg 1978) under Santa Ana conditions. Historically, FWI was developed to track the diurnal variability and short-term impacts of weather on wildfire potential and wildfire management (Goodrick 2002). FWI is a nonlinear filter in which surface temperature and humidity are used to compute equilibrium moisture content, which is then combined with wind speed to approximate flame length as suggested by Byram (1959). FWI assumes a fine fuel type but does not include information about fuels on the landscape, in contrast to the National Fire–Danger Rating System (Cohen and Deeming 1985). Specifically, FWI is calculated as

$$\text{FWI} = \frac{\sqrt{1 + V^2}}{0.3002} (1 - 2a + 1.5a^2 - 0.5a^3), \quad (1)$$

where V is surface wind speed (in mph) and a is the equilibrium moisture content given by

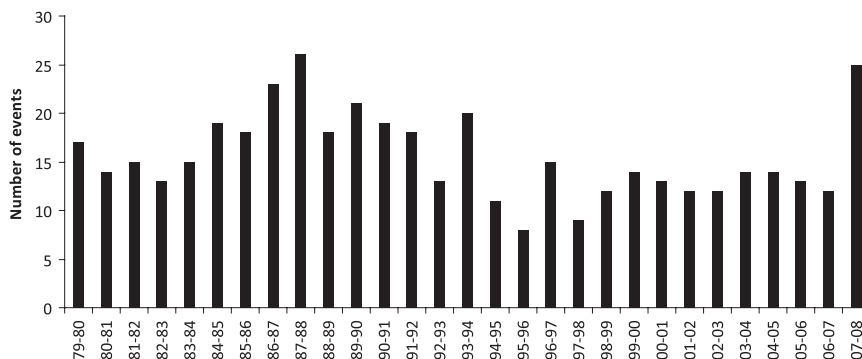


FIG. 6. Interannual distribution of number of Santa Ana wind events. Events were identified with the NCEP–DOE reanalysis and counted from 1 Sep to 30 Apr of the following year.

$$a = \begin{cases} -0.03229 + 0.281073RH - 0.000578TRH & \text{if } RH < 10 \\ 2.22749 + 0.160107RH - 0.01478T & \text{if } 10 \leq RH < 50, \\ 21.0606 + 0.005565RH^2 - 0.00035TRH - 0.483199RH & \text{if } RH \geq 50 \end{cases} \quad (2)$$

where RH is relative humidity (%) and T is surface temperature ($^{\circ}\text{F}$). Here, if the hourly precipitation $P \geq 0.25$ mm, then $a = 30$. FWI is defined to range between 0 and 100, so that FWI values greater than 100 are set to 100. Typically, if temperatures are above 60°F , RH less than 20%, and sustained surface winds above 20 mph, FWI values are above 50. The NCEP Storm Prediction Center uses this value as the minimum threshold for critical fire weather conditions (Taylor et al. 2003).

Figure 7 shows the composite of FWI patterns during synoptic conditions that lead to SAW events. The overall pattern indicates that NARR realistically characterizes northeasterly winds over most of the mountains and coastal areas over Southern California. Although the resolution of NARR is not high enough to resolve terrain features that influence SAW, it nevertheless shows the intensification of wind speeds from the Mojave Desert toward the coast. In particular, intense

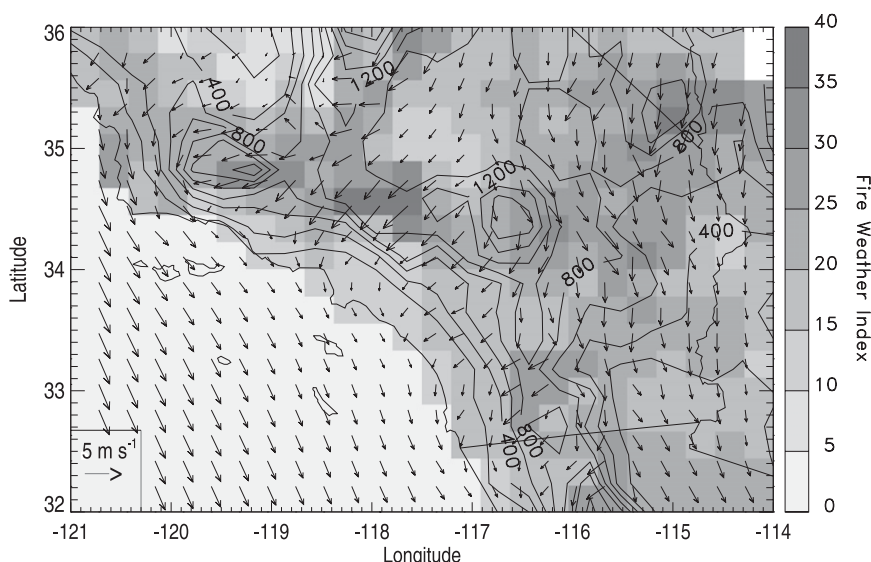


FIG. 7. Composite of Santa Ana winds represented by NARR data. A total of 936 Santa Ana wind days were identified with NCEP–DOE reanalysis. The vectors indicate 10-m surface winds and the shading indicates the fire weather index. The inset shows the scale for vectors. The contours indicate an elevation at a 200-m interval.

surface winds are seen over the Santa Clara River Valley to the southeast of the San Rafael Mountains, in the San Gabriel Mountains, and in a small area farther south near San Diego and Imperial Counties. Note also that since criteria I–III do not involve thresholds in SLP differences and surface wind speeds, the composite includes a broad range of weak-to-intense SAW events, and FWI values are typically 30–40 over the main mountain passes.

An apparent limitation of the low resolution of NARR is that it depicts SAW from an unlikely northwest direction over most of the coastal waters. In contrast, Kanamitsu and Kanamaru (2007) produced a 57-yr California Reanalysis Downscaling at 10 km (CaRD10) using a regional spectral model forced with initial and boundary conditions from the NCEP–DOE reanalysis (Kanamitsu et al. 2002). Their comparison of NARR and CaRD10 for one case study showed that the 10-km resolution extended northeasterly winds offshore of Southern California (Kanamaru and Kanamitsu 2007), a result dramatically illustrated by smoke plumes that extended southwestward from fires in Southern California under Santa Ana conditions (see their Fig. 4). Moreover, CaRD10 air temperature anomalies at 2 m indicated greater warming than NARR on the lee side of the coastal mountains.

Likewise, Hu and Liu (2003) compared ocean surface winds from the Quick Scatterometer (QuikSCAT) satellite data and NCEP Eta model (12-km grid spacing) during an intense SAW event. While the NCEP Eta model was successful in predicting offshore winds over Southern California, there were considerable discrepancies between the forecast winds and QuikSCAT winds over the oceans. The Eta model predicted less intense and alongshore surface winds. They speculated that the differences were likely associated with the vertical coordinate used in the NCEP Eta model (also used in NARR). According to Gallus and Klemp (2000), the step-terrain coordinate used in the NCEP Eta model cannot properly simulate downslope flow because, instead of descending, the flow separates downstream of the mountain and produces a zone of artificially weak flow.

4. Forecasts of synoptic-scale conditions during Santa Ana winds

In this section, we examine in detail the forecast skills of synoptic-scale conditions associated with SAW. The focus here is on the period 1 October–31 March, when SAW activity is highest. The first task was to assess the forecast bias in the CFS model (Saha et al. 2006). This was accomplished by computing the mean systematic error between CFS and NCEP–DOE reanalysis for each lead time of 1–28 days during the period 1 October–31

March. Figure 8 shows the mean model bias in SLP averaged during October–March and lead times of 1–4 weeks. In general, the model bias is less than ± 1 hPa over most of the western United States. The model bias shows positive values over California, Arizona, and parts of Nevada, Utah, and New Mexico, and negative values elsewhere. Likewise, the CFS model bias in the surface zonal U and meridional V wind components were computed and indicate an anticyclonic bias centered over central California (Fig. 9). In general, the model bias in surface winds is on the order of 1 m s^{-1} or less. Presumably because of the small model climate drift on short time scales, the model bias also does not change significantly during weeks 1–4.

a. Nonprobabilistic forecasts of synoptic-scale conditions during SAW events

Nonprobabilistic forecasts of synoptic conditions associated with SAW were evaluated by cross validation (Wilks 2006). For each extended winter season (October–March) during 1981–2008, the mean model bias was subtracted from the forecasts of SLP and surface winds with a “one out approach,” that is, that season was excluded from the computation of mean model bias [see Saha et al. (2006) for additional discussion]. Next, the forecasts of SLP and surface winds were analyzed for each validation day during 1 October–31 March and lead time 1–28 days. If criteria I–III (section 3) were met, the forecast was “yes”—synoptic-scale conditions indicated SAW development at that lead time. If the conditions were not met, the forecast was “no,” indicating no conditions for SAW development. The observed records of SAW occurrences derived from NCEP–DOE reanalysis (section 3) were used to validate the forecasts.

The total number of pairs of forecasts–observations for each lead time of 1–28 days varied between 2430 and 2457 because the CFS reforecasts were initialized in groups of 5 consecutive days separated by 5 days. The pairs of forecasts–observations were aggregated into a 2×2 contingency table and several forecast skill measures computed [Table 1; see Wilks (2006) for details]. Figure 10 shows some skill score measures. The forecast bias as a function of lead time (Fig. 10a) indicates that nonprobabilistic forecasts derived from CFS reforecasts tend to overforecast the synoptic conditions associated with SAW events (unbiased forecasts have bias equal to 1). It is interesting to note that the forecast bias increases almost linearly from 1- to 13-day lead time.

As a measure of forecast accuracy, Fig. 10b shows the proportion of forecasts correctly indicating a maximum of 0.71 at a 1-day lead, steadily decreasing to about 0.39 at an 11-day lead and remaining in the range of 0.34 for long lead times. The threat score (Fig. 10c) starts from

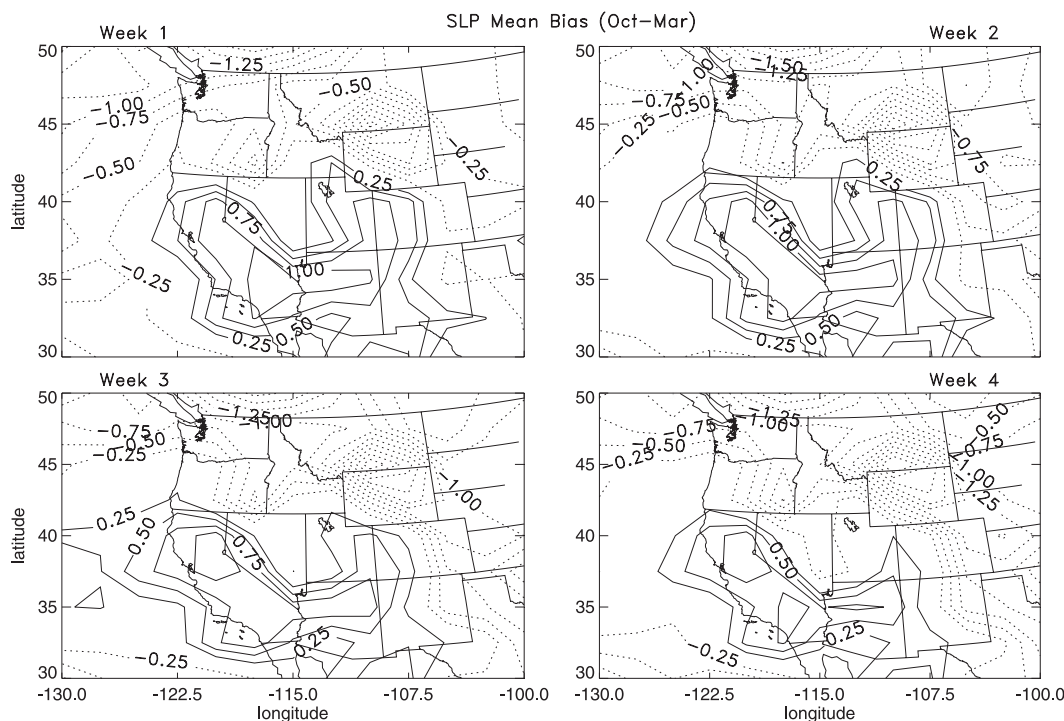


FIG. 8. CFS mean model bias in sea level pressure (hPa; CFS minus NCEP–DOE reanalysis). The model bias was averaged during October–March and shows the mean at 1–4-week lead times. The contour interval is 0.25 hPa and the zero line is omitted.

0.60 for a 1-day lead and decreases rapidly to 0.21 at an 11-day lead time. The false alarm ratio measures the reliability of the forecasts (Fig. 10d) and shows a value of 0.38 at a 1-day lead, increasing to 0.76 at a 9-day lead, and then becoming nearly constant afterward.

The Heidke skill score (HSS) is a forecast skill metric frequently used to summarize the results of nonprobabilistic forecasts; it measures the normalized proportion of correct forecasts after eliminating those forecasts that would be correct just by chance (Wilks 2006). Perfect forecasts have $HSS = 1$ and forecasts with no skill have $HSS = 0$. The HSS (Fig. 11) starts at ~ 0.45 for 1-day lead and decreases to 0 at 9-day lead time.

The CFS model forecast skill of SAW conditions was further evaluated by considering two pairs of forecasts and observations. The first one is the maximum sea level pressure difference between the Great Basin and the Los Angeles Basin, while the second is the surface wind speeds in the Los Angeles Basin. Figure 12 (top) shows correlations between forecasts and observations. The correlations start from about 0.7 at a 1-day lead and drop to about 0.2 at ~ 7 -day lead time. Likewise, the root-mean-square error between forecasts and observations (Fig. 12, bottom) indicates errors of about 3 hPa

at a 1-day lead in the maximum sea level pressure difference, increasing almost linearly to ~ 6 hPa at a 6-day lead time. The errors in the surface wind speed grow from 2.6 m s^{-1} at a 1-day lead to 3.1 m s^{-1} at a 7-day lead.

Taken together, the metrics above suggest that nonprobabilistic forecasts of synoptic-scale conditions that lead to SAW development have some skill up to about a 6–7-day lead time. Interannual variations in HSS were further investigated by computing the score for each extended winter season separately (Fig. 13). $HSS \geq 0.2$ extends to about a 5-day lead time during most seasons, while positive HSS values are still observed at a 9–12-day lead time in some seasons. The large interannual variations in HSS reflect the interannual variability in the frequency of synoptic conditions associated with Santa Ana winds. As previously discussed, ENSO can partially explain some of the interannual variations in SAW activity (Raphael 2003).

The results above emphasize the challenge of obtaining accurate medium-to-extended range forecasts of conditions conducive to dangerous wildfires in Southern California. Additional study of high-resolution mesoscale numerical models to provide detailed spatiotemporal structures of SAW events is needed.

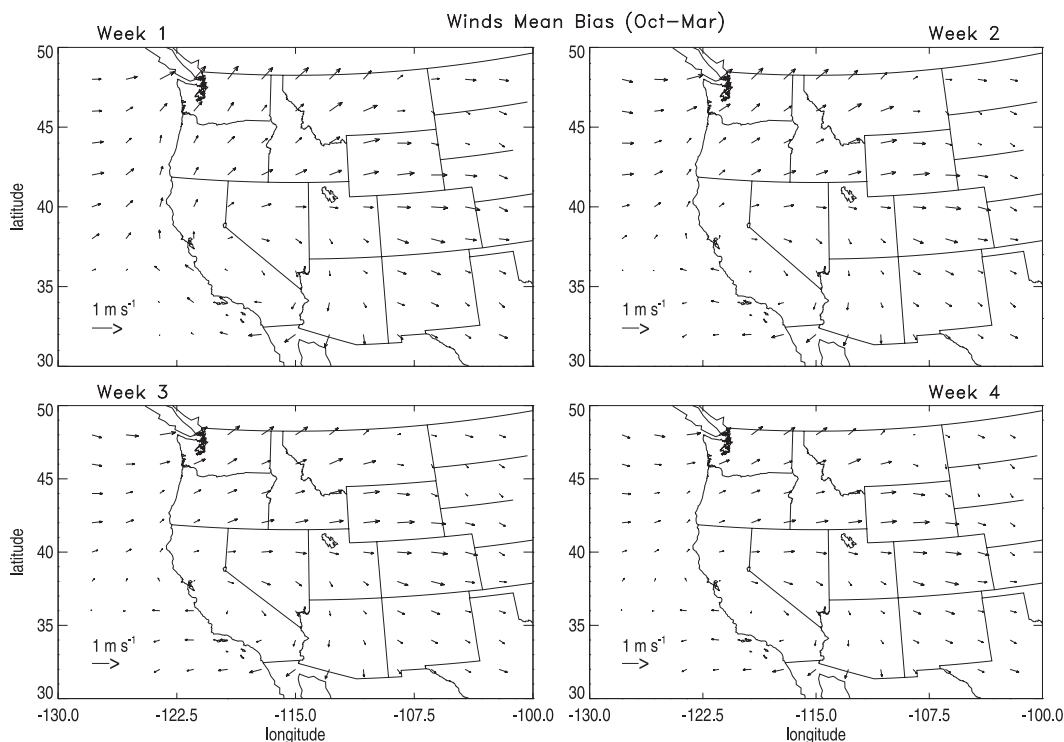


FIG. 9. CFS mean model bias in 10-m surface winds (CFS minus NCEP–DOE reanalysis). The model bias was averaged during October–March and shows the mean at 1–4-week lead times. The inset shows the scale for the vectors.

b. Probabilistic forecasts of synoptic-scale conditions during SAW events

Probabilistic forecasts of SAW conditions were developed in the following manner. As before, for each SAW season (October–March) during 1981–2008, the mean model bias was subtracted from the forecasts of SLP and surface winds with a “one-out approach.” Next, each group of five consecutive ICs was taken together and used to compute the probability of SAW development. For example, the ensemble members initialized on the 9th–13th of each month were taken as one group. The lead times were considered relative to the ensemble member initialized in the middle of the group (i.e., the 11th of each month) and probabilistic forecasts computed for 1–28-day lead times. This approach essentially represents errors in the initial conditions by taking forecasts initialized at different times but verified at a same time together. The same procedure was followed for the other two groups of 5 consecutive days of ICs. Because of the design of the NCEP CFS reforecasts being initialized in groups of 5 consecutive days separated by 5 days, probabilistic forecasts at a 1–2-day lead are not available.

The criteria I–III (section 3) of synoptic-scale conditions for SAW development were applied to each forecast

member in the group. Thus the probability of SAW conditions at each lead time was computed as

$$y_k = \frac{\text{number of members forecasting SAW}}{\text{total number of forecast members in the group}} \quad (3)$$

Note that since each group has five members, the forecast probabilities have six possible values: 0.0, 0.2, . . . 1.0.

TABLE 1. Contingency table of forecasts and observations and measures of forecast skill.

		Obs	
		Yes	No
Forecast	Yes	<i>a</i>	<i>b</i>
	No	<i>c</i>	<i>d</i>
Forecast bias	$B = (a + b)/(a + c)$		
Proportion of correct	$PC = (a + d)/n$		
Threat score	$TS = a/(a + b + c)$		
False-alarm ratio	$FAR = b/(a + b)$		
HSS	$HSS = 2(ad - bc)/[(a + c)(c + d) + (a + b)(b + d)]$		
Total No. of pairs	$n = a + b + c + d$		

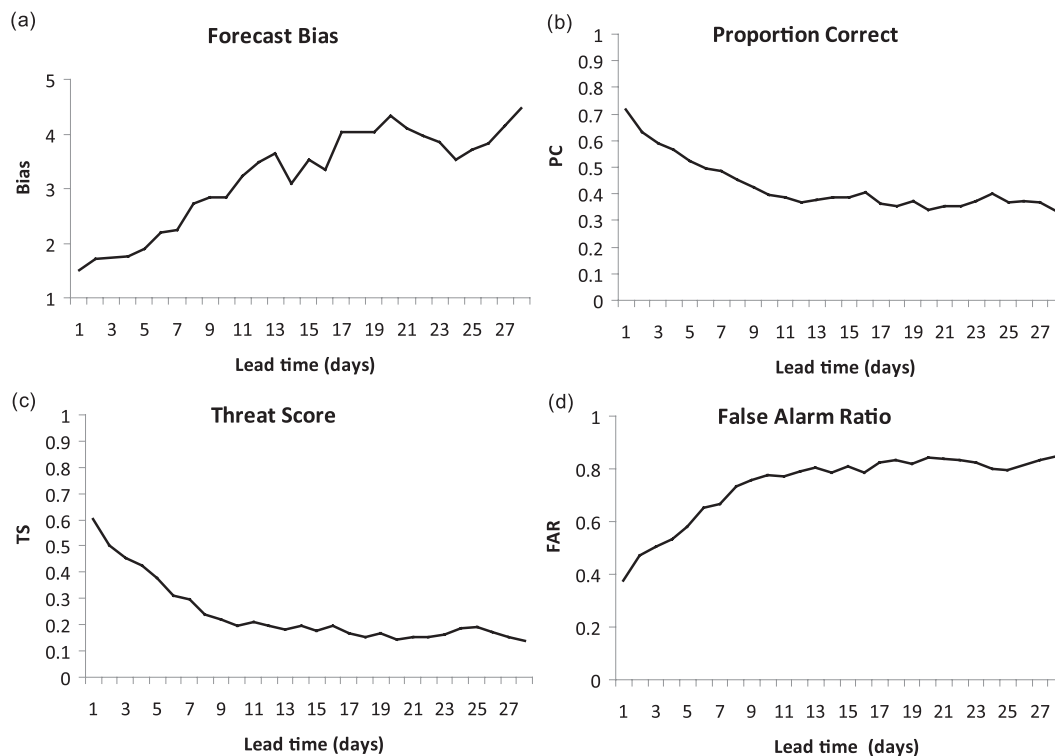


FIG. 10. The skill of nonprobabilistic forecasts of synoptic conditions associated with Santa Ana winds: (a) bias, (b) proportion of correct, (c) threat score, and (d) false alarm ratio. Forecasts were performed with CFS model and verified against the NCEP–DOE reanalysis.

The probabilistic forecasts were validated using the Brier skill score (BSS) defined as

$$\text{BSS} = \frac{\text{BS}}{\text{BS}_{\text{Ref}}},$$

$$\text{BS} = \frac{1}{n} \sum_{k=1}^n (y_k - o_k)^2,$$

$$\text{BS}_{\text{Ref}} = \text{clim}(1 - \text{clim}), \quad (4)$$

where BS is the Brier score, y_k is the forecast probability, o_k is the observation (1 = SAW, 0 = no SAW), and clim is the probability of SAW event in any given day, which was estimated from the frequency of SAW occurrences (clim = 0.16).

Figure 14 shows BSS as a function of lead time and indicates that probabilistic forecasts of SAW conditions derived from CFS reforecasts have about 24% improvement over climatological forecasts at a 3-day lead. The skill drops quickly to 3%–5% improvement at a 5–6-day lead. This result might seem surprising when compared to the forecast skill of nonprobabilistic forecasts, which extends to about a 6–7-day lead (e.g., Fig. 11). In fact, the decay in skill of probabilistic forecasts of SAW is partially related to the application of CFS

reforecasts to this particular phenomenon. The meteorological conditions associated with SAW development have time scales of a few days (i.e., synoptic scale). We recall that the CFS reforecast members were performed in groups of 5 consecutive days separated by 5 days. Thus, the forecast skill of members in the same group at a given lead time is different, since they were initialized

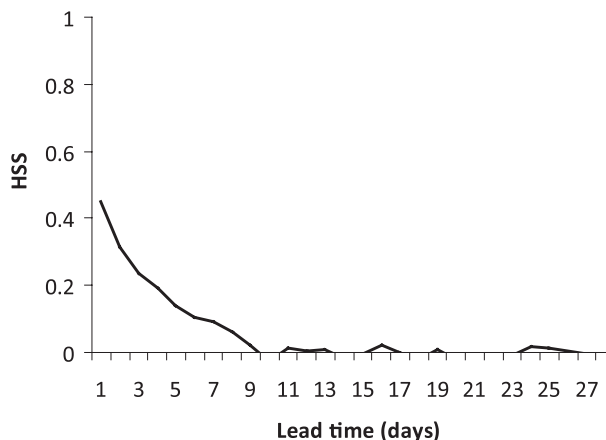


FIG. 11. HSS of forecasts of Santa Ana wind conditions.

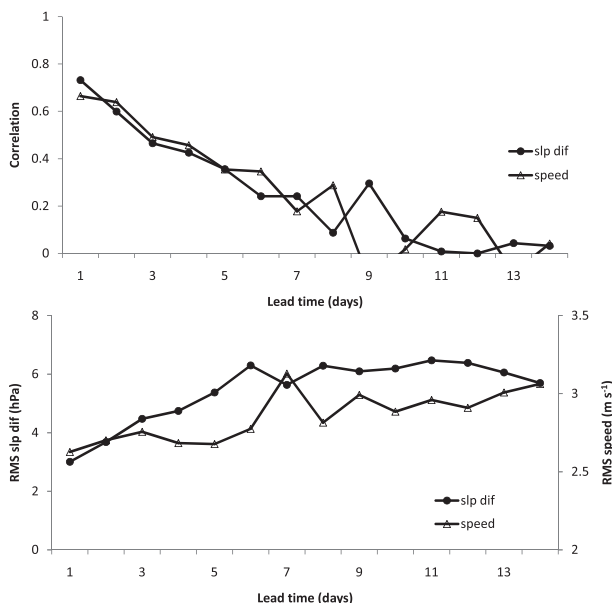


FIG. 12. (top) Correlations between forecasts and observations of maximum sea level pressure difference (slp dif) between the Great Basin and Southern California and surface wind speeds in the Los Angeles Basin (speed). (bottom) As in (top), but for rms differences in sea level pressure differences (hPa) and wind speeds (m s^{-1}). Forecasts are from the CFS model and verification is from the NCEP–DOE reanalysis.

on different days. Ideally, one would like to construct ensemble members in which each day would have perturbations in the initial conditions of that day, and those members used for probabilistic forecasts. As discussed by Saha et al. (2006), in addition to the enormous computational requirements needed to create the reforecasts, the primary purpose was to calibrate the CFS model for seasonal forecasts.

To complement the evaluation of probabilistic forecasts, calibration characteristics are shown in attributes diagrams for four lead times (Fig. 15). At a 3-day lead, the forecasts are moderately calibrated and exhibit characteristics of overforecasting, since the probabilities are too large relative to the conditional frequency of observations (1:1 line). The refinement distributions $p(y)$, shown in parentheses, are highest at low probabilities consistent with the small frequency of SAW events and indicate high forecast confidence (Wilks 2006). As the lead time increases, the resolutions of the probabilistic forecasts decay such that the curves of observed relative frequencies approach the no-resolution line at a 7–9-day lead.

5. Discussion and conclusions

Santa Ana winds are distinct mesoscale features in Southern California during the fall and winter seasons.

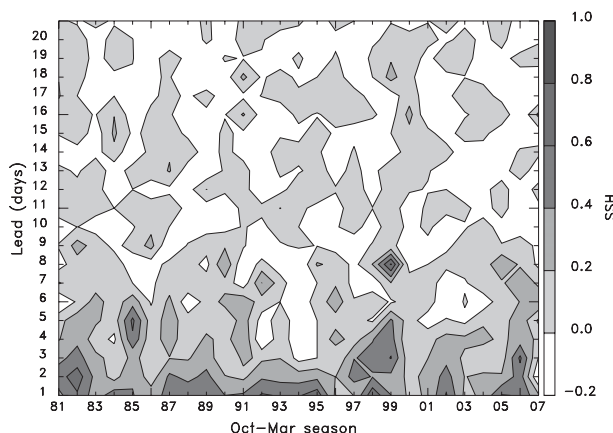


FIG. 13. Interannual variations in HSS. Forecasts are from the CFS model and verification is from the NCEP–DOE reanalysis.

The synoptic-scale conditions characteristic of SAW events are the development of high surface pressures over the Great Basin, low surface pressures off the coast of Southern California, and surface winds from the northeast quadrant over the Los Angeles Basin. Because of the complex topography, SAW can reach extremely high speeds and low relative humidity and pose a number of environmental hazards to local communities. Occurrences of SAW are particularly dangerous during wildfire incidents because strong dry winds enhance fire intensity and spread. This study investigated the climatological characteristics of synoptic conditions associated with SAW in the NCEP–DOE reanalysis and NCEP CFS model. A simple set of criteria was used to identify synoptic conditions associated with SAW. Consistent with other studies, SAW starts in late summer and early fall, peaks in December–January, and decreases by early spring. The typical duration of SAW conditions is 1–3 days, although extreme cases can last more than 5 days. In addition, SAW events exhibit large interannual

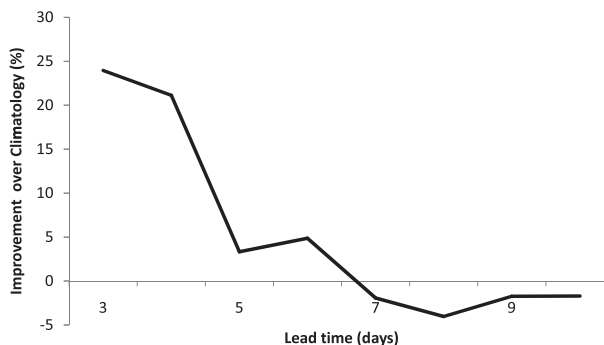


FIG. 14. BSS of probabilistic forecasts of Santa Ana wind conditions. Vertical axis indicates improvement (%) over climatology. Lead time axis starts at day 3. Forecasts are from the CFS model and verification is from the NCEP–DOE reanalysis.

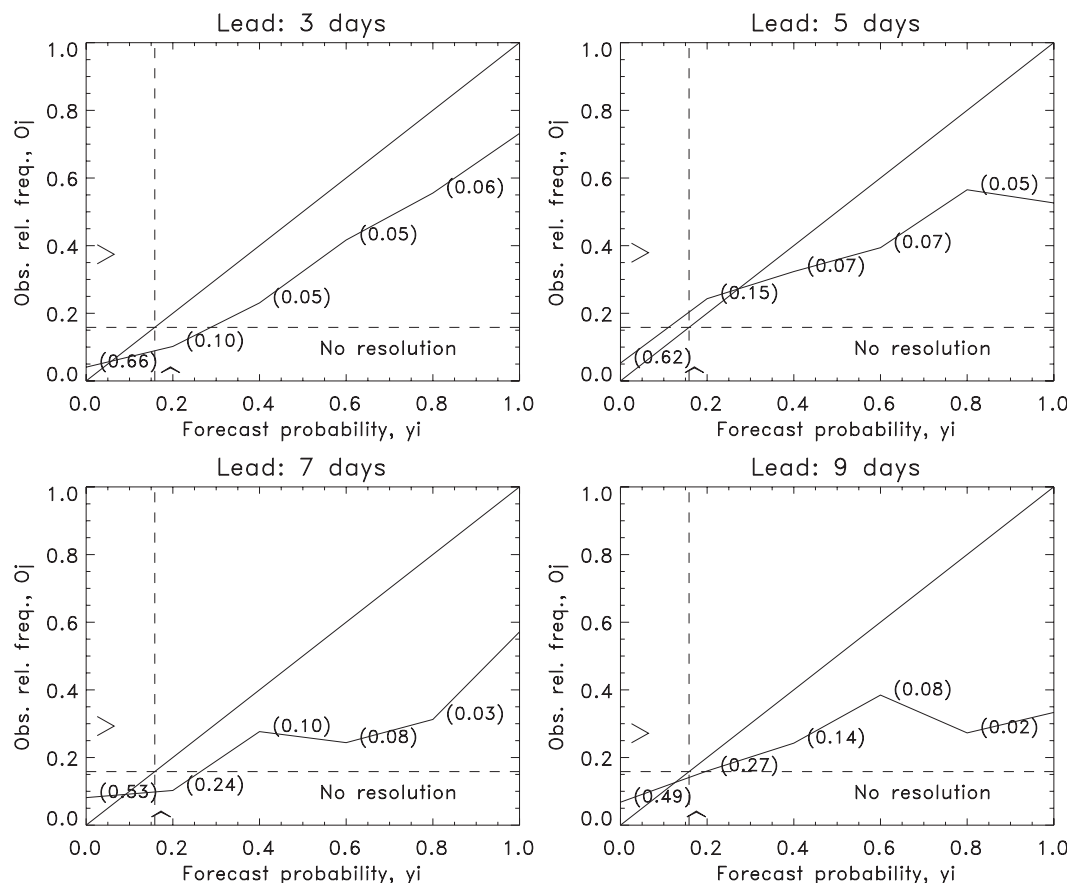


FIG. 15. Attributes diagrams of probabilistic forecasts of Santa Ana wind conditions at lead times of 3, 5, 7, and 9 days. Curves show observed relative frequency of Santa Ana winds conditional on $I = 6$ possible probability forecasts. Numbers in parentheses indicate relative frequency of use of forecast values, $p(y_i)$. The “>” symbols show average frequencies of observations (in the vertical axis) and forecasts (horizontal axis). Solid 1:1 lines indicate perfect calibration. Forecasts are from CFS model and verification from NCEP–DOE reanalysis.

variations and possible mechanisms responsible for trends and low-frequency variations need further study. A climate run of the CFS model showed good agreement with the observed climatological characteristics of SAW conditions and generally small differences (roughly, mean sea level pressure differences ± 1 hPa and mean surface wind differences of 1 m s^{-1} or less), which is an encouraging result for the prospect of forecasting such conditions.

Nonprobabilistic and probabilistic forecasts of synoptic-scale conditions associated with SAW events were derived from NCEP CFS reforecasts. The CFS model exhibits small mean systematic biases in SLP and surface winds in the range of a 1–4-week lead time. Several skill measures indicate that nonprobabilistic forecasts of SAW conditions extend to about a 6–7-day lead time. In contrast, probabilistic forecasts of SAW conditions show less skill and improvements upon climatological forecasts extend to about a 5–6-day lead. The decrease in skill of probabilistic forecasts arises from the design of the

CFS reforecasts, in which the ensemble members were generated by ICs in groups of 5 consecutive days separated by 5 days. A different approach to constituting ensemble members might be needed to produce probabilistic forecasts of synoptic-scale conditions of SAW on lead times of 2–3 weeks.

Evidently, the most important aspect of Santa Ana winds for fire managers is the strong surface winds coupled to high temperatures and low humidity, which are highly conducive to the spread of wildfires. These meteorological aspects were not addressed here because of the low spatial resolution of the NCEP–DOE reanalysis and CFS model. The NARR dataset realistically represents monthly frequencies of SAW occurrences (not shown) and spatial patterns of northeasterly winds over Southern California. The 32-km horizontal grid spacing of NARR, however, is not able to resolve local details associated with SAW, especially its extension over coastal waters and formation of surface wind jets. Nevertheless, the

comprehensive NARR products derived with advanced data assimilation system can be useful to further down-scale atmospheric conditions associated with SAW events. High-resolution dynamical downscaling studies of SAW currently under way will be presented in a future paper.

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