Subseasonal prediction of impactful California winter weather in a hybrid dynamical-statistical framework

Kristen Guirguis[1], Alexander Gershunov[1], Benjamin J. Hatchett[2], Michael J. DeFlorio[1], Aneesh C. Subramanian[3], Rachel Clemesha[1], Luca Delle Monache[1], and F. Martin Ralph[1]

[1]*Scripps Institution of Oceanography, University of California San Diego, La Jolla, California*
[2]*Desert Research Institute, Reno, NV*
[3]*University of Colorado Boulder, Boulder, Colorado*

Corresponding Author: Kristen Guirguis, CW3E, Scripps Institution of Oceanography, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093, Mail Code: 0224, kguirguis@ucsd.edu.

Key points

- A hybrid dynamical-statistical model is developed for 1-4-week forecasts of high impact California winter weather using weather regimes.
- This hybrid framework reduces the number of forecasts available, but the ones issued can be interpreted with higher confidence.
- Skillful subseasonal forecasts extending lead time by 1-4 weeks could improve early warnings and outcomes during extreme weather events.

Abstract

Atmospheric rivers (ARs) and Santa Ana winds (SAWs) are impactful weather events for California communities. Emergency planning efforts and resource management would benefit from extending lead times of skillful prediction for these and other types of extreme weather patterns. Here we describe a methodology for subseasonal prediction of extreme winter weather in California, including ARs, SAWs and temperature extremes. The hybrid approach combines dynamical model and historical information to forecast probabilities of impactful weather outcomes at weeks 1-4 lead. This methodology (i) uses dynamical model information considered most reliable, i.e., planetary/synoptic-scale atmospheric circulation, (ii) filters for dynamical model error/uncertainty at longer lead times, and (iii) increases the sample of likely outcomes by utilizing the full historical record instead of a more limited suite of dynamical forecast model ensemble members. We demonstrate skill above climatology at subseasonal timescales, highlighting potential for use in water, health, land, and fire management decision support.

Plain Text Summary

California winter weather can alternate between very wet conditions from atmospheric rivers making landfall along the Pacific coast to hot, dry, and windy conditions brought by Santa Ana winds blowing in from the Southwest interior. Atmospheric rivers are important for water resources while also causing flooding, whereas Santa Ana winds are often associated with wildfire, especially following prolonged dry periods. Preparing for these types of weather events is important for managing resources and protecting life and property, yet reliable forecasts beyond about 7-10 days remain a challenge. We have developed a new prediction system that combines information about approaching atmospheric weather patterns from weather forecast models along with historical information relating those patterns to impacts over California to predict the likelihood of impactful weather at 1-4 weeks lead time. By extending the window of opportunity to take action, this new approach should aid in resource and emergency planning in water, land, and fire sectors as well as protecting residents through improved warning systems.

1. Introduction

Extremes of California's winter weather variability sway between heavy multiday precipitation from Pacific storms associated with atmospheric rivers (ARs) and dry offshore downslope winds blowing from the elevated continental interior. Drought-busting ARs cause most of the region's floods (Ralph et al. 2006, 2011, Dettinger 2013, Corringham et al. 2019) while downslope winds are often associated with coastal heat waves as well as wildfire and smoke impacts (Hughes and Hall 2010; Abatzoglou et al. 2013; Guzman-Morales et al. 2016; Aguilera et al. 2021, Gershunov et al. 2021, Cayan et al. 2022). Winter heat waves and dry spells accelerate mountain snowmelt (Hatchett et al. 2023), exacerbate drought and, particularly at the densely populated coast, endanger human health (Schwartz et al. 2020, Gershunov et al. 2021). Improved prediction of these types of impactful weather events is of great importance for emergency preparedness and planning to mitigate impacts to society (DeFlorio et al. 2021). Climate change is increasing the likelihood and intensity of extreme weather in California (e.g., Gershunov et al. 2019, 2021, Corringham et al. 2022, Huang and Swain 2022, Michaelis et al. 2022), highlighting the need for improved forecasts across a range of lead times to aid planning and ameliorate outcomes (e.g., DeFlorio et al. 2021; Oakley et al. 2023).

ARs are low-tropospheric jets of water vapor that produce up to 50% of California's annual precipitation (Dettinger et al. 2011, Gershunov et al. 2017). They can be beneficial and hazardous (Ralph et al. 2019); replenishing water supplies, while also causing the most damaging California floods (Corringham et al. 2019, Guirguis et al. 2020, 2021). Santa Ana winds (SAWs) — the downslope winds of Southern California — are characterized by strong, dry, gusty northeasterly-easterly winds that warm by adiabatic compression as they flow over and through the Transverse and Peninsular Ranges down to sea level. SAWs can bring hot or cold temperatures, but the hot variety are associated with Southern California's wildfires (Gershunov et al. 2021, Guirguis et al.

2022). These hot SAWs are increasing in frequency over the historical record raising concerns about future wildfire risk.

Numerical weather prediction has made notable advancements in recent years. Multi-ensemble probabilistic forecasts provide improvements over deterministic forecasts because they account for uncertainty arising from observational error, model limitations, and the chaotic nature of the earth-atmosphere system (Baurer et al. 2015, Palmer et al. 2017). This improvement, along with computational and satellite advances, has led to encouraging progress towards extending forecast skill and lead time. However, the time limit of predictability for high-impact weather events remains limited to about 1-2 weeks (Bauer et al. 2015) and warnings of heat waves or fire weather are typically issued on the order of a week or less.

Skillful prediction of large-scale weather patterns and regime transitions has been demonstrated at leads of a month or longer (Baurer et al. 2015; Gibson et al. 2020; Robertson et al. 2020). This has motivated work to extend forecast lead time by focusing on atmospheric circulation patterns and then inferring associated impacts for a region; leading to new operational forecast products (e.g., Ferranti et al. 2015, DeFlorio et al. 2021). These studies show dynamical models do have some skill at longer lead times in forecasting certain large-scale circulation features, but this skill is not consistent from forecast to forecast. Progress could be made by developing ways of recognizing when a subseaonal forecast is likely to be skillful or less reliable. In absence of dynamical model skill, a forecast could be supplemented or replaced by a statistical forecast. Here, we describe and evaluate a dynamical- statistical hybrid prediction system that uses dynamical model forecasts to predict four key modes of atmospheric variability on subseasonal timescales (1-4 weeks lead), filters for uncertainty and error, and then draws on known relationships between these modes and high-impact West Coast weather to predict the likelihood of impactful weather events.

Winter weather variability in California is largely modulated by four modes of atmospheric variability over the North Pacific Ocean (called the “NP4 modes”, Guirguis et al. 2018, 2020a, 2022), named as the Baja-Pacific (BP), Alaskan-Pacific (AP), Canadian-Pacific (CP) and Offshore-California (OC) modes (Figure 1a). They collectively explain most of the variance (up to 89% in some locations) in mid-tropospheric circulation over a vast region over the North Pacific Ocean and West Coast (Figure S1). Daily interactions between these modes result in reoccurring weather patterns (Figure S2) responsible for much of California’s daily weather variability and extremes, including wildfires, heat waves, and damaging floods (Figure S3, Guirguis et al. 2022a, hereinafter GGR’22). These modes are also influential for California precipitation on seasonal timescales due to their tendency to persist in one phase or another during a season (Guirguis et al. 2020a, hereinafter GGR’20).

Our forecast system uses the circulation regime methodology of GGR’20 and GGR’22 applied to 20 years of multi-ensemble hindcasts from the European Center for Medium-Range Weather Forecasts (ECMWF) model as well as real-time forecasts from water year 2022 (WY2022). We then apply a statistical model that relates these circulation regime-based forecasts to extreme weather over California. Using this dynamical-statistical hybrid approach, we demonstrate skillful probabilistic forecasts of ARs, SAWs, and hot/cold temperature extremes in California at subseasonal (1-4 week) lead times. By filtering out uncertain forecast periods, we improve the accuracy and reliability of the forecasts relative to dynamical model skill without filtering. In this novel approach, we use dynamical model information when it is likely to be reliable, attempt to filter error and uncertainty, and then combine the filtered dynamical model information with a statistical model to forecast an impactful weather event. At shorter lead times (~1 week) the forecast is largely determined by the dynamical model information, whereas at longer lead times (when the dynamical model skill degrades) the statistical information becomes more important. The aim of this work is to provide tools and information for decision support to improve outcomes from extreme weather events.

2. Data

2.1. Time period of study

The focus of this study is extended winter (November-February) spanning 2001-2022.

2.2. Four Key Modes of Atmospheric Variability over the North Pacific Ocean (NP4 modes)

Daily amplitudes of the NP4 modes are from Guirguis et al. (2020b, hereinafter GGR'20b), which was extended through WY2022. These circulation regimes are represented using daily 500 mb geopotential height (Z500) anomalies from NCEP/NCAR 2.5° Global Reanalysis (R1, Kalnay et al. 1996). Anomalies were calculated by fitting and removing annual and semiannual cycles using least-squares regression (Guirguis et al. 2018).

2.3. Atmospheric Rivers (ARs)

ARs landfalling the West Coast are identified using the SIO-R1 catalog of Gershunov et al. (2017), available 1948-present. The methodology uses vertically integrated horizontal vapor transport (IVT) and integrated water vapor (IWV) to identify elongated plumes (>1500 m) of concentrated moisture (IVT>250 kg $m^{-1}s^{-1}$ and IWV>15mm). AR landfalls are identified when a coastal location is within the AR footprint for at least one 6-hourly timestep in a day.

2.4. Santa Ana Winds (SAWs)

Santa Ana winds are identified using the daily Santa Ana Winds Regional Index (SAWRI, Guzman-Morales et al. 2016). This record uses hourly surface winds spanning 65 years (1948-2012) from dynamically downscaled R1 using the California Regional Spectral Model (CaRD10, Kanamitsu and Kanamaru, 2007) and statistically thereafter (Guzman Morales and Gershunov 2019). The methodology identifies SAWs impacting coastal Southern California when northeasterly wind speeds exceed local 75th percentiles.

2.5. Precipitation and Daily Maximum Temperature

Precipitation and daily maximum temperatures (tmax) are from Gridmet (Abatzaglou 2013), available 1979-present at ~4km spatial resolution. Daytime hot (cold) temperature extremes are defined as temperatures above (below) the historical 90th (10th) percentile after removing the seasonal cycle. We focus on three regions: the Central Sierra Nevada (1) for their importance for snow accumulation and water resources, as well as coastal Southern California (2) and the San Francisco Bay area (3) where millions of people are exposed to hazards (Figure S4).

2.6. ECMWF Ensemble Hindcasts

We use global hindcasts of Z500 from the S2S Project database (Vitart et al. 2017) for 2001-2020. We selected one model, the ECMWF model, a state-of-the-art dynamical weather forecast model shown to outperform other models (e.g., Gibson et al. 2020, DeFlorio et al. 2019). Ocean coupling is included in these hindcasts, but sea ice coupling is not. Data were produced with the Integrated Forecast System (IFS). Hindcasts are made twice weekly yielding 34 forecasts per year over the

20-year period (680total), including one control and 10 perturbed ensemble members for lead times out to 46-days. We focus on days 1-30 for this study.

2.7. ECMWF Realtime Forecasts WY2022

We use real-time forecasts of Z500 from the ECMWF during WY2022, produced twice weekly using fifty perturbed ensemble members.

3. Description of the Dynamical-Statistical Hybrid Model

The methodology (Figure 2) uses the best available information about evolving atmospheric circulation from the ECMWF, filters for error and uncertainty, and applies a statistical model to predict the likelihood of an impactful weather event for a region of interest.

3.1. Dynamical Model Input

The dynamical model input consists of ECMWF forecasts of Z500 fields over a domain spanning 20°S-80°N and 120-250°E for each ensemble member and lead time (Figure 2, step 1).

3.2. Post Processing

Anomaly maps are created by removing the seasonal cycle at each grid point (Section 2.2). These anomaly maps are projected onto each of the four NP4 mode EOFs (e.g., GGR'20) to calculate the forecast amplitude of the BP, AP, CP, and OC modes for each ensemble member and lead time (Figure 2, step 2). These amplitudes provide information about the forecasted strength and position of ridges and troughs over the North Pacific and along the West Coast (c.f. Figure 1a). There is generally strong agreement among ensemble members about the phase of the NP4 modes at short lead times (on the order of 7-10 days), but uncertainty can become prominent at longer lead times (e.g., see growing dispersion in mode amplitudes shown in Figure 2, step 2).

3.3. Consensus Filtering

We filter for error and uncertainty using a consensus threshold of 70% (Figure 2, step 3). That is, if 70% of ensemble members agree about the phase of a given mode, then we assume this information is reliable. If this criterion is not met, then we consider the mode phase to be uncertain. The choice of 70% is based on exploratory analysis demonstrating that a lower threshold (50-60%) leads to lower skill (Figure S5a) and a higher threshold (80%) is too rarely met in weeks 3-4 (Figure S5b). In Figure 2, step 3, the green and yellow shading indicates where the 70% consensus criterion is met for each mode, with the remaining forecasts classified as uncertain. In physical terms, this means at least 70% of ensemble members agree that a ridge or trough will persist or develop over a certain location at a certain lead time. In this example, the Alaska-Pacific mode is forecast to become negative around day 7 and then persist in that phase for over two weeks. The negative phase of this mode is associated with a ridge over the Gulf of Alaska (c.f. Figure 1a). Knowledge about a developing persistent ridge over the Alaskan Gulf is useful information for West Coast weather prediction (Gibson et al. 2020, GGR'20). This forecast also indicates long-lead confidence about the Baja-Pacific mode transitioning into the negative phase, and the Offshore-California mode remaining negative into week 3. The model is less confident about the phase of the Canadian-Pacific mode beyond day 12.

3.4. Input to the Statistical Model

The filtered dynamical model information is used as input into the statistical model. For a given forecast and lead time, each of the BP, AP, CP, and OC modes can be positive, negative, or unknown (Figure 2, step 4). We track the error in these dynamical NP4 phase forecasts (seen as a red "x" for the CP mode in days 23-24) for the skill assessment. In this example, most of the remaining forecast information (after filtering) is correct, albeit with much uncertainty at longer lead times.

3.5. Statistical Model

A conditional probability model is used to predict the probability of a weather impact, X, over different regions of the West Coast. Specifically, the model is represented as

$$P(X|BP, AP, CP, OC) = \frac{P(X, BP, AP, CP, OC)}{P(BP, AP, CP, OC)} \qquad \textit{Eqn (1)}$$

Where P(X) is the historical conditional probability of X, and BP, AP, CP, and OC represent the phase of the four NP4 modes as forecast by the dynamical model, which (from Section 3.4) can be positive, negative, or unknown. The weather impact X can be any weather outcome that is driven by atmospheric circulation in this region. To determine P(X), we use the NP4 dataset of GGR'20b to identify days in the historical record when the same mode phase combination occurred, and then compile observed outcomes on those days to quantify the historical probability of different weather impacts for different locations. The statistical model will vary in complexity for each forecast and lead time. Some forecasts will have 4 modes available as predictors while other forecasts will only use 3, 2, or 1 mode due to uncertainty in the remaining modes. Additional detail is provided in the supplement (Text S1, Figure S6). We focus on predicting AR landfalls at different West Coast latitudes (32.5-55°N), SAWs in Southern California, and hot/cold temperature extremes over the Sierra Nevada, Coastal Southern California, and the San Francisco Bay area.

3.6. Hindcast Skill Assessment Methodology

For the hindcast skill assessment, we bin the probabilistic forecasts P(X) into three categories: "low probability", "above normal probability", and "much above normal probability", where the upper/lower bounds for each category were determined relative to local climatology. The definitions for the three categories are: <50% of climatology, 120-160% of climatology, and >160% of climatology, respectively (Figure S7).

To assess skill, we compare the forecast conditional probability P(X) with the observed frequency for each type of event. A "low probability" forecast is considered skillful if the observed frequency of extreme temperatures, SAWs, or ARs following these forecasts is low relative to climatology (falls below the 10^{th} percentile of the resampled distribution). The "above normal" and "much above normal" forecasts are considered skillful if the observed frequency is higher than the 90^{th} percentile.

4. Realtime Skill Assessment: Forecasts from WY2022

Figure 1 shows real-time forecast information for WY2022. Verified ECMWF forecasts of the NP4 modes after filtering are shown in Figure 1b. Probabilistic AR forecasts for different regions along the coast are shown in Figure 1d, with the regions defined in Figure 1c. Here, the NP4 mode phase information shown in Figure 1b is used as predictors for the AR forecasts shown in Figure 1d (i.e., using equation 1 where X is an AR landfall at a coastal region).

As a first skill measure, we evaluate if the phases of the NP4 modes (Figure 1b) were accurately predicted by the ECMWF model, and if the consensus filtering methodology was effective at removing error (i.e., accuracy of the information used as input to the statistical model). In Figure 1b, most of the information in weeks 1-2 is correct (red/blue shading) but at longer lead times, an increasing number of forecasts are classified as uncertain (gray shading), and by week 4 most of the dynamical model information has been filtered due to uncertainty, although useful information remains in week 4 for some modes. The information that remains after filtering is overwhelmingly correct (91%) with only 9% error. Figure S8a examines what the forecasts would look like if the NP4 mode phases were calculated from the ensemble mean without filtering. Figure S8b shows the forecasts issued using the ensemble mean reference model, but which were removed by the consensus filtering method. Of the forecasts removed by filtering (Figure S8b), 41% would have been incorrect. Unfortunately, 59% of accurate data was also eliminated by filtering, but this is preferable over retaining many incorrect forecasts. To summarize, applying uncertainty filtering in this hybrid dynamical-statistical framework decreases the number of incorrect forecasts obtained by the raw dynamical model output by ~32%. Although the number of forecasts issued in this hybrid framework are lower, the ones that are issued can be interpreted with much higher confidence and reliability.

In WY2022, the dynamical model skillfully predicted important atmospheric circulation features in week 3 and occasionally into week 4 (Figure 1b). The ECMWF skillfully predicted the negative phase of the Alaskan-Pacific mode 3-4 weeks in advance during Dec-Feb, which in physical terms is characterized by a ridge over the Gulf of Alaska (c.f. Figure 1a). In December, the positive phase of the Canadian-Pacific mode was skillfully predicted at 3-4 weeks lead time, which is associated with a trough over British Columbia. There was also skill in forecasting the negative phase of the Offshore-California mode in week 3 during January and weeks 3-4 during February, which is associated with a ridge offshore from California. This persistent ridge during January-February is responsible for the extremely dry conditions that occurred in California and contributed to the continuation of the drought during WY2022 (Figure S9).

Figure 1d shows real-time AR forecasts from WY2022 for four coastal regions shown in Figure 1c. In Figure 1d, the top panels show the observed coastal AR IVT from Nov 1-Feb 28 and the bottom panels show the AR landfall probability forecasts using the hybrid model. The forecasts represent the observed AR landfall behavior that occurred in WY2022 very well with 3 weeks lead, and with some skill seen at 4 weeks. In general, above (below) normal AR forecasts were issued for days when AR landfalls occurred (did not occur). For example, the mid-winter dry spell during December in British Columbia was correctly forecast, along with the wet periods that preceded and followed. Also notable are wet December conditions followed by a dry January-February along the US West coast, which was well represented in the forecasts for the Pacific Northwest and Northern/Southern California.

5. Hindcast Skill Assessment

Figure 3 shows the skill assessment for 20 years of hindcast data for the NP4 modes (Figure 3a) and impactful weather events (Figures 3b-d).

5.1 NP4 Modes

The hindcast skill assessment for the NP4 modes, after filtering, is shown in Figure 3a. For lead times of 1-2 weeks, the hindcasts are significantly skillful for all seasons (i.e., the full distribution of seasonal forecasts lies above the 95% significance line). In week 3, most seasons exhibit significant skill. In week 4 most seasons remain skillful, but this is less consistent where the first quartile (Q1) often falls below the significance line, meaning that more than 25% of forecasts are in error. In general, the forecasts of the NP4 modes, after filtering, show skill in weeks 1-4.

5.2 Hot and Cold Temperature Extremes

Figure 3b shows hindcast skill for heat extremes. The hybrid model forecasts are significantly skillful at weeks 1-3 lead for all regions and forecast categories. In general, “low probability” forecasts are followed by a low frequency of extreme heat occurrence, whereas “above normal” and “much above normal” forecasts are followed by a much higher frequency of occurrence. These forecasts are statistically skillful at the 90% level.

There is evidence of skill in predicting extreme out-of-season heat at 4 weeks lead, but the skill is not as reliable (i.e., more data points fall within the 10^{th}-90^{th} percentiles of the resampled distribution). For Coastal Southern California and San Francisco Bay, the “low probability” forecasts are not skillful at 4 weeks lead, suggesting a tendency to underestimate heat wave occurrence. These regions also show inconsistent skill in week 4 forecasts for the other two categories. Forecasts for the Central Sierra Nevada show significant skill at 4 weeks lead for all forecast categories.

Figure S10 shows the skill assessment for cold extremes. The forecasts for weeks 1-3 are generally skillful for the three regions and forecast categories. However, skill becomes less reliable in weeks 4, especially the “below normal category. In general, extreme heat appears more skillfully predictable than extreme cold. A possibility is that transient cold fronts are less predictable than stationary highs, however more research is needed to identify the cause of these skill differences.

5.3. Santa Ana Winds

Figure 3c shows hindcast skill for Santa Ana winds over Southern California. The results are similar as for heat extremes, where the outcomes for the three forecast categories are well separated and significantly skillful at weeks 1-3 lead and in week 4 for some forecast categories. There is a drop in skill for the "above normal category" at 3 weeks lead, where SAWs do not materialize as often as forecast, as seen by many orange data points falling below the 90th percentile significance line. This drop in skill is not evident for the highest probability category, suggesting that higher confidence might lead to higher skill.

5.4. Atmospheric Rivers

Figure 3d shows hindcast skill for AR landfalls at different coastal latitudes. The hybrid forecasts are skillful for most locations at weeks 1-3 lead. The "below normal" forecasts are followed by a low frequency of AR landfalls while the "above normal" and "much above normal" forecasts are followed by an elevated frequency of AR landfalls, and these results generally show significant skill at weeks 1-3 lead. At week 4, the observed AR frequency corresponding to the different forecast categories is generally correct with respect to climatology. However, the skill is not statistically significant across latitudes, except for the "much above normal" category, which shows significant skill over latitudes 35-42 °N (much of coastal California). Overall, these results are encouraging for predicting AR landfalls along the coast on subseasonal timescales.

6. Discussion

We have described and evaluated a new statistical-dynamical hybrid model, which produces skillful probabilistic forecasts of temperature extremes, Santa Ana winds, and landfalling ARs over California at subseasonal timescales. The model is skillful in weeks 1-3 for each impact and region studied. Week 4 also shows skill, though the skill is not consistent among all variables and forecast categories.

Because we use a hybrid approach, the potential skill is not strictly limited by the dynamical weather forecast, and near-future improvements are possible through continued development of the statistical model. For example, signals from lower frequency climate teleconnections could be incorporated at longer lead times when the dynamical model is uncertain. Impacts of climate-scale teleconnections on offshore atmospheric ridges (Gibson et al. 2020a) as well as the NP4 modes (GGR'20) have been identified, and such relationships could be incorporated to extend skill and lead time using this hybrid approach.

We focused on four impact types (hot/cold temperature extremes, SAWs, and ARs). However, other applications are possible including hot/cold temperature anomalies more generally, conditions driving mid-winter snowmelt (Hatchett et al. 2023), high snow level storms (Shulgina et al. 2023) with rain-on-snow (Heggli et al. 2022), and other decision-specific variables not represented in dynamical forecasts. The offshore wind forecasts — essential ingredients for Southern California's wildfires — focused on Santa Ana winds, which were amenable to this analysis given the long SAW catalog of Guzman-Morales et al. (2019). Related applications could include Diablo and Sundowner winds of Northern and Central California; however the seasonality of these winds requires an extension of the methodology into earlier fall and later spring (Abatzoglou et al. 2020). Identifying relationships between the GGR'22 weather regimes and observed live/dead fuel moisture could inform development of long-lead fire hazard models and advanced warning systems using this hybrid approach.

Predictability of extreme precipitation in a probabilistic sense could also be explored. This is especially important as both extreme winter precipitation and winter wildfires become more common (Gershunov et al. 2019, Cayan et al. 2022), raising the possibility of compound extreme events such as short-duration high-intensity rainfall, which can cause devastating post-fire debris flows (Oakley et al. 2017, 2018a) and landslides (Rengers et al. 2020, Oakley et al. 2018b), rain-on-snow flooding (Haleakala et al. 2023), as well as other precipitation patterns driving mass movements such as avalanches (Hatchett et al. 2017). Improving lead time to prepare for these types of events and likelihood of occurrence is crucial to prevent loss of life and mitigate damage to property (Oakley et al. 2023). This approach could be applied in climate change studies, where changes to atmospheric circulation identified in global climate models along with thermodynamic responses could be linked to future impacts (Michaelis et al. 2023; Rhoades et al. 2023). We envision these results and future updates will form the basis for real-time forecast tools with possible applications for early warning systems and decision support across many sectors including water resources, public health, land, and fire management in a varying and changing climate.

Open Research

The NP4 dataset is available at https://doi.org/10.6075/J0154FJJ. The Santa Ana winds regional index and the SIO-R1 AR catalog are available at https://weclima.ucsd.edu/data-products/. The temperature gridMET dataset is available at https://www.climatologylab.org/gridmet.html.

NCEP/NCAR reanalysis is available at https://psl.noaa.gov/data/reanalysis/reanalysis.shtml. The EMWF hindcast data are available at https://www.ecmwf.int/en/research/projects/s2s.

Acknowledgements

This research was funded by the U.S. Department of the Interior via the Bureau of Reclamation (USBR- R15AC00003) and the California Department of Water Resources (4600010378 UCOP2-11). This study also contributes to the Regional Integrated Sciences and Assessments (RISA) California–Nevada Climate Applications Program, the International Research Applications Program of the National Oceanic and Atmospheric Administration (NA17OAR4310284), the Southwest Climate Adaptation Science Center (G18AC00320), and the National Science Foundation (NSF CoPe award no. 2209058).

References:

Abatzoglou, J. T., 2013: Development of gridded surface meteorological data for ecological applications and modelling. *Int. J. Climatol*., **33**, 121–131.

Abatzoglou, J. T., Hatchett, B. J., Fox-Hughes, P., Gershunov, A., & Nauslar, N. J. (2021). Global climatology of synoptically-forced downslope winds. *International Journal of Climatology*, **41**(1), 31– 50. https://doi.org/10.1002/joc.6607

Bauer, P., Thorpe, A. & Brunet, G., 2015: The quiet revolution of numerical weather prediction. *Nature.* **525**, 47–55. https://doi.org/10.1038/nature14956

Dettinger, M. D., F. M. Ralph, T. Das, P. J. Neiman, and D. R. Cayan, 2011: Atmospheric rivers, floods and the water resources of California. *Water*, **3**, 445–478

Cayan, D.R., L. DeHaan, A. Gershunov, J. Guzman Morales, J.E. Keeley, J Mumford and A.D. Syphard, 2022: Autumn precipitation – the competition with Santa Ana winds in determining fire outcomes in Southern California. *Int. J. Wildland Fire*. **31**(11), 1056–1067. https://doi.org/10.1071/WF22065

Corringham, T.W., F.M. Ralph, A. Gershunov, D.R. Cayan, and C.A. Talbot, 2019: Atmospheric Rivers drive flood damages in the western United States. *Sci. Adv.*, **5**, 12, eaax4631, DOI: 10.1126/sciadv.aax4631

Corringham, T.W., McCarthy, J., Shulgina, T., *et al.,* (2022): Climate change contributions to future atmospheric river flood damages in the western United States. *Sci Rep.* **12**, 13747. https://doi.org/10.1038/s41598-022-15474-2

Daly, C., R.P. Neilson, and D.L. Phillips, 1994: A statistical-topographic model for mapping climatological precipitation over mountainous terrain. *J. of App. Meteorol*. **33**(2): 140-158.

DeFlorio, M. J., D.E. Waliser, B. Guan, D.A. Lavers, F.M. Ralph, and F.Vitart, 2018: Global assessment of atmospheric river prediction skill, *J. Hydrometeorol.*, ***19***(2), 409-426.

DeFlorio, M. J., Waliser, D. E., Ralph, F. M., Guan, B., Goodman, A., Gibson, P. B., et al., 2019: Experimental Subseasonal-to-Seasonal (S2S) Forecasting of Atmospheric Rivers Over the Western United States. *J. Geophys. Res. Atm.,* **124**, 11242– 11265.

DeFlorio, M. J., F. M. Ralph, D. E. Waliser, J. Jones, and M. L. Anderson. 2021: Better subseasonal-to-seasonal forecasts for water management, *EOS, **102**,* https://doi.org/10.1029/2021EO159749

Dettinger MD, 2013: Atmospheric Rivers as Drought Busters on the U.S. West Coast. *J Hydrometeorol.* **14**, 1721–1732.

Gershunov, A., J. Guzman Morales, B. Hatchett, R. Aguilera, T. Shulgina, K. Guirguis, J. Abatzoglou, D. Cayan, D. Pierce, P. Williams, I. Small, R. Clemesha, L. Schwarz, T. Benmarhnia, A. Tardy, 2021: Hot and cold flavors of southern California's Santa Ana winds: Their causes, trends, and links with wildfire. *Clim. Dyn*. **57**, 2233-2248.

Gershunov, A., T. Shulgina, F. M. Ralph, D. Lavers, and J. J. Rutz, 2017: Assessing the climate-scale variability of Atmospheric Rivers affecting the west coast of North America, *Geophys. Res. Lett*. **44**, 7900-7908.

Gershunov, A., T.M. Shulgina, R.E.S. Clemesha, K. Guirguis, D.W. Pierce, M.D. Dettinger, D.A. Lavers, D.R. Cayan, S.D. Polade, J. Kalansky and F.M. Ralph, 2019: Precipitation regime change in Western North America: The role of Atmospheric Rivers. Nature Scientific Reports, **9**, 9944.

Gibson, P.B., D.E. Waliser, B. Guan, M.J. DeFlorio, F.M. Ralph, and D.L. Swain, 2020a: Ridging associated with drought across the Western and Southwestern United States: characteristics, trends and predictability sources. *J. Climate*, **33**, 2485-2508.

Gibson, P. B., Waliser, D. E., Goodman, A., DeFlorio, M. J., Delle Monache, L., & Molod, A., 2020b: Subseasonal-to-seasonal hindcast skill assessment of ridging events related to drought over the Western United States. *J. of Geophys. Res*. Atm., **125**, e2020JD033655.

Guirguis, K., Gershunov, A., Clemesha, R. E. S., Shulgina, T., Subramanian, A. C., & Ralph, F. M., 2018: Circulation drivers of atmospheric rivers at the North American West Coast. *Geophys. Res. Lett.*, ***45***, 12–576.

Guirguis, K., A. Gershunov, M.J. DeFlorio, T. Shulgina, L. Delle Monache, A.C. Subramanian, T.W. Corringham, and F. M. Ralph, 2020a: Four atmospheric circulation regimes over the

North Pacific and their relationship to California precipitation on daily to seasonal timescales. *Geophys. Res. Lett.,* **47**, e2020GL087609.

Guirguis, K., Gershunov, A., DeFlorio, M. J., Shulgina, T., Delle Monache, L., Subramanian, A. C., et al., 2020b: Data from: Four atmospheric circulation regimes over the North Pacific and their relationship to California precipitation on daily to seasonal timescales. *UC San Diego Library Digital Collections*, https://doi.org/10.6075/J0154FJJ

Guirguis, K., Gershunov, A., Hatchett, B. et al., 2022: Winter wet–dry weather patterns driving atmospheric rivers and Santa Ana winds provide evidence for increasing wildfire hazard in California. *Clim. Dyn*., **60**, 1729–1749.

Guzman Morales, J., A. Gershunov, J. Theiss, H. Li and D.R. Cayan, 2016: Santa Ana Winds of southern California: Their climatology, extremes, and behavior spanning six and a half decades. *Geophys. Res. Lett.*, **43**, 2827– 2834.

Guzman Morales, J. and A. Gershunov, 2019: Climate change suppresses Santa Ana Winds of Southern California and sharpens their seasonality. *Geophys. Res. Lett.*, **46**, 2772– 2780.

Haleakala, K., W.T. Brandt, B.J. Hatchett, D. Li, D.P. Lettenmaier, and M. Gebremichael, 2022: Watershed memory amplified the Oroville rain-on-snow flood of February 2017, *PNAS Nexus*, **2**, 1-15.

Hatchett, B. J., S. Burak, J. J. Rutz, N. S. Oakley, E. H. Bair, and M. L. Kaplan, 2017: Avalanche Fatalities during Atmospheric River Events in the Western United States. *J. Hydrometeor.*, **18**, 1359–1374.

Hatchett, B. J., Koshkin, A. L., Guirguis, K., Rittger, K., Nolin, A. W., Heggli, A., et al., 2023: Midwinter dry spells amplify post-fire snowpack decline. *Geophys. Res. Lett.*, **50**, e2022GL101235.

Heggli, A., Hatchett, B., Schwartz, A., Bardsley, T., & Hand, E. (2022). Toward snowpack runoff decision support. *IScience*, **25**(5), 104240. https://doi.org/10.1016/j.isci.2022.104240

Huang, X. and D. Swain, 2022: Climate change is increasing the risk of a California megafloood., *Sci. Adv*. **8**, eabq0995.

Hughes, M., & Hall, A., 2010: Local and synoptic mechanisms causing Southern California's Santa Ana winds. *Clim. Dyn.*, **34**, 847–857.

Kalnay, E., et al., 1996: The NCEP/NCAR 40-year reanalysis project, *Bull. Am. Meteorol. Soc*., **77**, 437–471.

Kanamaru, H., & Kanamitsu, M., 2007: Fifty-Seven-Year California Reanalysis Downscaling at 10 km (CaRD10). Part II: Comparison with North American Regional Reanalysis, *Journal of Climate*, ***20***, 5572-5592.

Mariotti, A., et al., 2020: Windows of Opportunity for Skillful Forecasts Subseasonal to Seasonal and Beyond. *Bull. Am. Meteorol. Soc.,* **101**, E608-E625.

Michaelis, A. C., Gershunov, A., Weyant, A., Fish, M. A., Shulgina, T., & Ralph, F. M., 2022: Atmospheric river precipitation enhanced by climate change: A case study of the storm that contributed to California's Oroville Dam crisis. *Earth's Future*, **10**, e2021EF002537.

Oakley, N.S., Lancaster, J.T., Kaplan, M.L., and Ralph F.M*., 2017:* Synoptic conditions associated with cool season post-fire debris flows in the Transverse Ranges of southern California. *Nat Hazards* **88,** 327–354.

Oakley, N., J. Cannon, F., Munroe, R., Lancaster J., Gomberg D., and Ralph F.M., 2018a: Brief communication: Meterological and climatological conditions associated with the 9 January 2018 post-fire debris flows in Montecito and Carppinteria, California, USA. *Nat. Hazards Earth Syst. Sci., **18**, 3037-3043.*

Oakley, N. S., J. T. Lancaster, B. J. Hatchett, J. Stock, F. M. Ralph, S. Roj, and S. Lukashov, 2018b: A 22-Year Climatology of Cool Season Hourly Precipitation Thresholds Conducive to Shallow Landslides in California. *Earth Interact.*, **22**, 1–35.

Oakley, N. S., and Coauthors, 2023: Toward probabilistic post-fire debris-flow hazard decision support. *Bull. Amer. Meteor. Soc.*, https://doi.org/10.1175/BAMS-D-22-0188.1, in press.

Palmer, T., 2017: The primacy of doubt: Evolution of numerical weather prediction from determinism to probability, J. Adv. Model. Earth Syst., **9**, 730– 734.

Rengers, F.K., McGuire, L.A., Oakley, N.S. *et al., 2020:* Landslides after wildfire: initiation, magnitude, and mobility. *Landslides* **17**, 2631–2641.

Rhoades, A.M., Zarzycki, C.M., Inda Díaz, H.A., et al., 2023: Recreating the California New Year's flood event of 1997 in a regionally refined Earth system model. *ESS Open Archive.*

Robertson, A. W., Vigaud, N., Yuan, J., & Tippett, M. K., 2020: Toward Identifying Subseasonal Forecasts of Opportunity Using North American Weather Regimes, *Monthly Weather Review*, ***148***, 1861-1875.

Schwarz L., B.J. Malig, J. Guzman Morales, K. Guirguis, A. Gershunov, R. Basu and T. Benmarhnia, 2020: The health burden of fall, winter and spring heat waves in Southern California and contribution of Santa Ana Winds. *Env. Res. Lett.* **15**, 054017.

Shulgina, T., Gershunov, A., Hatchett, B.J. *et al.* Observed and projected changes in snow accumulation and snowline in California's snowy mountains. *Clim Dyn* (2023). https://doi.org/10.1007/s00382-023-06776-w

Vitart, F., and Coauthors, 2017: The Subseasonal to Seasonal (S2S) Prediction project database. *Bull. Amer. Meteor. Soc.*, **98**, 163–173.

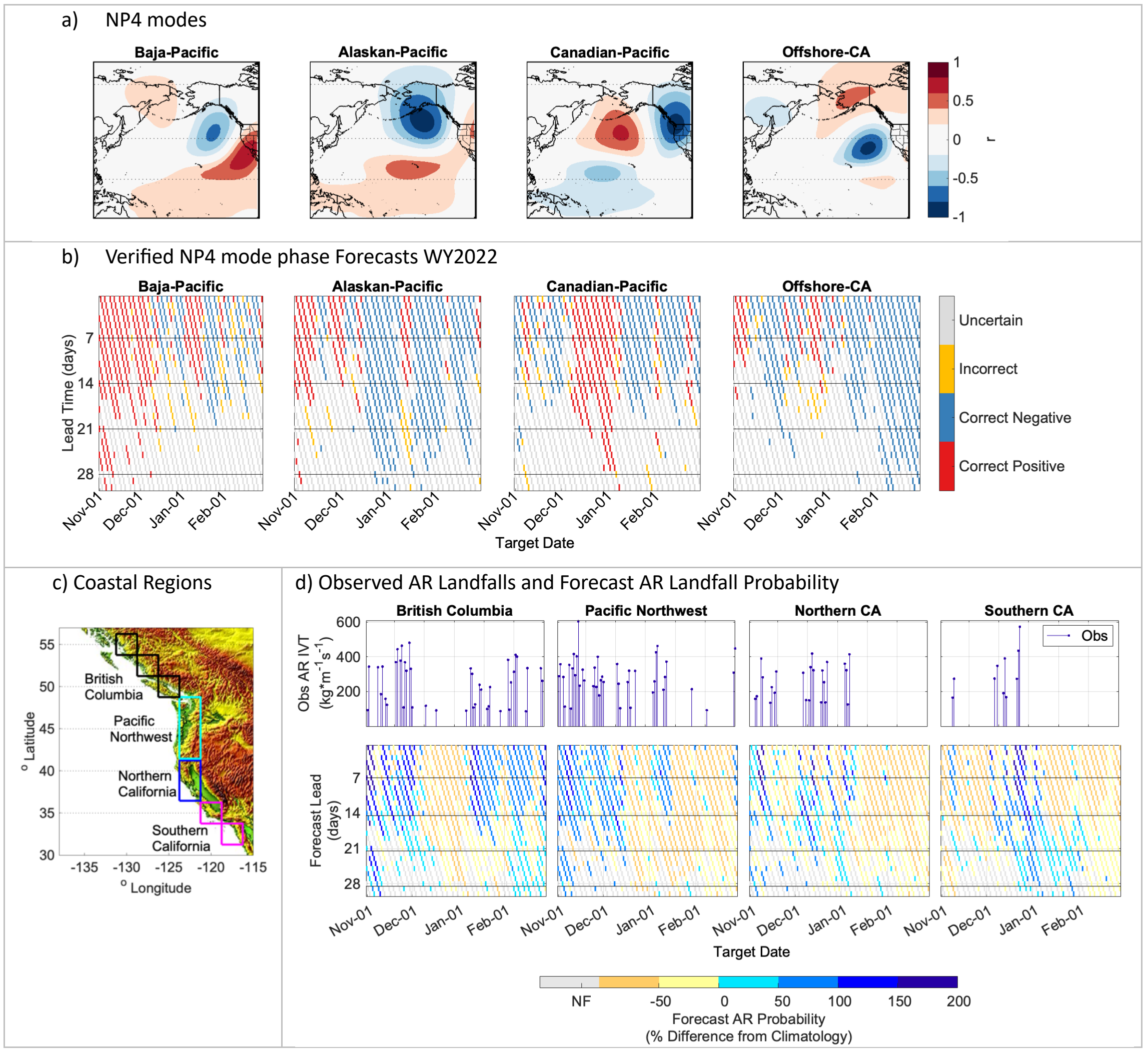

Figure 1. (a) Positive phase of the NP4 modes shown in units of correlation (r) between each mode and the raw Z500 data. (b) Validated real-time forecasts of the NP4 mode phase from WY2022, where each individual forecast is displayed on a diagonal line, the x-axis gives the target date from 1Nov-28Feb, the y-axis gives the lead time from 1-30 days, red (blue) shading indicates that a mode was correctly forecast to be in the positive (negative) phase, yellow shows forecast error, gray shows when forecasts were classified as uncertain. (c) Map showing four West Coast regions. (d) Observed and forecast AR behavior during WY2022 for the four regions shown in (c), where the top four panels (blue stem plots) show regionally averaged observed daily AR IVT during WY2022, the bottom four panels show the hybrid forecasts for each region at different lead times,

where each forecast is shown on a diagonal line, the x-axis gives the target date, the y-axis gives lead time, blue indicates above normal AR probability forecasts (wet), yellow/orange shows low probability forecasts (dry), gray indicates uncertainty (no forecast, NF).

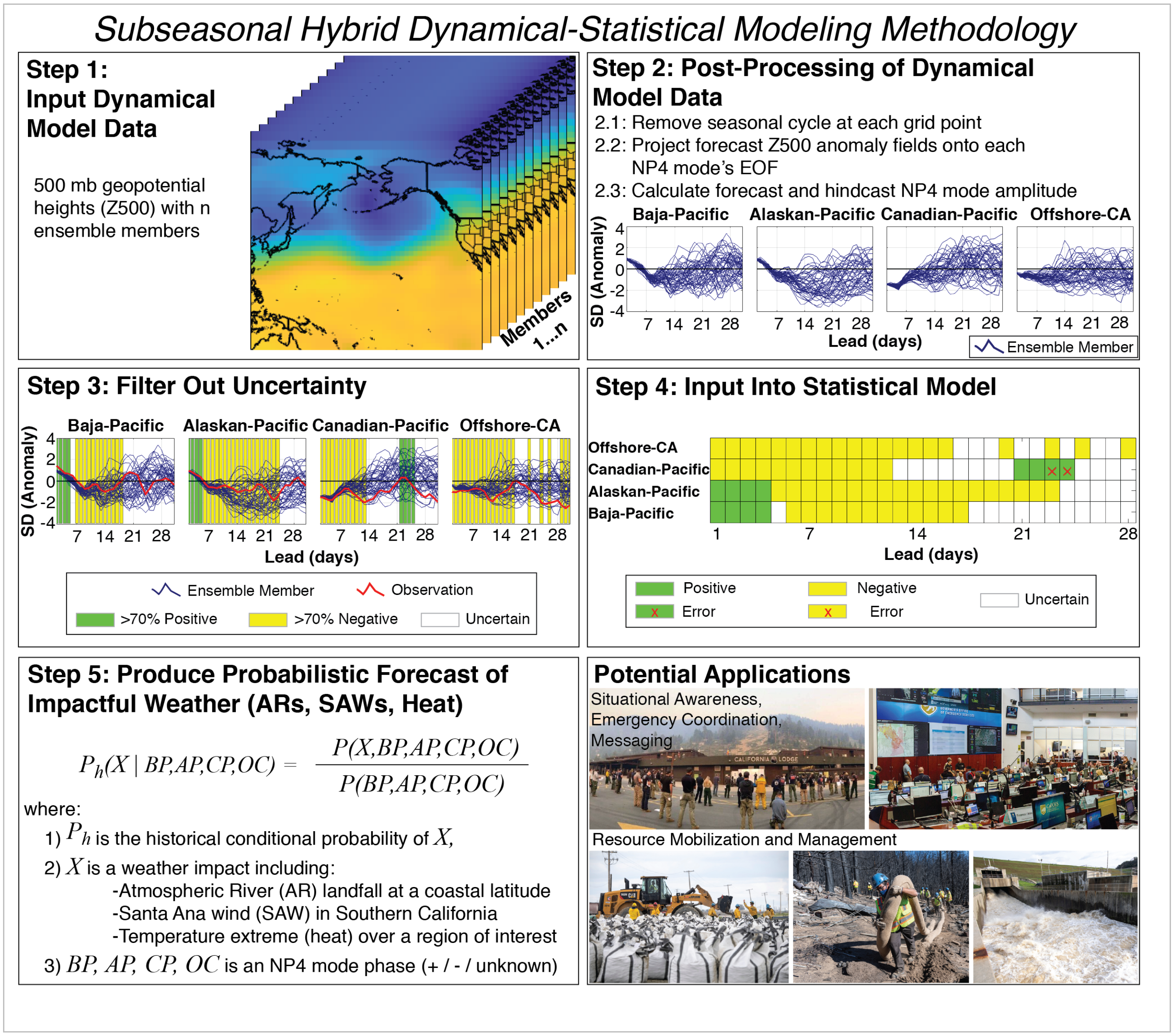

Figure 2. Description of the statistical-dynamical hybrid model. Step 1 describes the dynamical model input. Step 2 illustrates postprocessing, specifically the NP4 mode amplitudes (units of standard deviations) as calculated from Z500 forecasts from 50 ensemble members for 1-30 days lead. Step 3 shows consensus filtering where green (yellow) indicates >70% of ensemble members agree that the mode will be positive (negative), white indicates uncertainty, and the red line shows observations. Step 4 shows the input into the statistical model, where each mode is input as

positive, negative, or unknown/uncertain, and the red “x” shows error relative to observations. Step 5 describes the statistical model.

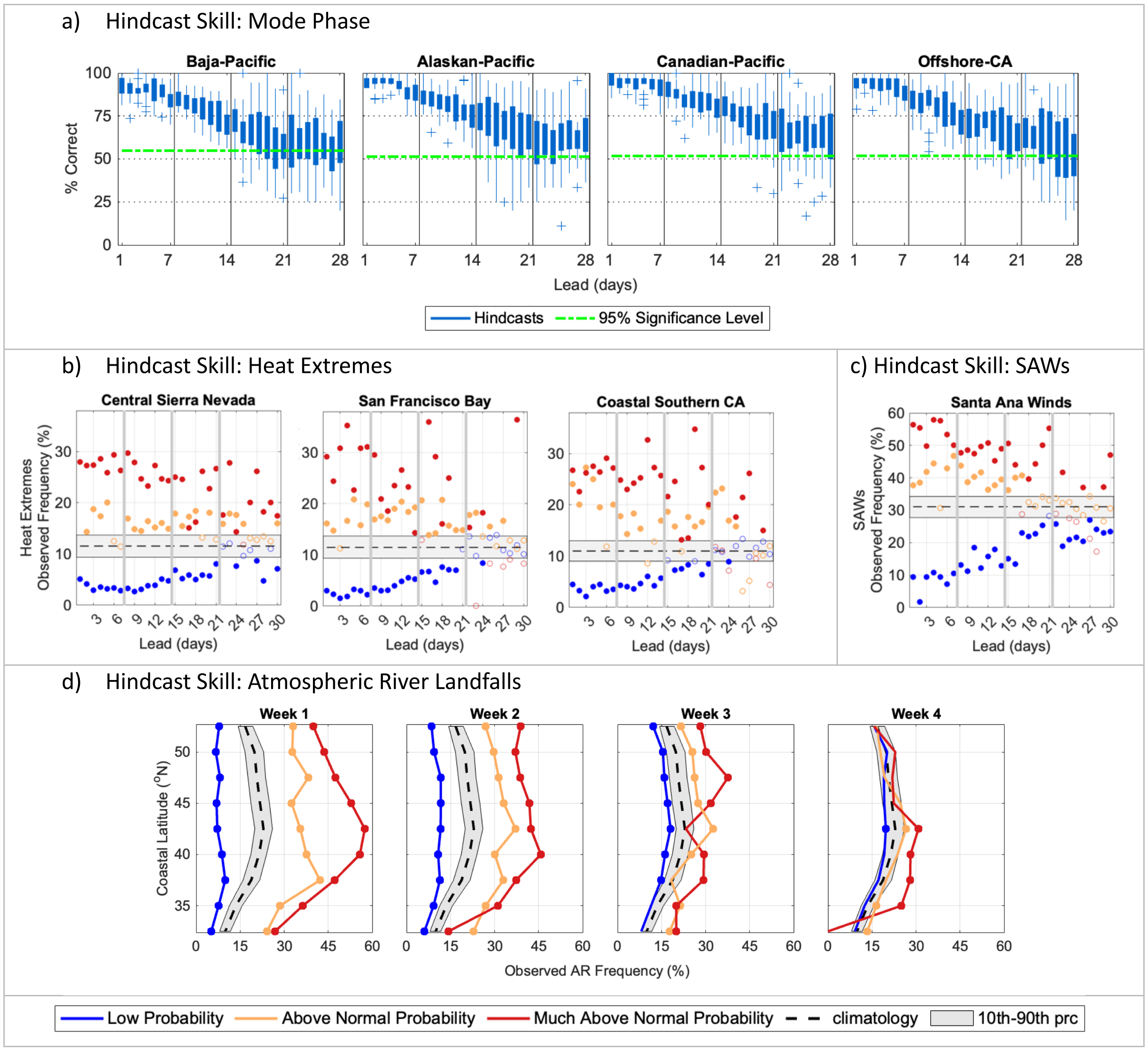

Figure 3. (a) Hindcast skill assessment of the NP4 mode phase, after filtering, where the y-axis gives the percent of forecasts in a season that were correct, the x-axis shows lead time, the boxes include datapoints falling within the interquartile range with lines extending to the 10^{th}-90^{th} percentiles, and the green line shows the 95% significance level. (b-c) Hindcast skill assessment of heat waves and SAWS, respectively, where the y-axis shows observed event frequency following three forecast categories: low (blue), above normal (orange), and much above normal (red) probability. (d) Hindcast skill assessment of AR landfalls at different coastal latitudes (y-axis) shown at the weekly resolution. The gray shaded area in b-d gives the 10^{th}-90^{th} percentiles

of the resampled distribution, and the dashed black line shows climatology. Filled markers indicate statistically significant skill (90% level).